Residential Segregation in Urban India*

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September 13, 2019

Abstract

Using new administrative data from 3000 cities and over 100,000 urban neighborhoods, we study residential segregation in urban India. We focus on two historically marginalized groups: Scheduled Castes/Scheduled Tribes (SC/STs) and Muslims. On average, both groups are concentrated in poorer cities, but Muslims much more so. Cities with more Muslims are characterized by worse access to schools, doctors and public hospitals, while cities with more SC/STs have *better* access. Within cities, lower consumption and access to public goods characterize both SC/ST and Muslim neighborhoods. The extent of segregation in India is similar to that in U.S. cities. Cities segregated along religious lines are also segregated along caste lines. In contrast with the U.S., cities with fewer minorities are more segregated. Caste segregation is associated with worse economic outcomes for *both* SC/STs and non-SC/STs, but the latter to a lesser extent. SC/STs have worse access to public goods in more segregated cities. Younger cities are less segregated than older cities by caste but not religion, suggesting that caste may be decreasingly salient in urban areas.

*We are grateful for stellar research assistance from Ryu Matsuura and Alison Campion, and for helpful discussions in seminars at the Center for Policy Research, Centre de Sciences Humaines, and IDinsight in Delhi. We expect equally constructive feedback from the Harvard Urban Development Workshop and the 2019 Fall NBER/BREAD Conference.

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1 Introduction

A large literature has documented how the characteristics of neighborhoods predict and affect socioeconomic outcomes at all ages in the United States and other developed countries (Kling et al. (2007); Chetty et al. (2015); Chetty and Hendren (2016)). In particular, the residential segregation of U.S. blacks is viewed as one of the major inhibitors of equality of opportunity and has been an important policy issue for decades (Ananat and Washington (2009); Boustan (2011); Cutler et al. (2008)). However, there has been very little systematic documentation or empirical analysis of residential patterns in the rapidly growing cities in poorer countries. As these countries become more and more urban, the characteristics of urban neighborhoods will become increasingly important as determinants of opportunity and overall economic development.

In this paper, we document some of the settlement patterns and socioeconomic outcomes of historically marginalized groups in Indian cities. We focus in particular on two groups that have historically experienced low socioeconomic status and discrimination: Scheduled Castes and Tribes (SC/STs) and Muslims.[1] While prior researchers have discussed the residential segregation of minority groups and highlighted circumstances in particular cities, there has been no systematic analysis of segregation across all of India due to an absence of data. We draw upon new administrative data to document outcomes for SC/STs and Muslims across 3000 towns and 100,000 urban neighborhoods (with only 100-125 households each) covering the whole country. We study how outcomes vary for all groups across neighborhoods with high concentrations of marginalized groups, and we study the relationship between residential segregation, public good provision, and socioeconomic outcomes.

Given the large literature on segregation and minority outcomes in the United States, we use data from the American Communities Survey to benchmark our measures against U.S. outcomes, defining our measures as similarly as possible across Indian and U.S. data

[1]Scheduled Castes make up 17% of the population, Scheduled Tribes 8%, and Muslims 14%. We pool results for SCs and STs, but de facto this largely refers to Scheduled Castes given the very small number of STs who live in cities.

sources. We find that in many ways the situation in urban India parallels that in the United States; this is a concerning finding, if not an entirely surprising one, because the adverse consequences of U.S. segregation are recognized to be severe.

We document five facts about residential segregation and group outcomes in urban India. First, both SC/STs and Muslims are more likely to live in poorer cities than the rest of the population. The relationship is much more stark for Muslims; a city with 40% less consumption per capita is predicted to have a Muslim share that is 8 percentage points higher, and a SC/ST population share that is 2 percentage points higher. The number for U.S. blacks is between these two; Muslims are thus more concentrated in poorer cities than blacks and SC/STs less so. Both groups also live in cities with less educated populations.

Second, cities with many Muslims have fewer schools, doctors and public hospitals per person (i.e. all of the public goods that we can measure). In contrast, cities with many SC/STs do *better* on all of these public goods measures. At the neighborhood level, however, both SC/ST and Muslim neighborhoods are worse off in all dimensions: they have fewer public goods, less education, and lower consumption than neighborhoods with fewer marginalized groups in the same cities.

Third, we show that the distribution of residential segregation for both SC/STs and Muslims across cities is similar to that of blacks in U.S. cities. SC/STs and Muslims have similar indices of dissimilarity to each other; the mean across cities is 0.05 points higher than the mean black/white dissimilarity in U.S. cities. Cities segregated along religious lines are also segregated along caste lines. However, cities in India with more SC/STs and Muslims are *less* segregated, the opposite of the pattern which is found in the U.S.

Fourth, we show that the socioeconomic character of segregated cities is decidedly different in India and the United States. While U.S. segregation is associated primarily with bad outcomes for U.S. blacks (but not whites), segregation in India is associated with markedly worse outcomes for both SC/STs and non-SC/STs. There is a slightly larger negative gradient at the city level for SC/ST consumption in segregation than there is for non-SC/ST consumption. However, analogous to the U.S., SC/ST neighborhoods in heavily segregated cities are worse off than SC/ST neighborhoods in less segregated cities. We cannot (yet) generate these measures for Muslim segregation, as we currently have religion coded at the household level only in one large city, which is Mumbai.

Finally, we examine differences in segregation between recently established cities and older cities of similar sizes. Because residential patterns are highly persistent, this provides suggestive evidence on whether the forces contributing to segregation have changed over time. We find that younger cities are less segregated by caste, consistent with other evidence that caste boundaries are becoming somewhat less rigid in Indian cities (Hnatkovska et al. (2012)). However, the segregation of Muslims is very similar in young and old cities, suggesting that the historical forces driving Muslim segregation remain powerful today.

Our work relates a long ethnographic and qualitative literature on patterns of settlement in individual Indian cities. Gist (1957) explores caste and religion based residential segregation in his study of Bengaluru. Lynch (1967) and Gould (1965) document how caste has played an important role in urban settlement focusing on the Jatav thoks and mohollas in Agra, and rickshawallas in Lucknow respectively. Hazlehurst (1970) looks at Puranapur and describes how neighborhood segregation interacts with substantial mixing in the marketplace; Mehta (1969) addresses similar questions of modernization in Pune. Miklian and Sahoo (2016) look at segregation in three Indian cities, focusing on both Muslims and SC/STs.

Systematic quantitative measurement of segregation in India has been elusive, however, because measures of segregation require comprehensive neighborhood-level data across the country Bharathi et al. (2018). Data on settlement patterns for small neighborhoods have not previously been widely available. Prior work includes a number of ward-level studies that use spatial units with population sizes of up to 30,000–200,000 people; these studies are seminal but may be at too high a level of aggregation to capture the true level of residential segregation which occurs at a finer geographic level.[2] These aggregate studies also tend to focus on SC/STs, due to the absence of neighborhood level data on religion. Vithayathil and Singh (2012) use the 2001 census ward-level data and show that residential segregation by caste is more prominent than by socioeconomic status for seven cities. In follow up work, 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. Bharathi et al. (2018) demonstrate that wards cannot approximate an urban neighborhood, and finds that for a typical ward, the EB-ward dissimilarity index is greater than the ward city dissimilarity index. They then use 2011 enumeration block (EB) level census data to measure segregation for five cities in India. There has not been a nation-wide study of urban segregation at the neighborhood level before this paper. An exception to the focus on caste is Susewind (2017), which measures Muslim segregation using polling booth data in eleven cities. This literature has also focused on measurement, with less of an emphasis on linking segregation to socioeconomic outcomes or city characteristics, likely due to a lack of neighborhood-level economic data.

In brief, the core contributions of our study are to (i) systematically document segregation and marginalized group outcomes across almost half of Indian cities, focusing on both Muslims and Scheduled Castes / Scheduled Tribes; and (ii) to document the relationship between marginalized group density, segregation, and economic outcomes for both marginalized groups and the rest of the population living in more and less segregated cities.

2 Context and Background

We will be focusing on two historically marginalized groups — Scheduled Castes and Scheduled Tribes (SC/STs) and Muslims. SC/STs are officially designated groups of historically disadvantaged people in India. Although the Indian constitution includes several protective

[2] We aggregate enumeration blocks to obtain population sizes comparable to the primary estimates in the U.S. literature, which define a neighborhood as a unit of at least 1000 households.

articles with regards to these groups and forbids discrimination on the basis of caste, the social and cultural practice of "untouchability" continues in modern India. A key socioeconomic disadvantage of being a member of a lower caste group has been the restriction of activities to a set of traditional occupations, such as scavengers and sanitation cleaners, with little upward mobility. These restrictions have been enforced with various social sanctions, including violence and death. There is evidence that these restrictions have held sway for thousands of years and that subcaste groups have been highly endogamous for much of this period.

The changing status (or lack thereof) of SC/STs has been a major subject of research on modern India (Hnatkovska et al. (2012); Emran and Shilpi (2015); Asher et al. (2019)). A substantial number of federal and state anti-poverty programs have specifically used caste identity as a targeting mechanism, and reservations in political office and higher education, which have been in place for decades, are a major topic of political debate.

