Community Heterogeneity and Political Participation in American Cities*

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Abstract

This paper analyzes the effects of racial diversity on political participation in American cities. Previous work on the relationship between diversity and participation has produced ambiguous results. Some find that diversity suppresses political participation while others maintain the opposite. I argue that incentives for participation are reduced by homogeneity. Heterogeneous places are characterized by more conflict over resources and more mobilized groups, leading to higher levels of political participation. However, I also argue that different racial groups react differently to diversity. The paper uses data from the 2000 Social Capital Community Benchmark Survey, respondents from which were matched with census data on their place of residence. The results of this analysis indicate that racial diversity affects the propensity to vote differently for different racial groups and that these differences vary across communities. While white people are less likely to vote the more racially diverse their city of residence is, the relationship is the reverse for minority populations.

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1. Introduction

By taking political action, citizens make their preferences known, determine who holds public office and try to influence the decisions made by politicians. Despite popular conceptions of the United States as a vast wasteland of apathetic and apolitical citizens, the reality is that Americans are participants. While it is true that voter turnout is lower in the US than in many other democracies, Americans are generally more likely to contact politicians and officials, work on a campaign, belong to and be active in political groups and participate in local politics than citizens in other countries (Brady, Schlozman, Verba & Elms 2002).

However, the issue of declining political participation has spurred a large literature and much debate not only the United States but also in many other western democracies. Much of the research on political participation and its decline, analyzes changes in the characteristics of *individuals* that may account for decreased voter turnout and other forms of activity. While changes in levels of education, income and other individual-level factors are no doubt important and should be analyzed, much of such research suffers from not taking adequate account of political and social context. This study analyzes data from a new large-scale survey and matches respondents with information about their city of residence from various sources in order to examine how the political and social environment in which individuals find themselves affects their political behavior.

As Verba, Schlozman & Brady note, democracy requires both a degree of voice and equality (1995, p. 1). However, far from all citizens make their voice known through voting and even fewer take part in other forms of political participation. Those that do participate are not representative of the larger population. As we know, participants differ in fundamental ways from non-participants—education, income, race, gender and a host of other individual-level characteristics set active citizens apart from inactive ones. However, it is not the case that participation is equal between equally rich, well educated, white males for instance. As I show in this paper, even after controlling for many of the characteristics of individuals associated with political participation, activity rates vary between people in different places in the United States. So it is not just a matter of *who* you are, (or even who you are connected to, as social capitalists would have us believe), but also *where* you are. In order to examine the effects of context on political action I compare participation across cities in the United States

Although cities in the Unites States vary on a large number of dimensions, in this paper I only focus on one: racial diversity. Race is of fundamental importance to American politics and one of the most striking trends in American society in recent years has been the increase in racial diversity. Are people living in cities characterized by high degrees of ethnic fractionalization more or less likely to take political action than those living in very homogenous places?

2. The Impact of Diversity on Political Participation

While issues of race and their influence on political behavior and attitudes have long been studied by scholars of American politics, the focus of most of this research has been on how the race of individuals affects various outcomes. Until recently it has been rare that race as a characteristic of community context or environment has been taken into account (Oliver 2001). Perhaps in response to the realization that diversity is increasing and patters of racial integration changing, there have been a number of new studies on the impact of racial heterogeneity (eg. Alesina & La Ferrera 2000, Costa & Kahn 2003, Oliver 2001). The majority of studies examining heterogeneity and participation argue that increased heterogeneity is detrimental to levels of engagement.[1] The social capital literature from Putnam forward argues

[1] Notable exceptions are Oliver (2001) who argues that increasing racial segregation between suburbs is related to decreased political and civic engagement and Campbell (2002) who argues that the relationship between diversity and political participation is curvilinear so that political activity is lower at both extremes of diversity and homogeneity.

that diversity may be a hindrance to social capital and more specifically to civic engagement. Ethnically diverse places tend to have lower levels of social trust—that is, trust in people in general, even those one does not know (Saguaro Seminar 2001). But what is the relationship between diversity and civic engagement? A number of authors make the claim that civic engagement is higher (or ought to be higher) in areas characterized by homogeneity (Alesina & La Ferrera 2000, Alesina & La Ferrera 2002, Mutz 2002, Costa & Kahn 2003). The reasoning being that individuals in these areas are a) more able to overcome collective action problems associated with participation and b) more willing to volunteer and engage in a community whose other citizens share their values and beliefs.

This argument has mostly been applied to non-political civic engagement but has even been used by scholars of political participation—which is what is of central concern here. Diana Mutz, for example argues that people exposed to "cross-pressures" in networks characterized by political disagreement (ideological heterogeneity) are less likely to participate than those who exist in more homogenous surroundings where they agree with those around them. The reasoning is that people in the former will be ambivalent in their political views because of the conflicting pressures put on them by others in their network, thus making it less likely that they will take action (Mutz 2002, p. 840). Alesina & La Ferrera (2000) also argue that people in areas in which racial heterogeneity and income inequality are high are less likely to participate as a consequence of group formation being more difficult in such areas.

