Rough Terrain: Spatial Variation in Campaign Contributing and Volunteerism

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We examine spatial patterns of mass political participation in the form of volunteering and donating to a major statewide election campaign. While these forms of participation are predictably associated with the political and socioeconomic characteristics of the precincts in which the participants reside, we find that these statistical relationships are spatially nonstationary. High-income neighborhoods, for example, are associated with stronger effects on participation at some locations more than at others. By using geographically weighted regression (GWR) to specify local regression parameters, we are able to capture the heterogeneity of contextual processes that generate the geographically uneven flow of volunteers and contributors into a political campaign. Since spatial nonstationarity may well be a rule rather than an exception in the study of many political phenomena, social scientific analyses should be mindful that relationships may vary by location.

The study of political participation has generated a robust literature, and rightly so as political participation is the cornerstone of democracy. In the United States, the legitimacy of government authority derives from the popular will. Liberal democratic tradition posits that good government is popular government, and public policies are considered well founded if they reflect the sentiment of the broad electorate rather than that of select subgroups (Gosnell 1948; Key 1956; Schlozman, Verba, and Brady 1999). Similarly, the political playing field appears tilted and unequal if some candidates are well funded while others are not. These concerns have fueled a research agenda that has focused on how individual characteristics are related to participatory behavior.

Recently, the research connecting participation to individual traits has expanded to considerations of social context. Some have shown that donors, individual traits aside, are concentrated in large metropolitan areas and are commonly part of professional, ethnic, or friendship networks that facilitate the extraction of larger donations than would be forthcoming from individual solicitation (Cho 2003; Dawes and Thaler 1998; Gimpel, Lee, and Kaminski 2006). The underlying message is that participatory acts should be observed within the context of the physical spaces in which they emerge, not solely as a function of individual attributes such as income, age, factual knowledge, or educational attainment (Huckfeldt and Sprague 1995; Zuckerman 2005). After all, donors contribute to campaigns only partly because of their own personal wealth; legions of affluent Americans have never contributed a dime. People volunteer for campaigns only partly because they have ample leisure time; volunteer activity may be more appealing, all else equal, if one lives in areas where voluntarism is a long-standing part of the social fabric. Similarly, in a neighborhood that is highly charged politically, politically active individuals may mobilize friends even if these friends' psychological dispositions predict disengagement and their demographic profile predicts apathy. These types of "neighborhood effects" trace back to Cox (1969), who coined the term upon noticing that an inverse relationship between distance and relationship formation existed and that shared political identity often tied these relationships. While the influence of neighbors may not be enough to change predispositions, Cox found them to have an important effect on political leaning. Others have provided empirical evidence for various neighborhood phenomena (Huckfeldt 1986; Johnston and Pattie 2006; Johnston

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and Taylor 1979; Pattie and Johnston 2000; Sampson, Morenoff, and Gannon-Rowley 2002).

Contextual effects are also created by political organizations through their uneven distribution of campaign efforts. Individuals across the nation do not experience the same presidential election, but instead are influenced by the campaign as it unfolds in their particular venue of life. Residents living in one area may be subject to vigorous outreach efforts, while others experience limited political activity. Critical elements of campaign strategy are dictated by the location of loyalists, opponents, and the nonaligned (Key 1956). Advertisements are broadcast with variable intensity across media markets, and candidate appearances are carefully targeted and orchestrated (Shaw 1999, 2006). Taking stock of the political landscape is essential for reaching individual voters in an efficient manner. In the process, campaigns encourage participation through the targeting of recruitment-related contact (Rosenstone and Hansen 1993). The uneven application of campaign stimuli affects individual propensities to participate even when these individuals have the same characteristics and traits.