Muslims occupy a similar share of the population to Scheduled Castes (14% for Muslims vs. 16% for SCs). Like SCs, they on average have lower socioeconomic status than non-Muslim non-SCs (see Figure 3). However, they experience fewer constitutional protections and they benefit from few if any reservations. The number of Muslim representatives in India's federal and state governments is correspondingly very small compared with SCs. The widely noted rising upward mobility of Scheduled Castes has occurred simultaneously with an almost symmetric decline in upward mobility for Muslims (Asher et al. (2019)).

The past five years have also seen a rise in hate crimes and discrimination against Muslims. Over 10,000 people have been killed in Hindu-Muslim communal violence since 1950 (El Amine (2009)). Prime Minister Narendra Modi and the majority Bharatiya Janata Party have faced longstanding accusations of marginalising Muslims with their promotion of Hindu nationalism. The Shiv Sena Party has called for compulsory family planning to curb the growth of the Muslim population.

We will frame our results around the literature on black segregation in the United States.

The causes and consequences of segregation are most well-studied in the United States, making it a useful benchmark for our study. There are several other baseline similarities between these two contexts; blacks comprise 12% of the U.S. population, a similar proportion to that of SCs, STs, and Muslims in India. Reports of discrimination against SCs and Muslims in India have many similarities with reports from the U.S., and include labor market discrimination, discrimination in access to public goods, and discrimination in treatment from civil authorities, like police officers.[3] Reports of Muslims "ghettos" in India's large cities are also reminiscent of the U.S. context, though to our knowledge the residential segregation of either Muslims or SCs has not been previously systematically measured. Needless to say, the marginalization of these groups has deep historical roots in both countries.

One relevant difference between these contexts is that residential segregation has been a central policy issue in the United States for decades, such that many government policies have directly targeted residential settlement patterns of blacks and whites.[4] The rapid pace of urban development in India has largely prevented any effective systematic government policy determining access to housing. Dysfunctional land markets, however, have given groups with political influence the greatest advantages in obtaining high value urban land.

3 Conceptual Framework

A growing literature emphasizes that neighborhood effects are important in the formation of skills and value (Kling et al. (2007); Chetty et al. (2015); Chetty and Hendren (2016)). Theoretical work has shed light on potential costs and benefits of segregation (Cutler and Glaeser (1997)). If segregation separates poor minorities from middle class society, they may learn fewer skills and acquire norms that are in conflict with mainstream society. They may also have poor networks which result in worse economic opportunities. Informational

[3]See, for example, the famous Sachar Commission Report (Sachar Committee Report (2006)), which documented the status of Muslims in India in detail.

[4]Among the most famous of these was the practice of "redlining," the refusal by government to insure mortgages in and near African-American neighborhoods.

isolation may also hurt minorities if it means that non-minorities end up relying more on stereotypes of minorities rather than actual experience. Another disadvantage of spatial segregation could result if there are neighborhood-specific public goods, then segregation may mean that minorities will be cut off from high quality public goods. Similarly, minorities may be cut off from employment due to spatial mismatch. Lastly, concentrations of poverty within these segregated neighborhoods may deter human capital accumulation and encourage crime. However, it is possible that segregation along caste lines keep rich and poor minorities together when otherwise they would live apart, potentially helping poor minorities. Also, minorities may face less "everyday discrimination" and increased safety from anti-minority violence through isolation.

4 Data

Analyzing segregation requires socioeconomic data at high spatial resolution to capture variation at the neighborhood unit. We leverage rich household microdata from the Socioeconomic and Caste Census (SECC), which describes every household and individual in India. This dataset was collected by the Government of India mostly in 2012 to determine eligibility for social programs. It was made publicly available on the internet in a combination of formats; we scraped and processed over two million files covering over 200 million urban individuals. After extracting text from the PDF tables, we translated fields from various languages into English, classified occupations into standardized categories and matched locations to the 2011 Population Census based on village and town names. This process yielded a range of variables covering both household characteristics (assets and income) and individual characteristics (age, gender, occupation, caste, education etc). Importantly, residential units are defined at the level of enumeration blocks (EBs) which consist of 100-200 households, with a mean population of 650–700. We aggregate neighboring enumeration blocks to produce units with population over 1000, making them comparable to the neighborhoods used in work on

U.S. segregation.

Consumption is not directly measured in the SECC, but we generate small area estimates of consumption of the basis of all of the household assets and characteristics on the SECC schedule. To generate this proxy consumption measure, we predict consumption in a survey (IHDS-II, 2011-12) that contains the same asset, income, and land data as the SECC but only contains district-level geographic identifiers. We then impute consumption for each individual in sample villages following the small area estimation methodology of Elbers et al. (2003). This allows us to generate not only average consumption in small neighborhoods, but the entire consumption distribution.

We also supplement our data with the 2013 Economic Census, which covers every economic establishment in India for data on public good provision and firm owner demographics at the enumeration block level. The Population Census 2011's Town Directory is another supplemental source of city-level data on population demographics. For comparison to the United States, we will use segregation measures from the Diversities and Disparities project which is calculated from Census 2010 tract level data, and data on economic outcomes from the American Community Survey.

5 Methodology

5.1 Measuring segregation

There are many measures of segregation. In this paper, we choose to follow the most commonly used measure in the literature, the Index of Dissimilarity. The dissimilarity index is:

$$D = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{\text{SC/ST}_i}{\text{SC/ST}_{\text{total}}} - \frac{\text{non-SC/ST}_i}{\text{non-SC/ST}_{\text{total}}}\right|$$

where SC/ST_i is the number of SC/STs in neighborhood i and SC/ST_{total} is the total number of SC/STs in the city. This index ranges from zero to one and answers the question:

What share of the SC/ST or non-SC/ST population would need to change neighborhood for the races to be evenly distributed within a city? Values between 0.3 and 0.6 are considered moderate, and above 0.6 is considered high (Massey (1990)). We pool adjacent block groups to form neighborhoods of just over 1000 residents, following recommendations from Fossett (2017). By pooling, our neighborhoods also become more comparable to U.S. tracts which range between 1000 and 8000 people.

We have also constructed other measures such as isolation, interaction, gini and others and find that they are highly correlated with dissimilarity.

5.2 Measuring Religion Shares

In the SECC, we have an indicator for Scheduled Caste identity but not for religion. For city-level minority Muslim and SC/ST population shares, we use data from the Population Census urban PCA. We will always use this definition at the city-level, unless otherwise stated. We show in Appendix Figure A.1 that this is close to an equivalent measure to the SECC for potentially a slightly different year.

We construct two proxies of the population share of Muslims at the neighborhood level. First, we can calculate the share of firm owners who are Muslim in the Economic Census. This measure is obviously not ideal, since the share of Muslims who become form owners may be correlated with other characteristics of neighborhoods or with relative Muslim status in each neighborhood. However, we can to some extent validate this proxy by generating a similar proxy for SC/ST population share in the Economic Census. We show in Appendix Figure A.2 that the share of firm owners who are SC/ST status is extremely highly correlated with the residential population share of SC/STs as reported in the SECC. The SC/ST dissimilarity indices for towns as measured on the basis of population and on firm ownership are also highly correlated.

Given the potential bias in the firm ownership measure of the Muslim population share, we construct a second measure on the basis of individual names, which were recorded in the posted SECC. Using a training set of 13.7 million names from the Delhi voter rolls, we trained a classifier to predict Muslim identity on the basis of individuals' first and last names. For each first or last name, we determined whether greater than 90 percent of individuals with that name were classified as Muslims in the training data. If so, we classified that first or last name as Muslim. We then took all the classified first and last names from the voter rolls and carried out a fuzzy match with the names from the SECC. If an individual has either a classified Muslim first or last name, we classify that individual as Muslim. If more than half of a household's members were classified as Muslim, we classified the whole household as Muslim. We validate this procedure by showing in Appendix Figure A.3 that enumeration block level Muslim shares based on our classified names are highly correlated with the firm proxy shares from the Economic Census. Thus far, we have only classified names for the city of Mumbai but we are in the process of extending this to cover the full SECC. As a result, our results on the impact of segregation on subgroup outcomes will be reported for SCs only, as we do not observe Muslim-specific socioeconomic outcomes in a sufficient number of towns at this time.

6 Results

In this section, we present our main results. We present an analysis of the patterns of segregation in urban India and compare our results to what we know about black segregation in the United States.

We focus on urban segregation because it is in cities that we see the *largest* disparities between minority and non-minority groups. In Figure 3, we see that the monthly consumption per capita gap between non-minorities and SC/STs in rural areas is less than 300 rupees, while in urban areas the gap is greater than 600 rupees. This gap is even larger for Muslims. The monthly consumption per capita gap between non-minorities and Muslims in rural areas is less than 400 rupees, while in urban areas the gap is about 800 rupees. This suggests that it is particularly important to understand how segregation is linked to these large economic disparities in the cities of India.

6.1 High Minority Share Cities

First, we show that cities with more SC/STs are poorer than cities with fewer SC/STs, and that cities with more Muslims are *much* poorer than cities with fewer Muslims. This is consistent with trends in the United States where cities with a greater share of blacks tend to have lower incomes per capita and levels of educational attainment. In Figure 4(c), we present the relationship between a city's consumption level per capita and minority share for SC/STs and Muslims. A 10% increase in SC/ST population share is linked to a 2.5% decrease in consumption per capita, and a 10% increase in Muslim population share is linked to a 4% decrease in consumption per capita. We see a similar pattern for educational attainment in Figure 4(d).