There are however, a number of difficulties with these arguments. Alesina and La Ferrara lump together very disparate forms of participation in their study. A clear distinction needs to be made between political participation and participation in non-political groups. The motivations for engaging in these will be very different. It may be that civic, that is non-political, engagement is higher in more homogenous areas for the reasons Alesina and La Ferrara cite. However, as we see below, these same reasons may well be good arguments as to why we could expect *political* participation to be lower in such areas. While the social capital literature argues that increased diversity leads to decreased generalized trust and, therefore, less political participation, a strong case can be made that the diminished trust in diverse communities should mean more participation. If one is distrustful of others in one's community, it makes sense to ensure that one's own voice is heard through taking part in politics.

In contrast to this literature, I argue that community heterogeneity—racial heterogeneity in particular—should lead to a higher likelihood of people participating in politics. One potential reason for this is that cities or communities characterized by heterogeneity will tend to have more conflicts over resources and policies and more mobilized groups leading to more political participation. Recent work in group conflict theory shows that racial attitudes and policy preferences are strongly influenced by group identities and the perception that what other groups gain, the own group loses. As Glaser puts it, "In essence, this theory posits that individuals have a zero-sum view of politics, that they think in group terms, in 'us' and 'them' terms, and that they see the possibility that their own group could lose something valued to a rival group" (Glaser 1994, p. 23). In other words, individuals view politics, at least in part, as a competitive struggle between groups for scarce resources and are motivated to attempt "to affect the process and pattern of their distribution" (Bobo 1988, p. 95). Not only is the individual-level race important for the development of these attitudes and related behaviors, but the racial environment is crucial. People living in more racially diverse areas will be inclined to express these kinds of attitudes more than those in less heterogeneous areas (Glaser 2003). Race and racial identity become more salient in more racially heterogeneous places.

3. Data

The convoluted nature of American local government has led to difficulties in studying political participation and these difficulties have been exacerbated by the lack of data on participation in sub-national units. There are number of studies looking at individual cities or small-n comparisons (Fuchs, Minnite & Shapiro 2000, Garbaye 2002) but because they sample very few cities, these studies do not allow for a systematic analysis of institutional or environmental variables. One exception to this is the work of Eric Oliver which examines the effects of suburbanization on civic and political participation in a large set of municipalities (1999, 2000, 2001). There is also a literature in which large-scale cross-country comparisons of political participation are made. However, here we run into other difficulties such as being able to isolate the effects of institutional factors and taking account of cultural differences, for instance.

As Rahn & Rudolph (2001, 5) point out, many of the studies in this field have used data from nationally representative samples. However, the problem with most nationally representative samples is that they have been designed to analyze individual-level characteristics and as such, more often than not, contain too few higher-level units—cities, neighborhoods, communities, Congressional Districts or whatever the unit of interest may be—to allow for meaningful inferences to be drawn about differences across places. Stoker & Bowers (2002) convincingly illustrate how increasing the number of higher-level units has a much more dramatic impact on the power of analyzes than increasing the number of individuals sampled (2002, 244–48). As Snijders & Bosker put it:

> A relevant general remark is that the sample size at the highest level is usually the most restrictive element in the design. For example, a two-level design with 10 groups, i.e. a macro-level sample size of 10, is at least as uncomfortable as a single-level design with a sample size of 10. Requirements on the sample size at the highest level, for a hierarchical linear model with q explanatory variables at this level, are at least as stringent as requirements on the sample size in a single level design with q explanatory variables (1999, 140).

Thus, if one wants to analyze both individual and contextual effects on individual behavior, a dataset that combines both micro and macro factors while also containing data from enough higher-level units is required. The recently available Social

Capital Community Benchmark Survey allows a more systematic study the effects of contextual variables on behavior. The survey consists of a nationally representative sample of 3003 respondents as well as 40 different sub-national representative samples. These samples had varying geographical boundaries including states and regions within states (some were at the county level, some at the city level and some at other regional levels determined by the local community foundation funding the project in each area). The total sample size for the combined surveys is 29,733. Through an agreement with the Roper Center I was able to obtain detailed geocodes for the data, enabling me to identify respondents' places of residence. Using these Federal Information Processing Standards (FIPS) codes (the unique identification code used by the Census Bureau to identify every place in Untied States) respondents were sorted into their city of residence regardless of what sub-sample they belonged to originally, thereby avoiding the sometimes awkward sampling geographies determined by the sponsors. I have then matched respondents to the survey with data about their place of residence from the US Census and US Census of Governments contained in the *County and City Data Book*. This produced a file with census data on the city level for 14,017 of the respondents who lived in 634 identifiable city areas.

