Exposure and Preferences: Evidence from Indian Slums

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Abstract: *How is physical proximity to ethnic outgroups related to intergroup 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, which 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 India to test whether individual residential exposure is associated with outgroup hostility and coethnic voting. I find that 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.*

Verification Materials: The materials required to verify the computational reproducibility of the results, procedures and analyses in this article are available on the *American Journal of Political Science* Dataverse within the Harvard Dataverse Network, at: https://doi.org/10.7910/DVN/AV8PLT.

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 article 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 interethnic physical proximity—and thus exposure—is related to interpersonal attitudes toward the ethnic outgroup, *and* to 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; Nathan 2016; Post 2018; Thachil 2017).

I argue that outgroup hostility and coethnic voting are *distinct* phenomena, and that spatial ethnic distributions affect them in 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: following 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

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I thank Adam Auerbach, Pablo Beramendi, Emily Rains, Cynthia Rudin, Livia Schubiger, Juan Tellez, Jason Todd, and Erik Wibbels for their helpful comments. This project was funded by support from Bass Connections, International Growth Centre, and Omidyar Network. Financial support from Princeton's Politics Department and the Mamdouha S. Bobst Center for Peace and Justice is acknowledged. I am responsible for any errors.

American Journal of Political Science, Vol. 00, No. 00, XXXX 2020, Pp. 1–16

 DOI: 10.1111/ajps.12570

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 fundamental measurement problems that 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* neighborhoods. I then test my theory within the context of an original survey data set from urban slums in three Indian cities, including geocoded interviews with 7,198 individuals in 149 slums in Bengaluru (Bangalore), 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 regarding 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,[1] I am able to estimate the relationship between residential proximity and the extent to which coethnicity conditions individuals' preferences for leaders and for neighbors.

I find persuasive evidence that individuals who live in 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. The results are robust to possible alternative explanations, such as residential sorting. 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.

[1]Although preferences are measured experimentally, individuals are not randomly assigned to integrated or segregated residential environments.

Theory

An ethnicity is defined by Max Weber as a "subjective belief in 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, 3 and Horowitz 2000, 53). A single individual may identify with multiple cross-cutting ethnicities (Dunning and Harrison 2010), and the salience of these dimensions of identity varies over time and space. This fluidity plays a role in electoral politics, and is exploited by politicians: 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" (2006, 2004).

The contingent nature of ethnic boundaries and their salience implies that "[ethnic] conflict takes different courses, depending . . . on how groups are distributed in relation to territory and state institutions" (Horowitz 2000, 53). Racial threat theory, holding that proximity to outgroups increases ethnic mobilization, has been a mainstay of the literature on American race relations (e.g., Enos 2016; Key 1949). In the context of developing democracies, it is echoed by Bates' modernization theory (Bates 1973). Moreover Wilkinson (2006) finds that the common perception in India is that conflict peaks when Hindus and Muslims are present in similar numbers. In this view, physical proximity to outgroup members increases ethnic political mobilization.

Building on racial threat 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 heightens the salience of ethnicity for distributive conflict. People living near non-coethnics can *see* the social significance of ethnicity playing out in a way that is not visible in homogeneous environments. Although 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 *intraethnic* networks, which in turn heightens the salience of ethnicity as a locus of distributive politics. Outgroup proximity makes individuals aware that their own network is delimited by ethnicity, and moreover that the other group is also mobilizing in the same way. This awareness reifies and reinforces the importance of ethnic networks and coethnic voting. I expect the theory to hold under the following scope conditions: patronage politics along ethnic lines, combined with low state capacity[2] giving rise to weak programmatic linkages and information constraints[3] on the part of voters. In addition, the theory requires parties to follow divisive distributive strategies. As discussed next, these conditions hold in the Indian context, particularly in slums. I also expect the conditions to hold in many areas of the Global South.

In many developing countries, information constraints and weakly defined programmatic platforms create incentives to rely on ethnic identities to solve commitment problems (Thachil and Teitelbaum 2015). Parties mobilize voters along ethnic lines because ethnic labels provide information shortcuts (Chandra 2004; Chauchard 2015; Feree 2011) that allow rational, self-interested voters to choose among competing patronage networks. In doing so, parties reinforce the very ethnic divisions that they are mobilizing. For example, by using promises of delivering particular public goods and patronage to Muslim constituencies in a bid for Muslim votes, parties reify the notion that Muslims and Hindus are locked in a zero-sum distributive competition.

In addition to "divide-and-conquer" distributive strategies, parties have been known to encourage interethnic violence to make particular identities more salient around elections, as explicated in Wilkinson (2006). In some situations, there is an electoral incentive for the state to decline to quell incipient riots. This allows sectarian incitement to metastasize into long riots with numerous fatalities. These lethal riots reinforce religious identities, as opposed to class identities, inducing Hindu voters to support the party perceived as being more "pro-Hindu" and thus more able to ensure their safety. Wilkinson (2006) enumerates approximately 2,000 riots and more than 10,000 deaths from 1950 to 1995.

