Maps in our Heads: Socio-political Attitudes and Demographic Awareness

Ryan D. Enos Tess Wise [1]

[1]Department of Government, Harvard University; renos@gov.harvard.edu; wise@fas.harvard.edu

Abstract

Research on the relationship between the awareness of social groups and socio-political attitudes towards these groups has ignored a central attribute of groups: their geographic location. Instead researchers often (implicitly) assume that the proportion of an outgroup in certain population is the most important attribute of a group. We propose an alternative measure of demographic contextual awareness: *spatial accuracy* which is a measure of the ability to place groups in space. This measure is consistent with theories of group representation in cognitive and evolutionary psychology and it resolves the tension between Group Threat findings and the well-established fact that people are generally demographically innumerate. In this paper, we present results from a preliminary investigation of spatial accuracy. Using a novel online survey instrument which asks subjects to place social groups on a map of their local area, we find that survey respondents have a generally refined ability to accurately locate social groups in space and that the ability of respondents to do so is correlated with political and intergroup attitudes.

1 Introduction

When an individual thinks about social groups what do they think about? What are the most important features of a group? Is it the history of the group? The size of the group? Cultural stereotypes about the group? In this paper, we argue that geographic location is an overlooked salient feature of groups and that the "spatial awareness" of groups has important socio-political implications.

Research on the relationship between the awareness of social groups and socio-political attitudes towards these groups has ignored a central attribute of groups: their geographic location. Instead researchers often (implicitly) assume that the population proportion of an outgroup within a certain geographic area is the most important attribute of a group. We propose an alternative measure of awareness: *spatial accuracy*. This measure is consistent with theories of social cognition in cognitive and evolutionary psychology and resolves the tension between Group Threat findings and the well-established fact that people are generally demographically innumerate (see Wong (2007)). We suggest that studying *spatial accuracy* can help to resolve contradictory findings across the broad "contextual effects" literature.

Using a novel online survey instrument which asks subjects to place social groups on a map of their local area, we explore the relationship between spatial accuracy and socio-political attitudes. We find that survey respondents have a generally refined ability to accurately locate social groups in space. Additionally we explore some preliminary connections between this ability and socio-political attitudes. We find that the ability of white respondents to accurately place "non-threatening" groups (whites and Asian Americans) is correlated with higher values of racial resentment while the ability to accurately place "threatening" groups (African Americans and Latinos) does not predict higher values of racial resentment. Alternatively, the ability to accurately place outgroups is correlated with a higher likelihood of claiming to "share the political views" of these groups – suggesting, perhaps, that racially conservative respondents rely on abstract stereotypes of outgroups, even when locating these groups spatially. These findings suggest that the "maps in our heads" reveal important insights about our socio-political attitudes and are worthy of further investigation.

This paper proceeds as follows: First, we discuss the large literature of groups, context, and the measurement of threat and why spatial location fits naturally in this literature. Second, we describe our survey design. Then, we discuss the measurement of *spatial accuracy* and its relationship to socio-political attitudes. We close by discussing the implications of our findings and future extensions.

2 Background

Since at least Key's (1949) seminal work, there has been an interest in how demographic context affects political behavior. Although this literature is certainly nested in a wider literature encompassing deep research agendas in economics, psychology, and sociology, in the political science literature the study of demographic context has come to focus on a loose collection of concepts that are collectively termed "racial threat". In this section we point out that while the mechanisms through which racial threat operates have been under much debate, there has been less debate over the use of demographic proportions as the method for modeling demographic context. Recent work, however, has highlighted fruitful approaches such as considering *perceptions* of demographics and using psychologically relevant areal units (Wong, Bowers, Williams, and Drake 2012). Our work builds on the insights from this work, but also proposes a new independent variable: *spatial accuracy*, which we argue is more consistent with the cognitive processes underlying the way humans think about social groups.

Nearly all studies of racial threat, at least implicitly, are based on a model that individual political behavior is a function of the presence of a geographically proximate racial or ethnic outgroup. The outcome behaviors of interest are usually voting (turnout or vote choice) or intergroup attitudes. There is wide divergence in the mechanism(s) through which racial threat operates. Proposed mechanisms range from rational responses to material threat (Bobo 1983), to the competition over descriptive representation (Spence and McClerking 2010), stimulation of old-fashioned racial stereotypes (Giles and Buckner 1993), manipulation by interested elites (Key 1949), or preservation of "white power" (Voss 1996) – to name but a very partial list.

While the mechanisms have varied, the independent variables considered have remained remarkably constant: studies of of demographic context and racial threat usually explicitly or implicitly assume that individuals are reacting to the concentration of an outgroup in their proximate area. Despite the predominance of this independent variable, there is increasing evidence that very few people have anything close to an accurate sense of group population proportions (Nadeau, Niemi, and Levine 1993, Sigelman and Niemi 2001, Gallagher 2003, Alba, Rumbaut, and Marotz 2005, Wong 2007, Martinez, Wald, and Craig 2008). This presents a puzzle: How can individuals be reacting strongly to the proportions of outgroups when they are not aware of these proportions? Our new measure, *spatial accuracy* represents a step towards resolving this tension by showing knowledge of group location is correlated with both racial resentment and feelings of shared political identity.

While we are the first scholars to consider *spatial accuracy*, we are building on a strong tradition of other scholars who have recently brought new insight to the study of demographic context and socio-political attitudes. In studies of demographic proportions, some models such as Gay (2006) include characteristics of the outgroup, such as income, as mediators of the effect of population proportion. Other models, such as the one developed byHopkins (2010) use changes in the concentration of immigrants at the zip code and county levels combined with media attention as the independent variable of interest in explaining attitudes towards immigrants.

Recent work by Wong et al. (2012) highlights the inconsistency between psychologically relevant space and spaced measured by researchers. Wong et al. (2012) brings in a psychological model which relies on the difference between perceptions of demographic proportions and objective demographics. Their research finds that within pairs of white respondents in similar objective racial contexts (as measured by census data), the person perceiving more blacks tended to be the person with higher racial resentment. Our theory of spatial accuracy builds on this work by considering *perceptions* of location and also avoids the problem of psychologically relevant space by presenting individuals with un-bounded and manipulable maps, allowing the respondent to focus on what is relevant to them.

2.1 The cognitive basis of racial threat and spatial accuracy

Scholars (Wong 2007, Wong 2010, Wong et al. 2012) have begun to explore the psychological underpinnings of responses to group threat. We too are interested in the social cognition that translates the presence of an outgroup into something threatening that invokes a behavioral response. In other words, what is it about outgroups that concerns people?

Theories of behavioral responses to the presence of an outgroup rest on models of the "schema" that individuals attach to an outgroup. Schema are "mental representations of a category, that is, a class of objects that we believe belong together" (Kunda 1999, p.16). Schema are comprised of the attributes we attach to objects (e.g. people and groups). These attributes can be physical qualities, such as skin color, or social qualities, such as propensity for crime. Attributes are of varying accessibility: sometimes when presented with a group, one attribute might be the first and most powerful thing we associate with that group. In the context of the Racial Threat literature, when evaluating the "threat" of a group, an individual will consider the attributes of that group, some of which may be more or less accessible than others.

Theories of context, usually implicitly, model the population proportion of a group as the most accessible attribute an individual can use to evaluate the "threat" of a group. In other words, when individuals consider an outgroup in a political context, the most important feature of the outgroup is the proportion of that outgroup in the population. Here, we argue that an attribute that is also very important, perhaps more important, is the spatial location of the outgroup. In other words, when people think about a group, the first thing that comes to mind is not “how big is that group?”, rather it is “where is that group?”.

The assumption in the literature that outgroup proportions are the most important attribute of a group may come from rational actor models, in which an individual has no incentive to react to a group until they reach a large enough proportion of the population to threaten the interests of the individual – in politics, this usually will mean enough to enter a minimal winning coalition.

To illustrate why this assumption is unnecessary see the example of a recent prominent finding on threat: Hopkins (2010) makes an important contribution to the literature by connecting threat to prominent theories in political science and psychology by modeling threat from Latino immigrants in the United States as a function of signals from policy elites and changes in population levels. However, what Hopkins does not show (and is not necessary for the purposes of his paper) is the schema that individuals attach to immigrants that make them threatening. It could be that the changes in concentration prompt people to think about *how many* immigrants are in their local area, but it also could prompt individuals to think about *where* immigrants can be found in their local area. Here we argue that the question of *where?* is more likely what individuals are asking and that modeling the cognition of threat in this manner helps to resolve the inconsistency between racial threat findings like Hopkins (2010) and demographic innumeracy findings like Wong (2007).