Interestingly, we find that cities with more Muslims have worse access to healthcare and schools, while cities with more SC/STs actually have *better* access. Figure 5 shows that cities with higher Muslim shares have fewer doctors per capita, fewer primary schools per capita for both government and private schools, and fewer government hospitals. This result is robust to state fixed effects and controlling for how rich the city is as measured by city consumption per capita. We don't find a significant relationship for hospitals overall, which suggests that the private sector fills in for government neglect in these cities with high concentrations of Muslims. Figure 5 also shows the flipped result for SC/STs. Higher SC/ST share cities have more doctors per capita, more primary schools per capita for both government and private schools, and more government hospitals. Again, we don't find a significant relationship for hospitals overall, which is consistent with our filling in story. These differences for SC/STs and Muslims may reflect that affirmative action and development policies have often been targeted at SC/STs. Muslims, on the other hand, have been neglected.

6.2 High Minority Share Neighborhoods

Next, to frame our understanding of the negative consequences of segregation, we look within cities and investigate how living in neighborhoods with high concentrations of minorities may be bad for one's economic outcomes.

Table 1 shows that living in a neighborhood with high shares of SC/STs or Muslims makes *everyone* worse off. A SC/ST who lives in a neighborhood with 10% more SC/STs is 6% poorer as measured by consumption per capita, and a non-SC/ST is 3% poorer. This is partly explained by education. Controlling for the share of SC/STs and non-SC/STs who have at least completed a secondary education respectively, SC/STs are 3.5% poorer and non-SC/STs are only about 1% poorer. We find the magnitudes for Muslim neighborhoods to be even larger. A Muslim who lives in a neighborhood with 10% more Muslims is 7.5% poorer, and a non-Muslim similarly is 6% poorer. Here, controlling for education only reduces the magnitudes to 6% and 5% respectively. Note that for our Muslim result we are only using the city of Mumbai due to the availability of classified names by religion in the SECC. In Appendix Table B.1, we show that using EB firm owner shares as a proxy and pooling all cities in our data gives us consistent results – though we are not able to split consumption between Muslims and non-Muslims

Figure 6 shows that high minority share neighborhoods have worse access to various public goods. Increasing the share of SC/STs in a neighborhood by 10% is linked with 3% fewer people having access to drinking water within their premises, 3% fewer people owning a latrine, and 2% fewer people who have access to drainage. For Muslims, increasing the share of Muslim firm owners in a neighborhood by 10% is linked with 1% fewer people having access to drinking water within their premises and 1% fewer people owning a latrine. High minority share neighborhoods have fewer primary schools, hospitals and medical facilities. For hospitals and medical facilities, this is largely driven by the private sector. Living in a high minority share neighborhood worsens one's access to important public goods which may effect one's health and educational attainment.

6.3 Segregation

Now we turn to our core results on segregation. First, we show in Figure 1 that the distributions of segregation are similar across blacks in the United Sates and minorities in India. Black and Muslim dissimilarity is slightly more right skewed than dissimilarity for SC/STs. In Figure 2, we also find that SC/ST dissimilarity and Muslim dissimilarity are high correlated. Cities that tend to be segregated by caste also tend to be segregated by religion.

In the United States, higher minority share cities are more segregated. This reflects the American notion of small towns being relatively egalitarian, and the big cities being stratified and unequal. However, for India we show in Table 2 that the opposite pattern holds for both SC/STs and Muslims. Increasing the share of either minority group in a city by 50% increases the dissimilarity index from the EC for its corresponding minority group by 17 points. This may be due to government action. It is generally quite difficult to segregate large populations of minorities and it may require strong government action such as red lining policies in the United States to do so.

In the United States, segregated cities have worse college attainment and lower incomes. In India, Figure 7 shows that caste segregation is linked to worse educational attainment, measured by the percent of the population with at least a secondary education, and lower consumption as well. However, only education is negatively associated with Muslim dissimilarity.

A large literature has shown that segregation in the United States is linked with negative outcomes for blacks, but not whites. In Figure 8(a), we show that city income per capita for whites has a null relationship with black segregation. However, increasing the dissimilarity index for blacks by just one standard deviation is associated with a 11 percent drop in black income per capita. We find that in India both SC/STs and non-SC/STs have worse outcomes in segregated cities. In Figure 8(b), we see that there is strong negative relationship between SC/ST segregation and consumption per capita for *both* groups. A one standard deviation increase in SC/ST dissimilarity is linked to about a 7% decrease in SC/ST consumption per capita and about a 6% decrease in non-SC/ST consumption per capita. In Appendix Table B.2 to B.5, we show that these relationships are robust across specifications with and without state fixed effects and controls for city population, SC/ST city population share and education. Controlling for education, measured as the share of the corresponding population group that has at least a secondary level education, partly explains the relationship with magnitudes dropping to 4% and 2.5% for SC/STs and non-SC/STs respectively. We notice that the magnitude of the negative relationship is greater for blacks in the United States than the magnitudes for SC/STs or non-SC/STs in India. This may suggest that SC/STs and non-SC/STs are sharing the negative consequences of segregation, while in the United States the consequences squarely fall on blacks.

In Figures 9(a) and 9(b), we see that in the United States only blacks have worse educational attainment in segregated cities, but both SC/STs and non-SC/STs have worse educational attainment with similar magnitudes. In columns (1) and (2) in Table 3, we show that the educational gap between SC/STs and non-SC/STs has a null relationship with segregation. We calculate that consumption gap as such:

$$\textit{Education gap} = (1 - (\textit{Secondary}_{SC/ST} / \textit{Secondary}_{non\text{-}SC/ST})) * 100$$

where $\textit{Secondary}_i$ is the share of population i who has at least a secondary level education. This may suggest that affirmative action policies have prevented SC/STs from suffering more from segregation than non-SC/STs in education, and that they share the negative educational consequences of segregation.

However, although SC/STs are not doing worse in terms of education relative to non-SC/STs in segregated cities, the remaining columns in Table 3 show that the income gap between SC/STs is increasing with segregation. We calculate the consumption gap as such:

$$\textit{Consumption gap} = (1 - (\textit{Consumption}_{SC/ST} / \textit{Consumption}_{non\text{-}SC/ST})) * 100$$

where *$Consumption_i$* is consumption per capita for population i. This may indicate that government SC/ST targeted affirmative action has succeeded in enrolling SC/STs into schools in segregated cities. However, our results suggest that this has not been enough to close disparities in ultimate economic outcomes.

Next, we turn to looking at access to public goods in segregated cities. Table 4 shows that SC/STs have worse access to drinking water, latrines and drainage. Non-SC/STs only have worse access to latrines to a smaller magnitude than for SC/STs. Worse access to public goods may explain some of the economic disparities between SC/STs and non-SC/STs.

Finally, in Figure 10 we show that younger cities are less segregated along caste lines than older cities. However, there is no difference in Muslim segregation between young and old cities. This result is robust to controlling for state fixed effects to account for potential regional variation. We proxy age by the first year which that town or city appears in the Population Census Town Directory. Since residential patterns of segregation are persistent, this may suggest that caste is becoming less salient over time in urban India but not religion.

7 Conclusion

Scheduled Castes and Scheduled Tribes (SC/STs) and Muslims are worse off in cities. In this paper, we document a number of key facts about religion and caste-based segregation across urban India. We find that high SC/ST share cities are poorer than cities with fewer SC/STs, and that high Muslim share cities are *much* poorer than cities with fewer Muslims. Cities with more Muslims have worse access to schools, doctors and government hospitals, while cities with more SC/STs have *better* access. Although the distribution of segregation is similar between the United States and India, we have shown that patterns of segregation look quite different. Contrary to the United States, high minority share cities are more segregated in India. This may be due to differences in government action across both countries, suggesting the government has important influence over what urban segregation looks like. We also find that segregated cities are linked with worse economic outcomes for both SC/STs and non-SC/STs. In the United States, segregation is only linked to worse outcomes for blacks. Also contrary to the U.S., we also show that the SC/ST educational gap does not increase significantly with segregation, though the consumption gap does. This may partially be due to SC/STs having worse access to public goods in segregated cities. We document that cities segregated along religious lines are also segregated along caste lines. Finally, we find that younger cities are less segregated than older cities by caste but not religion, suggesting that caste is becoming less salient in cities.