[2]It bears noting that while patronage politics is often targeted at the poor (Kitschelt and Wilkinson 2007), poverty per se is not a scope condition of the theory.

[3]These information constraints have not been alleviated by the diffusion of social media, which is subject to systematic manipulation and disinformation (Tufekci 2017). Indeed, ethnic divisions in India have been increasingly fomented on social media, which have promulgated anti-Muslim incitements such as "love jihad."

Within individual neighborhoods, the fractious and sectarian nature of the parties' electoral strategies has the effect of undermining cooperation across religions. Auerbach (2018, 359) recounts an example of a slum in Jaipur that was majority Muslim but also had a significant Hindu population. Residents mobilized through a slum development committee to lobby for basic services from the city government, such as roads, streetlights, and sewers. This solidarity was fractured in 1992, when a wave of anti-Muslim riots swept through India. As discussed above, sectarian riots have been a key electoral mobilization strategy. Jaipur was the site of serious riots, undermining cross-religious political cooperation in the slum. First, the placement of a proposed water line to the neighborhood became contentious, with rival neighborhood leaders disputing whether the water line should terminate near the predominantly Hindu section, or near the mosque. After rioters from outside the neighborhood brought violence into the slum, the local Hindus moved out and formed a new majority-Hindu neighborhood. One Hindu resident is quoted saying, "we are living like slaves under these Muslims; why are we so weak that we don't have our own community and leaders?" (Auerbach 2018, 359). Thus, although common challenges can encourage intersectarian cooperation in slums (Burgwal 1995; Gay 2010; Jha, Rao, and Woolcock 2007), divisive electoral strategies fragment this cooperation.

Although proximity might lead to reduced prejudice by way of positive contact as discussed next, it also increases awareness of social conflicts tied to ethnicity. In the Indian context, distributive contests along religious, racial, and caste lines affect both programmatic and clientelistic distribution (e.g. Brass 2003; Huber and Suryanarayan 2016; Varshney and Gubler 2012; Wilkinson 2007). A Hindu living near Muslims might be disabused of personal stereotypes concerning the ethnoreligious other, but will also be more attuned to the fact that struggles over limited resources are occurring along religious lines, and that members of the other group are coordinating among themselves to gain a larger share. Although this integrated individual might be less personally prejudiced, she is also more inclined to view politics along ethnoreligious lines.

The distribution of public goods along ethnic lines is demonstrated by Tables 1 and 2, which show public goods provision, and individual satisfaction with services, respectively, in my household sample. Table 1 shows regressions where the dependent variables are whether a household has water piped into the home, a voter ID card, and a ration card. Meanwhile for Table 2 the dependent variables are feelings of security from eviction, and satisfaction with primary schools,

TABLE 1 Public Services by Religion

	Water connection (1)	Voter ID (2)	Ration card (3)
Muslim	-0.32^{*}	-0.48^{**}	-0.16
	(0.14)	(0.16)	(0.14)
Assets	0.09^{**}	0.17^{**}	0.12^{**}
	(0.01)	(0.01)	(0.01)
Constant	0.94	15.21	0.15
	(0.63)	(712.41)	(0.56)
Neighborhood dummies?	Yes	Yes	Yes
City dummies?	Yes	Yes	Yes
Observations	5,245	5,245	5,245
Akaike information criterion	4,568.10	3,689.55	4,980.04

**Note*: Levels of significance: $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

secondary schools, and waste removal. I control for household assets and neighborhood fixed effects. The results show that Muslim households, *even within a neighborhood*, tend to enjoy lower levels of public goods provision, and to report lower satisfaction with services and lower tenure security, than Hindus.

Moreover, the ethnic mobilization of neighborhood residents is exhibited by responses to "Can you give me the name of the first most important leader of your neighborhood?" I tabulated the most common response to this question separately for the Hindus and Muslims in each neighborhood. For the 99 neighborhoods in the survey waves containing the candidate conjoint experiment, 58 had responses to this question for both Hindus and Muslims, and the most common response differed between Hindus and Muslims in 37 of these 58 neighborhoods (64%). This provides evidence that bottom-up mobilization, in which neighborhood leaders are instrumental, is split along religious lines.