Indeed, it is important to remember that even Key’s (1949) insight was not about the specific proportions of African Americans in southern counties, but rather that whites in the counties with the highest concentrations acted differently than whites in the counties with the lowest concetrations. We do not know what attributes of the African American outgroup was most salient to these whites – however, even Key argued that it was obviously not that the African Americans would form a political majority because in no state did they have adequate numbers[1].

[1] Nor, of course, could they vote – a fact that often seems to be overlooked when Key’s findings are described by political scientists working in the rational choice tradition, see Enos (2011*b*).

With the assistance of modern cognitive science, we argue that the more likely explanation is that these whites were more concerned with the location of these African Americans than with their numbers.

2.2 Location and social cognition

In our theory of *spatial accuracy* we focus on space, because it has been shown that space occupies a central role in human cognition – indeed, “as humans, our ability to operate in large-scale space has been crucial to our adaptation and survival (Maguire 2006, p. 131).” There is evidence that the human ability for spatial navigation has evolved into the structure of our episodic memory (Burgess, Maguire, and O'keefe 2002), which is a crucial aspect of the unique human cognitive function. It is easy to imagine scenarios that illustrate this – in developing the capacity to process objects important to survival, for example food and enemies, while size may certainly have been important, a precise sense of size was probably not as important as a precise sense of spatial location: as long as a person knew there was enough food to eat, the exact number was not important to survival, but to not remember the precise location of the food may have been a clear threat to survival. The extension of the importance of space to groups is easy to see: a person could survive with an imprecise knowledge of size – simply knowing if any enemy is more or less numerous than your group might suffice – but not knowing precisely whether you had entered the enemies territory might be fatal. In a certain respect, location can be thought of as a heuristic, likely highly developed, for answering crucial questions about safety and other utility inputs.

We emphasize that we are not making a direct analogy between group conflict in the human evolutionary past and modern political conflict (although some scholars have recently done just that, see Haidt (2012)), rather we are emphasizing that groups and space are central components of human cognition and when considering the central role of groups in political behavior, space should also take center stage.

Moreover though, the usefulness space and groups as heuristics likely take on an even more crucial role when an individual is in complex urban environments such as those in which most people now live. Cities, with their complex spatial structures and dense activities put a great strain on human cognition – there are simply more environmental inputs than a person can process, making space a valuable heuristic. Stanley Milgrim described the cognitive strain induced by cities as "overload" and speculated that a good deal of human activity that characterized urban environments, including ethnocentrism, could be attributed to the need to reduce overload (Milgim 1970). So not only do groups and space have a central role in human cognition generally, they become perhaps more central in urban environments – the environment of most human activity and the scene of the greatest ethnic diversity.

Cities are also places of tremendous political activity and even in casually observing them, it is easy to see the role of location in intergroup relations. The arrangement of groups in space is part of the fabric of the urban environment. Imagine the meaning that would be removed from the names of parts of great cities if the areas were not associated with certain groups – and, moreover, notice that the names of famous areas are a direct reference to spatial location: London's East End, Chicago's South Side, Manhattan's Upper West Side, East Los Angeles, Detroit's Eight Mile Road, to name a few. These places conjure meaning – not because of the architecture or history, but because of the groups that are associated with specific geographic locations. As an intuitive thought experiment, imagine asking a group of people what proportion of a city, say New Orleans, is African American. The findings of many scholars and our intuition tells us most people would not know. Now, imagine asking a group of people where in New Orleans African Americans tend to live? You can probably imagine many places, such as the now infamous Lower 9th Ward, coming to mind. You might also imagine that, especially to white respondents, a slight feeling of threat might arise when they consider the Lower Ninth Ward and it's population. This thought experiment can be repeated almost anywhere.

Our test draws directly on this, seemingly widespread, tendency for humans to locate groups in space.

3 Design

Prior to beginning this research, we received permission from our university's Committee on the Use of Human Subjects in Research.

We implemented a web-based survey that asks respondents to place groups in their community. Subjects were recruited using Amazon's Mechanical Turk (see Berinsky, Huber, and Lenz (2012))[2].

We asked subjects for their zip codes and then rendered a map of that area using the familiar Google Maps interface. Respondents were asked to place a circle over their home so that we had a point of reference from which to calculate the distance to perceived group locations. Subjects were then shown a series of markers and asked to place the marker were "most [GROUP] persons live". The groups we asked about were Whites, African Americans, Latinos, Asians, rich, and poor. After placing each marker, subjects were allowed to move any markers they wanted to adjust and then submit their final placements. We also allowed respondents to indicate that the group did not live in their community – although we do not explore those results in this paper. A screenshot of this is shown in Figure 1. We also asked a series of survey questions to collect control variables such as partisanship, education, age, race which we describe in the next section. Finally, we collected data on socio-political attitudes such as racial resentment and shared political orientation (the nature of these variables will be described in the next section).

Using Mechanical Turk we were able to collect responses from across the United States. Figure 2 is a map of the locations of respondents. Each blue dot represents a single respondent. The map shows subjects from a variety of contexts: predictably concentrated in high population states and cities, but also in more rural locations.

Our central claim is that individuals have an accurate understanding of the spatial location of groups and that the spatial structure of these groups shapes intergroup attitudes

[2] The first 320 respondents were not forced to be in the United States. This is mitigated by the fact that the sample is subset to white respondents for the individual analysis. Additionally, the analysis of the individual results remains consistent if these respondents are excluded.

Figure 1: Screenshot of the map task for zip code 02139

and behaviors.

To examine this claim, we test two hypotheses, using a number of tests:

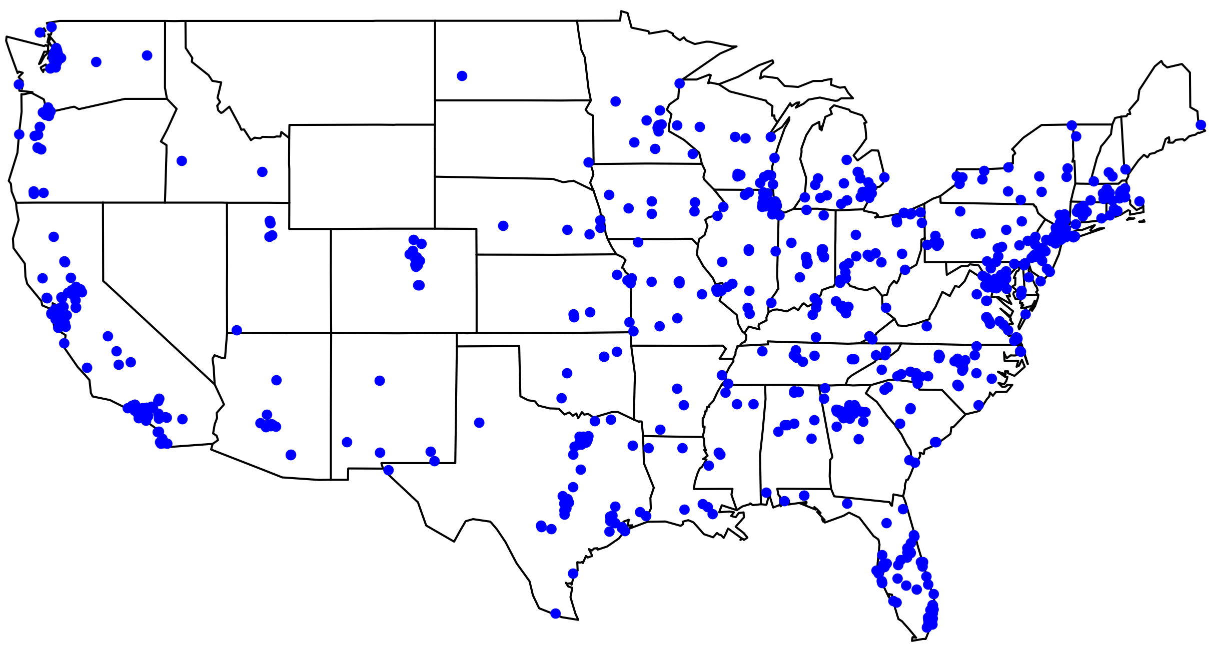
1. Subjects will be able to locate groups in their community in a manner better than chance alone.

2. The ability to locate groups will be related to the centrality of these groups to their socio-political attitudes.

4 Analysis of Spatial Accuracy

We will first demonstrate that, on average, our respondents have a fairly accurate sense of the location of groups in their communities. We will then turn to the relationship between

Figure 2: Map of respondents' homes



Each blue dot is the location of the home of a respondent.

accuracy and other individual level variables.