Moreover, where a citizen lives is consequential even aside from the variable allocation of campaign resources for a variety of reasons. First, information holding about politics is contextually conditioned (Knoke 1990; Krassa 1995; Krassa and Kuklinski 1990; Mutz 2006). An otherwise apathetic individual living in an information-rich environment is more likely to participate than one situated in a low-stimulus setting, suggesting that political environments can compensate for the indifference that might otherwise keep some at home (Gimpel, Kaufmann, and Pearson-Merkowitz 2007). The political socialization experience is place dependent, as accidents of location shape whether individuals grow up inspired or turned off by politics (Gimpel, Lay, and Schuknecht 2003). Second, a number of studies have shown that homogeneity of viewpoint in a community will exercise a positive influence on political participation even when individual-level variables are included (Alesina and LaFerrara 2000; Campbell 2006; Eagles and Erfle 1989; Lutz 1991, 1995). Small and homogeneous white communities exhibit a stronger sense of civic duty than larger, more diverse ones (Campbell 2006). Third, there is evidence that political participation is affected by racial context and the perception of threat by other proximate racial groups (Giles and Hertz 1994; Key 1949; Pantoja and Segura 2003). A group's cohesion is often a reaction against a disagreeable or unfriendly local environment (Finifter 1974; Huckfeldt 1986).

It follows, then, that a thorough understanding of political participation requires consideration of a variety of forces, sociological factors as well as individual characteristics. While few would suggest that sociological factors are unimportant, it is clear that this facet of participatory behavior has taken the backseat to the role of individual characteristics in spurring participation, perhaps because it is far simpler to inventory a wide variety of individual characteristics than it is to capture a citizen's ecological circumstances. Hence, while theories for the role of sociological facets and geographical structure on behavior are easy enough to articulate, the empirical analyses have not immediately or easily followed.

Here, we take on this challenge and aim to enrich our understanding of political participation by examining how the geographic and sociological perspective work part and parcel with well-understood individual-level influences on political participation. We begin by discussing how a contextual approach to the study of political participation might be useful and advantageous. This leads us naturally into considering the analytical complexities that accompany a geographic perspective. We consider how these complexities reveal themselves and can be dealt with in a unique data set that includes precinct-level tabulations of volunteer and contributor counts in a specific campaign. We discuss the various attributes of these data and the unique opportunities and challenges they create for estimation and inference. Finally, we present our analysis and discuss its implications.

Averages, Spatial Averages, and Participation Levels

Standard quantitative approaches to the study of political behavior are concerned with estimating average values for a population or study area. Average values are simple to understand. To compute an average, you sum up the individual values and divide by the number of units. It is also simple to see that an average is a summary statistic and a loss of information occurs if the description of data includes only the average value and not the individual values. The degree of information loss varies. If all of the individual values are the same, then there is no information loss in the average value. On the other hand, the individual values may, for instance, be normally distributed, be bimodally distributed, and/or have outlying values. In these cases, the average value, while imparting important and compact information, may not be very informative, since it does not allow a glimpse into the underlying data distribution.

Coefficients from an Ordinary Least Squares regression (or logistic regression or multinomial probit, depending on the relevant dependent variable) can be understood as average values. The coefficient provides a single estimate that summarizes the effect of interest. For example, for all of the respondents in a data set, is their personal income significantly related to their level of participation? Because these analyses yield a single coefficient to describe all respondents, these coefficients necessarily constitute an average—the average effect across all respondents. And since they summarize individuals across all geographic areas, they are spatial averages. Although these coefficients represent an average, they are informative and aptly describe a relationship of interest since we are not concerned per se with whether income is related to participation for a single individual, but instead, wish to determine if there is a general and significant pattern across all individuals. This analysis is global in the sense that it explores the "global effect" of income on political participation, across individuals who reside in a variety of settings. If the effect of income is uniform or randomly scattered across geographic regions, then the average effect would not be hiding much, if anything at all. If, however, the effect of income is distributed unevenly across space—magnified in some areas and virtually absent in others—then the coefficients are *spatial averages* that do obscure information in the data and may be misleading, perhaps limiting rather than enhancing our understanding.

Consider, for instance, that while one might control for the prevalence of high income in a neighborhood, not all high-income locales are the same, and the reasons for the differences may not be easily captured. Living among wealthy residents in, say, Manhattan's Upper East Side is not the same as living in an affluent Denver suburb. Lifestyles differ in a myriad of ways, as do neighborhoods, neighbors, and sources of wealth—elements variably associated with high income but not captured in the typical dollar measure of that construct. The presence and strength of aggregate-level influences on individual behavior may not be uniform across individuals, as not all residential environments will generate equally obvious perceptual cues for their inhabitants (Eagles 1995). If our primary interest is in whether income has an effect across a diversity of individuals, then a standard analysis adequately accomplishes the goal. However, if we are interested in delving deeper to develop a more nuanced and fuller understanding of the role of income on participation, we need to explore the variable effects that income may have on individuals who reside in different locations but share the same level of affluence.