This mechanism is strengthened by the well-established (Auerbach 2016; Kitschelt and Wilkinson 2007; Krishna 2007; but see Chhibber and Verma 2018) 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 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" (2004). In the face of this

TABLE 2 Services Satisfaction by Religion

	Tenure security (1)	Primary school (2)	Secondary school (3)	Waste removal (4)
Muslim	-0.10^{*}	-0.17^{**}	-0.17^{**}	-0.18^{**}
	(0.05)	(0.06)	(0.07)	(0.07)
Assets	0.03^{**}	0.01	0.01	-0.01
	(0.00)	(0.01)	(0.01)	(0.01)
Constant	1.66^{**}	-1.31^{**}	-1.94^{**}	-3.14^{**}
	(0.20)	(0.22)	(0.16)	(0.17)
Neighborhood dummies?	Yes	Yes	Yes	Yes
City dummies?	Yes	Yes	Yes	Yes
Observations	5,134	5,023	4,310	4,629
Adjusted R^2	0.41	0.08	0.08	0.15

Note: Levels of significance: $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$.

information constraint, physical proximity provides an opportunity to see rival patronage networks in action: individuals near outgroup members can actually watch their neighbors mobilizing along ethnic lines, see politicians visit their neighbors around election time, and watch the distribution of benefits 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 this awareness increases 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. 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.[4] 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 the finding in Auerbach (2016) 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 coethnics in office. Ethnographic work has found this in India, even where individuals do not expect 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 (Turner and Tajfel 1986), group status is defined *relative* to a comparison group. Thus, when a person is in proximity to another ethnic group organizing along partisan lines to elect their coethnics to office, it is sensible to expect that person to be particularly keen to elect her own coethnics, driven by a sense of competition for group status.

These arguments are summarized by Hypothesis 1: where political mobilization and distribution occur along ethnic lines, physical proximity to ethnic outgroups heightens the salience of ethnicity for distributive conflict. Thus, residential proximity is associated with the salience of ethnicity as a second dimension. 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.

Although proximity is associated with increased ethnic mobilization, a well-established theory predicts that intergroup hostility and prejudice should follow a contrary relationship. Contact theory holds that meaningful social contact reduces prejudice. According to Allport, "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"(1954). 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" (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, 3).

A meta-analysis by Pettigrew and Tropp finds decisive support for the contact hypothesis: the authors argue that there is "little need to demonstrate further" (2006) that contact reduces prejudice, and that the effect is *not* contingent on the four conditions. However, a later meta-analysis by Paluck, Green, and Green (2018) exposes gaps in the literature: although 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 took place in the United States, and few included respondents over 25 years old. Moreover, none of the experimental studies establish whether Allport's four conditions hold. 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 are weak; and that the importance of Allport's four conditions has not been tested.

This gap in the literature is addressed by the current study, which tests the relationship between ethnic

[4]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 to 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.

prejudice and outgroup exposure among a mixed-age sample, outside the United States.[5] In addition, this is a setting in which some but not all of Allport's four conditions are met. In particular, ethnic patronage (Chandra 2004) and the mobilization of religious tensions for political purposes (Wilkinson 2006) create a situation in which "common goals" and "the support of authorities" for intergroup cooperation are undermined. 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 underrepresented in the existing literature, and where not all of Allport's original conditions are seen to hold.

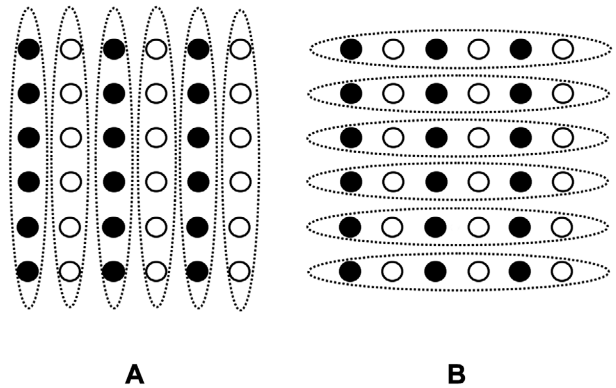
The present study affords an opportunity, facilitated by the new measure, to address the gap identified by Paluck, Green, and Green (2018). Hypothesis 2 is expressed as a "strong form" of the contact hypothesis, as put forward by Pettigrew and Tropp (2006). As noted above, this context constitutes a hard case for the contact hypothesis, particularly because the conditions of "common goals" and "support from authorities" are undermined by political parties' electoral strategies. As such, my test of Hypothesis 2 is intended to clarify whether the "strong form" of the contact hypothesis holds, or whether the contact hypothesis is subject to the caveats laid out by Paluck, Green, and Green (2018).

Hypothesis 2: Residential proximity to members of another ethnicity is associated with increased personal amity toward members of that ethnicity.

Heterogeneity, Segregation, and Exposure: The Challenge of Measurement

I focus on ethnic politics between Hindus and Muslims in the context of Indian slum neighborhoods, drawing on an innovative measurement. Existing studies of ethnic heterogeneity rely on measures that are too geographically coarse to capture variation in interpersonal contact. Moreover, existing measures are subject to ecological inference fallacy and the modifiable areal unit problem

FIGURE 1 Example of Modifiable Areal Unit Problem Applied to Segregation Metrics



Note: 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.

(MAUP). Ecological inference is a fundamental problem in empirical social science, due to the difficulty of accurately using aggregate data to study individual-level phenomena. The MAUP is a manifestation of ecological inference affecting analysis of spatial aggregates, making estimates drastically sensitive to scale and to locations of boundaries. 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 sensitive to divisions between units, and are unreliable for estimating individual-level quantities. I introduce a measure of outgroup exposure, the *k*-nearest-neighbors score, which sidesteps these issues 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.