"City" in this study refers to census-defined areas of populations of 25,000 or more and only those respondents residing in such areas were selected. Some of the missing data are due to not being able to identify a respondent's city FIPS code; this missingness is relatively random. There are, as if often the case with survey data, also a number of cases at the individual level that have missing data on some items due to non-response. This form of missing data is less random and needs to be addressed in a way other than the common strategy of deleting cases; a strategy that certainly leads to biased results and a loss of power in the analysis due to less information once cases have been discarded (King, Honacher, Joseph & Scheve 2001, p. 49). Instead of deleting cases—either listwise or pairwise—one can impute values for the missing data. Using Joseph Schafer's (1999) multiple imputation software, *NORM* I imputed values for the missing data, creating 5 complete data sets on which subsequent analyzes were carried out.[2]

The dependent variable for this study is electoral political participation. This was measured by asking respondents to the Benchmark survey the following question:

> As you may know, around half the population does not vote in presidential elections. How about you - did you vote in the presidential election in 1996 when Bill Clinton ran against Bob Dole and Ross Perot, or did you skip that one?

Clearly voting is not the only way Americans make their preferences known and try to influence policy and decision makers. I am working on another version of this paper where non-electoral political participation is analyzed. The Benchmark survey measured these kinds of political action with the following questions:

> Which of the following things have you done in the past twelve months: Have you signed a petition? Attended a political meeting or rally? Participated in any demonstrations, protests, boycotts or marches? Been involved in any public interest groups, political action groups, political clubs, or party committees?

Thus there are five distinct indicators of political participation in the survey: i) voting in the 1996 presidential election; ii) signing petitions; iii) rallying; iv) marching; v) involvement in a political group. What constitutes political participation as opposed to other forms of civic engagement is clearly not cut and dry. As such, there are activities like being an officer in a club or being involved in a community project that are left out which some could argue should be included. However, these kinds of activities need not be political at all. An attempt has been made to limit the dependent variable to those acts through which individuals explicitly try to exert pressure

[2] Imputation involves "filling in" missing data with plausible values. When imputing we are making a guess as to the values of the missing data, so the standard errors from any analyzes which use such imputed data will be too small—since they do not include this "guessing". Therefore, one needs to make several imputations. Multiple imputation provides the extra variation needed to account for the uncertainty about the imputed values. This approach involves imputing m values for each missing value, creating m complete data sets on which the analysis is carried out. Estimates from each data set are then combined using methods described by (**?**).

on politicians and decision-makers, try to influence the direction and character of policy and most obviously, have their say in the election of representatives. The five types of political participation differ considerably in many ways and the environmental factors I am interested in may indeed have different effects on different types of political activity; therefore they ought to be modeled separately and compared, however this paper deals only with voting.

While this study argues that contextual variables are highly important in predicting political participation, it is nevertheless the case that many individual-level factors play a role in people's propensity for taking political action and these clearly need to be included in any model of political participation. Individual participants differ from non-participants in several ways. One of the strongest findings in past work on political participation—especially turnout—is that individuals with higher socio-economic status (SES) participate more than those from low SES groups (Verba & Nie 1972, Wolfinger & Rosenstone 1980, Brady, Verba & Schlozman 1995, Conway 2000). Recent work has also focused on race and gender as key variables in explaining differences in political behavior between individuals (Burns, Schlozman & Verba 2001). Therefore, it is important to first outline and specify an individual-level model of political participation before differences across locations can be analyzed.

This study is chiefly concerned with the impact of contextual factors—community effects—on individuals' participation. As noted above, the Benchmark survey with its geocodes enables researchers to match large samples of individuals from a large number of cities to data on their place of residence, making it a particularly rich source of information on such community effects. There are of course many dimensions along which American cities can be differentiated—community heterogeneity is but one of these. Cities in the United States also vary to a great extent when it comes to political institutions, systems of governance and representation, size (in terms of both the number and variety of services provided and the sheer number of governments in a city) as well as how and how much they tax their residents. All of these may affect political participation but here I specifically concentrate my attention on community racial heterogeneity. Community heterogeneity is operationalized using a measure of racial fractionalization for each city in the sample. Following Easterly & Levine (1997), Alesina, Baqir & Easterly (1999), Alesina & La Ferrera (2000) and others, racial fragmentation is measured by a Herfindahl-based index constructed from the US Census defined as follows:

$$racialfractionalization = 1 - \sum_{k} S_{ki}^{2}$$

where i represents a given city and k the following races: (i) White; (ii) Black; (iii) American Indian, Eskimo, Aleutian; (iv) Asian, Pacific Islander; (v) Hispanic. Each term S_{ki} is the share of race k in the population of city i. The index measures the probability that two randomly drawn individuals in area i belong to different races and takes on values between 0 and 1. Higher values of the index represent more racial heterogeneity.