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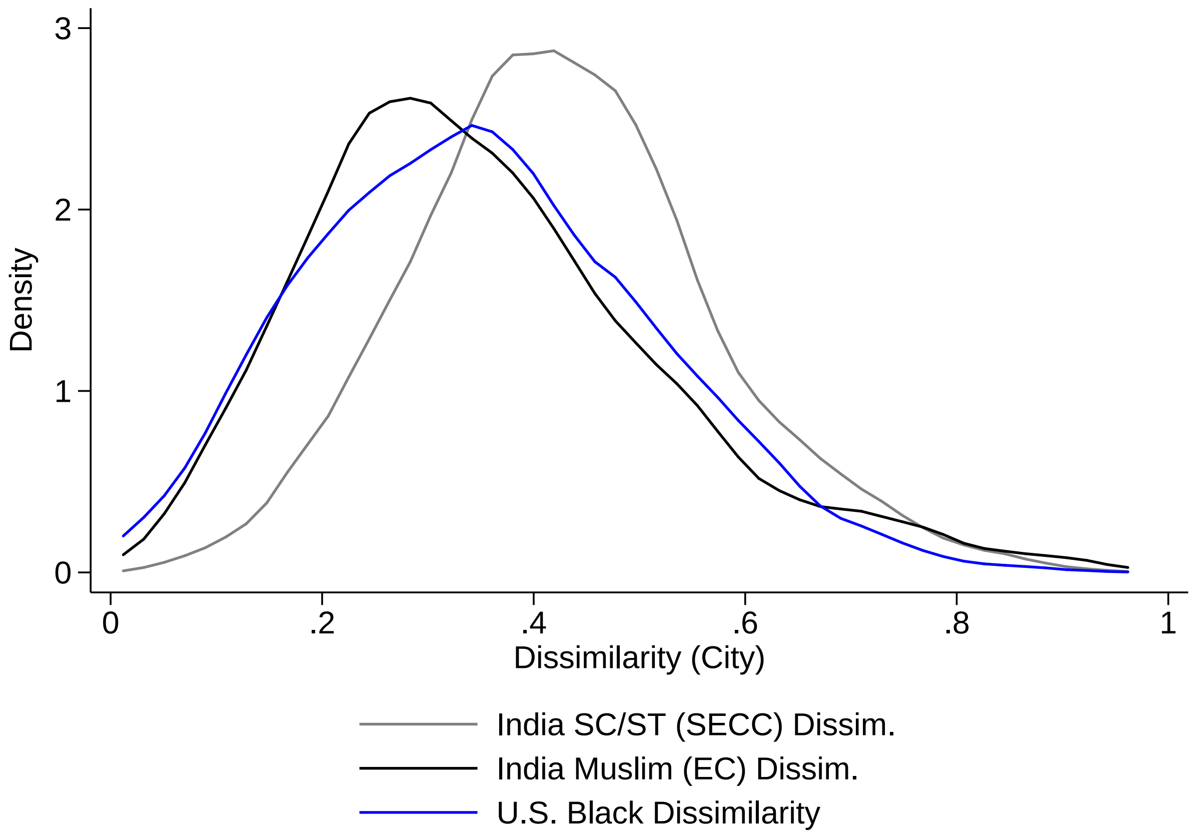
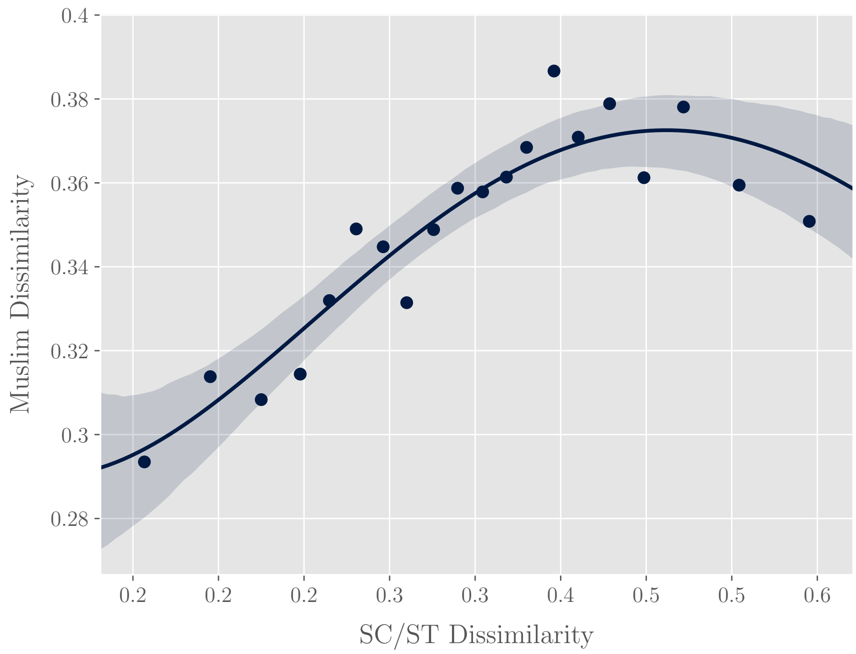
Figures

Figure 1: Distributions of Dissimilarity Measures Across Cities



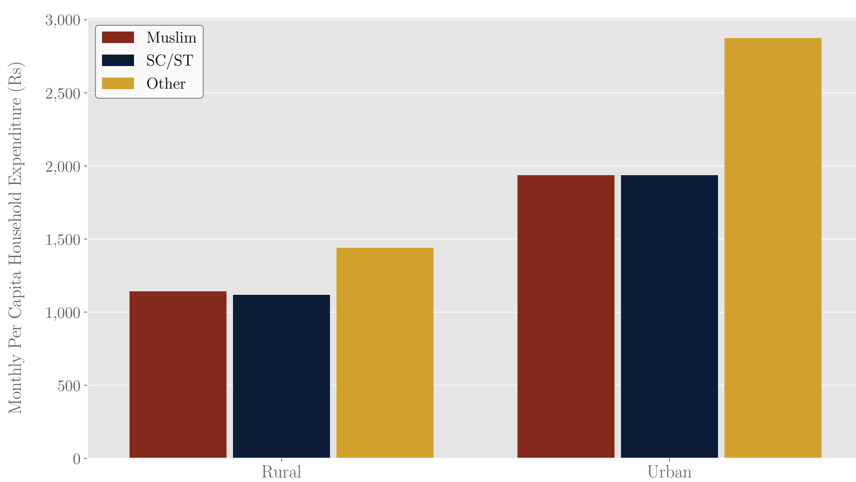
Notes: The figure shows the distribution of a dissimilarity measure of segregation across sample towns for SC/STs and Muslims in India, and for blacks in the United States. Dissimilarity for SC/STs is calculated with EB-level data from the Socioeconomic Caste Census. Dissimilarity for Muslims is calculated with EB-level firm owner shares from the Economic Census 2013. Dissimilarity for Blacks in the United States is from the Diversities and Disparities Project.

Figure 2: SC/ST vs Muslim Segregation



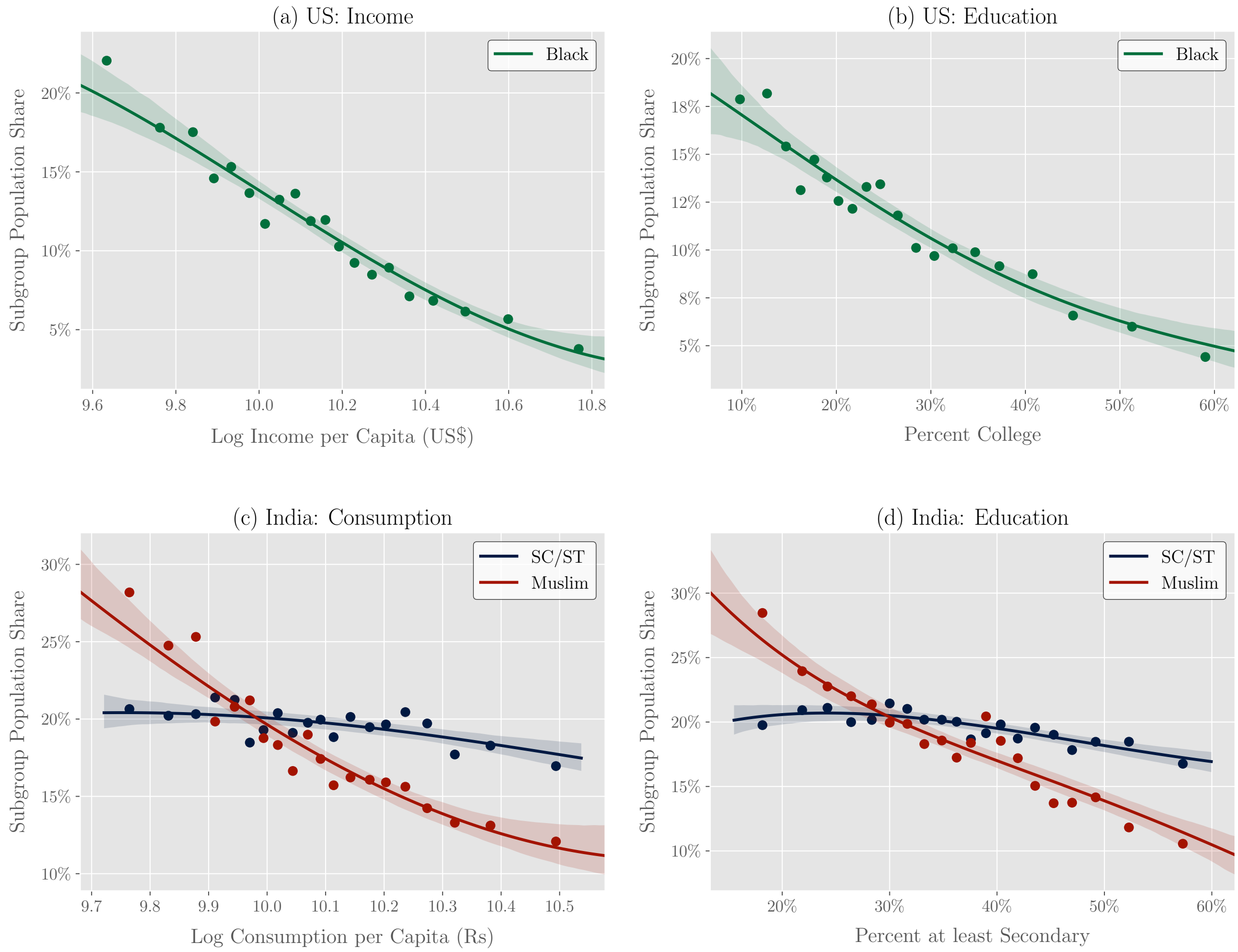
Notes: The figure shows a binscatter plot of SC/ST segregation against Muslim segregation using city-level data. Each point shows the mean Muslim dissimilarity of about 150 cities with SC/ST dissimilarity in the given bin. All measures are residual of state fixed effects. Both dissimilarity measures are calculated using city-level firm ownership shares from the Economic Census.