Figure 1 (adapted from Echenique and Fryer 2007) is a demonstration of the MAUP. The figure shows a "city" that has been divided into 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 being identical—all that differs is the arbitrary partition. This example demonstrates the sensitivity of segregation metrics to the placement of boundaries. Moreover, Table 3 shows how the dissimilarity index varies by level of aggregation for

[5]In addition, all of the studies in the Paluck, Green, and Green (2018) 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.

TABLE 3 Sensitivity of Segregation Indices to Level of Aggregation

Level	Bangalore	Jaipur	Patna
Country	0.14	0.14	0.14
State	0.17	0.14	0.13
District	0.05	0.12	0.19
City	0.26	0.28	

Note: Dissimilarity Index (Based on Scheduled Caste) for Bangalore, Jaipur, and Patna, at Various Levels of Aggregation (City-Level Data Are Missing for Patna).

the three cities in the study.[6] Bangalore appears to be the most segregated when analyzed at the state level, but the least at the district and city level, which highlights the sensitivity of segregation metrics to the choice of scale.

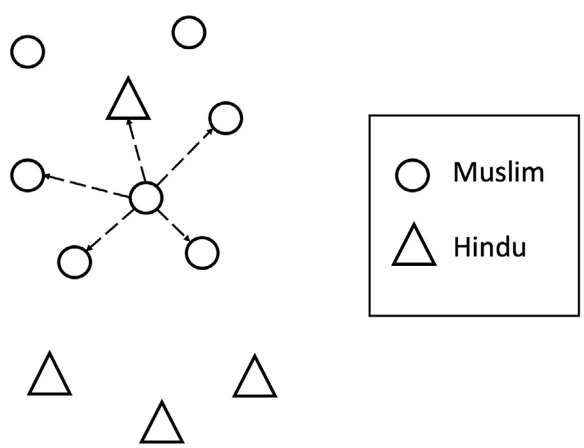
Echenique and Fryer (2007) create a segregation measure at the level of the individual, which avoids the MAUP and ecological inference. However, it relies on costly network data. Wong et al. (2012) address this by having respondents draw a map of their community, which provides a disciplined way of choosing the geographical unit that is salient to respondents, but at the cost of a more complex data-collection process. Dinesen and Sønderskov (2015) introduce a composition measure based on an 80-meter radius. However, by imposing a fixed radius, this method does not account for population density or sampling frequency.

We can characterize measures of segregation and exposure as being more or less responsive to individuals' microspatial environments. At the latter end of the scale are nonspatial segregation measures, such as Theil's index. Then come spatial segregation metrics, such as the spatial dissimilarity index, which do account for spatial relationships, 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.

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 10 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 coethnics. 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 choose an areal unit. The process adds no time to the survey, involving only the automated collection of geocoordinates.[7] The calculation of the metric is straightforward: one calculates the distances between the survey locations in the sample, and 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 values of *k* up to the local sample size, it is straightforward to check robustness to the choice of *k*.

FIGURE 2 Calculation of *k*-Nearest-Neighbors Score

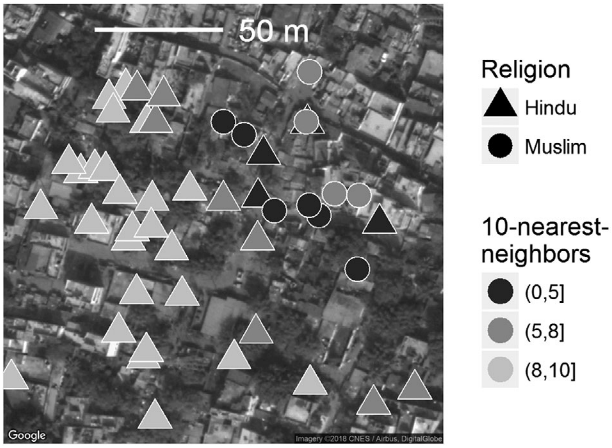


Note: The circles and triangles represent the spatial positions (geolocations) of Muslims and Hindus, respectively, within a neighborhood. The arrows point to the $k = 5$ neighbors who are nearest in space to the individual for whom the measure is being calculated. Because four of the five nearest neighbors are of the same ethnicity (Muslim) as the respondent in question, her 5-nearest-neighbors score is equal to 4.

[6]Census of India data, calculated for scheduled caste versus higher caste. The formula is: $D = \sum_{i=1}^{n} [t_i |p_i - P|/(2TP(1-P))]$, where T and P are the population and minority proportions of the unit of analysis, respectively, which are divided into n smaller units each with corresponding t_i and p_i (Massey and Denton 1988).

[7]Geocoded survey data is potentially identified, and for ethical and privacy reasons is subject to special handling procedures.