4. The Multilevel Model

The data I use here are nested, or clustered, in nature. I have data on individuals from the Benchmark survey and these individuals are clustered in cities, on which I also have data; as such observations have not been sampled independently of each other. As Snijders & Bosker (1999) note, dependence can be seen as both a nuisance and as an interesting phenomenon in itself (1999, p. 6-9). The nuisance is that dependence of observations needs to be corrected for in some way in order to avoid drawing incorrect inferences; for example, standard errors will tend to appear smaller than they actually are if dependence is ignored. However, I am also interested in analyzing the effects of different city characteristics on individual behavior. That is, I want to draw inferences on cities as well as individuals, making the clustering of observations of interest. In this paper, the question is whether living in a more ethnically diverse city affects an individual's propensity to take political action.

There are a number of empirical strategies for handling data structures of this kind. Steenbergen & Jones (2002, 220) note that political scientists have tended to opt for either "dummy variable models" or "interactive models." Dummy variable models, by assigning fixed effects for each higher-level unit, are able to overcome the statistical problems associated with dependence of observations in clustered data (Steenbergen & Jones 2002, Rahn & Rudolph 2001). However, one is often interested in how various aspects of different higher-level units impact on lower-level units; say how different city characteristics influence individuals' chances of participating in politics. A dummy variable model is inadequate in this respect. As Steenbergen & Jones put it, "Dummy variables are only indicators of subgroup differences; they do not explain why the regression regimes for the subgroups are different" (2002, 220). Past contextual analyzes on political behavior (Huckfeldt 1979, Huckfeldt 1984, Abowitz 1990, Oliver 1999, Oliver 2000, Oliver 2001, e.g.) have tended to use interactive models where contextual-level independent variables are included alone or in interactions with individual-level variables in order to account for contextual heterogeneity (Rahn & Rudolph 2001, 31). These types of models are not ideal either. As Humphries argues, this approach to modeling multilevel data "implicitly assumes a deterministic relationship between the contextual variable and individual-level parameters" (Humphries 2001, 684).

A more appropriate model for clustered data of the kind I have and where one is interested in explaining different sources of contextual variation is a hierarchical, or multilevel, model. Such a model provides robust standard errors (Raudenbush & Bryk 2002) and is better able to capture the unmodeled city effects through the inclusion of random effects. The multilevel model also makes adjustments to both within and between parameter estimates for the clustered nature of the data.

The hierarchical model begins with a level-1 structural model.[3] This model can be expressed as follows:

$$y_{ij} = \beta_{0j} + \beta_{1j}x_{1ij} + \epsilon_{ij} \tag{1}$$

Where y_{ij} is the individual-level dependent variable for an individual i (=1,...,N_j) nested in level-2 unit (in this case city) j (=1,...,J). The term x_{1ij} is the individual-level variable and ϵ_{ij} is the individual-level disturbance term. The model is in all respects the same as the traditional regression model except for the important difference that the parameters need not be fixed. That is, they can be allowed to vary across level-2 units as indicated by the j–subscripts on the β_{0j} and β_{1j} parameters. This addition is crucial and makes possible the testing of certain hypotheses that would be difficult or impossible otherwise. At level-2 (the city-level), I model the individual-level regression parameters as functions of city-level predictors:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}z_{1j} + \delta_{0j} \tag{2}$$

and

$$\beta_{1j} = \gamma_{10} + \gamma_{11}z_j + \delta_{1j}. \tag{3}$$

Equations 2 and 3 together make up the level-2 model where the γ-parameters are the fixed level-2 parameters and the δ-parameters are disturbance terms. The full model is achieved by substituting the expressions for β_{0j} and β_{1j} in (2) and (3) into (1):

$$\begin{aligned} y_{ij} &= \gamma_{00} + \gamma_{01}z_j + \delta_{0j} + (\gamma_{10} + \gamma_{11}z_j + \delta_{1j})x_{ij} + \epsilon_{ij} \\ &= \gamma_{00} + \gamma_{01}z_j + \gamma_{10}x_{ij} + \gamma_{11}z_jx_{ij} + \delta_{0j} + \delta_{1j}x_{ij} + \epsilon_{ij}, \end{aligned} \tag{4}$$

where γ_{00} is the intercept, γ_{01} denotes the effect of the level-2 (city) variable, γ_{10} is the effect of the individual-level predictor and γ_{11} is the effect of the cross-level interaction between the individual-level and city-level predictors with disturbance

[3]The development and notation of the multilevel model presented here draws heavily from the excellent discussions in Raudenbush & Bryk (2002, 16–30) and Steenbergen & Jones (2002, 221–3).

terms represented by δ_{0j}, δ_{1j} and ϵ_{ij}. In what follows I estimate three models: a "null" model with no predictors at either individual-level or city-level; a conditional model with fixed and randomly varying individual-level predictors; and a "full" model with both individual-level and city-level predictors. Since the dependent variable is binary (0 did not vote; 1 voted), the models I estimate are hierarchical generalized linear models (HGLM). Specifically, I estimate Bernoulli models with a logit link function (Raudenbush & Bryk 2002, 292–296).[4]