Similarly, we might expect that campaign volunteers and donors will emerge more plentifully from neighborhoods where the age distribution tips toward either young people and/or older people who have more discretionary time on their hands. While this pattern may hold generally, the age distribution of local electorates may have a variable effect on the emergence of volunteers and donors. Austin, and Central Texas, for instance, may be among the locations where young people are more strongly associated with volunteer emergence than other locales with similar proportions of young people, possibly because several large universities are located in this region, providing a unique atmosphere and fertile recruiting ground for volunteer workers. Examining the average effect of age across all geographic locations produces a coefficient that hides interesting aspects of how local context either enhances or impedes mass participation.

We hypothesize that local political environments stimulate political participation, but the degree varies systematically by venue, perhaps as the result of the overlay of campaign stimuli or the product of local institutions or culture. For instance, we surmise that the relationship between locally competitive environments and participation will be more positive in richer information environments than it would be in more remote or politically quiescent areas. Similarly, we believe that regions where the political party of the candidate traditionally does well will be productive of participants because of the large number of party adherents as well as the social support that permeates more homogeneous communities.

In short, we believe several factors may underlie spatial heterogeneity in the magnitude of the relationship between participation and common explanatory variables such as age, income, and partisan commitment. First, variables such as the vigor of campaign outreach can be expected to create spatial heterogeneity. Second, contextual sociological factors, including interaction patterns among residents and the proximity of rival groups, may play a role in heightening causal effects in some locations and depressing them in others. Third, there are enduring historical and cultural forces that shape the responsiveness of local populations to political stimuli—traditions of involvement and disengagement, prevailing attitudes relating to trust in government, and related attitudes going to the perceived efficacy of participation.

Data and Participatory Terrain

Adopting a spatial vantage point in the study of political participation may expose processes governing behavior that are not well understood. We pursue this less traveled path in our examination here of a unique data set collected during the 2006 election cycle on the neighborhood origins of contributors and volunteers. The data originate from the confidential files of the *Texans for Rick Perry* 2006 gubernatorial campaign and include volunteer recruitment and campaign contributions from January 1, 2006, to Election Day that year.[1] For each donor or volunteer instance, we are able to attach an exact address, and so can geocode or map the data. This location information also allows us to merge in demographic and economic characteristics from 2006 U.S. Census estimates as well as the 2002 election data.[2] Together, this information provides a detailed view of the donor and volunteer activity in this campaign.[3]

Political Landscape

Our first step is to gain a broad understanding of the terrain under consideration. What defines this region politically? If donor and volunteer participation are the consequence of campaign stimuli, then Texas's organization into 20 Dominant Market Areas (DMAs) or media markets (see Figure 1) is an important consideration. Since campaigns are strategic and not all media markets are treated equally by campaigns and their media buyers (Herrnson 2004; Shea and Burton 2006), campaign professionals might expect larger effects from the same sociodemographic characteristics in major markets, such as Dallas-Fort Worth, Houston, San Antonio, and Austin, than in smaller markets such as Lubbock, Laredo, or Tyler-Longview.

Similarly, most campaigns invest a great deal of time in prior electoral targeting, focusing on the number of potential voters each county holds. In the particular campaign we examine, the focus was concentrated on the top 40 most populous counties in the state, also depicted in Figure 1. Campaign managers know that their resources are limited. Travis Griffin, the Perry campaign's field director, explains,

> Basically, Mike Baselice [campaign's pollster] comes up with turnout goals for every county. We are looking for 51 percent of the total vote—that's our goal. The vote goals are prioritized by county. We focus on the top-40 counties, which contain 77% of the total vote in Texas. . . . Some counties are left to their own devices. For them, we just have to be available by phone. We can print them a list and mail it to them. I don't want my reps spending time in small towns or out-of-the-way places. I want them in the top-40 counties. They'll sometimes call and say, I'm in [some small county] and I'll say get out. You can help them on the phone or send 'em something. But don't go there. There's no time for that.