FIGURE 3 Map of Respondents from a Particular Neighborhood in the Household Sample Survey



Note: 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 gray fill indicates a score greater than 8 and less than or equal to 10.

The metric[8] 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 metric and social contact, I leverage an original network data set 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 contact.

The eight neighborhoods for the network data set were selected to capture the range of social heterogeneity. Given the importance of contact in non-residential environments, such as job sites (Thachil 2018), it bears noting that the eight neighborhoods selected reflect a wide range of employment patterns. Looking at the three most common nonhomemaker occupations in each slum, three of the eight have basic jobs like laborer or construction worker; four include corporate jobs or professional services; and one includes agriculture in the top three jobs. Moreover, Table 4 demonstrates that the network data reflect the same broad employment outcomes as the household data. To the extent that proximity within the neighborhood increases the likelihood of neighbors sharing job sites, workplace contact could provide yet another mechanism whereby residential proximity is related to the salience of ethnicity to distributive politics.

The network data set includes responses to 11 questions in which respondents are asked to identify people with whom they have contact.[9] I measure a respondent's ingroup contact as the proportion of questions for whom a person of the same religion is named.[10] Table 5 shows the correlations between the k-nearest-neighbor scores and ingroup contact. For example, the correlation between the 10-nearest-neighbors score and same-religion contacts 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.[11] Only 1% of individuals with 10-nearest-neighbor 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.

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 be-

[8]The k-nearest-neighbors measure is related to the composition of the neighborhood. However, the former reflects variation at the individual level: it distinguishes between individuals *within the same neighborhood* who live relatively close to outgroup members versus those who live further away. To demonstrate that the results are not merely due to neighborhood composition, I also conduct the analysis using a demedianed version of the metric that subtracts the neighborhood-level median.

[9]The 11 questions in the network data set 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?"

[10]The average respondent provided names for 4.2 of the 10 network questions (nonresponses mean the respondent does not have this type of connection within the neighborhood). Of these 4.2 names, an average of 1.7 names were repeated across questions, while an average of 2.5 were not repeated by that respondent. Thus, although there was some incidence of respondents naming the same person for multiple questions (such as visiting and borrowing from the same person), more than half of the answers given were unique (for that respondent) names.

[11]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 (Appendix, p. 3).

TABLE 4 Comparison of Most Common Occupations

Network		Household	
Housewife	34.83%	Housewife	22.87%
Laborer	16.00	Laborer	18.92
Other	10.58	Other	10.86
Corporate	5.70	Professional services	5.58
Professional services	5.00	Driver	5.18
Student	4.42	Construction	5.14
Driver	3.45	Corporate	4.66
Factory	2.91	Maid	3.87
Government	2.48	Factory	3.01
Tailor	1.90	Student	2.66

Note: The entries in the table show the percentage of respondents in the network census and household sample datasets, respectively, indicating that they belong to each profession.

tween contact, attitudes, and preferences. In contrast to existing measures, this novel metric is not subject to ecological inference fallacy or the MAUP, 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 whether this holds in other empirical contexts. I expect the correspondence to be strongest in sociospatial circumstances similar to those treated here, with active public spaces where neighbors regularly interact. In particular, for the relationship between the *k*-nearest-neighbors metric and individual contact to hold, it is necessary that individuals are more likely to interact with people who live closer to them than they are with people who live further away. This is likely to be true in a variety of contexts, but may not hold in others, such as in suburban neighborhoods in the developed world.

Empirical Strategy

The slums[12] 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 has 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 frequently lack basic services such as water and sanitation, and are often characterized by informal land title and insecure tenure. 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. 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 9,000 interviews in 149 distinct slums.[13] 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

[12]A slum is defined as an area with "precarious legality" and a low level of services (Habitat 2016).

[13]"Slums" and "neighborhoods" are used interchangeably throughout.

TABLE 5 Correlations of *k*-Nearest-Neighbors Metric with Ingroup Social Links

k	Ethnic dimension	Correlation
5	Religion	0.38
10	Religion	0.42
15	Religion	0.42
5	Caste	0.48
10	Caste	0.52
15	Caste	0.53

Note: The *k*-nearest-neighbors values are calculated from neighborhood census network data. These substantial correlations demonstrate that the *k*-nearest-neighbors metric is a valid proxy for intergroup contact.

TABLE 6 Summary of Survey Waves Used for the Present Study

Description	City	Year	Interviews	Slums	Empirics
Household sample	Bangalore	2017	1,948	50	Neighbor conjoint
Household sample	Bangalore	2016	609	20	Candidate conjoint
Household sample	Jaipur	2015	2,669	45	Candidate conjoint
Household sample	Patna	2015	1,972	34	Candidate conjoint
Network census	Jaipur	2016	1,593	4	Candidate conjoint and metric validation
Network census	Patna	2016	988	4	Candidate conjoint and metric validation

Note: The table describes the survey waves used in this study. Each row provides the sampling method, city, year, number of interviews, number of slums, and empirical analysis for a particular survey wave.

in Bangalore (Karnataka). These cities are chosen to reflect the variation in India's cities. They span India's land mass, with Bangalore situated in the south, Jaipur in the northeast, and Patna in the northwest. They cover the range of development outcomes; Bangalore is the center of India's information technologies and aerospace industries and is among India's wealthiest cities, while Patna is among the poorest, with Jaipur in between. Furthermore, the three cities reflect India's linguistic diversity. Jaipur and Patna are located in the "Hindi belt," while the Kannada language is predominantly spoken in Bangalore. 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 6.