5. Results and Discussion

5.1. The Empty Model

Before estimating the individual-level model, it is appropriate to begin by asking whether there in fact exists significant variation in the dependent variable across contextual units—cities—and, if so, what proportion of the total variance is accounted for by the city-level. To gauge the magnitude of variation between cities in political participation it is useful to begin by estimating an unconditional or, so-called, empty model; that is, a model with no predictors at either level. This produces point estimates for the grand mean as well as providing information on the variance at the individual and city-levels (Raudenbush & Bryk 2002, 24). The individual-level model is thus simply

$$\textit{political participation}_{ij} = \beta_{0j} \tag{5}$$

and the city-level model is

$$\beta_{0j} = \gamma_{00} + \delta_{0j}, \qquad \delta_{0j} \sim N(0, \tau_{00}). \tag{6}$$

[4]The models presented here were estimated using the software *Hierarchical Linear Models for Windows* (version 5.45q) developed by Raudenbush, Bryk, Cheong & Congdon (2003). HLM produces "empirical Bayes estimates of the randomly-varying level-1 [individual-level] parameters, generalized least squares estimates of the level-2 [city-level] coefficients; and maximum likelihood estimates of the variance-covariance components" (Raudenbush, Bryk, Cheong & Congdon 2002, 4). See Raudenbush & Bryk (2002) for details on estimating the various coefficients.

Table 1: ANOVA[a]

Parameter	Voting
Fixed Effects	
Intercept (γ_{00})	1.101*
	(0.036)
Random Effects	
City-Level Variance (τ_{00})	0.330*
	(0.025)
Intraclass correlation (ρ)	0.091
-2 $\times$ Log Likelihood	38073.001

[a] * significant at .01%. N=14,153; J=690. Dependent variable is "voted in 1996". Estimates are from a logistic model estimated using restricted maximum likelihood in HLM; robust standard errors in parentheses..

This model is equivalent to a one-way ANOVA with random effects. Here γ_{00} is the average log-odds of political participation across US cities (the grand mean), while τ_{00} is the variance between cities in city-average log-odds of political participation.

The results from the empty model for voting—presented in table 1—are $\hat{\gamma}_{00}$=1.101 (se=0.036), $\hat{\tau}_{00}$=0.330 (se=0.025). Thus, for a city with a typical voting rate, that is, for a city with a random effect δ_{0j}=0, the expected log-odds of voting is 1.101, corresponding to an odds of exp(1.101)=3.007 or a probability of 1/(1+exp(-1.101)=.750.

Table 1 also shows that there exists statistically significant variance at the city-level for voting, making it clear that political participation is more fruitfully modeled as a multilevel phenomena, or at the very least, that the multilevel nature of political participation should not be ignored.[5] In order to get an idea of how much of the

[5] To determine whether variance components are statistically significant, I perform a likelihood ratio test by comparing the deviance statistics of two models (Raudenbush & Bryk 2002, Snijders & Bosker 1999, Steenbergen & Jones 2002). The deviance is -2 $\times$ the log likelihood (Raudenbush & Bryk 2002, p. 64). First, I estimate a model with an unrestricted variance component (i.e. a randomly varying intercept), producing a deviance D_1. Next, a model where the variance component is restricted to zero is estimated, giving a deviance D_0. Subtracting D_0 from D_1 generates a statistic with a χ^2 distribution with 1 degree of freedom, allowing me to calculate a p-value for the test.

overall variance in political participation is attributable to either the individual-level or the city-level, it is useful to calculate the intraclass correlation coefficient (ICC).[6] The ICC measures the proportion of the variance of the dependent variable that is between cities. As Steenbergen & Jones note in their analysis of support for the European Union, it is unsurprising that the individual-level accounts for a great deal of the variance when data are measured at the individual-level, as they are in my study (2002, p. 231). Nonetheless, the proportion of the variance in political participation that is between cities is still considerable—for voting it is 9.1% (that is, $100 \times .330/(.330 + 3.29)$).

5.2. The Individual-level Model

Now I turn to the conditional models. The first conditional model is as follows:

$$turnout_{ij} = \gamma_{00} + \Sigma\gamma_{10}Race_{ij} + \Sigma\gamma_{20}IND_i + \delta_{0j} + \Sigma\delta_{1j}Race_{ij} + \epsilon_{ij}\,. \qquad (7)$$

Here *Race* is a set of dummy variables for the race of individual respondents and *IND* is a vector of individual-level controls (gender, education, age and age squared). Note that the effect of *Race* is allowed to vary randomly across cities. The estimates from this model are presented in table 2. The results for the individual-level variables are largely consistent with existing research. Individuals with higher socio-economic status (SES) tend to be more likely to vote than others (Verba, Schlozman & Brady 1995, Wolfinger & Rosenstone 1980). Here education has a strong positive effect on voting. The coefficient for the gender variable is also positive; women are more likely

[6] The intraclass correlation coefficient for linear multilevel models is obtained by the following formula: $\rho = \frac{\tau_{00}}{\tau_{00}+\sigma^2}$ where σ^2 is the individual-level variance. However, in nonlinear models, such as the logit models estimated here, this formula is less useful because the individual-level variance is heteroscedastic (Raudenbush & Bryk 2002, p. 298). Snijders & Bosker describe an alternative definition of the ICC for nonlinear models as follows: $\rho = \frac{\tau_{00}}{\tau_{00}+\pi^2/3}$. This definition treats the dependent variable as an underlying latent continuous variable following a logistic distribution, the variance (i.e. the individual-level variance in my models) for this distribution is $\pi^2/3$ (Snijders & Bosker 1999, pp. 223–224).

Table 2: Individual-level effects on voting[a]

Variable:	Estimate	Odds-ratio
Intercept	1.257	3.517
	(0.039)***	
Black	0.099	1.104
	(0.070)	
Asian	-1.766	0.171
	(0.128)***	
Hispanic	-1.055	0.348
	(0.066)***	
Female	0.169	1.182
	(0.051)***	
Education	0.803	2.233
	(0.032)***	
Age	0.122	1.130
	(0.007)***	
Age^2	-0.001	0.999
	(0.000)***	
Random effects:		
Intercept (τ_{00})	0.300***	
Black (τ_{02})	0.353***	
Asian (τ_{03})	0.715***	
Hispanic (τ_{04})	0.246*	

[a] N=14,153; J=690. Dependent variable is "voted in 1996"; * significant at 10%; ** significant at 5%; *** significant at 1%. Estimates are from a logistic model estimated using restricted maximum likelihood in HLM; robust standard errors in parentheses. Excluded category for race is "white".

to vote than men, controlling for other factors in the model. While some researchers do report that women participate to a lesser extent than men, much recent research points to the gender gap closing (Conway 2000, 36–7) (Rosenstone & Hansen 1994, 140–1). Age has a positive effect on an individual's propensity to vote. As people get older, it is more likely that they turn out. The squared term of *Age* is also significant indicating that as people get very old, the positive effect of age on voting tapers off. Again, the result for age is consistent with previous work (see for example Blais 2000, Wolfinger & Rosenstone 1980).

As the results in table 2 indicate, Asians and Hispanics are both less likely to vote than whites. The odds of Asians voting are 17% of those for whites, while the odds of Hispanics turning out are 35% of those for whites. The coefficient for blacks is insignificant. Examining the bottom part of the table, it is evident that the estimates of the variance components of the random portion of the model—the randomly varying individual-level intercept, β_{0j}, and the randomly varying dummy variables for race—are significant. That is, after controlling for the individual-level factors, there still remains a significant amount of variation both in voter turnout across cities and in the differences in voting between various racial groups across communities in the United States. The next step is to specify a model that tries to predict those varying slopes.

5.3. The Racial Diversity Model

Finally, I turn to the full model with both individual-level variables and city-level predictors. This model contains the same individual-level variables as the previous model but here I also include the measure of racial heterogeneity, or fractionalization, described above. While the previous model estimated the slopes for each racial category by specifying these individual-level terms as random, in the full model I attempt to predict those slopes with my measure of racial heterogeneity. That is, I include cross-level interaction terms between the individual-level race dummies and racial fractionalization. In other words, in (7) I am testing the hypothesis that differences in voting between groups are not constant across cities; now I want to predict this variation using the level of racial heterogeneity in each city. The full model is as follows:

$$\begin{aligned} turnout_{ij} = \gamma_{00} + \gamma_{01} RF_j + \Sigma\gamma_{10} IND_i + \Sigma\gamma_{20} Race_{ij} \\ + \Sigma\gamma_{21} RF_j * Race_{ij} + \delta_{0j} + \Sigma\delta_{2j} Race_{ij} + \epsilon_{ij} \, . \end{aligned} \tag{8}$$

Of interest here are the estimates for the effects of racial fractionalization on the random slopes of the four race categories included at the individual-level; the cross-level interactions. The other individual-level estimates remain largely unchanged in this model. Turning to the variables of interest, it is instructive to first examine the estimates of the variance components for the random effects. All the variance components have decreased from the previous model with the addition of the city-level factor of racial fractionalization, though only modestly, suggesting that the new variable is doing some work in reducing the unexplained variance across cities. The variance components remain significant, however, indicating that the city-level variables in the model do not explain all the variance across communities.[7]

The cross–level interactions for whites and blacks are both significant and suggest that racial heterogeneity affects these racial groups differently.The effect of racial fractionalization on voting for whites is significant and negative. Increasing racial diversity, according to this model, decreases the likelihood of voting for white people. The *Racial fractionalization×black* interaction, on other hand, has a positive sign

[7]While the tables contain the variance components, it also instructive to consider their co-variances. In the model presented in Table 3, the intercept is positively correlated with Asian, but negatively with black and Hispanic indicating that if white participation is high, the difference between white and Asian tends to be relatively small, but that between white and black or Hispanic relatively large. Note that in such a case black participation may still be relatively (compared to other cities) high, but the difference between blacks and whites is larger than usual. The correlations between the race effects tell a similar story. They are positive between black and Hispanic but negative between Asian and black or Hispanic. This implies that in a city where the difference between white and black is large, it also tends to be large between white and Hispanic but relatively small between white and Asian.

Table 3: Estimates of the effect of racial diversity on voting[a]

Variable:	Estimate	Odds-ratio
Intercept	1.251	3.495
	(0.033)***	
Black	-0.270	0.764
	(0.091)***	
Asian	-2.154	0.116
	(0.158)***	
Hispanic	-1.407	0.245
	(0.090)***	
Female	0.232	1.262
	(0.046)***	
Education	0.672	1.960
	(0.028)***	
Age	0.123	1.130
	(0.007)***	
Age^2	-0.001	0.999
	(0.000)***	
Contextual effects:		
Racial fractionalization×white	-0.289	0.749
	(0.174)*	
Racial fractionalization×black	0.961	2.613
	(0.458)**	
Racial fractionalization×Asian	0.814	2.257
	(0.751)	
Racial fractionalization×Hispanic	-1.407	0.245
	(0.402)	
Random effects:		
Intercept (τ_{00})	0.290***	
Black (τ_{02})	0.348***	
Asian (τ_{03})	0.696***	
Hispanic (τ_{04})	0.244*	

[a] N=14,153; J=690. Dependent variable is "voted in 1996"; * significant at 10%; ** significant at 5%; *** significant at 1%. Estimates are from a logistic model estimated using restricted maximum likelihood in HLM; robust standard errors in parentheses. Excluded category for race is "white".

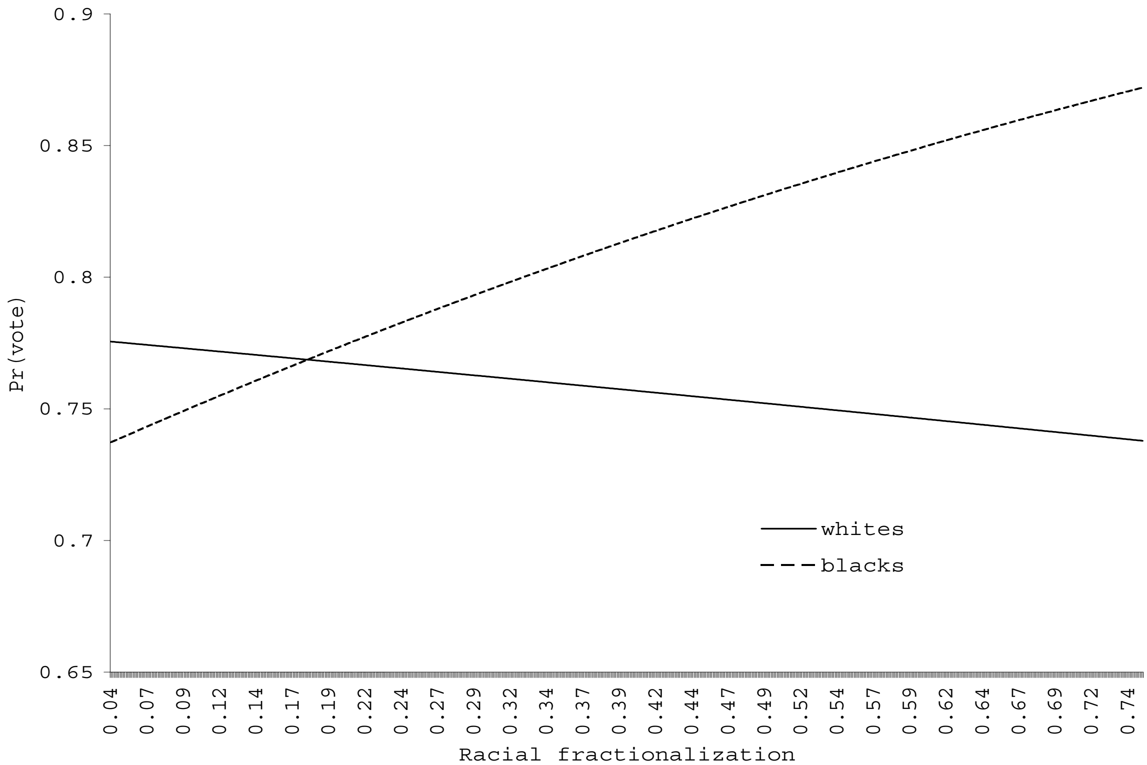

Figure 1: The Effect of racial diversity on the probability of voting among racial groups

and is statistically significant. That is, racial diversity positively predicts voting among blacks—as diversity increases, so do the odds of voting for a black person. While the estimates from the main effects for Asian and Hispanic are significant, the interaction terms for these with racial fractionalization fail to meet conventional levels of statistical significance. Figure 1 illustrates graphically the effect of letting racial diversity predict the probability of voting for blacks and whites.[8] If you are black, your odds of voting increase with increasing levels of racial diversity. The effect on blacks of racial diversity strong enough to make blacks more likely to turn out than whites as one moves up the racial fractionalization scale. A black person moving from a very homogenous community with a score at the bottom of the racial fractionalization index to a city at the high end of the diversity scale would represent a jump in the probability of voting from .737 to .872, holding all other factors constant.