4.1 Defining Accuracy

Our central claim is that individuals can accurately describe the spatial location of groups. In demonstrating this claim, we make several choices. One of the most consequential, perhaps, is to define an areal unit in which to define a population to measure. While Census and other administrative units may not fit with with individual constructs of neighborhood (e.g. Wong et al. (2012)), in order to measure accuracy we need an areal unit to which we can attach Census data. Here we report results for Census Tracts because it is a commonly used unit. In essence, our measures of accuracy are all simply whether or not a respondent placed a group inside the Census Tract where that group was most likely to be found. Of course, both because this might not be a psychologically meaningful unit our and single choice of unit to measure accuracy will be a conservative measure of accuracy – for example, a person may place a group at a single location and be extremely close, but not exactly in the Census Tract that would indicate exact accuracy. We can use "K Nearest Neighbor" techniques to overcome this problem. In unreported results, we demonstrate that combining individual units with then nearest neighbors improves accuracy. Future work should also explore results using other choices of areal unit.

For each respondent, we also have to define the relevant universe of areal units. Should respondents be accurate within a defined distance, say 5 or 10km? Should this area be based on an administrative unit, like a zip code or county? For the results below, we make the relevant universe for each respondent the Census Tracts within 6km of her home, which is approximately the area displayed on their computer screen, and means that the relevant universe is a circle of Census Tracts with a 12km diameter. A 12km area may be too large of an area to reasonably expect a respondent to be knowledgeable about. And, of course, 12km in two different areas are not necessarily the same thing because the meaning of distances is, of course, defined by the people that live there – moving 12km through a dense area like New York City is much different than moving 12km through rural Iowa.

There are many ways that accuracy may be defined. Here we define four measures of accuracy. To define these four measures, we first define $TRACT_{i,g,1}$ as the Census Tract with the largest concentration of group g in $TRACT_{i,1}$ ... $TRACT_{i,n}$, which are all the tracts in U_i, the universe of tracts available to respondent i.

Each of the four measures represents the spatial relationship between $TRACT_{i,g,1}$ and $POINT_{i,g}$, which is the location chosen by a respondent i when asked were most of group g lived in their community. The measures are:

1. **Binary Accuracy**: Is $POINT_{i,g}$ in $TRACT_{i,g,1}$? E.g. Did the respondent place African Americans in the single Census Tract where the largest group of African Americans lives with 6km of of her home? In the analysis that follows, this variable is coded

1 if yes and 0 otherwise. This is perhaps the most strict definition of accuracy: either a respondent located the highest concentration or they did not.

2. **Weighted Accuracy (w)**: What was the population concentration of the Census Tract chosen by the respondent compared to $TRACT_{i,g,1}$. This is a continuous variable between 0 and 1. $TRACT_{i,g,1}$ is coded as 1 and every other tract between 0 and 1 based on the proportion of the population found in $TRACT_{i,g,1}$.

3. **Rank Accuracy**: What was the rank of the tract in which the respondent placed the group from $TRACT_{i,g,1}$ to $TRACT_{i,g,n}$, where n is the number of tracts in the universe of tracts.

4. **Distance Accuracy**: How far was $POINT_{i,g}$ from the nearest edge of $TRACT_{i,g,1}$ in meters?[3]

For non-discrete groups, in this case "rich" and "poor", $TRACT_{i,g,1}$ is defined by the highest and lowest median household incomes, respectively.

4.2 Aggregate Accuracy

The respondents were able to place groups on a map in a way that clearly demonstrates that the modal individuals has a refined awareness of the location of groups. First, examining the *Binary Accuracy* in Figure 3. The plot on the left shows responses when only tracts less than 3000m from the respondents home are included in U_i. The panel on the right is when approximately the entire area visible to respondents on the displayed map (6000m) is in U_i. In all cases that follow, respondents become more accurate as the area included in U_i decreases, indicating, intuitively enough, that respondents are more familiar with people and places closer to their home. Having demonstrated this briefly, in all subsequent analysis, we focus on U_i where 6000m are displayed, which is the most conservative test for accuracy and does not involve the censoring of any responses.

[3]Measuring distances to the centroid of hte nearest tract yields similar results.

This red bars in Figure 3 represent the percent of times that respondents chose $TRACT_{1g}$. For example, when locating $TRACT_{1white}$, respondents correctly located that tract over 20% of the time. The gray bars represent the proportion of times that $TRACT_{1g}$ would be chosen at random by a person choosing among n tracts. We constructed these measures by weighting each tract by its land-area and then randomly simulating 1000 draws from U_i for each respondent. This simulation reflects that a person that truely was choosing randomly would be more likely to choose spatially large tracts simply because they occupy more space on the map.[4] This demonstrates that a person choosing randomly likely would have selected $TRACT_{1white}$ around 6% of the time. These results clearly demonstrate that subjects were not just choosing at random.

At both distances, for every group, a T-test for the difference of means between the simulated accuracy and the observed accuracy yields $p < 10^{-10}$, indicating difference of means that we obtain would be extremely unlikely to observe if respondents were truly choosing randomly. This might be considered an impressive demonstration of accuracy, given the strict definition of accuracy used here: for example, a respondent may have chosen $TRACT_{2white}$, where $TRACT_{2white}$ has a white population of 99 and $TRACT_{1white}$ has a population of 100, but this respondent would still be scored 0.

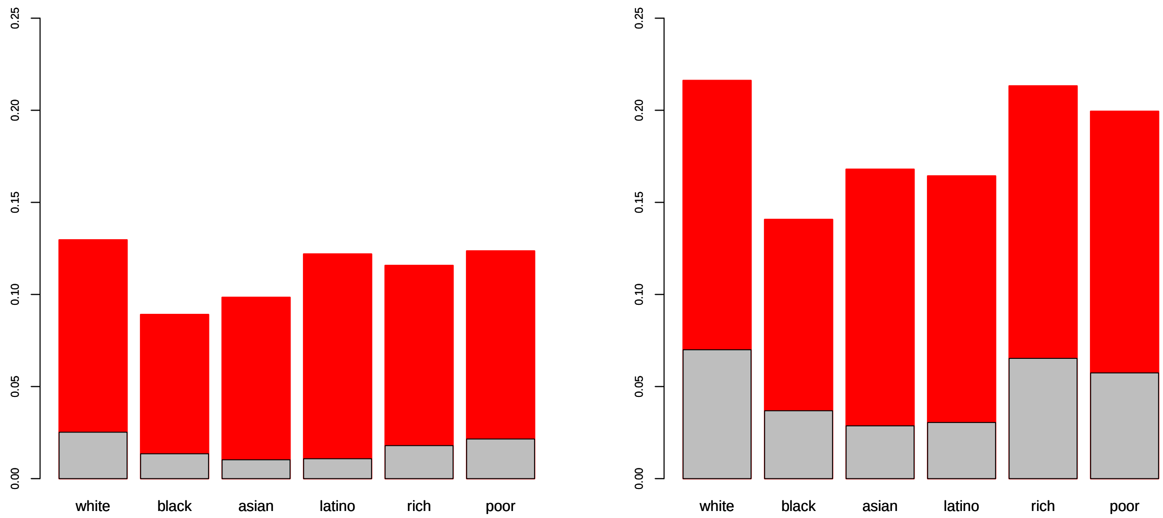
To give more weight to approximately correct answers such as this example, we turn to Weighted Accuracy in Figure 4. In this figure, we demonstrate that the average respondent chose a tract with a high weight. For example, when asked to choose a location where most "rich" people live, the average respondent chose the location where the median income was almost 80% of the highest income in U.

Of course, *Accuracy Weight*, like many of the measures used in this paper, is context dependent: for example, if a group is perfectly evenly distributed across tracts, then a respondent cannot help but choose a tract with $w = 1$ even if they are guessing at random. On the other hand, in a universe where the population is very unevenly distributed, say

[4] The substance of the results is completely unchanged if tracts are given equal weight in the simulation.

Figure 3: Binary accuracy by group compared to expected accuracy

(a) Distance = 6000 meters (b) Distance = 3000 meters

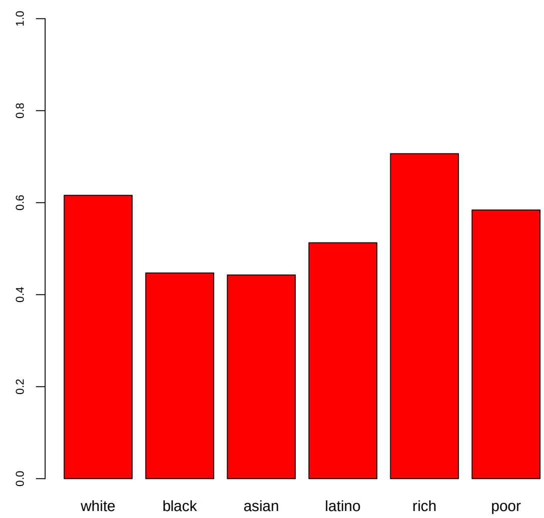


Binary accuracy by Group are the red bars. The expected accuracy, calculated by simulated draws from a map accounting for land area of each tract are gray bars.