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). Forty 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. From each neighborhood, 30 (Bangalore 2016), 40 (Bangalore 2017), or 60 (Jaipur and Patna) households were randomly selected for interviews, which lasted approximately 45 minutes, and took place in the respondents' homes. The interviews were collected on tablets running the Open Data Kit platform. Each interview was geocoded (latitude and longitude) by the tablets; the geocodes are used to calculate the k-nearest-neighbors metrics.

I also develop a demedianed version of the score, in which individuals' scores have the neighborhood-level median subtracted from them, so that the resulting scores are not systematically affected by neighborhood composition. This allows me to address alternative explanations related to neighborhood composition: for example, that neighborhood heterogeneity (as distinct from individual exposure within the neighborhood) could be related to individual attitudes, to party mobilization strategies, or to some other omitted variable. The demedianed measure allows me to ensure that the resulting variation in the dependent variable is due to individual position within the neighborhood, rather than the overall level of neighborhood heterogeneity. The empirical distribution for the demedianed score is shown in the SI Appendix (Figure A8, p. 2). For 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 household sample survey where respondents 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.[14] Conjoint experiments, by presenting choices with multiple attributes, address social desirability bias by providing an alternative reason for

[14]Neighborhood leaders are "otherwise everyday residents who amass a following within their settlement through demonstrations of efficacy in problem-solving" (Auerbach 2018, 352). These leaders are frequently elected.

making a particular selection. Each candidate has two randomly chosen characteristics. Each respondent is asked to answer three such questions. 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 (scores *above* the median). Per Hypothesis 1, I expect that individuals with higher exposure will have higher coefficients[15] for "A member of your caste or religion." The AMCEs are calculated relative to the base category "An educated person," which presents a valence characteristic not related to ethnic voting or ideology. This hypothesis is tested for both the household sample survey[16] and for the network census survey.[17] For both hypotheses, the treatment components are chosen and weighted according to a uniform distribution (Hainmueller, Hopkins, and Yamamoto 2014).

Testing Hypothesis 2. I test Hypothesis 2 with a conjoint experiment where respondents 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.[18] The characteristic bearing on Hypothesis 2 is the ethnicity of the neighbor: to support the hypothesis, Hindus with higher exposure (lower k-nearest-neighbors) should have higher preferences for Muslim neighbors, and likewise for Muslims. 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.

Results and Discussion

Figures 4 and 5 show the results of testing Hypothesis 1, using the candidate conjoints in the household sample and network census surveys, respectively. The AMCEs for candidate coethnicity (preferences for coethnic candidates) are shown on the y-axis, for low-exposure (high nearest-k score) and high-exposure groups. Standard errors are double clustered by respondent and by neighborhood. The results are shown for a range of values of k, demonstrating that the results are fairly robust to the choice of k. The shading of the points indicates the p-value of a z-test[19] for the difference between the

[15]The quantity of interest is the Average Marginal Component Effect (AMCE), which I estimate through a simultaneous linear regression (Hainmueller, Hopkins, and Yamamoto 2014).

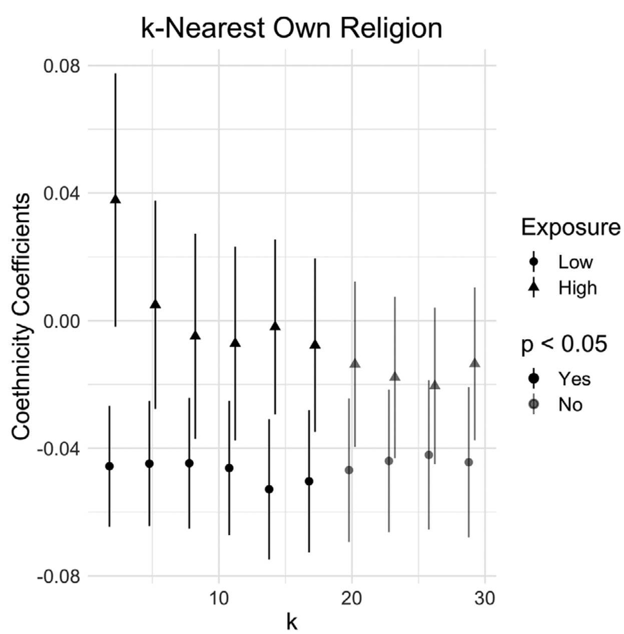
[16]In the household sample survey, the first characteristic takes one of the following levels: "A member of Congress party"; "A member of BJP"; "A member of your caste or religion"; "An educated person" (base category). The second characteristic takes the levels "Promises private benefits to your or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

[17]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."