Spatial nonstationarity in the effect of an explanatory variable on donations or voluntarism may certainly be the result of uneven field operations and campaign contacting across the state. Heterogeneity in effects is likely when campaign stimuli are so irregularly distributed.

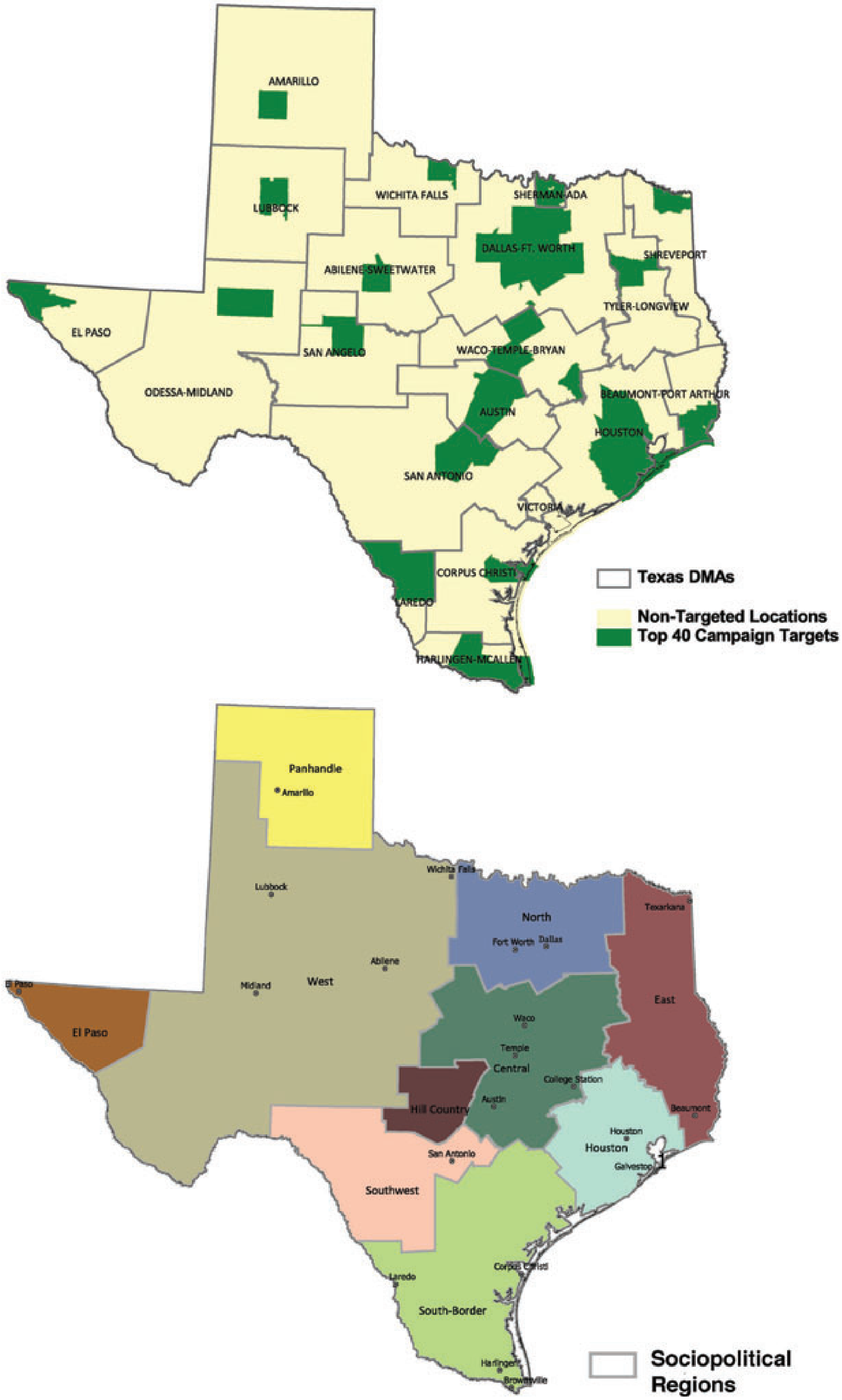
Another source of spatial heterogeneity stems from long historical precedent. Texas historians and political analysts have commonly divided the state into nine or ten major regions, depicted in the bottom map of Figure 1. These regional identities reflect some combination of economic activity (oil production, cattle ranching, cotton), and ethnocultural settlement (German immigration, Mexican immigration and ancestry), and the settlement of white slaveholders and consequent black populations. They are commonly labeled by ordinary directional terms (e.g., "North," "Central") or topographical features.