$pop(TRACT_{1,white}) > 2 * pop(TRACT_{2,white})$, then even if a person chose $TRACT_{2,white}$, the weight of the tract they chose would be no greater than $w = .50$. We attempt to separate these situations by simulating random draws from the distribution of weights that each respondent could possibly make and comparing these to the actual selections.

In Figure 5 we displays the distributions of means from 1000 simulated draws for each respondent (gray) against the distribution of actual responses (red) by target group. In all cases, the actually responses are shifted considerably to the right, indicating that the respondents chose the higher weighted Census Tracts much more often than they would have if they were just guessing at random. It is notable though that when the target population is both African American and Asian American, the distributions have fat tails, indicating that they respondents not only did better than would be expected at random, but at times also did worse than would be expected at random. A Wilcox Rank Sum test for a difference in the actual and simulated distributions yields $p < .005$ for each group, indicating that we

Figure 4: Weighted accuracy by group



Weighted accuracy by Group: the average population of Group G in the Tract containing $POINT_{i,g}$ as fraction of the population in $TRACT_{i,g,1}$.

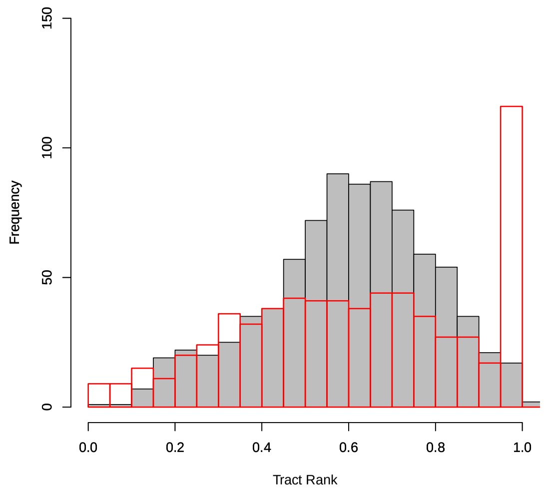
would be very unlikely to observe distributions this different if the distributions were really the same.

We also consider *Rank Accuracy* – the rankings of Census Tracts from $1...n$. This does not have the features of allowing for relative population differences like measuring *Weighted Accuracy*, but is ordinal so it allows us to distinguish between tracts of lesser or greater concentrations of the group. Of course, the meaning of a ranking is also context dependent, so that finding the highest concentration tract when $n = 1$ cannot distinguish spatial awareness from guessing. However, using similar strategies to those above, we demonstrate that our typical respondent was clearly not guessing.

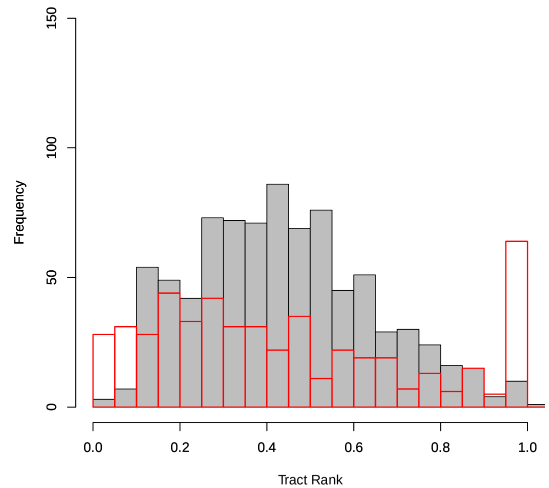
In Figure 6 we display the number of tracts in U_i on the x-axis and the rank of the tract selected by the respondent on the y-axis. The points are jittered for display purposes. Points in the lower right are respondents that either have a very developed spatial awareness or are quite lucky. Points in the lower left are responses which are more difficult to distinguish guessing from accuracy because of the low number of tracts in U_i. However, the general

Figure 5: Actual Weighted accuracy compared to simulated weighted accuracy

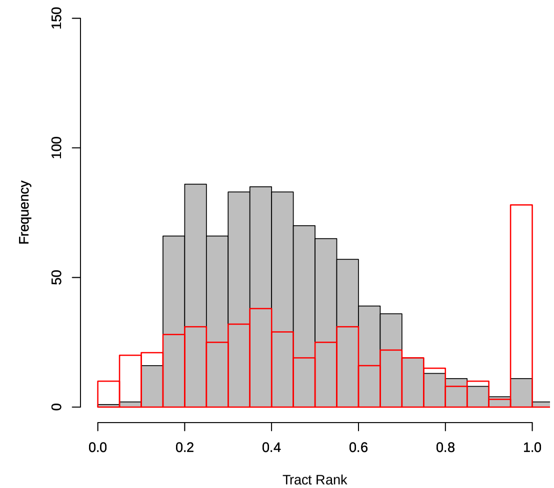
(a) white



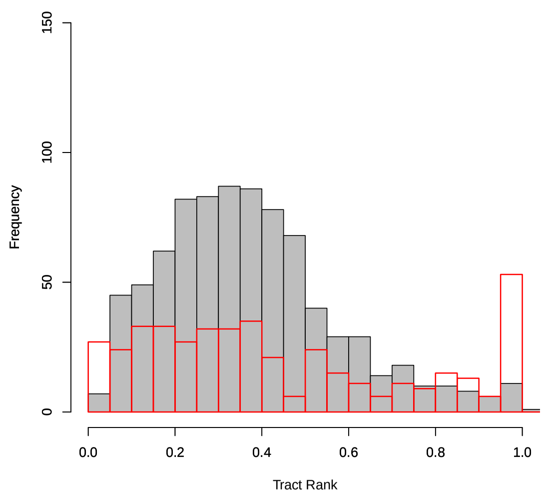
(b) African American



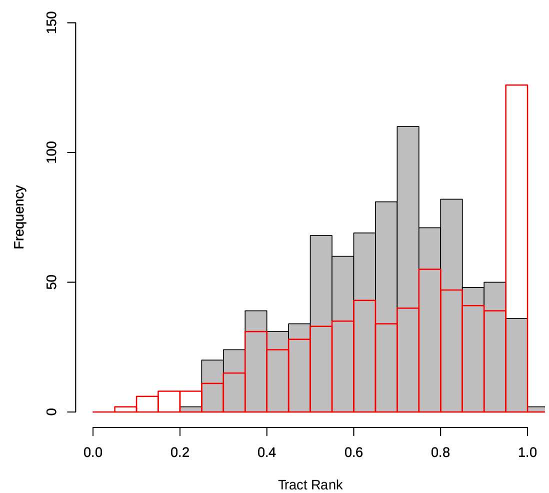
(c) Latino



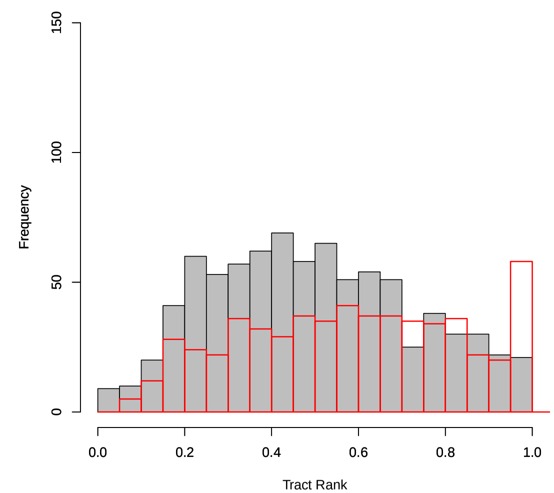
(d) Asian



(e) Rich



(f) Poor



pattern is a strong clustering in the lower portions of the plots, indicating that respondents are able to place responses in low ranked (high population tracts).

Another way to check for *Rank Accuracy* is using the same simulation strategy we used above. In Figure 7 we again simulate 1000 possible choices by each respondent and display the distribution of means in gray. We overlay the actual distribution of rank choices in red. In this case, lower ranks mean more accuracy, so if respondents are not simply guessing we should expect to see the red distribution shifted to the left of the gray distribution. In every case, the distributions are shifted to the left with a strong mode at $rank = 1$. As before, the respondents seem particularly good at placing whites, rich, and poor. It is noteworthy that the modal response for every group is to choose the single best tract and that the choices are clustered in the top ranked tracts: individuals are choosing the correct location of groups or close enough to it that we might conclude that individuals are good at placing groups in space.