[18]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."

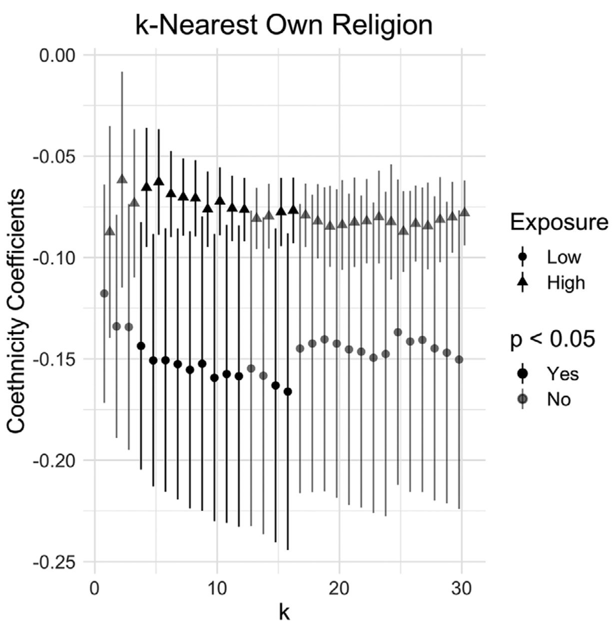
[19]The z-value is given by $z = (c_1 - c_2)/\sqrt{s_1^2 + s_2^2}$, where c_1, c_2 are the estimated coefficients and s_1, s_2 are the standard errors. Under the null hypothesis $c_1 = c_2$, the z-value is distributed as a standard normal.

FIGURE 4 Coethnic Voting Preferences in Candidate Conjoint Experiment, Comparing High- to Low-Exposure Respondents



Note: The results are shown for a range of values of k, demonstrating that the results are fairly robust to the choice of k. Points plotted in black indicate that the null hypothesis—that high- and low-exposure respondents have the same coefficients—is rejected at the 5% level.

FIGURE 5 Coethnic Voting Preferences in Candidate Conjoint Experiment



Note: These results are for the network data set, comparing high- to low-exposure respondents. The results are shown for a range of values of *k*, demonstrating that the results are fairly robust to the choice of *k*. Points plotted in black indicate that the null hypothesis—that high- and low-exposure respondents have the same coefficients—is rejected at the 5% level.

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 most values of *k*, more exposed individuals have a higher estimated preference for coethnic candidates than less exposed individuals.[20] The difference is substantively meaningful: high-exposure respondents in the household survey were approximately five percentage points more likely to choose a coethnic candidate than low-exposure respondents. For respondents in the network survey, the difference was approximately 10 percentage points.

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.

As shown in the SI Appendix (Figures A12, A13, A23, and A24, on pp. 11, 12, 23, and 24), 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 results are not simply reflecting differences between Hindus and Muslims. Similar analysis is reported to verify that the results hold when other nonbalanced observables[21] are accounted for by restricting the sample to individuals with particular values of each variable (see SI Appendix, Figures A14– A22, pp. 13–22). 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.[22] Moreover, Fig. A11, p. 10, shows the results excluding the Bangalore wave. The similarity of the results with and without Bangalore allays concerns that the contrast between the candidate and the neighbor experiments, when the latter was only present in a Bangalore survey, was due to some difference between Bangalore and the other cities.

I also calculated a demedianed version of the metric, which is normalized by the neighborhood-level median, separately for Hindus and Muslims.[23] This metric is constructed to be compositionally invariant, that is, to not be systematically affected by differences in the

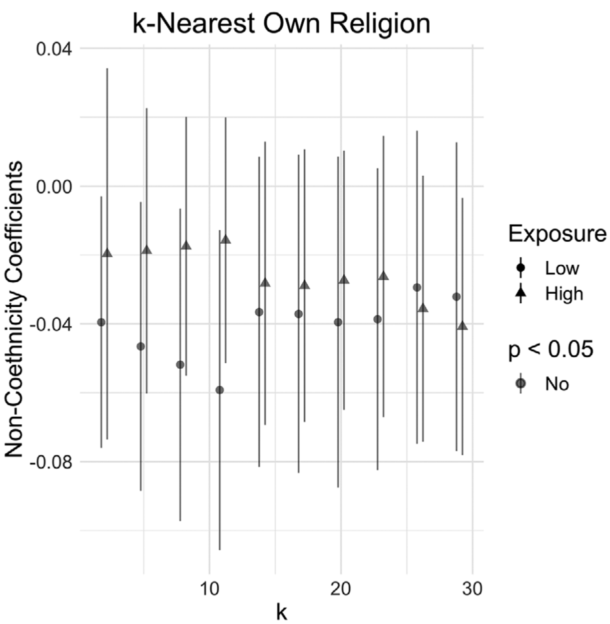
[20] It is worth emphasizing that the coefficients for the conjoint experiment are relative to the base category, "A well-educated person." The important result is the significant difference between the coefficients for the low- and high-exposure groups, not necessarily the significance of each of the coefficients relative to zero. It bears noting, however, that for the high-exposure group, preference for a coethnic candidate is not significantly different than that for well-educated candidate. This is meaningful given the high salience of education for representative preferences (Auerbach and Thachil 2018). Meanwhile, the low-exposure group's coethnic preference is significantly lower than their preference for a well-educated candidate.