Figure 3: Average Population Subgroup Consumption by Urban Status



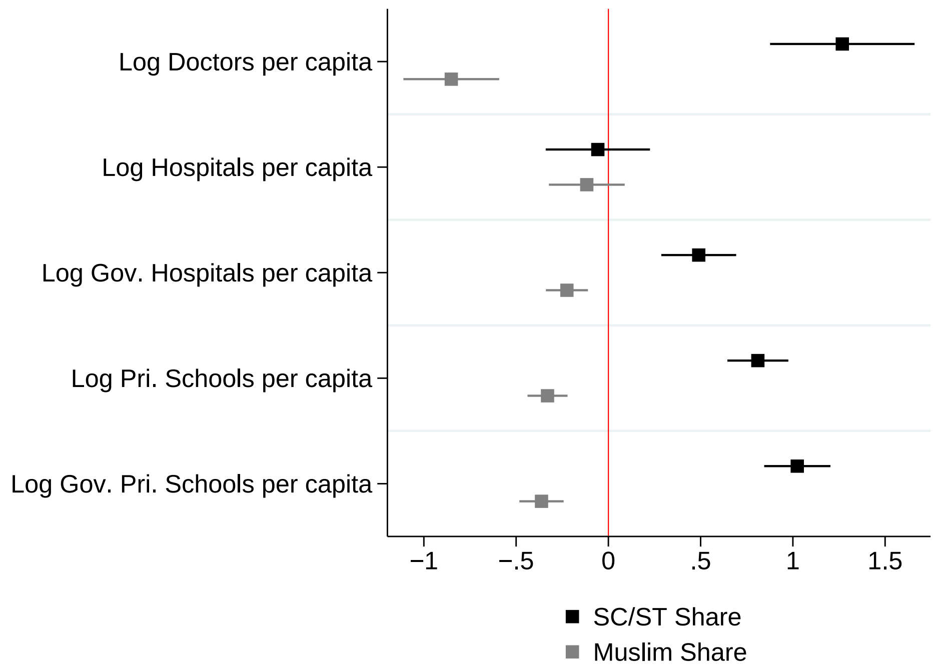
Notes: The figure shows consumption for Muslims, SC/STs and non-Muslim non-SC/STs, disaggregated by rural and urban residents. Household-level microdata are from the National Sample Survey 2011-12 (68th round).

Figure 4: Subgroup Share vs Income/Consumption and Education



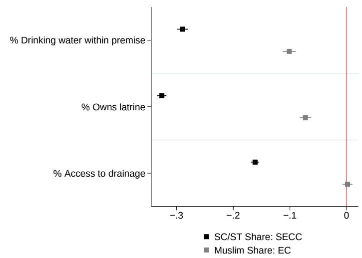
Notes: The figure shows binscatter plots of subgroup outcomes against subgroup population shares using city-level data. Each point shows the mean subgroup city population share of about 150 cities with outcomes in the given bin. Panel (a) shows a binscatter plot of city log income per capita against black population share; Panel (b) shows the same for the share of the city's population with a college degree; Panel (c) shows a binscatter plot of the city log consumption per capita against both SC/ST and Muslim population share; Panel (d) shows the same for the share of the city's population with at least a secondary level education. All measures are residual of state fixed effects. United States data is from the American Community Survey. For India, subgroup population shares is from the Population Census Town Directory, and consumption and education are from the SECC.

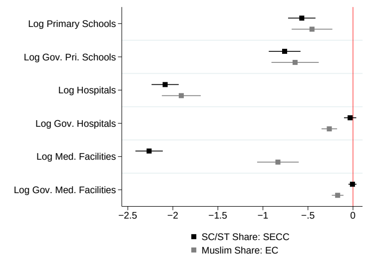
Figure 5: City-level Population Subgroup Share vs Public Goods per Capita



Notes: The figure shows a coefficient plot which plots estimates from a city-level regression of various public goods per capita on the share of minorities in the city. Each regression includes state fixed effects and controls for city log consumption per capita. Each point plots a regression coefficient. Blue points are for city SC/ST population shares; Red points are for city Muslim population shares. The error bars represent the 95% confidence interval. The top panel shows coefficients from regressions of log doctors per capita on the share of minorities in the city; the second panel shows the same for log hospitals per capita; the third panel shows the same for log government hospitals pre capita; the fourth panel shows the same for log primary schools per capita; the bottom panel shows the same for log government primary schools per capita. All data is from the Population Census 2011 Town Directory except data for Hospitals which are from the Economic Census 2013.

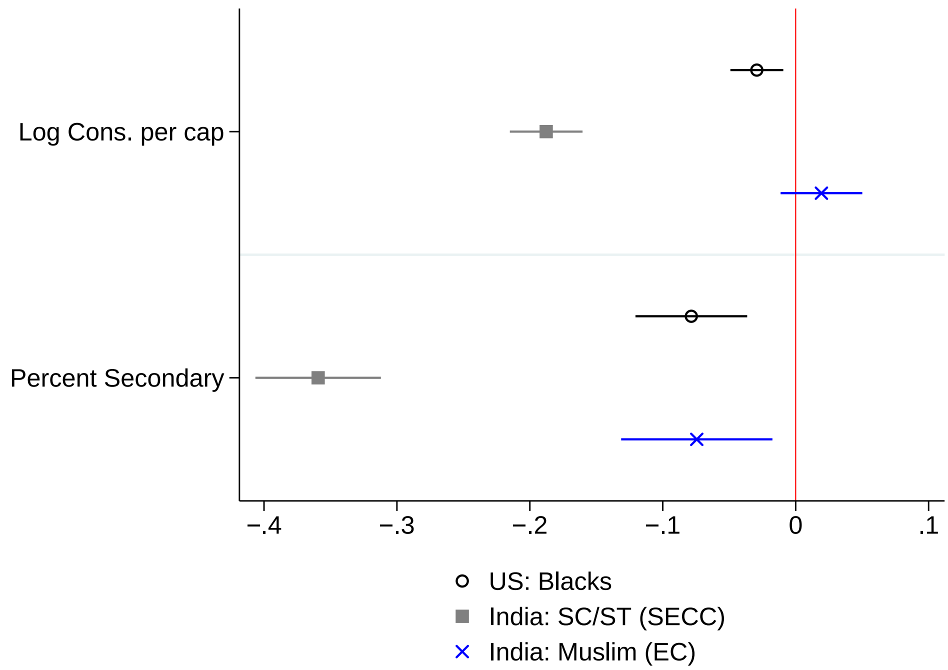
Figure 6: Neighborhood-level Subgroup Population Share vs Public Goods





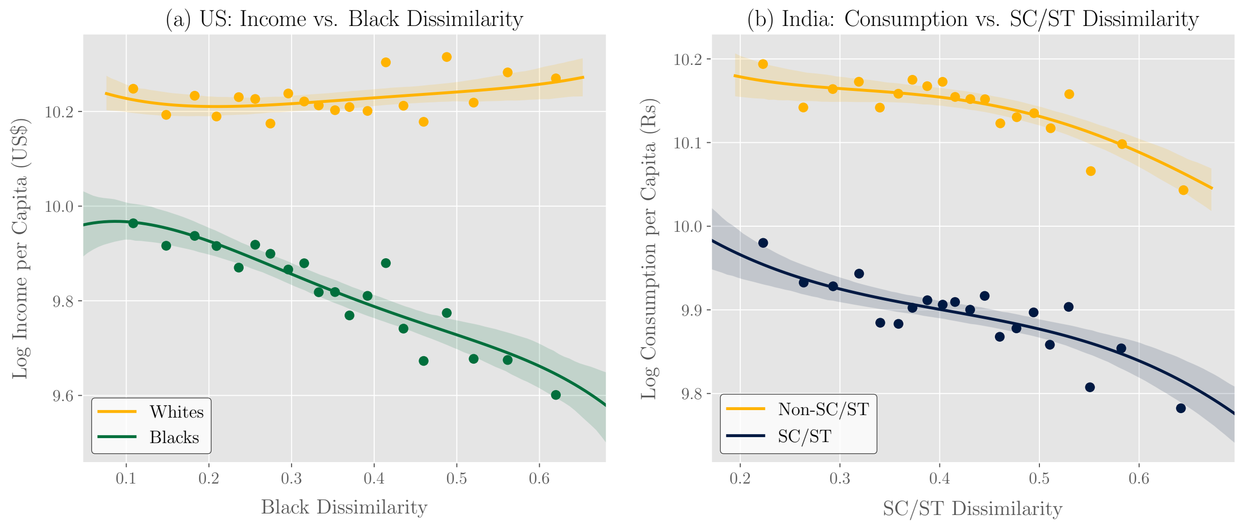
Notes: The figure shows coefficient plots which plots estimates from a neighborhood-level regression of various measures of access to public goods on the share of minorities in the neighborhoods. Each regression includes city fixed effects and controls for log EB population. Each point plots a regression coefficient. Blue points are for enumeration block SC/ST population shares from the SECC; Red points are for enumeration block Muslim firm owner shares from the EC. The error bars represent the 95% confidence interval. Sub-figure (a) focuses on sanitation related public goods. The top panel of (a) shows coefficients from regressions of the share of the population with access to drinking water within premise on the share of minorities in the EB; The second panel of (a) shows the same for the share of the population that owns a water-sealed latrine; The bottom panel of (a) shows the same for the share of the population with access to drainage. Sub-figure (b) focuses on Schools and Hospitals. The top panel of (b) shows coefficients from regressions of log primary schools on the share of minorities in the EB; The second panel of (b) shows the same for log government primary schools; The third panel of (b) shows the same for log hospitals; The fourth panel of (b) shows the same on log government hospitals; The fifth panel of (b) shows the same for log medical facilities; The bottom panel of (b) shows the same for government medical facilities. All data is from the Economic Census 2013 except EB-level minority shares are from the Socioeconomic Caste Census for SC/STs. Schools, hospitals and facilities are measured by their total employment.

Figure 7: City-Level Average Income/Consumption and Education vs. Segregation



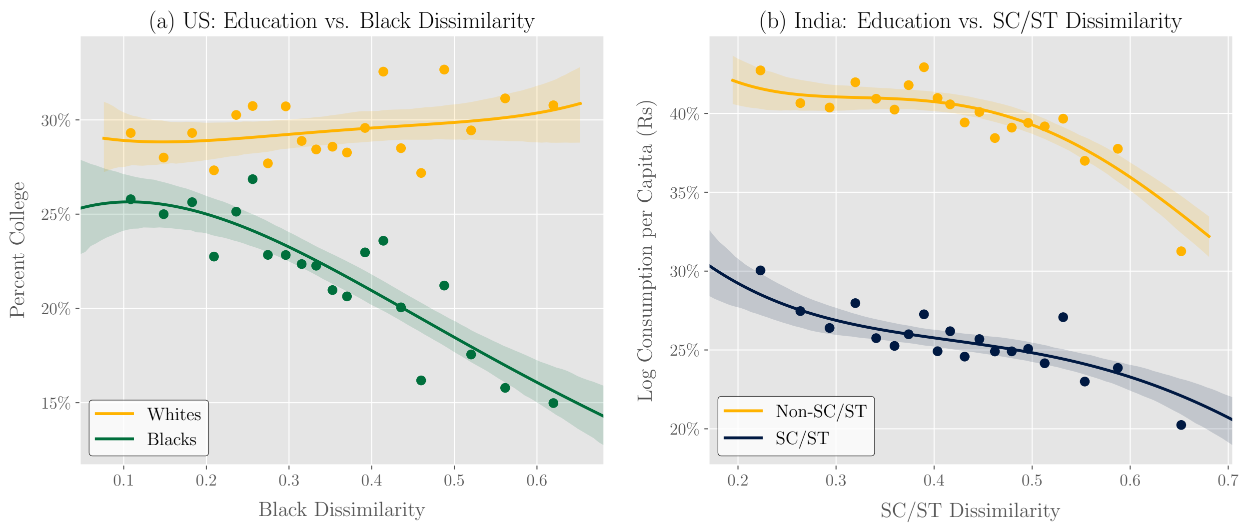
Notes: The figure shows a coefficient plot which plots estimates from a city-level regression of socioeconomic outcomes on indices of dissimilarity for different minority groups in the city. Each regression includes state fixed effects and controls for city log population. Each point plots a regression coefficient. Blue points are for black dissimilarity in the United States; Red points are for SC/ST dissimilarity in India; Green points are for Muslim dissimilarity in India. The error bars represent the 95% confidence interval. The top panel shows coefficients from regressions of log income per capita for the US or log consumption per capita for India on the city index of dissimilarity; the second panel shows the same for the share of the city population with a college degree for the US or the share of the city population with at least a secondary education for India. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC. Muslim dissimilarity is calculated with EB-level Muslim firm owner shares from the EC. All other data for India is from the SECC. Black dissimilarity for the United States is from the Diversities and Disparities Project and all other data is from the American Community Survey 2005-2009.

Figure 8: City-Level Subgroup Income/Consumption vs. Segregation



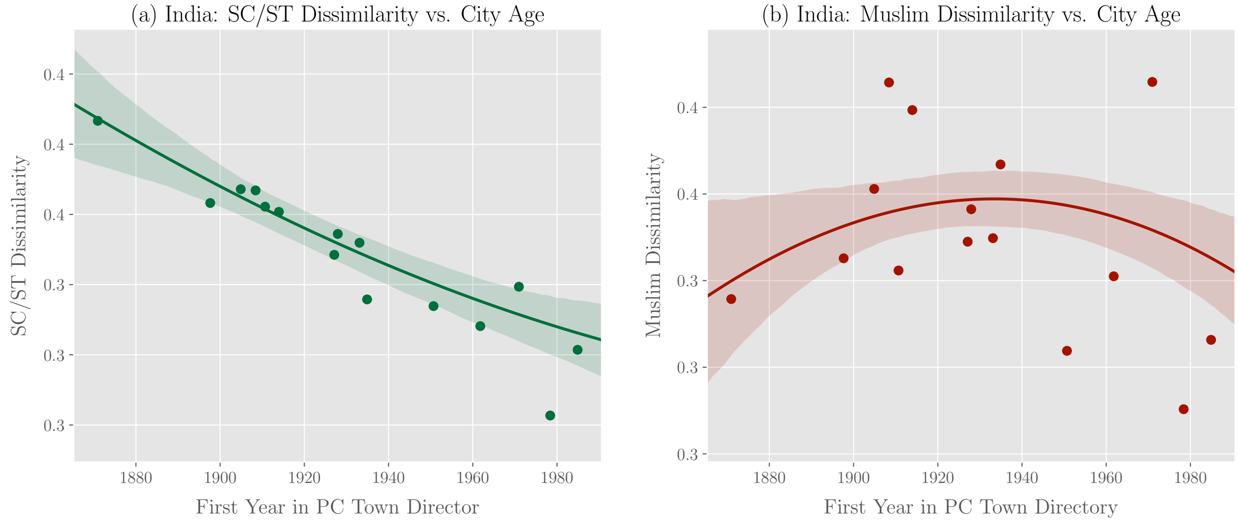
Notes: The figure shows binscatter plots of dissimilarity against subgroup log income or consumption per capita using city-level data. Each point shows the mean subgroup log income or consumption per capita of about 150 cities with dissimilarity in the given bin. Panel (a) shows a binscatter plot of black dissimilarity against city log income per capita for blacks in blue and whites in red; Panel (b) shows a binscatter plot of SC/ST dissimilarity against city log consumption per capita for SC/STs in blue and non-SC/STs in red; All measures are residual of state fixed effects, log city population, and black or SC/ST population share. Black dissimilarity is from the Diversities and Disparities project and the rest of the data is from the American Community. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC, city population and SC/ST shares are from the Population Census 2011 Town Directory, and consumption is from the Socioeconomic Caste Census.

Figure 9: City-Level Subgroup Education vs. Segregation



Notes: The figure shows binscatter plots of dissimilarity against subgroup education using city-level data. Each point shows the mean subgroup education of about 150 cities with dissimilarity in the given bin. Panel (a) shows a binscatter plot of black dissimilarity against city college share for blacks in blue and whites in red; Panel (b) shows a binscatter plot of SC/ST dissimilarity against city secondary level education share per capita for SC/STs in blue and non-SC/STs in red; All measures are residual of state fixed effects, log city population, and black or SC/ST population share. Black dissimilarity is from the Diversities and Disparities project and the rest of the data is from the American Community. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC, city population and SC/ST shares are from the Population Census 2011 Town Directory, and education is from the Socioeconomic Caste Census.

Figure 10: Segregation by City Age



(a) India: SC/ST Dissimilarity vs. City Age

(b) India: Muslim Dissimilarity vs. City Age

Notes: The figure shows binscatter plots of a proxy for age against dissimilarity using city-level data. Each point shows the mean index of dissimilarity of about 150 cities with age in the given bin. Age is proxied by the first year that the city or town appears in the Population Census Town Directory. Panel (a) shows a binscatter plot of age against SC/ST dissimilarity; Panel (b) shows the same for Muslim dissimilarity; All measures are residual of state fixed effects. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC (SC/ST dissimilarity calculated from the EC is included in Appendix Figure 10(a)). Muslim dissimilarity is calculated with EB-level Muslim firm owner shares from the EC.