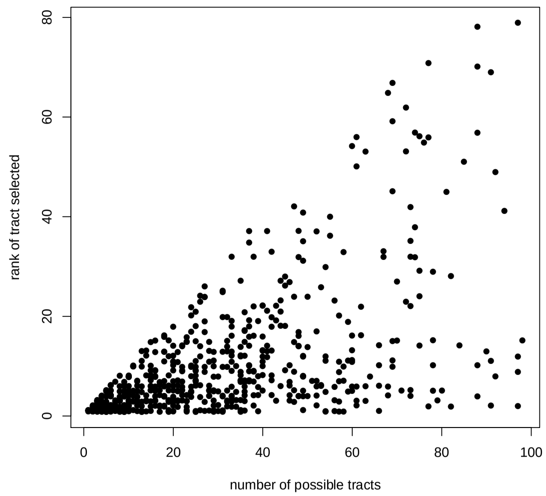
Finally, we turn to *Distance Accuracy*, which measures the linear distance between $POINT_g$ and $TRACT_{1g}$.[5] This measure allows us to see if respondents, even if not exact in their placement, are selecting $POINT_g$ in an approximately correct location. A continuous measure like this less subject to the Modifiable Areal Unit Problem (MAUP) than is *Binary Accuracy*.

As with our previous measures, *Distance Accuracy* is context dependent, so that distances in low-density areas, where tracts are likely very spatially large should not be directly compared to distances in high-density areas, where tracts might represent a small area. As such, in Figure 8, we display *Distance Accuracy* by the average distance between $POINT_{i,g}$ and $TRACT_{i,g,1...n}$. As with Figure 6, points near the bottom the plots indicate more accurate responses, all else equal. However, in this case, it is responses closer to the lower left corner that are less likely to be due to guessing. This is because areas with a smaller average

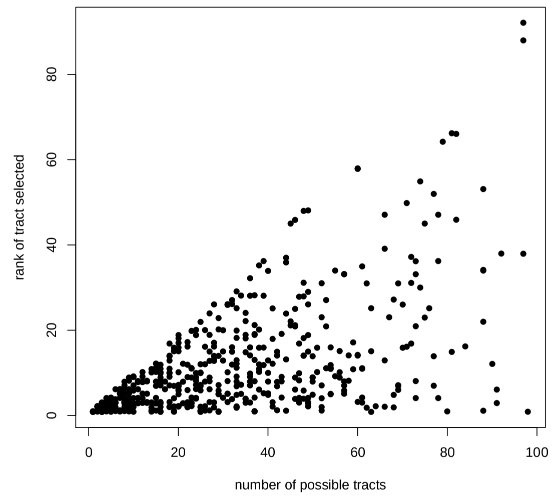
[5]In results reported here, we are measuring the distance from $POINT_g$ and the nearest edge of the tract. We also use the distance between the the point and the centroid of the tract. Future work should explore non-linear specifications of distance.

Figure 6: Ranked accuracy compared to number of possible tracts by group

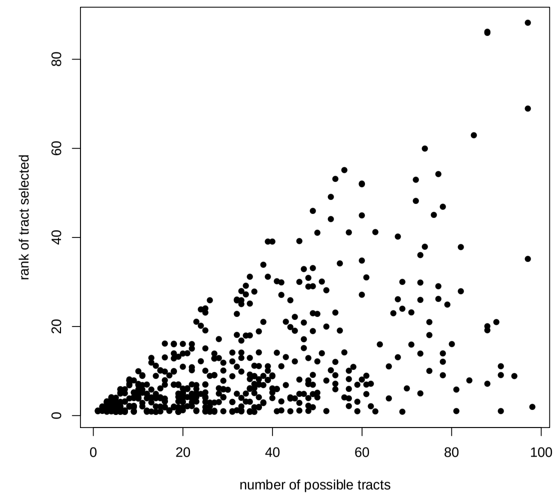
(a) white



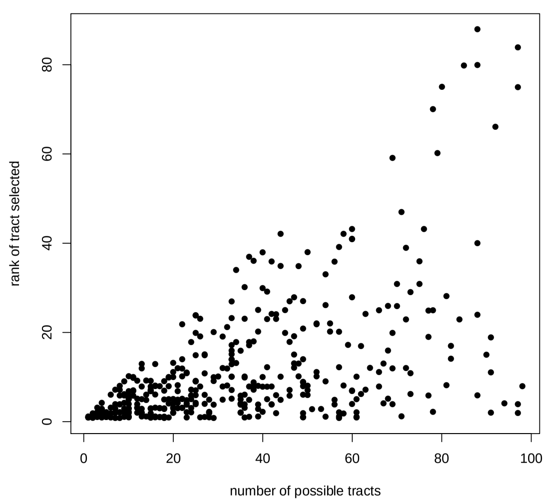
(b) African American



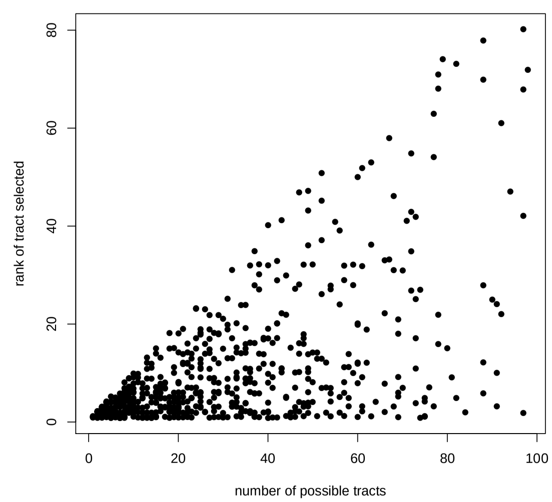
(c) Latino



(d) Asian



(e) rich



(f) poor

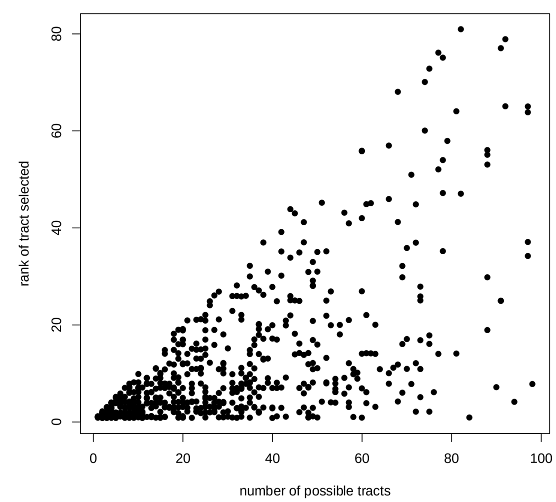
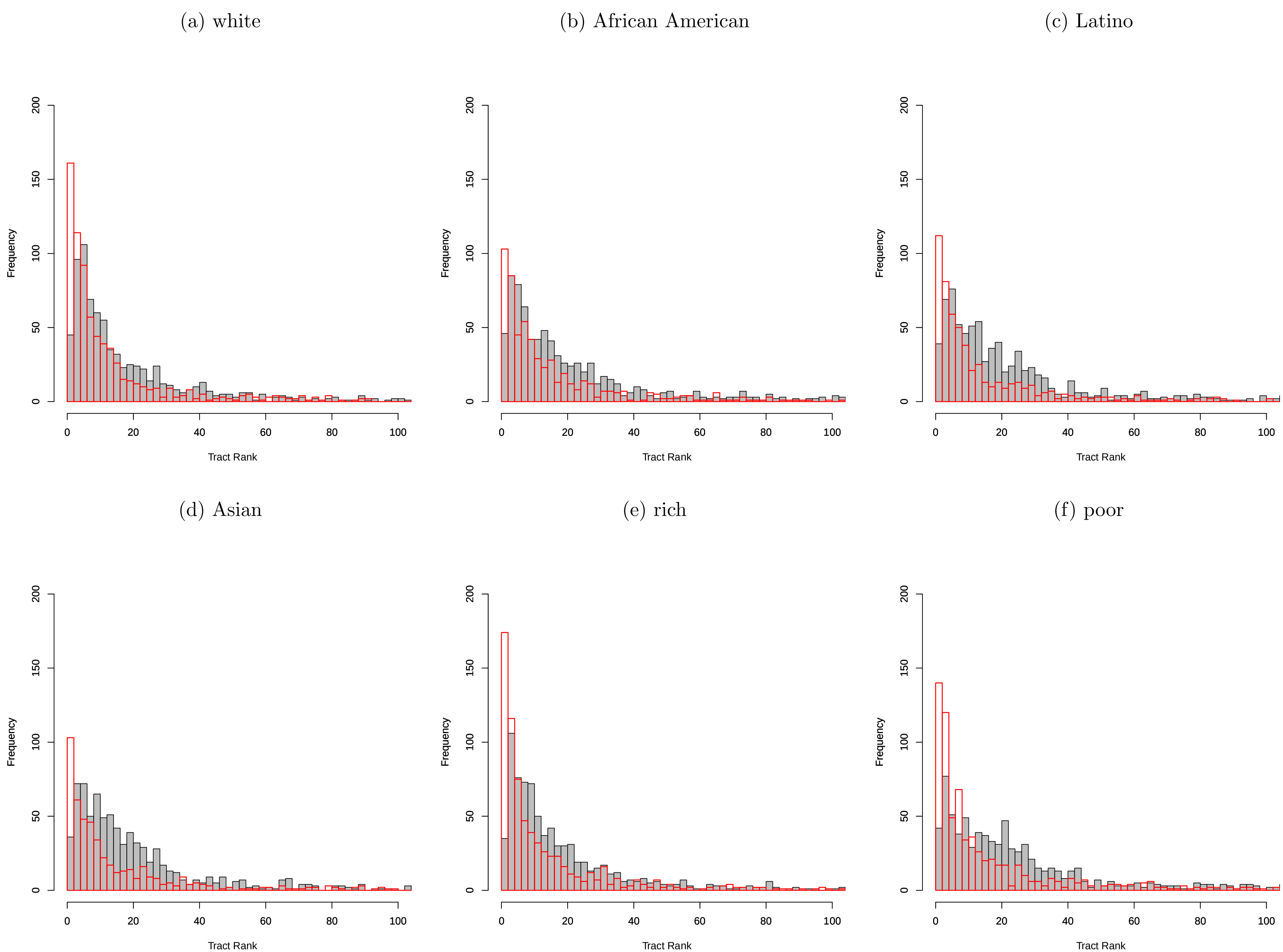