[21] 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.

[22] The sample size for these analyses is smaller than for the main result: by restricting the sample to Hindus, Muslims, high-asset, high-caste, Jaipur, and Patna respondents, we lose 19%, 82%, 45%, 50%, 49%, and 62% of the sample, respectively. This reduction in sample size reduces power, leading to fewer of the subsample analyses producing statistically significant results.

[23] For example, if the median values of the 10-nearest-neighbors metric were 10 for Hindus and 3 for Muslims in a neighborhood, then a Hindu with a score of 7 would be given a demedianed score of −3, while a Muslim with a score of 7 would be given a demedianed score of 4.

FIGURE 6 Preferences for Non-Coethnic Neighbor



Note: These results compare high- to low-exposure respondents in the neighbor conjoint experiment. The results are shown for a range of values of *k*, demonstrating that the results are fairly robust to the choice of *k*. Points plotted in gray indicate that the null hypothesis—that high- and low-exposure respondents have the same coefficients—cannot be rejected at the 5% level.

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 demedianed score (i.e., greater than or equal to zero) to respondents below the sample median; these results are shown in the SI Appendix (Figure A10, p. 9).[24] The results from the analysis of the demedianed 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 neighborhood composition.

Figure 6 shows the results of testing Hypothesis 2, using the neighbor conjoint experiment in the household sample survey. The AMCEs for neighbor *non-coethnicity* (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 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. The null result could reflect a lack of power; comparing the number of respondents in the survey wave that included the neighbor experiment (Bangalore 2017) to the others, and noting that statistical power goes with the square root of sample size, we observe that our test of Hypothesis 2 is only 61% as powerful as our test of Hypothesis 1. Again, it should be emphasized that this context constitutes a "hard case" for the contact hypothesis, and the results demonstrate the need for further study of the importance of the particular structure of interethnic 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, 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 evidence that individuals choose the location of their residence for reasons unrelated to ethnicity. When asked for the one primary reason they had chosen that neighborhood instead of another (present in Bangalore 2017 survey), 35% of respondents indicated that they had been born there. Twenty-five percent said that it was close to work, and 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.

Another sorting narrative could be that 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 SI Appendix (Figure A14, p. 13) that the result holds for well-off individuals, measured by the asset score. The same is true for other observables that differ significantly between more and less exposed groups.

[24]Note that this figure shows the difference between the coefficients for the high- and low-exposure groups, rather than the coefficients themselves.

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 proximity to outgroups is associated with higher preference for coethnic voting but not with an increase in ethnic prejudice. People living near non-coethnics prefer to vote for their own coethnics, 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.

Because the present study does not randomly assign respondents to locations, it cannot definitively rule out alternative explanations such as sorting. In future work, it would be worth revisiting these questions in a context with quasi-experimental assignment of proximity. One possibility would be to leverage the unplanned nature of city expansion by interviewing respondents living near a new slum where outgroup members have recently moved. Another possibility would be to conduct a study in a neighborhood that has been split by a new infrastructure project, such as flyover, which impedes movement between the two sides.

To better understand 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 reduces prejudice. In the present context, the condition of elite support is violated by the divisive patronage strategies pursued by political parties. One strategy is to pursue a similar project in a context with ethnic divisions, but where patronage politics is less present or where parties do not pursue divisive strategies. If contact in such a context were associated with better interethnic personal relations, it would be further support for the theory.

Likewise, the observed relationship between proximity and coethnic voting is theorized to stem from the pervasiveness of ethnic patronage networks in a context of limited information. Further evidence of this correspondence could be found by testing whether the strength of the relationship varies according to the structure and importance 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: I expect a stronger relationship between proximity and coethnic voting in localities with higher incidence of patronage distribution. Moreover, a growing middle class is seen to eschew patronage politics in favor of ideological linkages (Chhibber and Verma 2018) and programatic policies (Kitschelt and Wilkinson 2007). Paradoxically, however, Hindu nationalist ideology has found fertile ground precisely among the urban middle class (Auerbach 2015). An interesting extension, then, would be to test the relationships between proximity, personal prejudice, and ethnic salience among India's urban middle class.

As developing cities grow apace, new infrastructure projects must be implemented quickly. The layout of urban infrastructure has crucial implications for ethnic geography, with a profound power to integrate or segregate (Nall 2018; Trounstine 2018). 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 interreligious 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.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix