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Pollution Prophylaxis?
Social Capital and Environmental Inequality

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The authors shall share all data and coding for replication purposes.

Abstract

Objective: One major theory of environmental inequality is that firms follow a political path of least resistance when locating polluting facilities in low-income and minority communities. Such communities, this theory suggests, lack the social capital that allows others to keep such facilities at bay. We test this argument. *Methods:* We investigate whether communities across the U.S. are located further from stationary sources of airborne toxins depending on their levels of social capital. *Results:* At some scales, we found that communities with more of some types of social capital do indeed tend to be located further from such facilities, though the differences are slight. We also found that, by some measures, minority communities possess no less social capital than others, and that controlling for differences in social capital barely attenuates the associations between demographics and proximity. *Conclusion:* The theory that differences in social capital explain environmental inequality is not supported.

Introduction

The environmental justice literature suggests that firms take the Path of Least Resistance (POLR) when deciding where to locate facilities emitting toxic pollutants (see Taylor 2014 for an excellent review of this literature). That is, they site such facilities in areas where community power is perceived to be the weakest. The POLR hypothesis represents a key component of one influential explanation of environmental inequality: If affluent and/or White communities possess more social capital, as they are commonly assumed to (e.g., Konisky and Reenock 2013; Saha & Mohai, 2005), then they will be better able than poor and minority communities to mobilize to resist the incursion of polluting facilities (Mohai et al., 2009; Pastor et al., 2001). Differences in communities' power may therefore explain why minorities and the poor are disproportionately exposed to pollution in the United States. This paper provides an empirical test of the POLR hypothesis.

We emphasize three key findings. First, some types of social capital are associated with better protection from pollution at some spatial scales, though many are not, and what differences there are between areas rich and poor in social capital are small. Second, areas with larger racial and ethnic minorities are not universally lacking in social capital; by several measures, African-American communities have substantially more social capital than White communities with equivalent incomes. Third, across the United States, controlling for differences in social capital barely attenuates African-American, Hispanic, and poor communities' disproportionate exposure to air toxins. Taken together, these findings offer modest support for the POLR hypothesis that social capital empowers communities seeking to avoid exposure to environmental harms, but not the theory that minority and/or poorer communities are more exposed to industrial toxins because they lack social capital.

Empirically, this paper overcomes a variety of methodological and data limitations that have previously limited efforts to test whether social capital works as a prophylactic against pollution. We employ detailed measures of seven different types of social capital from the 2000 Social Capital Community Benchmark Survey, the most comprehensive inventory of social capital in America. We utilize the restricted access version of these data, which provide geocoded information for respondents. Geographic locations of respondents allow us to generate estimates for community social capital indicators at three different spatial scales: census block groups, counties, and states. To our knowledge, our study is the first to test the relationships among demographics, social capital, and pollution exposure at such a diversity of spatial scales, and using such a broad set of measures. We first investigate the individual- and community-level demographic correlates of different kinds of social capital. We then identify community demographics that correlate with pollution exposure at each spatial scale, before then testing what types of social capital—such as bonding, bridging, and more direct forms of civic action—are associated with reduced exposure to environmental harms. As a measure of communities' exposure to environmental harms, we use the natural log of their distance to the nearest known stationary source of industrial air pollution, as taken from the Environmental Protection Agency's 2000 Toxic Release Inventory (TRI).

Background

Since the 1980s research has shown that exposure to pollution varies across racial and economic lines, with minorities and the poor more exposed to environmental harms (e.g., UCC/CRJ, 1987). The literature provides three main explanations of this inequality: (1) racial prejudice and institutional discrimination; (2) market forces; and (3) community power (Taylor, 2014; Grant et al., 2010; Mohai et al., 2009; Hamilton, 1995). The first approach emphasizes institutional and personal prejudice of key decision makers. According to this perspective, minority communities are discriminated against by local politicians and administrators as well as through the embedding of privilege in norms, regulations, and informal rules. The second approach, defined here as "market forces", emphasizes the economically rational efforts by firms and residents to minimize costs in placing facilities, and in acquiring housing, by choosing the least expensive real estate, such as that found around polluting industries. The third approach stresses the role of a community's capacity to prevent polluting facilities from entering or expanding in the local area; in contrast to the first two, then, this more political perspective turns the focus on the internal characteristics of communities themselves. Research on the first two explanations has outpaced the third, with scholars noting that operationalizing the latter has been difficult, due to the challenge of measuring communities' power (Downey, 2007).

The difficulty with measuring "community power" stems from ambiguous definitions in the environmental justice literature about what exactly defines a Path of Least Resistance. In one of the earliest works in this literature, Bullard and Wright (1986) suggested that many black communities, "do not have the organization, financial resources, or personnel to mount and sustain effective long-term challenges" to the siting of hazardous sites. More recently, Konisky and Reenock (2013, p. 507) state that poor and minority communities "have fewer resources with which to document and protest noncompliance" of industrial facilities. Similarity, Saha and Mohai (2005, p. 619) maintain that, "because of their political and economic vulnerability, low-income and minority neighborhoods are less likely to defeat siting proposals and are more likely to receive proposals deflected from more politically powerful (i.e., affluent, White) areas." A sentiment reflected by Mohai et al. (2009, p. 414) who agree that firms "seek to avoid communities that are most capable of mounting an effective opposition. These communities are those with abundant resources and political clout and also tend to be affluent, White, and well connected."

Early empirical work seeking to test this perspective has often measured communities' power via their political efficacy, operationalized as turnout in elections. Hamilton (1993, p. 102), for instance, utilized the percentage of a county that voted in the 1980 presidential election as a measure of, "the potential for residents to engage in political activity." Examining expansion decisions of toxic storage facilities in 156 counties from 1987 to 1992, he found that a one standard deviation increase in voter turnout decreased the probability of a facility expanding in a county by 0.19. Similarly, Hamilton (1995) examined expansion decisions for 84 zip codes with waste facilities and found voter turnout to be strongly and negatively related to expansion decisions of toxic sites. However, Arora and Cason (1999) examined emissions of TRI facilities in California and found no significant difference in the emissions of facilities in zip codes with lower electoral turnout. They also found the percentage of residents who voted for an environmentally protective ballot measure had no appreciable association with emissions.

Those few studies that have ventured away from measuring communities' power via voter turnout have used a range of other measures and found mixed results. For example, Konisky and Reenock (2013) found no relationship between the campaign donations made by residents and the compliance of polluting facilities in a county. However, Kassinis and Vafeas (2006) found that on- and off-site pollution from TRI facilities was negatively related to the number of paying members of environmental organizations at the state level. Zahran et al. (2008) operationalized power as the total assets of non-profits in a census tract area divided by the total number of persons in the tract. They found an increase of $1,000 in assets per capita decreased the probability a toxic facility was present by approximately seven percent. Finally, Konisky and Reenock (2013) showed the presence of environmental justice organizations in Hispanic communities decreased the likelihood of polluting facilities' non-compliance, although this was not supported for African-American communities.

Another empirical approach has been to test community characteristics assumed to influence power, and thereby pollution exposure. In their longitudinal study of toxic storage and disposal facilities in Los Angeles County, for instance, Pastor, Sadd and Hipp (2001) found areas with high turnover of minority residents were more likely to receive a polluting facility. They argued that residential turnover weakens, "…neighborhood social capital and increasing the area's vulnerability to siting locally undesirable land uses" (Pastor et al., 2001, p.10). Our approach here is similar, though rather than only testing a causally prior condition (such as residential turnover), we investigate social capital directly.