Figure 7: Actual rank accuracy compared to simulated rank accuracy



(a) white (b) African American (c) Latino

(d) Asian (e) rich (f) poor

distance between tracts are high-density areas with smaller and more tracts, which makes it less likely that a respondent would place $POINT_g$ close to an edge of $TRACT_{g,1}$ by chance. On the other hand, responses in the upper left corner more clearly demonstrate a lack of spatial accuracy while responses in the upper right and lower right are more ambiguous. With all groups, there is a strong clustering in the lower left. The groups that respondents seem to have the most trouble placing are the poor and Latinos.

4.3 Using Spatial Accuracy to Predict Socio-Political Outcomes

We have established that many individuals have an accurate sense of the spatial location of groups – so much so that the modal person, when presented with dozens of Census Tracts on a map, which may be unfamiliar to them, can locate the single highest concentration of that group on the map. With this established, we now undertake a preliminary analysis of how Spatial Accuracy interacts with individual socio-political attitudes about groups.

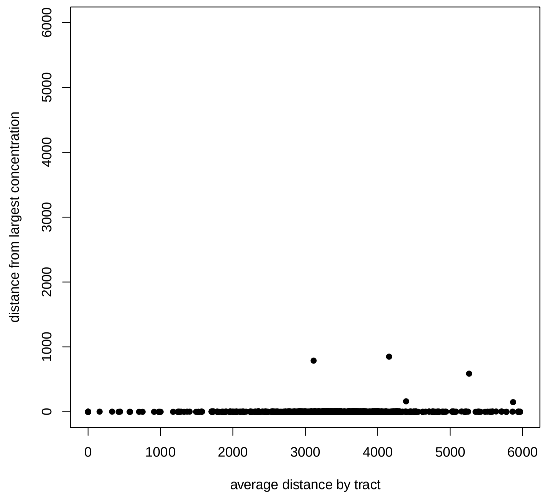
We consider two dependent variables of interest: *political closeness to outgroups* and *racial resentment of African Americans*. We run OLS regressions to test the predictive power of spatial accuracy on these dependent variables. We then test the predictive power of spatial accuracy as compared to demographic innumeracy. In this section we limit our sample to white respondents in order to explore the difference between accuracy for ingroups and outgroups relative to the respondent.

To simplify presentation we only measure examine the relationship of Binary Accuracy with socio-political variables. The independent variables of are divided by accuracy groups that might be considered, roughly, "threatening" and "non-threatening" to a white respondent. These results generally remain unchanged if we divide the accuracy measures into each separate group. We use the following variables in this analysis (see the previous section for an explanation of how the spatial accuracy variables are constructed).

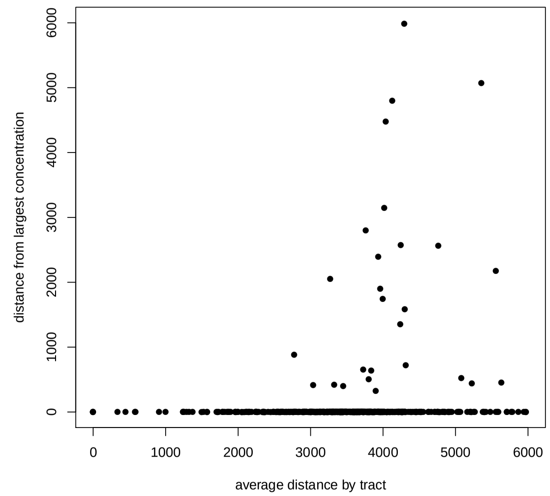
- *non-threatening spatial accuracy*: The average of a respondent's binary spatial accuracies for Whites and Asians.

Figure 8: Distance accuracy compared to average distance between tracts

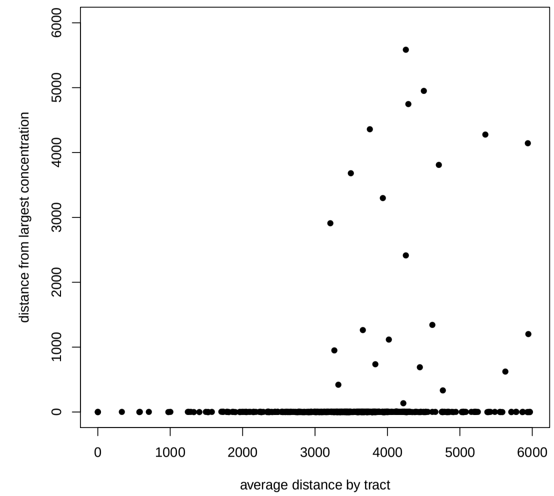
(a) white



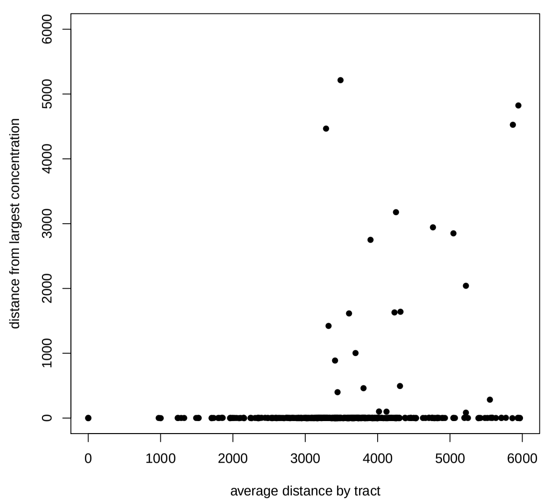
(b) African American



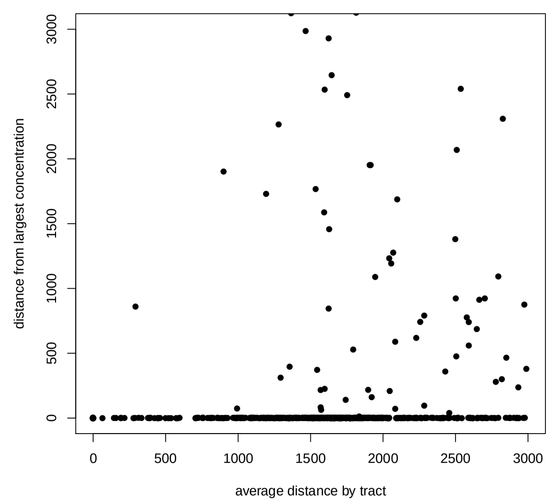
(c) Latino



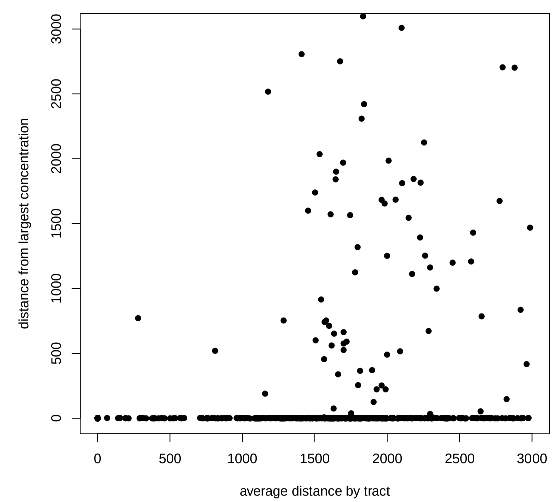
(d) Asian



(e) rich



(f) poor



- *threatening spatial accuracy*: The average of a respondent's binary spatial accuracies for African Americans and Latinos.