[1]In our data, "volunteers" are those who have added their name to a website list indicating that they would be willing to volunteer if called upon to do so. As is usually the case in typical solicitations for volunteer labor, far more people added their names to the list as potential volunteers than actually spent time as a volunteer. Even so, those responding had to seek out the campaign website, suggesting a high level of self-initiative was involved. For each volunteer, the time and date of sign-up was precisely recorded. "Donors" are simply identified as individuals who ever contributed any amount to the campaign (multiple donations are ignored since we are counting donors, not donations).

[2]Although there were changes between 2002 and 2006 in many locations as precincts were added and consolidated in some locales, we chose to use the 2002 precincts because 2002 election results were commonly employed by the campaign in its internal research and planning. The 2002 precincts also permitted us to employ 2002 election results at the precinct level as measures of local competition and previous political support. The 2002 precinct GIS shapefiles and data were supplied by the Texas Legislative Counsel's office within the Texas State Legislature.

[3]To be sure, our data are not a nationally representative sample of the United States, and so one might question our case selection and raise issues of external validity. However, a national representative sample is not always ideal and obtaining a representative sample of volunteers and contributors for locations across the entire nation would demand extraordinary resources that are not at hand. In this case, and in many others, one needs to take a more detailed approach to gain headway. We also find Cook and Campbell (1979) and Campbell and Stanley (1963) persuasive on this point. First, attaining complete external validity is impossible given that generalization involves extrapolation to an unknown realm outside one's sample. No single study proves a theory. Second, this article offers a well-implemented study of a limited sample, and the best practical alternative available for evaluating relationships that have been rarely studied at this point. No implementable research practice is sufficient to attain externally valid research findings. The most important means for attaining external validity is gaining some understanding of the determinants of the behavior in question. This is done through repeated studies in a variety of settings and circumstances.

FIGURE 1 Texas Dominant Market Areas, Top 40 Targeted Counties, and Sociopolitical Regions



Evidence suggests that these regions are part of a well-anchored vernacular, emerging out of the spatial perceptions of average people, and are not just the ad hoc representations of political pundits or academics (Jordan 1967, 1978; Meinig 1969).

Long-standing geographic structures, whether informal such as sociocultural regions, or institutionalized by Designated Market Area boundaries shaping outreach efforts, reinforce particular patterns of socialization, shape information flow, and steer electoral strategy. They help to define the quantity and quality of campaign outreach in a certain area as well as affect intangibles such as habits of thought and action and the creation and sustenance of social networks.

Lastly, the metropolitan/rural continuum is less specific to Texas, but certainly relevant to all populous states and often serves to define communities. Unlike historical precedent and factors that are specific to this campaign, such as the top 40 county targeting strategy, the metropolitan/rural distinction has an enduring history in studies of political participation. These various geographic identifiers are germane and interconnected, yielding a variegated political landscape.

Analysis and Results

If our data exhibit the spatial nonstationarity strongly implied by our theoretical expectations, a technique that might be especially helpful with these data is a geographically weighted regression (GWR) (Fotheringham, Brunsdon, and Charlton 2002; Huang and Leung 2002). GWR allows us to assess the possibility of and examine the potential spatial nonstationarity in parameters.[4]

In a classical regression framework, for a dependent variable, **Y**, and a set of independent variables, **X**,

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}. \tag{1}$$

Here, the vector of coefficients, β, is $(k + 1) \times 1$ and constant over space. A GWR framework is similar, but instead,

$$\mathbf{Y} = (\boldsymbol{\beta} \otimes \mathbf{X})\mathbf{1} + \boldsymbol{\epsilon}, \tag{2}$$

where β is now an $n \times (k + 1)$ matrix of coefficients, **X** is an $n \times (k + 1)$ matrix of independent variables, **1** is a $(k + 1) \times 1$ vector of 1s, n is the number of observations, and k is the number of independent variables. In the GWR framework, the number of estimated coefficients increases by a factor of n, allowing a separate coefficient estimate for each spatial location.