[8]The predicted effects are obtained by holding all independent variables at their mean and allowing the racial fractionalization index to vary over its full range found in the data.

For a white person, the same move entails a drop in the probability of voting from .775 to .738. As figure 1 demonstrates, the impact of racial diversity is considerably stronger for blacks than for whites.

6. Conclusion

Much previous research on the effects of racial diversity on civic engagement, social capital and political participation maintains that increased levels of diversity will serve to decrease political activity. In this paper I have argued the opposite; that people living in more diverse communities will be *more* likely to participate in politics. Inter–racial attitudes tend to be more conflictual in more diverse places where race and racial identity are more salient. That is, individuals see race relations in terms of a zero–sum competition over resources and their distribution. More racially diverse places should as a result be characterized by more conflict, more issues and therefore more political participation. I also hypothesized that the differences in voting between racial groups will vary between cities and this variability can, in part, be explained by racial heterogeneity.

The analysis shows that the effect of racial diversity on whites' likelihood of voting is negative. That is, living in a more racially diverse place tends to suppress turnout among whites. However, when racial fractionalization was used to predict the slope of each individual racial group, this relationship reversed for non-Hispanic blacks. For black people, living in a more diverse community *raises* the probability of voting. The results from this analysis indicate that the relationship between racial diversity and political participation is not straightforward and that it impacts differently on people from distinct racial groups. Specifying a model where the individual effect of race is allowed to vary randomly across cities uncovers different results which remain "hidden" in models where race effects are fixed. In this model, racial heterogeneity becomes a strong predictor of participation for members of minority groups while the participation of whites remains negatively related to diversity. One needs to explicitly model the effect of diversity on separate racial groups in order to get at these associations.

Data Appendix

The data used in this paper come from two principle sources:

1. individual–level data come from the Social Capital Community Benchmark Survey. The survey was conducted by telephone using random–digit–dialing during July-November 2000. The survey consists of a national sample of 3003 respondents as well as 40 community samples whose sampling geography were determined by the local sponsors, totaling an additional 26,533 respondents;

2. city-level data come from the United States Census and Census of Governments and were extracted from the County and City Data Book CDROM.

In order to match each individual to data about their city of residence, geocodes for each respondent were obtained through an agreement with the Roper Center. Having the Federal Information Processing Standard (FIPS) code for each respondent, it was possible to determine the city of residence of each respondent and then to create a data set with information on those cities.

Level-1 variables

The dependent variable, electoral political participation, was measured by the Social Capital Community Benchmark Survey by the following question:

> "As you may know, around half the population does not vote in presidential elections. How about you - did you vote in the presidential election in 1996 when Bill Clinton ran against Bob Dole and Ross Perot, or did you skip that one?" Coded: 1=voted, 0=no.

The independent variables were coded as follows: *Female*: 1=female, 0=male; *Black*: 1=black, 0=all others; *Asian*: 1=Asian, 0=all others; *Hispanic*: 1=Hispanic, 0=all others; *White*: 1=white, 0=all others; *Education* is coded: 1=less than high school, 2=high school diploma, 3=some college or 2 year associate degree, 4=Bachelor degree or higher.

Level-2 variables

Racial fractionalization is an index constructed from the US Census according to the following formula:

$$racial fractionalization = 1 - \sum_k S_{ki}^2$$

where i represents a given city and k the following races: (i) White; (ii) Black; (iii) American Indian, Eskimo, Aleutian; (iv) Asian, Pacific Islander; (v) Hispanic. Each term S_{ki} is the share of race k in the population of city i. The index measures the probability that two randomly drawn individuals in area i belong to different races and takes on values between 0 and 1. Higher values of the index represent more racial heterogeneity. *Percent black* is the percentage of the African-American population in the city.

Table 4: Descriptive statistics

Variables	N	Min.	Max.	Mean	S.D.
Individual–level variables					
Voted in '96	14153	0	1	0.70	0.45
Female	14153	0	1	0.59	0.49
Black	14153	0	1	0.18	0.38
White	14153	0	1	0.61	0.48
Asian	14153	0	1	0.04	0.19
Hispanic	14153	0	1	0.12	0.33
Education	14153	1	4	3.02	0.95
City–level variables					
Racial fractionalization	690	0.04	0.75	0.35	0.17

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