We test the relationship between these variables and two dependent variables intended to explore individual attitudes about racial groups and politics:

Racial Resentment: Respondent's racial resentment score. We use racial resentment as developed by (Henry and Sears 2002), which is based on four survey questions designed to measure white respondents attitudes about African Americans.[6] It is scaled from 0 to 1, where 1 is the most racially resentful.

We also developed a measure to test how much respondents think that different groups share their political views.

Closeness: Respondents were asked whether they Strongly Disagreed, Somewhat Disagreed, Somewhat Agreed or Strongly Agreed with the following statement "In general, I share the political views of most Latinos/African Americans/Caucasians/Asian Americans." This was then scaled from 0 (strongly disagree) to 1 (strongly agree).

We include the following control variables in our OLS regressions:

- *Partisanship*: Respondent's self-reported partisanship. Has a value of 1 for Strong Democrats, 0 for Strong Republicans and 0.5 for Independents.
- *Logged Population Density of Zip Code*: Is the log of the population of the respondent's zip code divided by the land area of the zip code.
- *Education*: Respondent's reported education level. Ranges from 0 (some high school) to 4 (post graduate degree).
- *County-level demographics*: We include the percent White, African American, Latino and Asian in the respondent's county to account for the influence of local demographics.

[6]Survey respondents are given four response choices ranging from strongly agree to strongly disagree about the following assertions: 1) Irish, Italian, Jewish and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors. 2) Generations of slavery and discrimination have created conditions that make it difficult for blacks to work their way out of the lower class. 3) Over the past few years, blacks have gotten less than they deserve. 4) It's really a matter of some people not trying hard enough; if blacks would only try harder they could be just as well off as whites.

4.4 ***Spatial Accuracy*** and ***Racial Resentment***

Table 1 presents the results of the analysis of *spatial accuracy* as a predictor of *racial resentment*. We find that while an increase in *non-threatening spatial accuracy* is correlated with higher *resentment* an increase in *threatening spatial accuracy* is not predictive of *resentment*.[7]

Table 1: spatial accuracy and racial resentment

	non-threatening groups	threatening groups
Intercept	0.22	0.33
	(0.62)	(0.62)
spatial accuracy	0.08^{*}	0.01
	(0.04)	(0.04)
partisanship	-0.57^{*}	-0.56^{*}
	(0.04)	(0.04)
education	-0.03^{*}	-0.04^{*}
	(0.01)	(0.01)
population density	−0.00	−0.00
	(0.01)	(0.01)
county % white	0.01	0.01
	(0.01)	(0.01)
county % Black	0.01	0.01
	(0.01)	(0.01)
county % Asian	0.01	0.00
	(0.01)	(0.01)
county % Latino	0.01	0.00
	(0.01)	(0.01)
N	552	543
R^2	0.31	0.29
adj. R^2	0.30	0.28
Resid. sd	0.23	0.24

Cell entries are OLS regression coefficients with white survey respondents only. Dependent variable is racial resentment. Standard errors in parentheses. * *indicates significance at* $p < 0.05$

These results are preliminary and further investigation of how this relationship varies with context is an important next step. For example, the complex relationship between segregation, attitudes, demographic perceptions, and spatial accuracy should be investigated.

[7]Interestingly, this result is also recovered when using the binary accuracy of placing wealthy Americans (instead of White and Asian) vs. poor Americans (instead of African Americans and Latinos). This may reflect a correlation between these sets of variables, either in perception or reality.

These preliminary results are interesting though. On the one hand, we might expect an individual with strong racial attitudes to have a heightened awareness of the location of an outgroup – and our results are inconsistent with this. On the other hand, the results here might indicate that individuals that carry racially conservative attitudes rely on stereotypes and other heuristics when thinking about the outgroup, rather than developing a more refined sense of spatial location. This result is also consistent with the findings of Wong et al. (2012) that indicate that individuals with a distorted perception of reality are most likely to be racially resentfull. The results for *closeness* that we display next are consistent with this. In future work, we plan to test for variation in these relationships across spatial context to see if the results might simply reflect an inability of respondents that do not live near threatening outgroup to accurately place those outgroups.

4.5 *Spatial Accuracy* and *Closeness*

Table 2 presents the results of the analysis of *spatial accuracy* as a predictor of *closeness*. We find that an increase in *threatening spatial accuracy* is correlated with higher *closeness* to these groups but that an increase in *non-threatening spatial accuracy* not predictive of *closeness*[8]. This result is consistent with the interpretation, offered above: that negative attitudes about threatening groups are associated with a reliance on stereotypes that are not associated with spatial accuracy. It also suggests that high spatial accuracy may be a proxy for positive interaction with outgroups leading to a sense of shared political orientation. Of course, our *closeness* measure is an entirely new construct that we need to further validate before drawing any strong conclusions.

[8] Again, this result is also recovered when using the binary accuracy of placing poor Americans (instead of African Americans and Latinos).

Table 2: spatial accuracy and closeness

	non-threatening groups	threatening groups
Intercept	0.79	0.72
	(0.56)	(0.55)
spatial accuracy	−0.01	0.11*
	(0.04)	(0.04)
partisanship	0.38*	0.39*
	(0.04)	(0.04)
education	0.00	0.00
	(0.01)	(0.01)
population density	−0.00	0.00
	(0.01)	(0.01)
county % white	−0.01	−0.01
	(0.01)	(0.01)
county % Black	−0.01	−0.00
	(0.01)	(0.01)
county % Asian	−0.00	−0.00
	(0.01)	(0.01)
county % Latino	−0.01	−0.01
	(0.01)	(0.01)
N	552	543
R^2	0.18	0.19
adj. R^2	0.17	0.18
Resid. sd	0.21	0.21

Cell entries are OLS regression coefficients with white survey respondents only. Dependent variable is political closeness. Standard errors in parentheses. * *indicates significance at* $p < 0.05$

4.6 *Racial Resentment*, *Demographic Innumeracy*, and *Spatial Accuracy*

In this section we briefly consider the relationship between *demographic innumeracy* (Wong et al. 2012), *spatial accuracy*, and *racial resentment.* Table 3 shows the results from this analysis. *Innumeracy* is a measure of the respondents over-estimate of % Black in US: A 1-unit increase in this variable corresponds to a 10 percentage point overestimate of demographic concentration of Blacks in the United States. Because the accuracy of non-threatening groups was significantly related to attitudes above, we use the average accuracy of whites and Asians again.

In column 1 of Table 3 we recover a finding similar to (Wong et al. 2012) – higher *demographic innumeracy* is correlated with *resentment*[9]. When both *demographic innumeracy* and *non-threatening spatial accuracy* are included in the regression, we find that both remain predictors of *resentment*, although the effect of spatial accuracy is greater[10].

Table 3: spatial accuracy, demographic innumeracy, and racial resentment

	Innumeracy	Innumeracy & Accuracy
Intercept	0.33	0.14
	(0.61)	(0.61)
innumeracy	0.02*	0.02*
	(0.01)	(0.01)
non-threatening spatial accuracy		0.09*
		(0.04)
partisanship	−0.56*	−0.55*
	(0.04)	(0.04)
education	−0.03*	−0.03*
	(0.01)	(0.01)
population density	−0.00	−0.00
	(0.01)	(0.01)
county % white	0.01	0.01
	(0.01)	(0.01)
county % Black	0.01	0.01
	(0.01)	(0.01)
county % Asian	0.00	0.01
	(0.01)	(0.01)
county % Latino	0.00	0.01
	(0.01)	(0.01)
N	564	552
R^2	0.32	0.33
adj. R^2	0.31	0.32
Resid. sd	0.23	0.23

