Exposure and Preferences: Evidence from Indian Slums

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Abstract

How is physical proximity to ethnic outgroups related to outgroup hostility and coethnic voting? These relationships remain murky despite extensive study, in part because existing measures of heterogeneity are too geographically coarse and provide little insight into interpersonal contact. I introduce a measure of outgroup exposure, the $k$-nearest-neighbors score, that sidesteps fundamental measurement issues by disaggregating to the level of the individual. Using original geocoded network data from eight neighborhoods, I confirm that this metric reflects social contact at the individual level. I then apply this exposure metric to an original, large-$n$ survey experiment from surveys in 149 neighborhoods in cities across the Indian subcontinent to test whether individual residential exposure is associated with outgroup hostility and coethnic voting. I find that residential proximity to an ethnic outgroup is associated with a preference for coethnic candidates, but is not associated with greater hostility toward members of the outgroup.
Introduction

Rapid urbanization and globalization continue to result in closer and more frequent contact between ethnic groups worldwide, with implications for the salience of identity and ethnicity for politics. However, the impact of physical and social contact among ethnic groups on political attitudes and behaviors remains poorly understood (Enos 2017; Paluck, Green, and Green 2018.). Existing studies often do not distinguish between interpersonal attitudes and intergroup relations, conflating personal prejudice and intergroup rivalries. Moreover, most studies on physical proximity are conducted over geographical units that are too coarse to capture individual contact. This paper contributes two innovations to rectify these lacunae. First, I make explicit the inherently spatial and physically interactive elements of standard theories linking ethnic or religious differences to prejudice and political preferences. Second, I measure how inter-ethnic physical proximity – and thus exposure – is related to interpersonal attitudes toward the ethnic outgroup, and the salience of ethnicity to political competition, using a large-n survey experiment, combined with a novel measure of outgroup exposure at the individual level. In doing so, I contribute to an emerging literature on comparative urban political economy, focusing on the salience of ethnicity to political organization and claims-making in rapidly growing cities of the Global South – a context often marked by high ethnolinguistic diversity, rapid population growth, informal employment, insecure property rights, and unequal access to essential services (Auerbach 2016; Auerbach et al 2018; Post 2018; Thachil 2017; Nathan 2016).

I argue that outgroup hostility and coethnic voting are distinct phenomena, and that spatial ethnic distributions affect them in fundamentally different ways. First, proximity can facilitate meaningful social contact, which can under certain circumstances reduce prejudice and hostility toward individual members of outgroups (Allport 1954). Second, however, proximity can heighten the salience of internecine conflict over limited state resources: fol-
lowing Bates (1973), ethnicity tends to be a focal point for distributive conflict, and physical proximity tends to heighten the salience of ethnic divisions. These two effects are hypothesized to give rise to a complicated relationship between spatial proximity and ethnic politics. Proximity may increase personal amity between members of different ascriptive groups, but also sharpens intergroup political rivalry. This understanding reconciles certain tensions that are present in the literature, which has found conflicting evidence regarding the relationship between proximity and ethnic politics.

To test my theory, I develop a novel measure of outgroup exposure – the $k$-nearest-neighbors score – that bypasses the fundamental problems of ecological inference and the MAUP which have hampered previous efforts to measure the relationships between space and preferences. I demonstrate that my measure is able to reflect differences in intergroup contact within a single neighborhood. I then test my theory within the context of an original survey dataset from urban slums in three Indian cities, including geocoded interviews with 7198 individuals in 149 slums in Bengaluru, Jaipur, and Patna. This household survey includes two conjoint experiments: one measures the respondents’ preferences with regard to the traits of hypothetical political leaders, and the other measures preferences regarding the traits of potential neighbors. These two conjoint experiments allow me to test the two aspects of my theory. I use the leader experiment to test my contention that physical proximity conduces toward political contestation along ethnic lines, and the neighbor experiment to test my hypothesis that physical proximity is associated with personal amity. I do this by measuring the importance of the ethnicity of a putative leader or neighbor on an individual’s propensity for choosing that leader or neighbor. By comparing the results of these conjoint experiments for integrated versus segregated individuals, I am able to estimate the relationship between residential proximity and the extent to which co-ethnicity conditions individuals’ preferences for leaders and for neighbors.

I find persuasive evidence that individuals who live in closer proximity to members of
ethnic outgroups tend to have stronger preferences for coethnic candidates, as measured by the candidate-comparisons conjoint experiment, even though they do not harbor more personal prejudice, as measured by the neighbor-comparisons conjoint experiment, relative to individuals whose immediate residential environments are more homogeneous. These results support my theoretical distinction between ethnic prejudice and coethnic voting, and help to elucidate the complex relationships between space and preferences. Moreover, they demonstrate the efficacy of the proposed measurement method.

**Theory**

An ethnicity is defined by Max Weber as a “subjective belief in their common descent because of similarities of physical type or of customs or both, or because of memories of colonization and migration . . . whether or not an objective blood relationship exists” (quoted in Wilkinson 2006, p. 3; and Horowitz 1985, p. 53). A single individual may identify with multiple cross-cutting ethnicities (Dunning and Harrison 2010), and the salience of these dimensions of identity may vary over time and space. This fluidity plays a key role in electoral politics, and is exploited by political entrepreneurs: Wilkinson (2006, 4) notes that “individuals have many ethnic and nonethnic identities with which they might identify politically. The challenge for politicians is to try to ensure that the identity that favors their party is the one that is most salient in the minds of a majority of voters.”

The contingent nature of ethnic boundaries and of their relative salience implies that “[ethnic] conflict takes different courses, depending . . . on how groups are distributed in relation to territory and state institutions” (Horowitz 1985, 53). Racial threat theory, the observation that proximity to racial outgroups is conducive to political mobilization along ethnic lines, has been a mainstay of literature on American race relations (e.g. Key 1949; Enos 2015). In the context of developing democracies, it is echoed by Bates’ modernization
Moreover Wilkinson (2006) finds that this view is colloquially ubiquitous in India among slum dwellers and bureaucrats alike; the common perception is that distributive conflict tends to reach its apex when members of both religions are locally present in roughly equal numbers. In this view, physical proximity to large numbers of outgroup members is seen to increase political mobilization along ethnic lines.

Building on racial threat theory and modernization theory, I argue that in contexts where political mobilization and distribution along ethnic lines already exist, physical proximity between members of different ethnic groups tends to heighten the salience of ethnicity for distributive conflict. This is because people living near non-coethnics can see the social significance of ethnicity playing out before them in a way that is not visible to people living in ethnically homogeneous environments. While proximity might improve interpersonal relations, it also heightens the visibility and salience of sociopolitical fault lines.

I contend that in the presence of patronage politics along ethnic lines, physical proximity to members of another group heightens awareness of the existence and predominance of intra-ethnic networks, which in turn heightens the salience of ethnicity as a locus of distributive politics. Proximity to an outgroup makes individuals aware that their own network tends to be delimited by ethnicity, and moreover that the other group is also mobilizing in the same way. This awareness tends to reify and reinforce the importance of ethnic networks and coethnic voting.

While proximity might lead to reduced prejudice by way of positive contact as discussed below, it also increases individuals’ awareness of existing social conflicts tied to ethnicity. In the context of India, distributive contests along religious, racial, and caste lines affect both programmatic and clientelistic distribution (e.g. Brass 2003; Gubler and Varshney 2013; Huber and Suryanarayan 2016; Wilkinson 2006). A Hindu living near Muslims might be disabused of personal stereotypes concerning the ethno-religious other, but will also be more attuned to the fact that struggles over limited resources are occurring along religious lines.
on the levels of city, state, and national politics, and that members of the other group are in fact coordinating amongst themselves to gain a larger share of the distributive pie. While this integrated individual might be less personally prejudiced, she is also more inclined to view politics along ethno-religious lines.

This mechanism is strengthened by the well-established (Auerbach 2016; Kitschelt and Wilkinson 2007; Krishna 2007) importance of clientelistic or patron-client linkages in Indian politics, which creates an information constraint that reinforces the importance of ethnicity. In a democratic context, patronage transactions are necessarily below-board, giving rise to a severe information constraint regarding who benefits: as Chandra (2004) points out, “the normative and legal constraints of modern democratic government ensure that politicians can send only surreptitious signals about whom they intend to favor in the implementation of policy, announcing their intent by unofficial action but not by open declaration in the official public sphere” (p. 58). In the face of this information constraint, physical proximity provides an opportunity for people to see rival patronage networks in action: individuals who are physically close to members of another ethnicity can actually watch their neighbors mobilizing politically along ethnic lines, see politicians visit their neighbors around election-time, and watch the distribution of benefits to their neighbors on the basis of ethnicity. Physical proximity, I argue, leads to individuals becoming more aware that political mobilization and distribution are in fact occurring within ethnic networks, and that this awareness leads to an increased propensity to engage in such mobilization.

This is particularly the case in a context in which ethnicity and partisanship are intimately linked. In India, the Congress party (INC) represents itself as inclusive of all religions, while the BJP espouses a Hindu-nationalist ideology of “Hindutva.” Muslims are accordingly much more likely to support the INC than the BJP. In my survey data, Hindu respondents in all three cities are more likely to indicate support for the BJP than for the INC, while the
opposite holds for Muslims. When ethnicity and partisanship are closely tied, proximity to non-coethnics implies exposure to mobilization efforts on behalf of a rival party. This is especially important in light of Auerbach’s (2016) finding that the presence of competing party networks within a single slum is associated with reduced neighborhood service provision, as the rival networks vie to undermine one another’s efforts to obtain important neighborhood-level services.

Apart from service provision, people gain self-esteem and “ego rents” from seeing co-ethnics in office. Ethnographic work has found this to be the case in India, even in cases where individuals do not expect any service benefits: “this feeling [of happiness at having a co-ethnic in office] was not related to material benefits but to who the representative is” (Jensenius 2012). According to social identity theory (Tajfel and Turner 2004), group status is defined relative to a comparison group. Thus when a person is in close proximity to another ethnic group organizing along partisan lines to elect their co-ethnics to office, it is sensible to expect that person to be particularly keen to elect her own co-ethnics, driven by a sense of competition for group status.

These considerations give rise to Hypothesis 1, stating that residential proximity is associated with the salience of ethnicity as a second dimension in distributive politics. The empirical implications of this argument are given in the next section.

**Hypothesis 1.** In a context of patronage politics along ethnic lines, residential proximity to members of another ethnicity is associated with increased salience of ethnicity for distributive politics.

While proximity is associated with increased mobilization along ethnic lines, a well-established theory predicts that intergroup hostility and prejudice should follow a contrary

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1 Among Jaipur Hindus, 773 support the BJP while 672 support the INC; for Muslims the numbers are 77 and 415 respectively. Likewise in Patna, Hindus are for the BJP over INC by 442 by 172, while Muslims are for INC over BJP by 36 to 17 (with pluralities supporting third parties); and in Bangalore, Hindus support BJP over INC by 642 to 401, while Muslims support INC over BJP by 167 to 44.
relationship. Contact theory holds that meaningful social contact reduces prejudice between groups. According to Allport (1954, p. 268), “Contacts that bring knowledge and acquaintance are likely to engender sounder beliefs concerning minority groups, and for this reason contribute to the reduction of prejudice.” This effect is conditional: prejudice “may be reduced by equal status contact between majority and minority groups in the pursuit of common goals. The effect is greatly enhanced if this contact is sanctioned by institutional supports (i.e., by law, custom, or local atmosphere), and provided it is of a sort that leads to the perception of common interests and common humanity between members of the two groups” (p. 281). Stated differently, the contact hypothesis is subject to four conditions: “equal status between the groups in the situation; common goals; intergroup cooperation; and the support of authorities, law or custom” (Paluck, Green and Green 2018, p. 3).

Allport’s contact hypothesis has laid the groundwork for much subsequent work on ethnic politics (Forbes 1997). A meta-analysis by Pettigrew and Tropp (2006) finds decisive support for the contact hypothesis: the authors argue that there is “little need to demonstrate further” (p. 751) that contact reduces prejudice, and moreover that the effect is not contingent on the satisfaction of Allport’s four conditions. However, a later meta-analysis by Paluck, Green, and Green (2018) exposes surprising gaps in the literature. They note that while existing experimental studies show that contact causally reduces prejudice, the effect is weakest for contact with racial and ethnic outgroups. Furthermore, nearly all of the studies in their meta-analysis took place in the U.S., and few of the studies focusing on race and ethnicity included respondents over 25 years old. Moreover, none of the experimental studies systematically establish whether Allport’s four conditions are in place. In short, their meta-analysis finds that little work has been done to establish the contact hypothesis outside of college-age Americans; that the results for race and ethnicity – Allport’s original subject –

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2 One study included in their meta-analysis, Barnhardt (2009), finds that residential integration at the level of an apartment hallway tends to improve relations and attitudes between Hindus and Muslims.
are weak; and that the importance of Allport’s four conditions has not been properly tested.

This gap in the literature is addressed by the current study, which tests the relationship between ethnic prejudice and outgroup exposure among a mixed-age sample, outside the United States.\(^3\) In addition, this is a setting in which some but not all of Allport’s four conditions are met. In particular, as elaborated above, ethnic patronage (Chandra 2004) and the mobilization of religious tensions for political purposes (Wilkinson 2004) creates a situation in which “common goals” and “the support of authorities” for intergroup cooperation are undermined. In short, the present empirical context is one that addresses the gaps identified by the Paluck, Green and Green (2018) meta-analysis: it is outside the United States, includes adult respondents, and is a case when not all of Allport’s conditions are met. It thus constitutes a “hard case” for the contact hypothesis, in that it focuses on interethnic prejudice – for which existing literature finds the weakest effects from contact – in a sample with demographic characteristics that are under-represented in the existing literature, and in a context where not all of Allport’s original conditions are seen to hold.

Hypothesis 2, stating that residential proximity is associated with good *personal relations* between members of different groups, is a restatement of the contact hypothesis, combined with the empirical premise that residential proximity is positively associated with exposure. As noted above, this context constitutes a “hard case” for the contact hypothesis. The empirical implications of this argument are given in the next section.

**Hypothesis 2.** In a context characterized by ethnic patronage, *residential proximity to members of another ethnicity is not robustly associated with increased personal amity toward members of that ethnicity.*

To test these hypotheses about the relationships between residential exposure and indi-

\(^3\)In addition, all of the studies in the Paluck, Green, and Green meta-analysis rely on self-reported feelings of prejudice, which may be subject to social desirability bias. The present study is based on conjoint experiments, which reduce this source of bias by providing multiple criteria to inform the respondent’s choice, and thereby to mask individual prejudice as the determining factor.
individual preferences, I develop a novel measure of exposure at the level of the individual. In the next section I establish the need for such a measure, describe how it is constructed, and demonstrate its useful properties.

**Heterogeneity, Segregation, and Exposure: The Challenge of Measurement**

Existing studies of heterogeneity and ethnic preferences tend to rely on measures of heterogeneity that are too geographically coarse to capture variation in interpersonal contact between groups. For example, Kasara (2013, 2017) calculates a segregation index for administrative locations that cover an average of 102 sq km and are home to 13,000 people, while Ejdemyr, Kramon, and Robinson (2017) calculate a segregation index for electoral districts that are each home to approximately 64,000 people and cover nearly 400 sq km. Likewise, Ichino and Nathan (2013) divide Ghana’s 28 million people into only 631 enumeration areas. By assigning *the same* proximity or segregation score to *all* of the tens of thousands of individuals in each of these vast areas, these measures elide differences between individuals’ physical proximity to members of other ethnic groups.

Moreover, all existing measures are subject to ecological inference fallacy and the modifiable areal unit problem (MAUP). Ecological inference is a fundamental problem in empirical social science, due to the difficulty of accurately “using aggregate data to infer discrete individual-level relationships of interest” (King 1997). The modifiable areal unit problem (MAUP) is a manifestation of the ecological inference problem that affects the analysis spatial aggregates (Sui 2009), making estimates drastically sensitive to the choice of scale and to the placement of administrative boundaries between and within the units of analysis. All measures of heterogeneity or segregation over spatial aggregates are subject to ecological inference fallacy and to the MAUP. This means that existing measures are highly sensi-
tive to arbitrary areal divisions, and are unreliable for estimating individual-level quantities.

I introduce a measure of outgroup exposure, the $k$-nearest-neighbors score, that sidesteps ecological inference fallacy and the MAUP by disaggregating to the level of the individual. Moreover, unlike existing efforts to bypass the MAUP, my method requires no additional data collection beyond geocoded interviews with a random sample of area residents, making the proposed method easily applicable to a wide range of empirical work.

Composition and segregation are two distinct measurement concepts used to study heterogeneity. Composition metrics are based on the proportion of groups living within an areal unit, without comparing between areal units and without any spatial component. Composition is subject to the MAUP and prone to ecological inference fallacy. Moreover, by eliding spatial relationships and variation among sub-units, composition metrics are not sensitive to differences in ethnic mixing or contact. Many studies of ethnic diversity and attitudes or public goods provision rely on measures of composition, including Key (1949), Bannerjee, Iyer, and Somanathan (2005), Rugh and Trounstine (2011), Ichino and Nathan (2013), and Kaufmann and Harris (2015).

Segregation is a measure of the unequal distribution of groups, and is calculated as the heterogeneity of composition scores for smaller units within the main unit of analysis. Segregation is defined at the level of a geographic unit, which for the purpose of calculation is divided into smaller areal units. It therefore requires the specification of two units of analysis: the larger geographic unit whose segregation score is to be calculated (e.g., a city) and the smaller areal unit that is used in the calculation (e.g., a census block). The segregation score of the larger geographical area is calculated from the ethnic compositions of the smaller areal units that compose it. When the ethnic compositions are relatively similar (different) across areal units, then the segregation score of the geographic area is low (high).

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4Ichino and Nathan (2013) use the spatially weighted population share, which is essentially a measure of composition, although it also incorporates distance by including the composition of other areal units within a certain radius, downweighted by distance.
Segregation metrics can be classified as spatial or aspatial. Aspatial metrics compare the compositions of all areal units within the geographic unit without reference to the distances between areal units. One example of an aspatial segregation metric is Theil’s Index, used by Kasara (2013, 2015). An important limitation of aspatial segregation metrics is the “checkerboard problem” (Reardon and O’Sullivan 2004, p. 123): these metrics are not sensitive to whether areal units with high concentrations of a particular group are clustered together, or are interspersed with other groups. To address this problem, spatial segregation metrics weight the comparison of areal units by the spatial proximity between units. One example is the spatial dissimilarity index (Reardon and O’Sullivan 2004), used in Ejdemyr, Kramon, and Robinson (2015).

Because they rely on the definition of areal units, measures of segregation and composition – both spatial and aspatial – are subject to the modifiable areal unit problem (MAUP):

The essence of the MAUP is that there are many ways to draw boundaries to demarcate space into discrete units to form multiple spatial partitioning systems. These units may serve administrative purposes, such as the counties in the U.S., or statistical or data gathering purposes, such as the census enumeration units of tracts, block groups and blocks below the county level. Although these boundaries are often drawn along some physical features (such as rivers or roads) that may serve as physical barriers separating areal units, there are multiple ways to draw those boundaries. Thus multiple datasets of the same area can be created and they will offer different descriptions of the areas and different analytical results. (Wong 2009, p. 106)

Figure 1 (adapted from Echenique and Fryer 2007) is a demonstration of how the MAUP can affect segregation calculations. The left and right sides of the figure show the same geographic unit (e.g. a city), which has been divided into areal units (e.g. census tracts) in
two different ways. The dissimilarity index is 0 (maximum integration) for the left side and 1 (maximum segregation) for the right side, despite the two sides having identical distribution of households – all that differs is the arbitrary partition into areal units. This example demonstrates the sensitivity of segregation metrics to arbitrary choices of how to partition a geographical unit into areal units. Moreover, Table 1 shows how one commonly-used metric, the dissimilarity metric, varies by level of aggregation for the three cities in the study.\textsuperscript{5} This exercise shows that Bangalore appears to be the most segregated when analyzed at the state level, but the least when analyzed at the district and city level, and thus highlights the sensitivity of segregation metrics to the choice of scale.

Another issue with most measures of segregation and composition is that, because the unit of analysis is a geographic or areal unit, every individual within the unit is assigned the same score. This can mask very real differences between the individuals within the unit. Existing measures of composition or segregation, by giving the same score to everyone in the neighborhood, assume away this rich and consequential variation. For example, by comparing segregation scores across enumeration areas, one implicitly assumes that everyone in the enumeration area (which may cover hundreds of square kilometers) has the same amount of contact with ethnic outgroups, even though some people in the area might live next door to outgroup members and others might live tens of kilometers away from the nearest non-coethnic. As Echenique and Fryer point out, an individual-level metric makes it possible “to analyze the full distribution of segregation, allowing researchers to move beyond aggregate statistics, which can be misleading.” An individual metric avoids this ecological inference problem by providing access to the entire distribution of individual scores, rather than one summary statistic for an entire geographical area. In doing so, we can obtain information about \textit{individual} proximity and contact which is masked by aggregate measures.

\textsuperscript{5}The calculations are based on data from the Census of India. Scheduled-caste is used because religion data is not available for lower levels of aggregation.
In order to sidestep the MAUP and the problem of eliding individual differences, Echenique and Fryer (2007) create a segregation measure that disaggregates to the level of the individual. This approach avoids the problem of having to choose areal units. Moreover, it greatly increases power: “Rather than correlate individual economic outcomes with city-wide segregation, one can correlate individual outcomes with individual measures of segregation” (p. 448). However, the Echenique and Fryer metric relies on network data, mapping the social connections of respondents, which can be costly and difficult to collect; their measure cannot be used when only the locations (and not the contacts) of respondents are known.

Wong et al (2012) address these issues by having each respondent hand-draw a map of their “local community.” This technique provides a disciplined way of choosing the geographical unit that is most salient to each respondent, for the purpose of calculating racial composition and exposure. However, this method requires asking respondents to hand-draw maps of their local community, which introduces a costly additional data collection step. Moreover, Dinesen and Sønderskov (2015) introduce a measure based on the proportion of outgroup members living within an 80-meter radius of an individual. However, by imposing a fixed radius, this method does not account for population density or sampling frequency.

We can characterize existing measures of segregation and exposure as being more or less responsive to individuals’ micro-spatial environments. At the latter end of the scale, we have nonspatial segregation measures, such as Theil’s index, that are subject to the checkerboard problem. Then come spatial segregation metrics, such as the spatial dissimilarity index, that do take spatial relationships between areal units into account, but are still subject to the MAUP. Finally we have exposure indices that bypass the MAUP by disaggregating to the level of the individual, such as those of Echenique and Fryer (2007), Wong et al (2012), and Dinesen and Sønderskov (2015). My metric falls into the last group, while offering practical and theoretical advantages outlined above.

I introduce a measure that bypasses the MAUP and the question of scale by taking the
individual as the unit of analysis. This method does not involve any additional data collection steps other than having the survey instrument automatically record the geolocation of the household where the survey is conducted, which is easily accomplished on common survey platforms. I use this measure to test the hypotheses discussed above. First, I describe how the measure is constructed, and establish its relationship with social interactions using a separate network dataset.

The individual exposure score that I propose is called the $k$-nearest-neighbors score. It is defined as the number of people, out of the $k$ people who live closest to the individual in question, who are of the same ethnic group as that individual. For example, if five of a particular Hindu’s ten closest neighbors are also Hindu, then that individual’s 10-nearest-neighbors score is equal to 5. The score is higher for individuals with lower outgroup exposure, because higher scores indicate that a higher proportion of that person’s closest neighbors are co-ethnics. Figure 2 shows a stylized example of how the $k$-nearest-neighbors score is calculated, while Figure 3 shows a map of a particular neighborhood with respondents shaded by their $k$-nearest-neighbors score.

This measure has several desirable properties. Because it is an individual metric, it is not subject to ecological inference fallacy or to the MAUP. It is based on a fixed number of people who are physically closest to the individual in question, so there is no need to arbitrarily choose an areal unit. The data collection process adds no additional time to the survey, involving only the automated collection of geocoordinates. The calculation of the metric is very simple and intuitive: one simply calculates the Euclidean distances between all the survey locations in the sample, and then counts the ethnic matches among the $k$ closest neighbors for each respondent. The value of $k$ is subject to choice, but because the $k$-nearest-neighbors score can be easily calculated for any value of $k$ up to the size of the local sample, it is straightforward to check that one’s results are robust to the choice of $k$.

Because the $k$-nearest-neighbors metric provides a fine-grained measure of an individual’s
residential context, it provides an effective measure of intergroup social contact, making it particularly suitable for the substantive questions hinging on social exposure for which segregation metrics are often used. To demonstrate the relationship between the $k$-nearest-neighbors metric and social contact for the empirical context of the present study, I leverage an original network dataset comprising interviews with every household in each of eight urban Indian slums, in which respondents are asked to name the other individuals in the neighborhood with whom they have various types of contact. By using this network dataset to confirm that individuals who have lower scores on the $k$-nearest-neighbors metric (i.e. those who live near members of another ethnicity) also have more social contact with members of other groups, I establish the validity of using the $k$-nearest-neighbors proximity measure as a proxy for social contact.

The network dataset includes responses to eleven questions in which respondents are asked to identify an individual with which they have a specific type of social contact, such as visiting their home or working together.\(^6\) I measure a respondent’s ingroup contact as the number of these questions for whom that respondent names a person who is the same religion as the respondent. This provides a measure of individual ingroup insularity, and thus allows us to demonstrate that coethnic contact is substantially correlated with my outgroup exposure measure. Table 2 shows the correlations between the $k$-nearest-neighbors scores and the proportion of network contacts, i.e. the proportion of each respondent’s out-connections, to members of the same ascriptive group, calculated for both religion and

\(^6\)The eleven questions in the network dataset that I use to measure social contact are as follows: “If you suddenly needed to borrow 1000 rupees [about $15] for a day, is there someone in this slum whom you could ask?”, “Who in the settlement would come to you if they needed to borrow 1000 rupees?”, “In your free time, whose house do you visit in this neighborhood?”, “Is there someone who lives here who might be able to help the neighborhood get [a needed] service?”, “Who usually leads these [neighborhood] meetings?”, “Is there anyone whose opinion matters a lot in how you vote?”, “Can you give me the name of the first most important leader of your neighborhood?”, “Did someone in this settlement help you find [your current] job?”, “When you go to work, do you regularly work with anyone else who lives in this settlement?”, “If you unexpectedly were unable to find work, is there someone in the settlement to whom you would turn for help?”, “Is there someone in the settlement who could help you sell or rent [your] house?”
caste, for various values of $k$. For example, the correlation between the number of the 10 nearest neighbors who are the same religion as the respondent, and the proportion of the respondent’s social ties who are the same religion as the respondent, is 0.42. These results indicate that the $k$-nearest-neighbors score is picking up a substantial portion of the variation in contact: individuals with a lower $k$-nearest-neighbors score have a higher degree of contact with members of an ascriptive outgroup.\(^7\) Only 1% of individuals with 10-nearest-neighbors scores of 10 (i.e. minimally exposed) have any contacts with members of the outgroup, compared to 26% of individuals with scores of 9 or below, and 75% of individuals with scores of 0 (maximally integrated).

These results demonstrate that the $k$-nearest-neighbors metric is a valid proxy for individual contact with members of other ethnic groups, even when only a fraction of the population is sampled, and is therefore useful for testing theories regarding the relationships between contact, attitudes, and preferences. In contrast to existing measures, this novel metric is not subject to ecological inference fallacy or the modifiable areal unit problem, and it can easily be calculated from geocoded survey data.

It bears noting that the present study verifies the relationship between the $k$-nearest-neighbors metric and individual contact only for the specific empirical context treated here. It remains to be verified, ideally by comparison with network census data, whether this holds in other empirical contexts. I expect the correspondence to be strongest in socio-spatial circumstances similar to those treated here, with active public spaces in which neighbors interact while undertaking daily life.

\(^7\)I also confirm that the value of the $k$-nearest-neighbors metric is highly correlated with contact when the measure is calculated from random subsets of the network data. This is to ensure that the metric works when calculated from neighborhood samples, as is the case in the main data set. As shown in the Appendix (Section 1.2, p. 3-6), the $k$-nearest-neighbors metric remains highly correlated with contact even when calculated from random subsets of the data, indicating that it is suitable for use with samples.
Empirical Strategy

The slums of urban India offer an empirical setting in which the dynamic interplay between proximity and preferences can be studied. The proportion of India’s population living in cities having increased from 17% in 1951 to 32% in 2011; it hosts three cities with over 10 million people, and by 2031 is expected to have six (United Nations 2012). The burgeoning urban population has tremendous social, economic, and political consequences. Many urban poor live in slums, which often lack basic services such as water and sewage, and are often characterized by informal land title and insecure tenure. In order to gain services and property rights, slum dwellers must mobilize politically, often by coordinating their votes through a “vote bank” in exchange for attention from political parties that can exercise influence with the municipal authorities (Auerbach 2016). Like many urban areas in the global south (Post 2018), this context is characterized by high informality, tenuous property rights, unequal access to services, and high ethnolinguistic diversity.

Political parties frequently use religious or ethnic tension as a “second dimension” that can shift attention and political competition away from the provision of services (Wilkinson 2006). Moreover, India’s colonial history has given rise to a contested system of reservations in schools and government for members of disadvantaged castes and minority religions. Three particularly important ethnic dimensions are religion (primarily Hindu and Muslim), caste, and mother tongue. As Wilkinson (2006, p. 21) points out, “A central problem facing individual politicians is how they can ensure that voters will identify themselves with a politician’s party and the group he or she claims to represent, at least on polling day, rather than with other ethnic or nonethnic groups, parties, and interests.” The various dimensions of identity can be, and are, selectively harnessed for electoral purposes. In the present study, I focus on the distinction between Muslims and Hindus, as members of these groups can be visually distinguished from one another, and because this distinction is of particular salience.
for contemporary Indian politics.

The swift influx of urban migrants and chaotic nature of the property market has resulted in a highly variegated urban landscape, with newcomers often landing wherever they can find a space. What is the relationship between an individual’s residential proximity to members of another religion, and the salience of that ascriptive division to that individual’s political preferences?

This study draws on a massive data collection effort spanning three cities over three years, comprising more than nine thousand interviews in 149 distinct slums. The main data set consists of household sample surveys, in which a random sample of households were interviewed in each neighborhood. These are complemented by a unique network census survey, in which every household in eight slums completed a survey instrument that includes questions regarding social, economic, and political linkages with other people in the neighborhood. The household surveys were collected in 2015 in Jaipur (Rajasthan) and Patna (Bihar); and in 2016 and 2017 in Bangalore (Karnataka). The network census surveys, which were introduced in the previous section, were conducted in 2016 in Jaipur and Patna. The survey waves are summarized in Table 3.

In Jaipur, the government provided a complete list of the 273 slums in the city. These slums were classified into four types, based on apparent dwelling quality from satellite photos (distinguishable vs. nondistinguishable dwelling units; geometrically uniform vs. haphazard layout). 40 slums were then randomly selected to preserve the distribution across slum types. In Patna, a similar process was followed, except that the slum classification and stratification were carried out according to the availability of local services (due to the availability of data, and to the similar appearance of the slums from satellite photos). For Bangalore, the slum classification and stratification were based on neighborhood-level data collected in 2013, using a sampling frame of 132 slums provided by the government. The precise boundaries of each neighborhood were geotagged by the enumeration teams in accordance with residents’ own
notions of the boundaries of the neighborhood. Thus, the neighborhoods that are present in
the data correspond to the local human geography.

Household surveys were conducted in neighborhoods in the sample frame. These house-
hold surveys are the main data source for the present study. From each neighborhood, 30
(Bangalore ’16), 40 (Bangalore ’17), or 60 (Jaipur and Patna) households were randomly
selected for interviews. The interviews lasted approximately 45 minutes, and took place
in the respondents’ homes. The interviews were collected on tablet computers running the
Open Data Kit (ODK) platform. Each interview was geocoded (latitude and longitude) by
the tablet computers; the geocodes are used to calculate the \( k \)-nearest-neighbors metrics.

To account for the fact that many respondents live in homogeneous neighborhoods con-
sisting entirely of one religion, I also develop a de-medianed version of the score, in which
individuals’ scores have the neighborhood-level median subtracted from them. The empirical
distribution for the de-medianed version of the \( k \)-nearest-neighbor score for religion is shown
in the Appendix (Figure A2, p. 2). For the comparisons based on this version of the metric,
I compare respondents with values greater than or equal to zero (relatively low exposure) to
those with negative values (relatively high exposure).

**Testing Hypothesis 1**

I test Hypothesis 1 by considering the results of two conjoint experiments: one in the house-
hold sample survey in which each respondent is asked to choose between two candidates
for ward leader, a local elected office; and another in the network census survey in which
respondents choose between candidates for neighborhood leader. Each candidate has two
randomly-chosen characteristics. Each respondent is asked to answer three such questions.
In order to ascertain the relationship between outgroup exposure and preferences, I split
the sample between individuals with high exposure (\( k \)-nearest-neighbors below the median)
or low exposure (\( k \)-nearest-neighbors above the median). Per Hypothesis 1, I expect that
individuals with higher exposure (lower $k$-nearest-neighbors) will have higher coefficients\textsuperscript{8} for “A member of your caste or religion.” This hypothesis is tested for both the household sample survey\textsuperscript{9} and for the network census survey.\textsuperscript{10} To test this relationship, I split the sample between individuals who have high (at or above median) and low (below median) scores for exposure, and compare the coefficients using a z-test.

Testing Hypothesis 2

I test Hypothesis 2 by considering the results of a conjoint experiment in which each respondent is asked to choose between two putative neighbors: “Imagine two people were thinking about moving into your neighbourhood. I am going to give you a few different scenarios. Please tell me which person you would rather have living in the neighborhood.” Each respondent is asked to answer three such questions.\textsuperscript{11} The characteristic bearing on Hypothesis 2 is the ethnicity (religion) of the neighbor: I expect that Hindus with higher exposure (lower $k$-nearest-neighbors) will have higher preferences for Muslim neighbors, and that more integrated Muslims will have higher preferences for Hindu neighbors. To test this relationship, I split the sample between individuals who have high (at or above median) and low (below median) scores for exposure, and compare the coefficients using a z-test.

\textsuperscript{8}The quantity of interest is the Average Marginal Component Effect (AMCE), which I estimate through a simultaneous linear regression (Hainmueller, Hopkins and Yamamoto, 2013).

\textsuperscript{9}In the household sample survey, the first characteristic takes one of the following levels: “A member of Congress party”; “A member of BJP”; “A member of your caste or religion”; “An educated person” (base category). The second characteristic takes the levels “Promises private benefits to your or your family”, “Promises better community services”, “Promises some religious or caste benefits”, and “Has the support of your neighborhood leader”.

\textsuperscript{10}First characteristic: “Lives in the slum”, “Is a member of your caste or religion”, “Is an honest person” (base category), “Supports the same party as you”; second characteristic: “Has a lot of personal resources s/he can spend on the slum”, “Has good connections to political parties”, “Has good connections to city administrators”, “Has good connections with the municipal corporation”, “Has lots of support in the neighborhood.”

\textsuperscript{11}The first characteristic takes one of the following levels: “Works for the municipal corporation”; “Owns a tea stall”. The second characteristic takes one of the following levels: “Is a Hindu”; “Is a Muslim”, “Is a non-Kannada-speaker” (base category). The third characteristic takes one of the following levels: “Is a little bit/lot richer/poorer than most people who live here”; “has about the same income as most people who live here.”
Results and Discussion

Figures 4 and 5 show the results of testing Hypothesis 1, using the candidate conjoint experiments in the household sample and network census surveys, respectively. The AMCE’s for candidate coethnicity (i.e. respondents’ preferences for coethnic candidates) are shown on the y-axis, for low-exposure (high nearest-$k$ score) and high-exposure groups. The standard errors are double-clustered by respondent and by neighborhood. The shading of the points indicates the p-value of a z-test\textsuperscript{12} for the difference between the coefficients between the low- and high-exposure groups: when the points are darkly shaded, it indicates that the difference between the groups is significant at the 5% level. For all values of $k$, more-exposed individuals have a higher estimated preference for coethnic candidates than less-exposed individuals.\textsuperscript{13}

It should be noted that Hypothesis 1 is supported by results from two separate data sources: the results from the household sample and network census are very similar. Moreover, the two conjoint experiments differ in that respondents in the household sample are asked to choose between two hypothetical ward leaders, whereas respondents in the network census are asked to choose between neighborhood leaders. The similarity between the results for two different local elected offices, from two separate survey waves, lends further support to Hypothesis 1.

This result is not limited to Hindus or to Muslims. As shown in the Appendix (Figures A5, A6, A16, and A17, on p. 10-11 and 22-23), the point estimates are similar when the sample is restricted to Hindus and Muslims. The fact that the results are similar for both subgroups provides reassurance that the observed results are not simply reflecting differences

\textsuperscript{12}The z-value is given by $z = (c_1 - c_2) / \sqrt{s_1^2 + s_2^2}$, where $c_1, c_2$ are the estimated coefficients and $s_1, s_2$ are the standard errors. Under the null hypothesis $c_1 = c_2$, the z-value is distributed as a standard normal.

\textsuperscript{13}It is worth emphasizing that the coefficients for the conjoint experiment are relative to the base category, “A well-educated person.” The important result is the significant difference between the coefficients between the low- and high-exposure groups, not necessarily the significance of each of the coefficients relative to zero.
between Hindus and Muslims. Similar analysis is reported to verify that the results hold when other non-balanced observables\textsuperscript{14} are accounted for by restricting the sample to individuals with particular values of each variable (see Appendix, Figures A7 - A15, p. 12-21). For each imbalanced variable, the results are similar for the subgroups as for the entire sample, increasing confidence that the differences in attitudes are due to exposure rather than some omitted variable.

As discussed above, I also calculated a de-medianed version of the $k$-nearest-neighbors metric, which is normalized by the neighborhood-level median, both for Hindus and Muslims.\textsuperscript{15} This metric is constructed to be compositionally invariant, i.e. to not be systematically affected by differences in the proportions of Hindus and Muslims living in particular neighborhoods. I repeat the analysis of the conjoint experiments, comparing the coefficients of respondents at or above the sample median of the de-medianed score (i.e. greater than or equal to zero) to respondents below the sample median; these results are shown in the Appendix (Figure A4, p. 9).\textsuperscript{16} The results from the analysis of the de-medianed version of the metric are very similar to those presented in this section, providing evidence that the results are due to individual differences in physical location within the neighborhood, rather than merely neighborhood composition.

Figure 6 shows the results of testing Hypothesis 2, using the neighbor conjoint experiment in the household sample survey. The AMCE’s for neighbor non-coethnicity (i.e. respondents’ relative preferences for non-coethnic neighbors) are shown on the y-axis, for low-exposure (low nearest-$k$ score) and high-exposure groups. The standard errors are double-clustered

\textsuperscript{14}The current study is not a randomized experiment. The balance checks are performed to identify other observables that differ between less- and more-exposed individuals, so that these observables can be included in the analysis to ensure that they are not driving the result.

\textsuperscript{15}For example, if the median values of the 10-nearest-neighbors metric were 10 for Hindus and 3 for Muslims in a particular neighborhood, then a Hindu with a score of 7 would be given a de-medianed score of -3, while a Muslim with a score of 7 would be given a de-medianed score of 4.