Tables

Table 1: EB Income/Consumption per capita vs SC/ST Share

	(1) SC/ST	(2) SC/ST	(3) Non-SC/ST	(4) Non-SC/ST	(5) Muslim	(6) Muslim	(7) Non-Muslim	(8) Non-Muslim
% SC/ST SECC	-0.594***	-0.342***	-0.320***	-0.0757***				
	(0.00618)	(0.00591)	(0.00572)	(0.00473)				
% Muslim SECC					-0.763***	-0.707***	-0.627***	-0.526***
					(0.0902)	(0.0869)	(0.0701)	(0.0697)
SC/ST % Sec		0.743***						
		(0.00644)						
Non-SC/ST % Sec				1.012***				
				(0.00422)				
block_sec_p_muslim_t						0.724***		
						(0.0926)		
block_sec_p_nonmuslim_t								0.970***
								(0.0930)
Observations	100283	100283	100283	100283	794	794	794	794
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pop. Control								
Sample								

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from a neighborhood-level regression of population subgroup consumption on the share of minorities in the neighborhood. Columns 1 to 4 regress SC/ST and non-SC/ST consumption on the SC/ST share of neighborhood; Columns 5 to 8 do the same for Muslims. Columns 2, 4, 6, and 8 control for the education level (secondary completion share) of the dependent variable subgroup. All observations are at the enumeration block level and data is from the SECC. The sample in columns 1-4 is all of India. The sample in columns 5-8 is only the city of Mumbai, due to current limitations on the sample of individuals where we can observe religion. All specifications include city fixed effects and a control for log city population.

Table 2: City Dissimilarity vs Minority Share

	(1) Black	(2) Black	(3) SC/ST SECC	(4) SC/ST SECC	(5) SC/ST EC	(6) SC/ST EC	(7) Muslim EC	(8) Muslim EC
City Black Share	0.0961***	0.0484**						
	(0.0212)	(0.0204)						
City SC/ST Share			-0.180***	-0.129***	-0.362***	-0.302***		
			(0.0293)	(0.0287)	(0.0226)	(0.0228)		
City Muslim Share							-0.358***	-0.401***
							(0.0149)	(0.0154)
Observations	2597	2597	3148	3148	2910	2910	2910	2910
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls								

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from a city-level regression of minority dissimilarity on the share of minorities in the city. Columns 1 to 2 regress black dissimilarity in the Unites States on the black share of city; Columns 3 to 4 do the same for SC/STs in India using dissimilarity as calculated with SECC EB-level population shares; Columns 5 to 6 do the same for SC/STs in India using dissimilarity as calculated with EC EB-level firm ownership shares; Columns 7 to 8 do the same for Muslims in India using dissimilarity as calculated with EC EB-level firm ownership shares. Columns 2, 4, 6, and 8 control for log city population and log income or consumption per capita for the United States and India respectively. All observations are at the city level. Data on city population shares are from the American Community Survey 2005-2009 for the US and Population Census 2011 Town Directory for India. All specifications include state fixed effects.

Table 3: Dissimilarity vs SC/ST Gap

	(1) Edu. Gap	(2) Edu. Gap	(3) Cons. Gap	(4) Cons. Gap	(5) Cons. Gap	(6) Cons. Gap
SC/ST Dissim.	0.0456	5.340	6.060***	5.246***	7.144***	5.386***
	(3.733)	(3.834)	(1.607)	(1.458)	(1.630)	(1.496)
Edu. Gap				0.197***		0.193***
				(0.0141)		(0.0141)
Observations	2480	2480	2420	2420	2420	2420
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Demo. Controls						

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table shows estimates from a city-level regression of the SC/ST education or consumption gap on the SC/ST dissimilarity index of the city. Columns 1 to 2 regress the SC/ST education gap on the SC/ST dissimilarity index of the city; Columns 3 to 6 do the same for the consumption gap. Columns 2, 5, and 6 control for the log city population and city SC/ST population share. Columns 4 and 6 control for the SC/ST education gap. The gaps are calculated as such: $\textit{Consumption gap} = (1 - (\textit{Consumption}_{SC/ST}/\textit{Consumption}_{non\text{-}SC/ST})) * 100$ and $\textit{Education gap} = (1 - (\textit{Secondary}_{SC/ST}/\textit{Secondary}_{non\text{-}SC/ST})) * 100$ where $\textit{Consumption}_i$ is consumption per capita for population i and $\textit{Secondary}_i$ is the share of population i that has at least a secondary level education. All observations are at the city level. City population and SC/ST shares is from the Population Census Town Directory. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC. Education and consumption data is also from the SECC. All specifications include state fixed effects.

Table 4: City Dissimilarity vs Access to Public Goods

	Water		Drainage		Latrine	
	(1)	(2)	(3)	(4)	(5)	(6)
	SC/ST	Non-SC/ST	SC/ST	Non-SC/ST	SC/ST	Non-SC/ST
SC/ST Dissim.	-0.0957***	-0.00685	-0.0820**	0.0103	-0.288***	-0.112***
	(0.0320)	(0.0296)	(0.0319)	(0.0243)	(0.0339)	(0.0266)
Observations	2977	2977	2977	2977	2977	2977
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls						

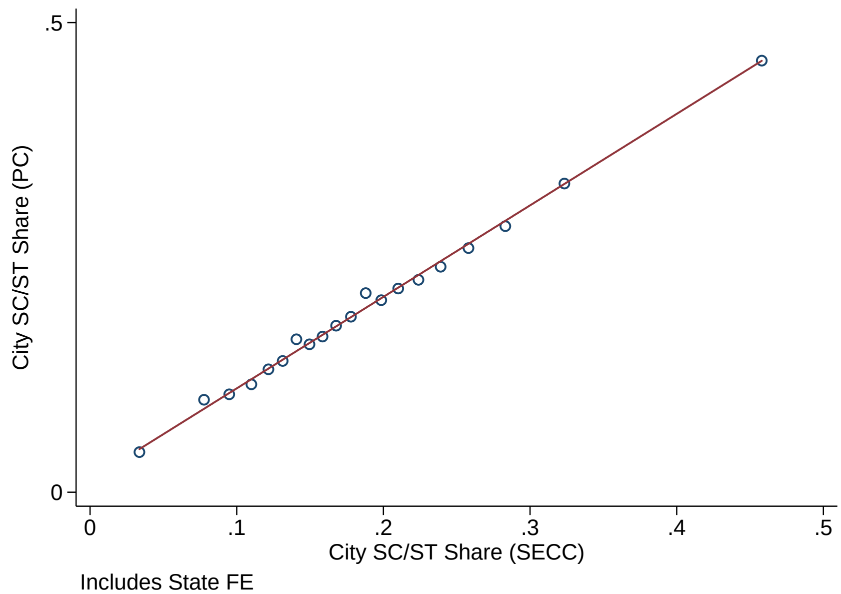
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows estimates from a city-level regression of population subgroup access to public goods on the SC/ST dissimilarity index of the city. Columns 1 to 2 regress SC/ST and non-SC/ST subgroup shares who who have access to drinking water within premise on the SC/ST dissimilarity of city; Columns 3 to 4 do the same for share with access to drainage; Columns 5 to 6 do the same for share who owns a water-sealed latrine. All observations are at the city level. SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC. Public goods data is from the SECC. City population and city SC/ST population shares are from the Population Census 2011 Town Directory. All specifications include state fixed effects and a control for log city population and city SC/ST share.

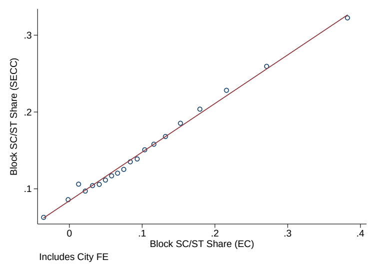
A Appendix A. Figures

Figure A.1: Comparing SECC vs Population Census SC/ST shares

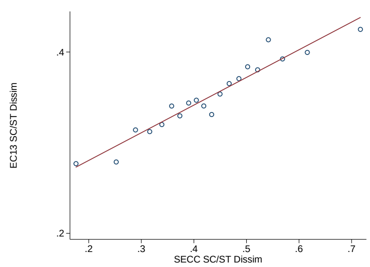


Notes: The figure shows binscatter plots of city SC/ST population share from the SECC against city SC/ST population share from the Population Census Town Directory. Each point shows the mean SC/ST population share from the Population Census of about 150 cities with SC/ST population share from the SECC in the given bin. All measures are residual of state fixed effects.