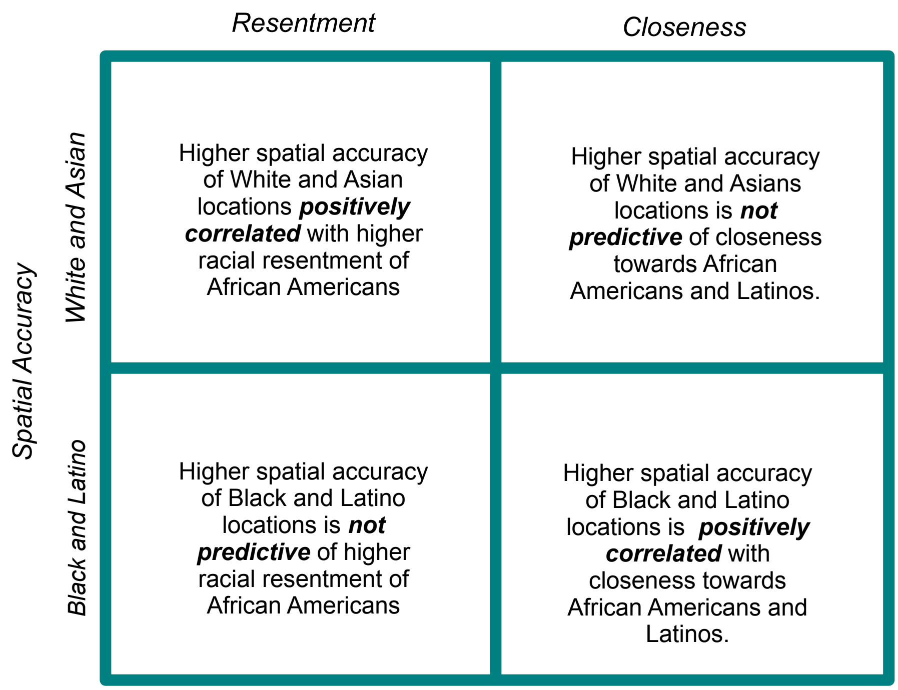
*Cell entries are OLS regression coefficients with white survey respondents only. Depedent variable is racial resentment. Standard errors in parentheses * indicates significance at* $p < 0.05$

To summarize, we find that for white respondents, while a higher spatial awareness

[9]This result is contingent on including respondents who gave wildly inaccurate responses for the percentage of African Americans in the United States (some as high as 100%). We test the degree to which this result hinges on the responses of such individuals by re-running the test and systematically excluding respondents who estimated over 80%, 60% and 50%. The result disappears both substantively and statistically once we remove those who guessed over 50%.

[10]We find a similar result for the over-estimate of Latinos.

Figure 9: Summary of Individual Spatial Accuracy Results



of Whites and Asians is correlated with higher racial resentment of African Americans a higher spatial awareness of African Americans and Latinos does not predict racial resentment towards African Americans. Alternatively, a higher spatial awareness of African Americans and Latinos is correlated with a higher likelihood of considering oneself to be politically close to these groups. These findings are summarized in Figure 9. We also find spatial accuracy to be a good predictor of racial resentment when compared to demographic innumeracy.

5 Discussion

In this paper we have demonstrated that individuals have an accurate sense of the location of groups in space. We also showed some preliminary results that indicate that their ability to place groups in space is correlated with socio-political attitudes – although in a manner that requires further investigation. We have argued that this ability follows from space being the most accessible attribute to individuals when they evaluate an outgroup.

The cause of spatial accuracy remains obscured and the cause of the correlation with some racial attitudes is also not something we understand. Do individuals know where groups live because of education, exposure, attitudes that fear closeness, or something else? Attempting to gain more leverage on the causal relationship is an important next step of this project. And of course, a more complete analysis of this phenomenon will have to involve a more robust set of controls and interactions to clearly delineate the relationship between context and spatial accuracy.

We close by discussing some implications for future work.

5.1 Implications for future research

We suggest that our findings are important for the understanding of socio-political cognition. We have demonstrated that location is an important attribute in the schema surrounding groups and, of course, it is well-understood that groups are centrally important to politics. We also suggest that our findings have implications for how we proceed with future work about group threat.

Spatial awareness might be a mediator of threat and scholars should include a measure of spatial awareness when attempting to measure the impact of threat. In the absence of technology that makes this easily available, they should use a subjective measure of awareness, such as whether a person *believes* that they know the location of groups. In the absence of a better measure, we might believe this would still be an improvement over the current, largely unmediated, look at the relationship between a proximate outgroup and individual behavior.

Furthermore, location becomes even more important in these findings and has to be more carefully considered and modeled when thinking about threat. Rather than threat relying on vague awareness of population proportions, we now see evidence that it might be based on a more concrete understanding of location. Because of this, the contextual variables that might mediate spatial awareness become more important. For example, residential segregation, which is often considered when thinking about interpersonal contact, might also have important implications for spatial awareness and, therefore, mediating threat. For example, can a group be more easily located in space as segregation increases (Enos 2011*a*)? And our evidence suggests that spatial proximity between groups and between an individual and a group might mediate spatial awareness. This implies that the effects of proximity, which are often merely assumed (Enos 2010) should be more explicitly measured and modeled (Enos 2009).

Spatial awareness should also be combined with Wong et al.'s (2012) insights and technology to help overcome the Modifiable Areal Unit Problem, which, of course can affect our findings in this paper, as we were forced to an arbitrary administrative boundary to measure the characteristics of our units.

References

Alba, Richard, Ruben G Rumbaut, and Karen Marotz. 2005. "A distorted nation: Perceptions of racial/ethnic group sizes and attitudes toward immigrants and other minorities." *Social Forces* 84: 901.

Berinsky, Adam J., Gregory A. Huber, and Gabriel S. Lenz. 2012. "Evaluating Online Labor Markets for Experimental Research: Amazon.com's Mechanical Turk." *Political Analysis* 20(3).

Bobo, Lawrence. 1983. "Whites' opposition to busing: Symbolic racism or realistic group conflict?" *Journal of Personality and Social Psychology* 45(6): 1196–1210.

Burgess, Neil, Eleanor A. Maguire, and John O'keefe. 2002. "The human hippocampus and spatial and episodic memory." *Neuron* 35(August): 625–641.

Enos, Ryan D. 2009. The Effect of African American proximity on Latino vote choice in the 2008 Presidential Primary. American Political Science Association, Annual Meeting Toronto: .

Enos, Ryan D. 2010. Spatial Impact: the influence of groups in geographic space on individual political behavior Dissertation University of California, Los Angeles Los Angeles: .

Enos, Ryan D. 2011*a*. Experimental Test of the Effects of Racial Segregation on Intergroup Attitudes. Midwest Political Science Association Chicago: .

Enos, Ryan D. 2011*b*. "Testing the elusive: a field experiment on racial threat.".

Gallagher, Charles A. 2003. "Miscounting Race: Explaining Whites' Misperceptions Of Racial Group Size." *Sociological Perspectives* 46(3): 381–396.

Gay, Claudine. 2006. "Seeing difference: The effect of economic disparity on black attitudes toward Latinos." *American Journal of Political Science* 50(October): 982–997.

Giles, Micheal W., and Melanie A. Buckner. 1993. "David Duke and black threat: An old hypothesis revisited." *Journal of Politics* 55: 702–13.

Haidt, Jonathan. 2012. *The Righteous Mind: Why Good People are Divided by Politics and Religion*. New York: Pantheon.

Henry, P. J., and David O. Sears. 2002. "The Symbolic Racism 2000 Scale." *Political Psychology* 23(June): 253–283.

Hopkins, Daniel J. 2010. "Politicized places: explaining where and when immigrants provoke local opposition." *American Political Science Review* 104(1): 40–60.

Key, V.O. 1949. *Southern politics in state and nation*. New York: Knopf.

Kunda, Ziva. 1999. *Social cognition: making sense of people*. Cambridge, MA: MIT Press.

Maguire, Eleanor A. 2006. *Neuroergonomics - The brain at work.* Oxford University Press chapter Spatial Navigation, pp. 131–135.

Martinez, Michael D., Kenneth D. Wald, and Stephen C. Craig. 2008. "Homophobic innumeracy?: Estimating the size of the gay and lesbian population." *Public Opinion Quarterly* 72(4): 753–767.

Milgim, Stanley. 1970. "The Experience of Living in Cities." *Science* 167(March): 1461–1468.

Nadeau, Richard, Richard G. Niemi, and Jeffrey Levine. 1993. "Innumeracy about minority populations." *Public Opinion Quarterly* 57(3): 332–347.

Sigelman, Lee, and Richard G. Niemi. 2001. "Innumeracy about Minority Populations: African Americans and Whites Compared." *The Public Opinion Quarterly* 65(1): 86–94.

Spence, Lester K., and Harwood McClerking. 2010. "Context, Black Empowerment, and African American Political Participation." *American Politics Research* 38(5): 909–930.

Voss, D. Stephen. 1996. "Beyond racial threat: Failure of an old hypothesis in the new South." *The Journal of Politics* 58(4): 1156–70.

Wong, Cara. 2010. *Boundaries of Obligation in American Politics: Geographic, National, and Racial Communities.* New York: Cambridge University Press.

Wong, Cara J. 2007. ""Little" and "big" pictures in our heads: Race, local context, and innumeracy about racial groups in the United States." *Public Opinion Quarterly* 71(September): 392–412.

Wong, Cara, Jake Bowers, Tarah Williams, and Katherine Drake. 2012. "Bringing the Person Back In: Boundaries, Perceptions, and the Measurement of Racial Context." *Journal of Politics* .