Operationalizing the Path of Least Resistance

The explosive growth of scholarly interest in the concept of social capital since the 1990s has identified several different phenomena—all subsumable under the general rubric of "social capital"—that might shape a community's ability to mobilize in self-defense against environmental harm. The multidimensionality of the concept provides several different pathways through which social capital might impact whether a facility emitting air toxins is closer to a community. To test how these different dimensions of social capital relate to communities' exposure to industrial hazards, we use a number of indices developed as part of Robert Putman's Social Capital Benchmark Survey. This survey, conducted in 2000, remains the largest ever attempt to measure social capital in America (Saguaro Seminar, 2014). Using factor analysis and theory researchers constructed a number of different indices of social capital (Saguaro Seminar, p. 8). We identify seven of these indices as being related to pollution outcomes. In the paragraphs below we lay out the theoretical arguments and evidence relating these indicators of social capital to the "community power" theorized about in the POLR literature. We use Putnam's (2000) typology of bonding and bridging capital for an organizational framework and highlight two direct indicators of political/civic engagement. See Table 1 for a summary of these measures.

Bonding (or exclusive) social capital is defined by Putnam (2000) as inward looking, related to relationships among individuals sharing a common social class, ideology or set of demographic characteristics. We hypothesize that bonding social capital could shape negotiations over the siting of facilities in allowing a community to speak with one voice and in conveying a united front to decision-makers. We use two indicators of bonding social capital in the following analyses. The first index is faith-based social capital (Faithba2), a concept previous studies have employed as an indicator of bonding capital (Liu et al., 2009; Austin 2006). Faith-based social capital is measured as the sum of a respondent's participation in organized religion: attendance, participation in church activities other than services, contributing money to church or religious causes, being a church member, volunteering for religion, and participation in an organization affiliated with religion. Faith groups' role in facilitating political mobilization has been well studied since the Civil Rights Movement (Williams 2002), with scholars observing that organized religion provides "mediating structures" that influence how people engage with social problems, providing a vital place for "community mobilization, activism and collaboration for social justice" (Houston & Todd 2013, p.273; Todd & Allen 2011). Using the General Social Survey, Harris (1994) found that for both African-Americans and White respondents, religious involvement provided organizational, as well as, psychological resources, such as promoting feelings of personal efficacy.

The second bonding measure theorized to impact community power is Informal Social Interaction (Schmooz), which is defined here as the average frequency of: having friends visit, visiting with relatives, socializing with coworkers outside of work, hanging out with friends in public places, and playing cards and board games. Previous work has shown informal social interaction is an independent predictor of political engagement and community organizing (Ikeda et al., 2012; McClurg 2003; La Due Lake & Huckfeldt, 1998). Scholars argue informal interaction promotes political participation through the expansion of one's social network, and thus information transfer, as well as through the development of social skills that promote collective problem-solving (Ikeda et al., 2012; Putnam 2003). In the neighborhood effects literature, Sampson et al., (1997) and others (Morenoff et al., 2001), argue that the ability to draw upon informal ties is essential for a community to control its social and physical environment by establishing and reinforcing norms that encourage residents to act on behalf of the common good.

Bridging (or inclusive) capital is defined by Putnam (2000) as being outward looking, made up of relationships among individuals of different classes, ideologies or demographic groups. While bonding measures capture in-group cohesion, bridging social capital captures out-group cohesion, which might be necessary for successful negotiations with respect to the siting of industrial facilities which requires collaboration across interest groups. Of the seven indices we use in this analysis, three fall under this category: social trust, inter-ethnic trust, and diversity (Soctrust, Racetrst, and Divrsity). The importance of generalized trust (Soctrust) for motivating collective action has been repeatedly emphasized in the literature, with the theory being that trust encourages civic engagement by raising people's confidence that others will cooperate (Putnam 1993; 2000). In a cross-national analysis, Sønderskov (2008) therefore found that residents of nations with higher mean generalized trust made more efforts to protect the environment. He notes that trust allows people to "overcome the collective action problem associated with membership" in environmental organizations (Sønderskov, 2008, p. 90). More recently, Sønderskov (2011) similarly found using cross-national data that people with more generalized trust are more likely to join "public good producing" organizations.

Generalized Social Trust is measured here as a respondent's trust in their neighbors, coworkers, local store employees, fellow congregants, police and "most people". Although these measures are collapsed here, social psychology scholars have examined whether trust in "most people" is distinct from trust of individuals in particular contexts (Freitag & Bauer 2013). Recent experimental research has shown that participants' generalized trust is reformulated after relatively brief experiences with individuals, as would be reflected in the particularized trust measures (Robbins 2016; Paxton & Glanville 2015). As Paxton and Glanville (2015, p.201) argue, "[w]e now have significant evidence that generalized trust is experience-based and responsive to social interactions." Even with the evidence that these psychological constructs are dynamically related and thus should be measured together, for the purposes of the POLR argument, we believe combining these measures reflects what Putnam (2000, p.136) calls the "would be collaborators" of a tightly knit community. Moreover, we have run the following analyses with "trust in most people" separated from trust of those in particular contexts and found similar effects. Thus we present results from the joint measures below.

The last two measures of bridging capital we use are: the mean level of trust respondents have for those outside of their racial/ethnic group (Racetrst) and the diversity of respondents' friendships (Divrsity). Diversity of friendship is measured by the count of how many friends a respondent has from different racial and socioeconomic groups. We theorize the trust one has for those outside of their racial group is likely to affect their ability to negotiate across interest groups, a trait we expect to be salient when communities are faced with the siting of a nearby toxic facility. In addition, the diversity of one's social networks can provide novel types of information and contacts (Granovetter 1973) and encourage more critical reflection and appreciation for alternative perspectives (Mutz & Mondak 2006). Macias and Nelson (2011) therefore find that people with diverse networks tend to be more concerned about the environment. Using panel data from 2006 and 2008, Quintelier et. al. (2012) found that when controlling for prior political participation and network diversity, the ethno-cultural diversity of a person's networks predicted later political participation.

While others have categorized indices of protesting (Protest) and organizational activism (Macher) under "bridging social capital" (Liu et al., 2009), we distinguish them here because unlike the other indicators used in this study, which are antecedents to the political strength of a community, these two indices are outcomes. Macher was created from a principal components analysis of four components: number of formal group involvements (excluding church membership), serving as an officer or on a committee, number of club meetings attended, and number of public meetings attended discussing school or town affairs. Protest was the mean score of seven different types of actions: belonging to any group that took local action for reform; attending a political meeting or rally in the past 12 months; signing a petition in the past 12 months; participating in a political group; participating in demonstrations, boycotts, or marches in the past 12 months; participating in ethnic, nationality, or civil rights organization; and participating in a labor union. We view these two indices as the clearest measures of political resistance that the environmental inequality literature hypothesizes protect White and/or affluent communities from environmental hazards.

[Table 1 about here]

Data

The restricted-use version of the social capital dataset includes 29,733 respondents, nested in 42 communities. Of these respondents, 593 had missing geocodes, and the remainder were nested in 14,609 unique block groups; 1,297 counties; and 49 states. Table 2 provides descriptive statistics and correlations of the variables measuring social capital and the three demographic variables we take from the 2000 Social Capital Community Benchmark Survey (dummy variables for being Hispanic or African-American, and total household income in 1999). Income was measured categorically, and we use the Benchmark Survey authors' recommended approach for calculating dollar equivalents to each category (see Saguaro 2014 for a more detailed explanation).

[Table 2 about here]

Our main unit of analysis is the Census block group—the smallest geographical unit to which respondents are linked in the Social Capital Benchmark Survey. Block groups are uniquely nested within counties and states, and we combine data from the Benchmark Survey with data at each of these three levels from the 2000 Census on: proportion non-Hispanic African-American; proportion (any race) Hispanic; proportion of families in poverty; median household income in 1999; proportion of people in a different house than 1995 (as a measure of residential churning); and population density (per square kilometer). Table 3 presents key characteristics of these variables at the block group level. As of the 2000 Census, there were a total of 211,267 block groups and 3,141 counties in the United States.

[Table 3 about here]

Previous studies have noted that it is not clear how best to define "communities" when investigating their exposure to pollutants (Mohai & Saha, 2006). Our approach has the advantage of investigating communities defined at a variety of spatial scales simultaneously, allowing for the possibility that social capital may "work" at any one of them—from the very local (block groups), to quite large (states), or something in between (counties). At the local level, Sampson et al. (1997) argue that neighbors, just by virtue of living in close proximity to one another, share priorities such as neighborhood safety, good schools, and a healthy environment. From this perspective, neighborhoods could be the key spatial scale. Alternatively, though, states and counties are formal jurisdictions within which policymaking and policy implementation occur, making them potentially more important. Empirically, while useful, our approach is no panacea, insofar as our estimates of social capital at the finest (block group) scale are subject to some measurement error, and thus attenuation bias. In addition, while census units are often used as proxies for neighborhoods, and they do not necessarily capture the actual social boundaries of neighborhoods.

Our dependent variable is the natural log of the distance (in kilometers) from a block group (specifically, its centroid) to the nearest facility in the EPA's Toxic Release Inventory. The TRI tracks regulated facilities that range from manufacturing, mining, utility operations, hazardous waste treatment, and disposal facilities, as well as chemical distributors and federal facilities (EPA, 2007). These locations can be mapped (using longitude and latitude) for each year they were in operation. The TRI data included 17,504 facilities in the year 2000. We use distance rather than presence/absence or counts of polluting facilities in a block group because the vast majority of block groups (97.5%) have no facility at all, such that there is little variance to explain, and we believe the closer a facility is to a respondent's home the more likely they will know of it and the issues around POLR become more salient. We calculated the distance between each TRI facility and the centroid of each block group with at least one survey respondent using the "gDistance" function in R's "rgeos" package (Bivand & Rundel, 2014). The 14,609 block group centroids are on average 5.71km from the nearest facility, but with some up to 252km away, such that we take the log in order to make the distribution approximately normal. Distance to the nearest TRI facility is not a completely accurate measure of exposure to actual environmental harm, but it is strongly correlated, and it has the advantage of being very visible. The presence of a facility would be difficult to hide from residents of an area, thereby being an easier target to rally political action around than an abstract idea of exposure to air pollution from a source far away. Because data on when the facilities were placed in these communities was not available, we work under the assumption that similar levels of social capital existed at the time of siting. Future work should evaluate these results with longitudinal data.

We do not know precisely where a given survey respondent lives within a block group, such that sometimes the centroid will not be a completely accurate way of assessing a given person's distance to the nearest facility. But block groups are typically quite small areas, containing about 600 to 3,000 people, and the variance in block groups' distance to the nearest facility is much greater than the variance in residents' locations within them (a figure for which we can calculate an upper bound based on the distance from the centroids of one block group to the nearest neighboring centroid). So our dependent variable is measured with some error, but we capture the vast majority of the relevant variation. TRI facilities' locations are accurate in almost all cases to within 200 meters (Pais et al., 2014).

Following Pastor, Sadd and Hipp (2001), we include a variable capturing the residential churning in an area, on the logic that areas may be less politically efficacious insofar as their residents turn over more rapidly (and so have less time, opportunity, and reason to invest in forming local bonds and getting involved in local civic life). Our measure of churning is the proportion of people who report not living at the same address as five years previously. Such a perspective has a long pedigree: As early as 1925, Chicago School sociologists Park and Burgess argued the rapid turnover of population in urban areas led these communities to become characterized by "social disorder" which broke down local attachments and social control.

Methods

Empirically, we aim to investigate whether areas with more social capital tend to be located further from polluting facilities, on the logic that such areas can better prevent toxic emitting facilities (for the reasons outlined above) from being established or kept open close by. Our analysis proceeds by the following steps:

First, we generate estimates of each type of social capital for block groups and the counties and states in which each block group is uniquely nested. We do so by fitting multilevel to the individual-level Social Capital Benchmark Survey data, with respondents nested in block groups, counties, and states:

$$y_{ibcs} = \beta_0 + u_{bcs} + u_{cs} + u_s + \epsilon_{ibcs}$$

where $u_{bcs} \sim N(0, \sigma_{u1}^2), u_{cs} \sim N(0, \sigma_{u2}^2), u_s \sim N(0, \sigma_{u3}^2), and\ \epsilon_{ibcs} \sim N(0, \sigma_{\epsilon}^2)$.

Thus the social capital of respondent *i* in block group *b*, in county *c*, in state *s*, is a function of an overall intercept and random intercepts at all three higher levels. From these models we extract Best Linear Unbiased Predictions (BLUPs, or EBLUPs as they are sometimes known, because they are estimated) of the random intercepts at each of the three higher levels. Because the random intercepts are generated under the assumption that they are distributed normally with a mean of 0, the BLUPs at the block group and county levels are intrinsically centered by the means of the counties and states in which they are nested, respectively. Such mean-centering is useful in multilevel modeling generally (see Enders & Tofighi, 2007), and in this instance it allows us at the next stage of our analysis to include social capital as a covariate at each of three levels (in models described further below), investigating separately but simultaneously whether social capital matters at each level or scale.

The models we use at this first stage to generate the BLUPs are null—they do not include any covariates—though we also tried including demographic covariates in these models, and while the variance of the BLUPs declined, the substantive results of our analyses were unchanged. We use BLUPs rather than simple means of the responses to each survey question by group because the latter are known to yield biased results in analyses based upon them (Croon & van Veldhoven, 2007). Unlike simple means, BLUPs of the random effects minimize mean-squared error, as they take advantage of one of the most useful properties of multilevel models: They shrink estimates for each group toward the overall mean to a degree that reflects their unreliability (see e.g., Snijders & Bosker, 2012). Random effects for higher-level units located further from the overall mean, and those with fewer observations are shrunk further toward the mean; this shrinkage is also (inversely) proportional to the intra-class correlation. While this means that the BLUPs are biased (toward the overall mean), they are nonetheless more accurate (Raudenbush & Bryk, 2002); it is in this sense that they are considered "Best". Particularly given the small number of respondents per block group (for most though not all block groups), such precision-weighting substantially reduces the total error of our social capital estimates. We use Bayesian/MCMC estimation here and for all other analyses, using the MCMCglmm package in R (Hadfield, 2010), with flat priors.

Second, we model individuals' social capital (using seven measures) as functions of individual demographics (household income, and dummy variables for being Hispanic and African-American) and demographics at each of the block group, county, and state levels. These are four-level models similar to the ones used in the first step—with survey respondents nested within each of three higher-level spatial units—though here the models include covariates. Seven models each adopt one measure of social capital as the outcome. The purpose here is to investigate the social capital of minorities and/or the poor—and of minority and/or poor communities, at each of three scales—relative to the social capital of others. To what degree do the poor and/or minorities, and residents of poor and/or minority communities, possess less (or more) of each type of social capital?

Finally, we fit three-level models of the log of distance in kilometers as a function of community social capital, at each of three levels: block group, county, and state. The first model is a null model. The second includes demographic controls only, including population density. The next seven models include different measures of social capital, plus demographic controls.

Our purpose in testing for an association between social capital and pollution exposure is to assess the plausibility of a causal relationship. For that reason, we control for other correlates of the latter, in order to rule out as many potential sources of spuriousness as possible; many demographic characteristics or circumstances could underlie both variables. If the relationship between some demographic variables and pollution changes substantially when controlling for social capital, then social capital would seem a mechanism linking that variable to pollution exposure. Nevertheless, while we believe that any positive statistical association should be taken as indicative of a causal relationship, some caution is in order. A causal interpretation would entail the assumption that we have indeed controlled for all relevant confounders, and that the causal relationship does not run in the opposite direction. Conversely, a finding of no association would seem stronger evidence against the hypothesis of a causal relationship.

Another challenge the above steps are intended to address is that the relationship we want to test may not be detectable, even with the very high-quality data we have, because of random measurement error. Estimates of social capital at the block group level are based on very few observations--in some cases, only a single individual. Unlike our dependent variable, then, the key covariate in our models is measured with substantial error, albeit only at the lowest (block group) level. At higher levels this is much less of a limitation, and because our measures of social capital are centered by the county mean, the inclusion of even a highly imprecise measure at the block group has no impact on the coefficient estimates at the county and state levels. For that reason, we do not simply remove the block group level from our analysis; doing so would result in unnecessary coarsening in the measurement of our outcome variable. Yet we place less emphasis on (non-significant) results at the block group level.

Results

First, Table 4 presents the fitted models used to generate the estimates of each type of social capital for block groups, counties, and states. These are null models, with no covariates other than a constant. The relative shares of the variance at each level differ across the seven measures, but in five out of seven cases there is more variance across block groups than at every other level (excluding the lowest, residual level). The variances of the BLUPs of the random effects are smaller than the random effects of variances, because the former are shrunk toward the mean, as explained above.

[Table 4 about here]

Second, Table 5 presents models of individuals' self-reported social capital as functions of individual and contextual demographics. Given our use of Bayesian/MCMC estimation, as opposed to the frequentist framework used more often by applied social scientists, in this table and the next, we label coefficient estimates as statistically significant where the posterior density falls predominantly on one side of zero. Significance therefore means there is only a very low probability (presented in parentheses) that the parameter actually has the opposite sign.

[Table 5 about here]

The tests presented here of the hypothesized relationship between demographics and (seven different types of) social capital at three spatial scales simultaneously is, to our knowledge, unprecedented in the literature. Each demographic variable appears at three levels in the model (and four in the cases of the variables for income, African-American, and Hispanic), corresponding to three spatial scales. All variables at the individual, block group, and county levels are entered as deviations from the corresponding variable at the next spatial scale up. For example, the variable for being African-American is either -0.3 or 0.7 in a block group where the proportion of residents who are African-American is 0.3. This group-mean centering allows us to tell separately, for example, whether African-Americans within a given block group have less (or more) social capital than non-African-Americans, and at the same time whether block groups with more African-Americans (relative to the norm for the county in which a block is located) have less (or more) social capital. These are superficially similar but nonetheless distinct questions, and failing to distinguish between them could lead to an ecological or atomistic/individualistic fallacy, wherein inferences are made at a level based on data collected from another (Diez Roux, 2003, p. 101). African-American individuals may or may not be different from non-African-Americans once community differences are accounted for, for example, and communities with more African-Americans may or may not differ from those with fewer, once differences among the individuals comprising them are accounted for.

Table 5 shows that, controlling for income, African American individuals have less of most kinds of social capital, but have significantly more Non-Electoral Political Participation (Protest), Organizational Activism (Macher), and Faith-Based Social Capital (Faithba2). Contrary to the impression of many that predominately African American communities are deprived of social capital, block groups and counties with higher proportions of African-American residents also have more of each of these three types of social capital. This was true at every spatial level with two exceptions at the state level for Organizational Activism, which lost significance, and Protest switched signs so that African-Americans had significantly less of this type of social capital at the state level. Hispanic individuals and block groups with more Hispanics have significantly less of all seven kinds of social capital, relative to non-Hispanics with the exception of Faith-Based Social Capital. This is also true at the county level, with the exception of Macher, which loses significance. At the state level, some of the negative relationships between the percentage of Hispanics and Divrsity, Macher and Protest lose their significance.

Higher-income individuals report significantly more social capital of all types, including when controlling for race. In addition, block groups and counties with greater incomes have significantly more of all types of social capital, with the exception of informal social interaction (Schmooz). At the state level, the picture changes only slightly. Those states with higher median incomes report significantly greater general social trust (Soctrust), inter-racial trust (Racetrst), diversity of friendships (Divrsity), and organizational activism (Macher). However, faith-based social capital (Faithba2) becomes non-significant and negative, and Schmooz continues to be negative, but is also not significant.

The population density of block groups was statistically significant for only two variables, Schmooz and Protest, both of which were positively related. However, the population density of a county and state was significantly negatively related to Soctrust, Racetrst, Faithba2, and Macher, without much variation in the strength of this relationship across social capital indicators. Those counties that were more populous were significantly more likely to have higher levels of non-electoral political participation (Protest). More populous states generally had less social capital.

Block groups with greater residential churning evidence less participation in organized religion (Faithba2), but more informal interaction (Schmooz). The friendship networks of residents of such block groups are also more diverse (Divrsity). The statistically significant relationships between churning and both Divrsity and Faithba2 are consistent across all levels. At the state level, however, churning is negatively associated with general interpersonal trust (Soctrust) and inter-ethnic trust (Racetrst).

The results in Table 5 demonstrate that the different dimensions of social capital vary across different spatial (or socio-administrative) scales. Overall they support the idea that marginalized individuals and communities possess less social capital in America. Lower-income areas tend to have less social capital than richer ones. But the picture is not entirely straightforward. Comparing racial/ethnic groups, Hispanics appear the most deprived of social capital. However, for at least for three measures:

Non-Electoral Political Participation, Organizational Activism and Faith-Based Social Capital, rather than having less social capital African-Americans have more.

Next, Table 6 presents models of log distance. These are three-level models, with block groups nested in counties, nested in states. Demographics and social capital are measured at all three levels. We present a model (M1) with only demographics (including churning and density), then seven models with demographics and social capital. Judging by the random effects variances from M0, the null model, 18% of the variance is at the state level, 37% at the county level, and 45% at the block group level. Model M1, with demographic covariates only, shows that, as expected, block groups and counties with higher median income are located farther away from industrial facilities. Generally, areas with more African-Americans and Hispanics tend to be located closer to a polluting facility, although this relationship is only significant at the block group level. Notably, counties with higher levels of poverty are located farther away from industrial facilities. The pattern does not hold at the block group or state level, however. Block groups experiencing more churning (residential turnover in the last five years) are located significantly closer to industrial facilities. This relationship, however, holds only at the block group level. Finally, density was strongly and significantly related to being closer to industrial facilities across all levels, reflecting that industry tends to be located in America's denser, more populated, central cities.

[Table 6 about here]

The rest of the models in Table 6 investigate whether social capital is associated with a community's distance to the nearest TRI facility, controlling for demographics (including churning and density). While, in most cases, the coefficient on social capital is positive, the relationship is not statistically significant for any dimension at the block group level. Certain measures, however, are significant at the county and state level. Specifically, controlling for all other variables, counties with more Organizational Activism (Macher) and Non-Electoral Political Participation (Protest) are significantly more likely to be farther away from industrial facilities. Generalized social trust, however, is related in the opposite direction. That is, counties with more general interpersonal social trust are closer to industrial facilities. The state level coefficients show that those states with greater inter-racial trust (Racetrst), Organizational Activism and Non-Electoral Political Participation are located farther away from industrial facilities.

An important, and startling, insight these models provide is that the relationship between the other explanatory variables and the distance to the nearest industrial facility are hardly affected with the inclusion of any of the social capital variables. If differences in social capital explain why poor and/or minority areas are less able to keep polluting facilities at bay, then we would expect the absolute value of the coefficients on the demographic variables to shrink when adding measures of social capital to the model. Comparing the models including social capital to the model without (M1), we can see that the coefficients on the demographics that were statistically significant in model M1 have barely changed.

[Figure 1 about here]

Figure 1 illustrates the magnitudes of the effects reported in Table 6 (with the exception of the null model). The magnitudes presented here are the expected percent change in a block group's distance to the nearest TRI facility, given a one standard deviation change in each covariate. The vertical lines represent 95% credible intervals—the middle 95% of all the samples returned by the MCMC chains. These are similar to confidence intervals, but with the more intuitive interpretation characteristic of Bayesian rather than frequentist statistics.

Contrasting the panels in Figure 1 shows how the differences in the outcome associated with a one standard deviation change in each demographic variable do not, for the most part differ much depending on the inclusion of any of the social capital measures. Again, then, controlling for social capital makes little difference to the relationship between key demographics and its expected exposure to pollution. Yet, as explained earlier, a number of the social capital variables are statistically significant (at the county and state levels, not block group levels). As such, some kinds of social capital (Racetrst, Macher, and Protest) appear, as the sociopolitical perspective predicts, prophylactic. Yet even controlling for social capital, clear differences remain between more and less privileged communities—and this is true at every spatial/administrative scale. Even though Hispanic communities seem to suffer from a more noticeable social capital deficit than African-American communities (per Table 5), the disproportionate exposure of Hispanic communities is less explainable by differences in social capital.

One of the largest and most consistent effects seen in Figure 1 is for population density, not surprisingly in light of the history of industry being located in America's urban areas. The magnitude and importance of the population density measure contrasts sharply with social capital indicators. The other large effects, for counties at least, are the proportion in poverty and median income. Interestingly, they are related to the distance from a facility in opposite directions. Counties with higher proportions of residents in poverty are farther away from industrial facilities, as are counties, with larger median incomes. This pattern remains at the state level, but only for median income.

As robustness checks, we tried re-estimating the models also controlling for education (the proportion of residents with some postsecondary education or more), and examining a slightly different form of our dependent variable (the log of the sum of the distances from a block group to the nearest ten facilities, not just the nearest facility). Though we found that education correlates with social capital, our substantive results were unchanged. Similarly, we found that operationalizing pollution in this alternative way made no difference to our substantive results. Though the coefficient on social capital is statistically significant in a small number of cases, the relationship is always quite weak, and in most cases there is no clear relationship at all.

Discussion and Conclusions

This paper has examined the hypothesis that communities of color, and/or of lower socioeconomic status, are more exposed to environmental hazards because they possess less social capital. From the beginning, scholars in the field of environmental inequality have theorized that low-income and communities of color were located nearer to industrial facilities because they represented the path of least resistance (POLR). That is, when firms were deciding where to place possibly contentious facilities, like those emitting toxic air pollutants, they looked for communities that would not offer much resistance; moreover, if firms attempt to place locally unwanted land uses in more powerful communities they are theorized to receive pushback and fail to successfully site a facility (Bullard & Wright 1986; Pastor et al. 2001; Saha & Mohai 2005). However, this theory has received little empirical attention compared to other theories of environmental inequality and to our knowledge no study has attempted to apply insights from the social capital literature to empirically examine this theory. This study fills this gap by taking advantage of one of the most ambitious attempts to measure social capital in the U.S. by surveying individuals nested within communities.

The evidence we have presented complicates the path of least resistance (POLR) hypothesis. Importantly, the assumption that African-Americans, and largely African-American communities, have less social capital than non-Hispanic Whites is not entirely accurate. In fact, even when controlling for income, we see higher levels of Non-Electoral Political Participation (e.g., signing a petition, participation in a public display of political protest) and Organizational Activism (e.g., formal group involvement excluding religious organizations) for African-Americans at the individual level, as well as for block groups and counties with higher proportions of African-Americans. However, those states with more African-American residents were significantly less likely to have high levels of Non-Electoral Political Participation, perhaps speaking to regional differences in political culture. Moreover, at every socio-administrative scale, a higher percentage of African-American residents are associated with significantly more Faith-Based Social Capital. African-American individuals and largely African-American communities have higher scores for our two direct measures of political engagement, protest behavior and organizational activism, compared to non-Hispanic white individuals and predominately white communities. We can see that, with respect to these types of social capital, African American communities do not represent the path of least resistance.

Another important finding inconsistent with the theory that differences in social capital explain environmental inequality is the fact that the inclusion of social capital in models predicting the distance to the nearest industrial facility barely affects the coefficients on demographic covariates. This is consistent across all seven measures of social capital, at every scale. The history of residential segregation has significantly limited African-Americans' mobility to areas outside of central cities (Farley et al. 2002; Massey & Denton 1988; Quillian 2003; Brodkin 1998). Zoning practices today continue to define areas with higher proportions of low-income and minority residents as industrial, in contrast to areas that are more affluent and/or White (Maantay, 2001). Moreover, more segregated metropolitan areas are more likely to have greater health risks from industrial air pollution (Ard 2016).

There were a few associations we found that were supportive of the POLR argument. The most important of which perhaps is that, when controlling for race, a higher median income is associated with significantly greater levels of social capital for all measures and for almost all levels. Also consistent with the argument is that America's Hispanic population has significantly less of all types of social capital (with the exception of participation in organized religion) than non-Hispanic Whites. That is true at the individual level as well as at the block group level. This is also true at the level of county and state, though some of these relationships are not statistically significant.

In addition, our models allowed us to test the argument that areas with higher rates of residential churning have less social capital and are thus more vulnerable to the siting of noxious facilities. This was partially supported. While block groups with higher residential turnover are located significantly closer to industrial facilities, they do not necessarily have significantly less social capital. In fact, block groups with higher churning have significantly higher levels of informal social interaction and diversity of friendships. At the block group level, however, increased churning was associated with significantly less engagement in organized religion. Longitudinal data would be needed for a better test of this hypothesis in order to isolate whether higher population churning happens before or after a siting of a facility. Nonetheless, the evidence provided here does not support the idea that social capital is the mechanism that explains the relationship between high population turnover and increased exposure to environmental hazards.

Why might social capital have as little impact as we have found here? One possibility, which would be worth investigating further, is that communities do not actually use their social capital to prevent the proximate siting of polluting facilities. While previous research has shown that low-income and minority individuals are generally just as, if not more, concerned about environmental issues than Whites (Parker & McDonough, 1999), such communities might choose to welcome a polluting facility in their area due to the perception that doing so could expand employment opportunities. Bullard (1990) found that residents of five towns in Texas, all with large African-Americans populations and polluting facilities, perceived the health risks posed by these facilities as a trade-off for jobs. Other case studies have shown that jobs and other economic benefits are often promised to communities in negotiations to site hazardous facilities nearby (Pellow, 2002; Ishiyama & Tallbear, 2001), something Bullard (1992) previously term “environmental blackmail”.

The major limitation of this study is that it is cross-sectional. Future work could make use of longitudinal data in determining whether differences in the social capital of communities prior to the siting of facilities changes after the siting. Moreover, longitudinal data would allow researchers to unravel whether African-Americans, and largely African-Americans communities, have higher rates of this political engagement *before* the polluting industry enters the community. It could be that these areas only began to have increased political engagement once they received a polluting facility. Without longitudinal data this scenario cannot be investigated. In addition, future work should consider other types of pollution measures. While the TRI database is a useful starting place for an examination of this kind, it does not encompass all type of environmental hazards, for example mobile sources.

To conclude on a practical note, governments have recently been investing in efforts to foster social capital at levels from the local to the international (World Bank, 2011; Coole, 2009). In validating that social capital helps communities maintain a clean and healthy local environment—even if it does not explain the exposure gaps among demographic groups—the results presented here provide further reason to continue and support such efforts. Yet the potential benefits should not be overstated, given the relatively minor effects of social capital we have found here in the context of the United States.

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Table 1. Measures of Social Capital

	Variable	Full Name	Explanation
Bonding	**Schmooz**	**Informal Social Interaction**	A continuous index calculated as the mean of the responses to five questions, based on national survey norms: frequency of having friends visit, frequency of visiting with relatives, frequency of socializing with co-workers outside of work, frequency of hanging out with friends in public places, frequency of playing cards and board games. At least two of these questions had to be answered for a score to be calculated. The scores for each component part are standardized using U.S. parameters.
	Faithba2	**Faith-Based Social Capital**	A sum of standardized measures of participation in organized religion: attendance, participate in church activities other than services, contributed money to church or religious causes, a church member, volunteered for religion, participated in organization affiliated with religion.
Bridging	**Soctrust**	**Social Trust**	An index comprising: general interpersonal trust, trust neighbors, trust co-workers, trust fellow congregants, trust store employees where you shop, trust local police. (At least three of these answers had to be provided for a score to be calculated.) Mean of the standardized responses to six questions, using national norms to standardize. Higher scores indicate higher social trust.
	Racetrst	**Inter-Ethnic Trust**	Mean trust of non-Hispanic Whites, non-Hispanic Blacks, Asians, and Hispanics (excluding trust of respondent's own ethnic group). This variable has been calculated whenever there were at least two non-missing responses of the three possible responses. Higher scores indicate higher inter-ethnic trust.
	Divrsity	**Diversity of Friendship Set**	A count of how many different kinds of personal friends the respondent has from 11 possible types of personal friends: owns a business, is Black or African-American, is gay or lesbian, who owns a vacation home, who is Asian, who is a manual worker, who is Latino or Hispanic, with different religious orientation, who is a community leader, who has been on welfare, who is White.
Civic Action	**Macher**	**Organizational Activism**	A continuous index consisting of the factor score resulting from a principal components analysis of four components: number of formal group involvements (excluding church membership), serving as an officer or on a committee, number of club meetings attended, number of public meetings attended discussing school or town affairs.
	Protest	**Non-Electoral Political Participation**	A mean (higher scores meaning more participation) in seven different types of actions: belonging to any group that took local action for reform; attending a political meeting or rally in past 12 months; signing a petition in past 12 months; participating in political group; participating in demonstrations, boycotts, or marches in past 12 months; participating in ethnic, nationality, or civil rights organization; participating in labor union

Table 2a. Descriptive Statistics for Individuals in the Social Capital Benchmark Survey (Total N = 29,140)

							Correlations								
Variable	**Mean**	**Min**	**Max**	**Unique**	**Valid**	**SD**	**Soctrust**	**Racetrst**	**Divrsity**	**Faithba2**	**Macher**	**Schmooz**	**Protest**	**Hispanic**	**Black**
Soctrust	0.04	-2.63	1.02	3436	29013	0.69									
Racetrst	2.09	0.00	3.00	14	24088	0.66	0.64								
Divrsity	6.30	0.00	11.00	12	29134	2.64	0.16	0.18							
Faithba2	-0.06	-1.11	1.58	719	28923	0.76	0.19	0.13	0.18						
Macher	0.07	-0.89	6.77	4487	28994	1.04	0.17	0.13	0.35	0.34					
Schmooz	0.00	-0.97	2.18	24222	29097	0.66	0.03	0.06	0.25	0.04	0.22				
Protest	1.14	0.00	7.00	18	29133	1.40	0.08	0.09	0.34	0.14	0.51	0.12			
Hispanic	0.09	0.00	1.00	2	28609	0.28	-0.23	-0.18	-0.09	-0.07	-0.10	-0.06	-0.07		
Black	0.12	0.00	1.00	2	28609	0.33	-0.28	-0.15	-0.03	0.09	0.02	-0.03	0.03	-0.12	
Income	52218	10000	125000	7	26292	34586	0.19	0.13	0.23	0.11	0.21	0.04	0.19	-0.13	-0.10

Table 2b. Descriptive Statistics for Block Groups (Total N = 14,609)

							Correlations					
Variable	**Mean**	**Min**	**Max**	**Unique**	**Valid**	**SD**	**Distance**	**Income**	**Black**	**Hispanic**	**Poverty**	**Churning**
Distance	5.71	0.01	252.39	14608	14609	11.18						
Income	47530	2499	200001	9887	14609	22578	-0.04					
Black	0.13	0.00	1.00	12620	14605	0.24	-0.13	-0.33				
Hispanic	0.10	0.00	0.99	12983	14605	0.17	-0.08	-0.18	-0.05			
Poverty	0.09	0.00	1.00	8632	14588	0.11	-0.02	-0.58	0.49	0.32		
Churning	0.46	0.04	1.00	14130	14602	0.15	-0.09	-0.22	0.03	0.18	0.22	
Density	2265	0.00	94027	14605	14609	3910	-0.14	-0.11	0.11	0.32	0.23	0.18

Table 3. Null Models of Social Capital

			Soctrust	Racetrst	Divrsity	Faithba2	Macher	Schmooz	Protest
Intercept (Coefficient)			0.064	2.107	6.185	-0.011	0.066	0.010	1.063
Random Effects Variances		**State - Intercept**	0.021	0.013	0.057	0.021	0.001	0.003	0.023
		County - Intercept	0.013	0.007	0.042	0.005	0.005	0.002	0.037
		Block Group- Intercept	0.045	0.015	0.107	0.010	0.020	0.002	0.051
		Residual	0.402	0.411	6.769	0.536	1.049	0.430	1.826
BLUPs of the Random Effects	**State**	**N**	49	49	49	49	49	49	49
		SD	0.117	0.087	0.158	0.120	0.010	0.035	0.103
		Min	-0.198	-0.131	-0.301	-0.248	-0.019	-0.075	-0.191
		Max	0.268	0.203	0.410	0.237	0.030	0.095	0.261
	County	**N**	1295	1150	1297	1294	1295	1297	1297
		SD	0.039	0.025	0.044	0.018	0.015	0.007	0.060
		Min	-0.284	-0.154	-0.226	-0.181	-0.121	-0.069	-0.261
		Max	0.195	0.134	0.427	0.098	0.140	0.057	0.652
	Block Group	**N**	14570	12816	14609	14536	14551	14598	14608
		SD	0.084	0.030	0.056	0.018	0.026	0.005	0.050
		Min	-0.552	-0.312	-0.474	-0.145	-0.149	-0.042	-0.424
		Max	0.316	0.211	0.561	0.139	0.207	0.034	0.491
N (Individuals)			29013	24088	29134	28923	28994	29097	29133
DIC			58320	47825	138898	64609	84222	58245	101057

Note: The empirical means of all BLUPs are 0, to several decimal places.

Table 4. Four-Level Models of Social Capital

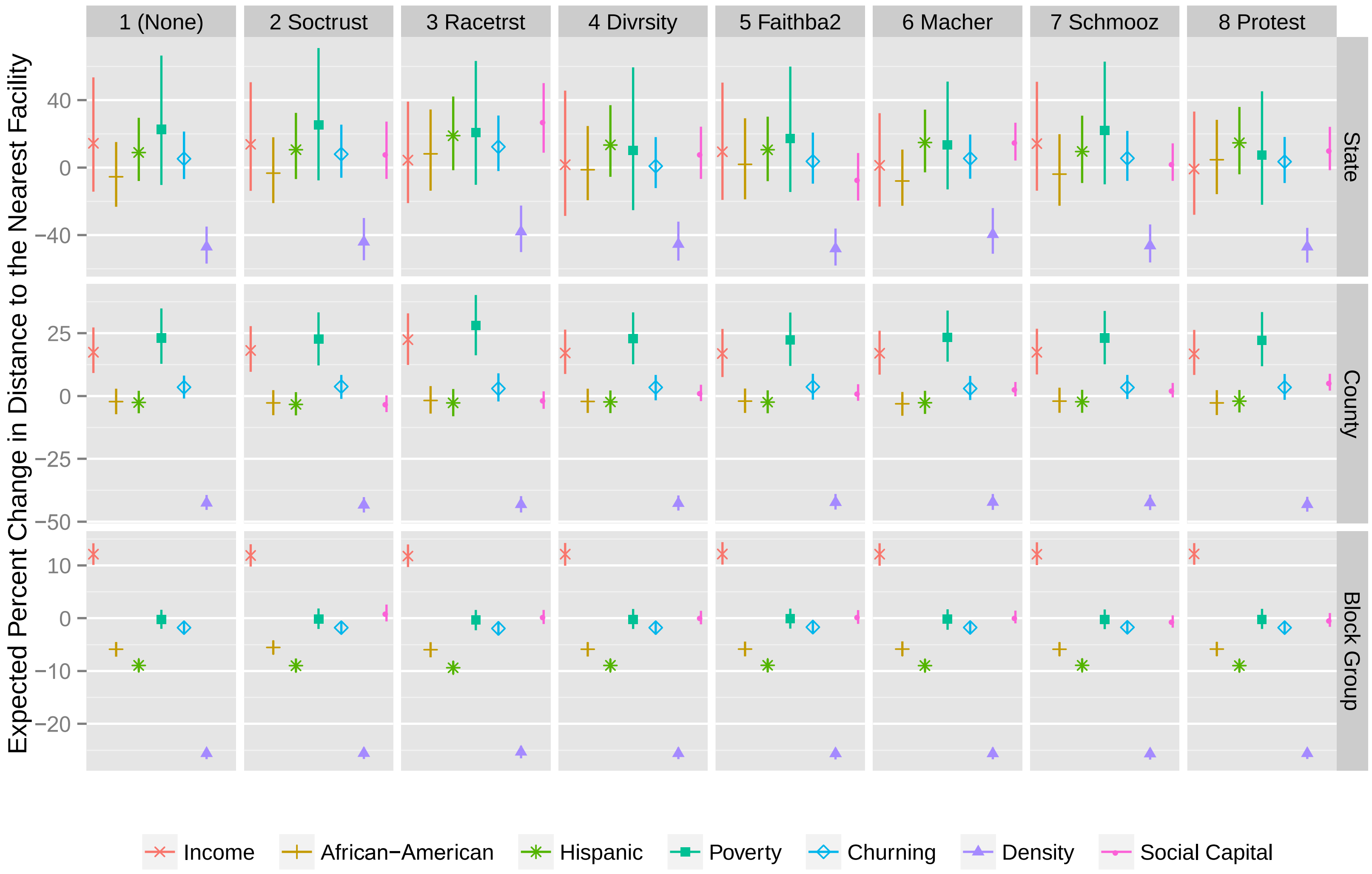
		Outcome:	Soctrust		Racetrst		Divrsity		Faithba2		Macher		Schmooz		Protest	
Fixed Effects Coefficients		(Intercept)	-5.03**	(0.00)	-2.24**	(0.00)	-7.01*	(0.04)	1.02	(0.27)	-3.95**	(0.00)	0.58	(0.27)	-4.01	(0.07)
	African-American	Individual	-0.47**	(0.00)	-0.21**	(0.00)	-0.12*	(0.02)	0.21**	(0.00)	0.07**	(0.00)	-0.04**	(0.01)	0.11**	(0.00)
		Block Group	-0.65**	(0.00)	-0.29**	(0.00)	-0.00	(0.49)	0.30**	(0.00)	0.25**	(0.00)	-0.11**	(0.00)	0.31**	(0.00)
		County	-0.46**	(0.00)	-0.15	(0.05)	-0.01	(0.49)	0.25**	(0.01)	0.64**	(0.00)	-0.19*	(0.02)	0.52**	(0.01)
		State	-0.55**	(0.00)	-0.54**	(0.00)	-0.21	(0.34)	1.11**	(0.00)	0.29	(0.05)	-0.29*	(0.01)	-0.98**	(0.00)
	Hispanic	Individual	-0.46**	(0.00)	-0.31**	(0.00)	-0.52**	(0.00)	-0.02	(0.18)	-0.16**	(0.00)	-0.10**	(0.00)	-0.19**	(0.00)
		Block Group	-0.83**	(0.00)	-0.58**	(0.00)	-1.01**	(0.00)	0.04	(0.18)	-0.36**	(0.00)	-0.19**	(0.00)	-0.43**	(0.00)
		County	-0.71**	(0.00)	-0.51**	(0.00)	-0.81*	(0.02)	0.21	(0.05)	-0.22	(0.07)	-0.30**	(0.00)	-0.44*	(0.04)
		State	-0.53**	(0.00)	-0.44**	(0.00)	0.01	(0.48)	-0.03	(0.44)	-0.04	(0.40)	-0.27*	(0.03)	-0.26	(0.23)
	Log Income	Individual	0.11**	(0.00)	0.08**	(0.00)	0.77**	(0.00)	0.13**	(0.00)	0.29**	(0.00)	0.06**	(0.00)	0.35**	(0.00)
		Block Group	0.21**	(0.00)	0.15**	(0.00)	0.77**	(0.00)	0.22**	(0.00)	0.36**	(0.00)	-0.02	(0.13)	0.35**	(0.00)
		County	0.19**	(0.00)	0.10*	(0.02)	0.56**	(0.00)	0.15**	(0.00)	0.22**	(0.00)	-0.07*	(0.04)	0.23*	(0.02)
		State	0.56**	(0.00)	0.48**	(0.00)	1.17**	(0.00)	-0.04	(0.39)	0.42**	(0.00)	-0.04	(0.33)	0.44	(0.06)
	Log Density	Block Group	-0.00	(0.41)	-0.00	(0.16)	0.00	(0.44)	-0.00	(0.38)	0.01	(0.11)	0.01**	(0.01)	0.03**	(0.00)
		County	-0.04**	(0.00)	-0.03**	(0.00)	0.03	(0.10)	-0.03**	(0.00)	-0.03**	(0.00)	0.01	(0.11)	0.05**	(0.00)
		State	-0.10**	(0.00)	-0.07**	(0.00)	-0.02	(0.39)	-0.07**	(0.00)	-0.07**	(0.00)	-0.00	(0.46)	0.06	(0.06)
	Churning	Block Group	-0.04	(0.10)	0.03	(0.16)	0.44**	(0.00)	-0.30**	(0.00)	0.01	(0.42)	0.18**	(0.00)	0.03	(0.33)
		County	0.08	(0.28)	0.09	(0.27)	1.87**	(0.00)	-0.35*	(0.02)	0.27	(0.08)	-0.03	(0.42)	0.49	(0.09)
		State	-0.77**	(0.00)	-0.64**	(0.00)	2.00*	(0.03)	-0.88*	(0.02)	-0.38	(0.12)	-0.12	(0.33)	0.46	(0.26)
Random Effects	Intercept	State	0.000		0.000		0.024		0.007		0.001		0.002		0.012	
		County	0.002		0.002		0.021		0.004		0.004		0.001		0.026	
		Block Group	0.010		0.002		0.063		0.004		0.009		0.003		0.043	
		Individual-Residuals	0.366		0.395		6.272		0.525		1.000		0.426		1.760	
Sample Size		State	49		49		49		49		49		49		49	
		County	1232		1107		1233		1232		1231		1233		1233	
		Block Group	13535		12117		13562		13529		13526		13560		13561	
		Individuals	25946		22134		26025		25929		25956		26021		26027	
		DIC	48270		42418		121954		57171		73936		51816		89267	

Table 5. Models of Distance to the Nearest Polluting Facility as a Function of Demographics and Social Capital

Model/Measure of Social Capital			M0	M1		Soctrust		Racetrst		Divrsity		Faithba2		Macher		Schmooz		Protest	
Fixed Effects Coefficients		(Intercept)	1.80**	-6.93	(0.25)	-6.96	(0.25)	-1.47	(0.44)	2.05	(0.44)	-3.47	(0.37)	1.62	(0.44)	-6.86	(0.25)	3.69	(0.37)
	Log Income	Block Group		0.28**	(0.00)	0.27**	(0.00)	0.27**	(0.00)	0.28**	(0.00)	0.28**	(0.00)	0.28**	(0.00)	0.28**	(0.00)	0.28**	(0.00)
		County		0.80**	(0.00)	0.83**	(0.00)	1.01**	(0.00)	0.79**	(0.00)	0.78**	(0.00)	0.79**	(0.00)	0.80**	(0.00)	0.77**	(0.00)
		State		0.91	(0.18)	0.87	(0.19)	0.29	(0.39)	0.11	(0.45)	0.60	(0.28)	0.09	(0.46)	0.90	(0.17)	-0.05	(0.49)
	African-American	Block Group		-0.30**	(0.00)	-0.28**	(0.00)	-0.30**	(0.00)	-0.30**	(0.00)	-0.30**	(0.00)	-0.30**	(0.00)	-0.30**	(0.00)	-0.30**	(0.00)
		County		-0.22	(0.19)	-0.28	(0.13)	-0.18	(0.26)	-0.22	(0.21)	-0.20	(0.22)	-0.31	(0.11)	-0.20	(0.20)	-0.27	(0.14)
		State		-0.47	(0.27)	-0.28	(0.38)	0.66	(0.23)	-0.10	(0.46)	0.16	(0.44)	-0.70	(0.19)	-0.33	(0.38)	0.38	(0.33)
	Hispanic	Block Group		-0.74**	(0.00)	-0.74**	(0.00)	-0.77**	(0.00)	-0.74**	(0.00)	-0.73**	(0.00)	-0.74**	(0.00)	-0.74**	(0.00)	-0.74**	(0.00)
		County		-0.31	(0.13)	-0.40	(0.07)	-0.32	(0.16)	-0.28	(0.15)	-0.29	(0.16)	-0.32	(0.13)	-0.27	(0.16)	-0.24	(0.18)
		State		0.96	(0.16)	1.12	(0.14)	1.93*	(0.04)	1.40	(0.09)	1.12	(0.13)	1.54*	(0.04)	1.02	(0.14)	1.53	(0.06)
	Poverty	Block Group		-0.02	(0.42)	-0.02	(0.44)	-0.03	(0.38)	-0.02	(0.41)	-0.01	(0.45)	-0.02	(0.44)	-0.02	(0.41)	-0.02	(0.40)
		County		4.89**	(0.00)	4.82**	(0.00)	5.93**	(0.00)	4.85**	(0.00)	4.75**	(0.00)	4.96**	(0.00)	4.90**	(0.00)	4.71**	(0.00)
		State		6.80	(0.09)	7.56	(0.07)	6.30	(0.11)	3.28	(0.28)	5.35	(0.14)	4.24	(0.19)	6.69	(0.10)	2.40	(0.32)
	Churning	Block Group		-0.13**	(0.00)	-0.13**	(0.00)	-0.14**	(0.00)	-0.13**	(0.00)	-0.12**	(0.00)	-0.13**	(0.00)	-0.12**	(0.00)	-0.13**	(0.00)
		County		0.55	(0.07)	0.59	(0.07)	0.47	(0.14)	0.54	(0.09)	0.57	(0.09)	0.47	(0.11)	0.54	(0.09)	0.54	(0.10)
		State		1.02	(0.22)	1.51	(0.13)	2.29	(0.05)	0.18	(0.47)	0.72	(0.31)	1.04	(0.20)	1.07	(0.21)	0.69	(0.30)
	Log Density	Block Group		-0.21**	(0.00)	-0.21**	(0.00)	-0.20**	(0.00)	-0.21**	(0.00)	-0.21**	(0.00)	-0.21**	(0.00)	-0.21**	(0.00)	-0.21**	(0.00)
		County		-0.43**	(0.00)	-0.44**	(0.00)	-0.43**	(0.00)	-0.43**	(0.00)	-0.43**	(0.00)	-0.42**	(0.00)	-0.43**	(0.00)	-0.44**	(0.00)
		State		-0.44**	(0.00)	-0.40**	(0.00)	-0.33**	(0.00)	-0.42**	(0.00)	-0.45**	(0.00)	-0.35**	(0.00)	-0.43**	(0.00)	-0.44**	(0.00)
	Social Capital	Block Group				0.11	(0.13)	0.10	(0.34)	0.03	(0.40)	0.17	(0.32)	0.06	(0.38)	-1.28	(0.15)	-0.07	(0.29)
		County				-0.82*	(0.04)	-0.67	(0.19)	0.28	(0.21)	0.61	(0.27)	1.79*	(0.04)	3.08	(0.05)	0.86**	(0.00)
		State				0.67	(0.16)	2.77**	(0.00)	0.49	(0.11)	-0.61	(0.15)	13.75**	(0.00)	0.67	(0.35)	0.96*	(0.04)
Random Effects (Co)Variances	State	Intercept	0.262	0.086		0.094		0.087		0.088		0.092		0.070		0.094		0.081	
		Cov				-0.041		-0.066		-0.052		0.277		0.038		-0.020		-0.015	
		Slope				0.419		1.041		0.367		3.152		1.142		2.750		0.201	
	County	Intercept	0.521	0.233		0.232		0.253		0.232		0.231		0.231		0.230		0.229	
		Cov				0.001		-0.021		-0.019		-0.041		0.063		0.222		0.020	
		Slope				0.291		0.561		0.121		2.575		0.356		2.025		0.165	
	Block Group (Residual)		0.639	0.495		0.493		0.486		0.495		0.494		0.495		0.495		0.495	
Sample Size		State	49	49		49		49		49		49		49		49		49	
		County	1297	1297		1295		1150		1297		1294		1295		1297		1297	
		Block Group	14609	14588		14549		12798		14588		14515		14530		14577		14587	
		DIC	35728	31826		31712		27725		31830		31653		31713		31812		31817	

Note: BG signifies block group, CT county, and ST state. All covariates at the block group and county levels are centered by the mean of the higher-level unit in which they are nested (counties and states, respectively). Measures of social capital are BLUPs, as described in the text. The slopes for social capital are random. Figures in parentheses are the estimated probabilities of the parameter having the opposite sign; coefficients are marked with * if that probability is less than 0.05, and ** if it is less than 0.01.

Figure 1. Results of Models in Table 6



Note: Modeled effect of a one standard deviation increase in each covariate, at each of three levels, with 95% credible intervals.