Figure A.2: Validating SECC and EC EB level SC/ST share measures



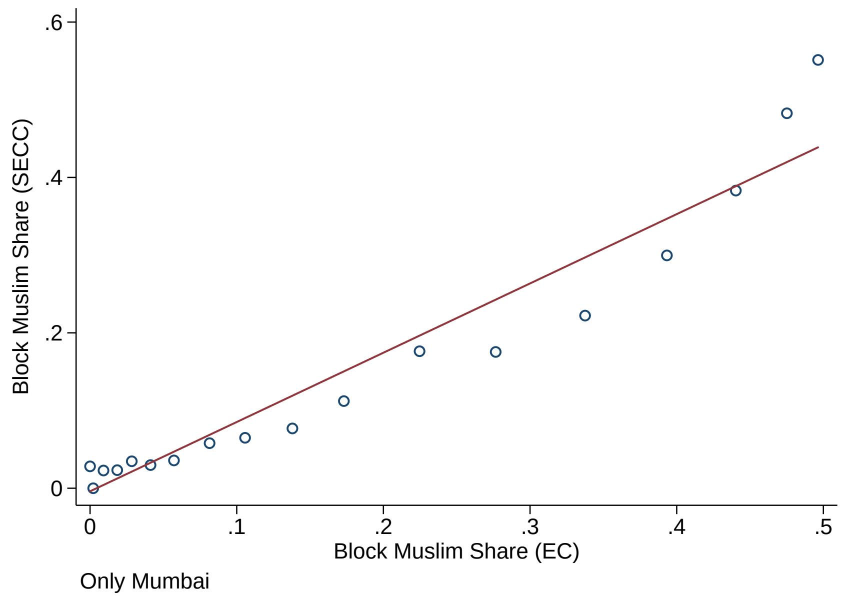
(a) EB-level SC/ST share



(b) City-level ST/ST dissimilarity

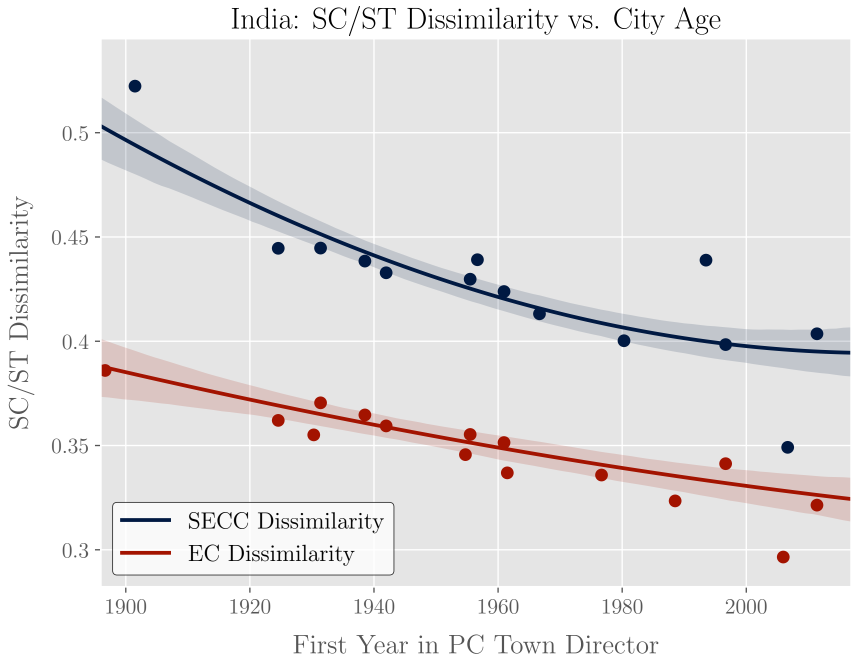
Notes: The figure in panel (a) shows a binscatter plot of EB SC/ST firm owner shares from the EC against EB SC/ST population shares from the SECC. Each point shows the mean SC/ST firm owner share from the SECC of about 5000 EBs with SC/ST population share from the EC in the given bin. All measures are residual of city fixed effects. The figure in panel (b) shows a binscatter plot of SC/ST dissimilarity calculated with EB SC/ST population shares from the SECC against SC/ST dissimilarity calculated with EB SC/ST firm owner shares from the EC at the city level. Each point shows the mean SC/ST dissimilarity index calculated from the EC of about 150 cities with SC/ST dissimilarity index calculated from the SECC in the given bin.

Figure A.3: Comparing EC vs SECC Classified names Muslim shares



Notes: The figure shows a binscatter plot of EB Muslim population shares from the SECC based on classified Muslim names against EB Muslim firm owner shares from the EC for the EBs within the city of Mumbai. Each point shows the mean Muslim population share from the SECC of about 120 EBs with EB Muslim firm owner shares from the EC in the given bin.

Figure A.4: City Age vs SC/ST Dissimilarity



Notes: The figure shows binscatter plots of a proxy for age against SC/ST dissimilarity using city-level data. Each point shows the mean index of dissimilarity of about 150 cities with age in the given bin. Age is proxied by the first year that the city or town appears in the Population Census Town Directory. All measures are residual of state fixed effects. In blue, SC/ST dissimilarity is calculated with EB-level SC/ST population shares from the SECC; In red, SC/ST dissimilarity calculated with EB-level SC/ST firm owner shares from the EC.

B Appendix B. Tables

Table B.1: EB Log Consumption per capita vs EB Minority Share

	(1) Cons.	(2) Cons.	(3) Cons.	(4) Cons.	(5) Cons.	(6) Cons.	(7) Cons.	(8) Cons.
% SC/ST SECC	-0.474***	-0.148***						
	(0.00484)	(0.00413)						
% SC/ST EC			-0.365***	-0.0976***				
			(0.00966)	(0.00737)				
% Muslim EC					-0.678***	-0.227***		
					(0.00761)	(0.00666)		
% Muslim SECC							-0.687***	-0.556***
							(0.0524)	(0.0502)
% Sec		1.022***		1.065***		1.026***		0.957***
		(0.00417)		(0.00431)		(0.00445)		(0.0731)
Observations	119022	119022	105582	105582	105582	105582	1267	1267
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows estimates from a EB-level regression of log consumption per capita against EB minority shares. Columns 1 to 2 regress log consumpiton per capita against the EB SC/ST population shares from the SECC; Columns 3 to 4 do the same for EB SC/ST firm shares from the EC; Columns 5 to 6 do the same for EB Muslim firm shares from the EC; Columns 7 to 8 do the same for EB Muslim population shares from the classified Muslim SECC names. Columns 2, 4, 6, and 8 control for the share of the EB population with at least a secondary education. The sample in columns 1-6 is all of India. The sample in columns 7-8 is only the city of Mumbai, due to current limitations on the sample of individuals where we can observe religion. City fixed effects are included in all specifications.

Table B.2: US: White Log Income per Capita vs Black Dissimilarity

	(1) White	(2) White	(3) White	(4) White	(5) White
Black Dissim.	0.0334	0.0924**	0.00155	0.0330	0.0351
	(0.0416)	(0.0407)	(0.0430)	(0.0424)	(0.0246)
Log Pop.			0.0505***	0.0573***	0.00516
			(0.00701)	(0.00688)	(0.00430)
Black Share.				-0.412***	-0.0945***
				(0.0394)	(0.0258)
White College					1.578***
					(0.0388)
Observations	2597	2597	2597	2597	2597
State FE	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows estimates from a city-level regression of white log consumption per capita against black dissimilarity. Column 1 has no fixed effects or controls; Column 2 adds state fixed effects; Column 3 adds log city population controls; Column 4 adds city black population share controls; Column 5 adds white college share controls. All observations are at the city level. Dissimilarity data is from the Diversities and Disparities project and all other data is from the American Community Survey.

Table B.3: US: Black Log Income per Capita vs Black Dissimilarity

	(1) Black	(2) Black	(3) Black	(4) Black	(5) Black
Black Dissim.	-0.754***	-0.662***	-0.766***	-0.741***	-0.413***
	(0.0597)	(0.0577)	(0.0658)	(0.0665)	(0.0599)
Log Pop.			0.0579***	0.0632***	0.0429***
			(0.00949)	(0.00937)	(0.00828)
Black Share.				-0.320***	-0.0340
				(0.0419)	(0.0312)
Black College					1.609***
					(0.0810)
Observations	2597	2597	2597	2597	2597
State FE	No	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows estimates from a city-level regression of black log consumption per capita against black dissimilarity. Column 1 has no fixed effects or controls; Column 2 adds state fixed effects; Column 3 adds log city population controls; Column 4 adds city black population share controls; Column 5 adds black college share controls. All observations are at the city level. Dissimilarity data is from the Diversities and Disparities project and all other data is from the American Community Survey.

Table B.4: SC/ST Log Consumption per capita vs SC/ST Dissimilarity

	(1) SC/ST	(2) SC/ST	(3) SC/ST	(4) SC/ST	(5) SC/ST
SC/ST Dissim.	-0.254***	-0.355***	-0.172***	-0.518***	-0.294***
	(0.0413)	(0.0361)	(0.0308)	(0.0343)	(0.0312)
SC/ST Sec. Share			1.129***		0.945***
			(0.0372)		(0.0386)
Observations	2439	2439	2439	2439	2439
State FE	No	Yes	Yes	Yes	Yes
Demo. Controls					

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows estimates from a city-level regression of SC/ST log consumption per capita against SC/ST dissimilarity. Column 1 has no fixed effects or controls; Column 2 adds state fixed effects; Column 3 includes only SC/ST secondary education share controls; Column 4 includes only city SC/ST population share and log city population controls; Column 5 includes both controls. All observations are at the city level. Dissimilarity data is from calculated from the SECC, city SC/ST shares and population are from the Population Census 2011 Town Directory, and consumption and education is from the SECC.

Table B.5: Non-SC/ST Log Consumption per capita vs SC/ST Dissimilarity

	(1) Non-SC/ST	(2) Non-SC/ST	(3) Non-SC/ST	(4) Non-SC/ST	(5) Non-SC/ST
SC/ST Dissim.	-0.144***	-0.271***	-0.0802***	-0.428***	-0.182***
	(0.0383)	(0.0333)	(0.0265)	(0.0317)	(0.0271)
Non-SC/ST Sec. Share			1.076***		0.913***
			(0.0310)		(0.0342)
Observations	2439	2439	2439	2439	2439
State FE	No	Yes	Yes	Yes	Yes
Demo. Controls					

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table shows estimates from a city-level regression of non-SC/ST log consumption per capita against SC/ST dissimilarity. Column 1 has no fixed effects or controls; Column 2 adds state fixed effects; Column 3 includes only non-SC/ST secondary education share controls; Column 4 includes only city SC/ST population share and log city population controls; Column 5 includes both controls. All observations are at the city level. Dissimilarity data is from calculated from the SECC, city SC/ST shares and population are from the Population Census 2011 Town Directory, and consumption and education is from the SECC.