\textsuperscript{16}Note that this figure shows the difference between the coefficients for the high- and low-exposure groups, rather than the coefficients themselves.
by respondent and by neighborhood. The point estimate for the high-exposure group is indeed higher, although the difference is not significant at conventional levels. These results do not provide strong support for Hypothesis 2, but they do provide limited evidence that residential proximity is not associated with a higher level of intergroup hostility. Again, it should be emphasized that the present context constitutes a “hard case” for the contact hypothesis, and the present results demonstrate the need for further study of the importance of the particular structure of inter-ethnic relations for the relationship between proximity and prejudice.

My results do not necessarily reflect the causal effects of exposure. It might be the case that people sort into physical locations based on unobservable characteristics that are correlated with the dependent variable. Residential sorting has been noted in a number of contexts, starting with Tiebout (1956), including urban India (Auerbach et al 2018). It bears noting, however, that the most obvious concern of this type – that people who are more prone to coethnic voting are less likely to choose to live among coethnics – would be expected to produce a result with the opposite sign from the result that I find in support of Hypothesis 1. Moreover, there is some evidence that individuals choose the location of their residence for reasons unrelated to self-selection into more- or less-exposed environments. The 2017 survey in Bangalore contains questions regarding respondents’ reasons for choosing to live in the their neighborhood. When asked for the one primary reason they had chosen that neighborhood instead of another, 35% of respondents indicated that they had been born there. 25% said it was close to work, while 11% indicated that it was close to friends or family. Only 4% and 2% reported coming to the neighborhood to live near members of their caste and religion, respectively.

One could still formulate narratives whereby residential sorting could produce the observed empirical result. For example, perhaps better-off respondents have less coethnic preference due to lower reliance on ethnic patronage networks, and also more ability to sort
into less-exposed locations. This would produce the observed correlation between exposure and coethnic preference. However, I demonstrate in the Appendix (Figure A7, p. 12) that the result still holds when restricting the sample to well-off individuals, as measured by the asset score. The same is true for other observables that differ significantly between more- and less-exposed groups.

**Conclusion**

This article has examined how residential proximity to ethnic outgroups is related to ethnic voting and outgroup hostility, drawing on a massive original data collection effort. I find that living in close proximity to members of ethnic outgroups is associated with a higher preference for coethnic voting, but not necessarily with an increase in ethnic prejudice. People living near non-coethnics prefer to vote for their own coethnics, which I argue is due to exposure to rival networks of political patronage. Moreover, by failing to find that intergroup contact is associated with a reduction in prejudice, this study underscores that the relationship between contact and ethnic prejudice, in a context where Allport’s conditions are not met, remains poorly understood.

To better understood the conditions under which contact reduces ethnic prejudice, one promising path forward is to explore variation in the extent to which Allport’s four conditions (equal status, common goals, intergroup cooperation, and the support of authorities, law or custom) hold, and whether this variation is correlated to the extent to which contact or exposure is related to differences in prejudice. Similarly, the observed relationship between proximity and coethnic voting is hypothesized to stem from the pervasiveness of ethnic patronage networks. Further evidence of this correspondence could be found by testing whether the strength of the relationship varies according to the structure of patron-client networks. Future work could explore these questions by collecting data in a larger number
of Indian cities that vary in the nature of local ethnic relationships and policies.

As developing cities grow apace, new infrastructure projects will need to be planned, approved, and implemented at a prodigious rate. The layout of urban infrastructure has crucial implications for the spatial distribution of groups of people, with a profound power to integrate or segregate (Massey and Denton 1993; Nall 2015). My results indicate that residential proximity between groups does not exacerbate interpersonal tensions, but that it is associated with higher salience of ethnicity for politics. Given the troubled history of inter-religious relations in India, and the continued process of rapid urbanization, these results point to the need for measures to increase interethnic harmony. In particular, there is a risk that ethnic patronage networks could become self-sustaining in growing cities, unless essential services are provided transparently and programmatically.
References


Secretariat: Department of Social and Economic Affairs


Tables

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<th>Level</th>
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<th>Patna</th>
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Table 1: Dissimilarity index (based on scheduled-caste) for Bangalore, Jaipur, and Patna, at various levels of aggregation. (City-level data is missing for Patna).

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Table 2: Correlations of $k$-nearest-neighbors metric, calculated from neighborhood census network data, with the proportion of social links to members of the same group. These substantial correlations demonstrate that the $k$-nearest-neighbors metric is a valid proxy for intergroup contact.
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<th>N slums</th>
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Table 3: Summary of survey waves used for the present study.
Figure 1: Example of modifiable areal unit problem applied to segregation metrics. According to measures of evenness, such as the Theil and dissimilarity indices, the city on left (a) is fully segregated and the city on right (b) is fully integrated, despite the two cities having identical population distributions. The only difference is how areal units (e.g. census tracts) are drawn.
Figure 2: Stylized map illustrating how the $k$-nearest-neighbors score is calculated for $k = 5$. The circles and triangles represent the spatial positions (geolocations) of Muslims and Hindus, respectively, within a neighborhood. The arrows point to the $k = 5$ neighbors who are nearest in space to the individual for whom the measure is being calculated. Because four of the five nearest neighbors are the same ethnicity (Muslim) as the respondent in question, her 5-nearest-neighbors score is equal to 4.
Figure 3: Map of respondents from a particular neighborhood in the household sample survey. The points indicate the geolocations of individual respondents, with the shape indicating the respondent’s religion and the color indicating their 10-nearest-neighbors score. For example, light grey fill indicates a score higher than 8 and less than or equal to 10.
Figure 4: Coefficients for same-ethnicity attribute in candidate experiment, for high- and low-exposure subsamples, based on religious exposure.
Figure 5: Coefficients for same-ethnicity attribute in candidate experiment, in network dataset, for high- and low-exposure subsamples, based on religious exposure.
Figure 6: Coefficients for non-coethnicity attribute in neighbor experiment, for high- and low-exposure subsamples, based on religious exposure.