The $n \times (k + 1)$ coefficient matrix takes the form

$$\begin{bmatrix} \beta_0(u_1, v_1) & \beta_1(u_1, v_1) & \ldots & \beta_k(u_1, v_1) \\ \beta_0(u_2, v_2) & \beta_1(u_2, v_2) & \ldots & \beta_k(u_2, v_2) \\ \vdots & & & \\ \beta_0(u_n, v_n) & \ldots & & \beta_k(u_n, v_n) \end{bmatrix},$$

where (u_i, v_i) signifies the spatial location of the ith observation. Each row of this matrix, β, is given by

$$\hat{\boldsymbol{\beta}}(\boldsymbol{i}) = (\mathbf{X}^T\mathbf{W}(\boldsymbol{i})\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}(\boldsymbol{i})\mathbf{Y}, \tag{3}$$

where $i = 1, \ldots, n$, and $\mathbf{W}(\boldsymbol{i})$ is an $n \times n$ matrix of spatial weights,

$$\mathbf{W}(\boldsymbol{i}) = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{iN} \end{bmatrix}, \tag{4}$$

where w_{in} is the weight given to data point n at location i. The GWR framework is similar to a weighted least squares estimator with nonconstant weights, but the weights vary according to the spatial location of i. The weights matrix (4) is computed for each location i, and the weights encompass a measure of proximity of each of the other locations to location i. The observations that are more proximate to i are weighted more heavily in the estimation of the parameter for location i.

The weights matrix is operationalized through spatial kernels. A spatial kernel is placed over each unit and determines the weight of each data point in the calibration of the model at location i. The specification of a spatial kernel relies on two critical decisions. One decision pertains to the "bandwidth" or size of the spatial kernel. We use a continuous decay function, so that points that are close have greater weight than points that are increasingly distant, and points beyond a certain range have no influence. A second decision is related to whether the spatial kernel should be a fixed size for all units or allowed to vary. In our data, a varying spatial kernel is implied by theory. In addition, a map of point densities of volunteer counts makes it clear that this behavior is primarily a metropolitan phenomenon. While there are pockets of volunteers in other parts of the state, these are exceptions

[4]There are other methods that are suitable for data that exhibit spatial heterogeneity. Hierarchical Linear Models (HLM), for instance, are another way to model spatial heterogeneity. Our theories for this particular application, however, point toward the structure of GWR where the local regression allows us to take spatial dependence into account while incorporating extreme heterogeneity. We also do not, a priori, have a firm guess about what the proper aggregation would be for the level-2 model in an HLM. GWR provides us with an opportunity to be more flexible about exploring the structure of the spatial heterogeneity.

to the general patterning. Accordingly, we allow the size of our spatial kernels to vary depending upon the density of observations over the region of interest, with smaller kernels in more populous regions and larger kernels in rural areas.[5]

In a GWR analysis, as in any statistical analysis, a number of modeling decisions must be made. Some of these modeling decisions involve bigger assumptions about the data while others involve smaller assumptions and thus have comparatively less impact on the final results. Two of the most consequential modeling decisions, the choice of how to specify the spatial kernel or bandwidth and the decision to use varying rather than fixed spatial kernels, are critical to the final results, so we pay extra attention to the decisions made here. In our case, these choices appear to be less controversial than they might be given the strength of our theoretical expectations.[6]

To produce a spatially varying kernel, one may rank the observations by their distance from location i so that R_{ij} is the rank of observation j from location i in terms of j's distance from i. In this scheme, the data point closest to i would have the highest weight, 1, while observations with higher rankings (i.e., further from i) would have increasingly larger ranks and smaller weights. When there are many points in a region, then, the bandwidth of kernels in these regions will be small. When there are few observations in a region, the bandwidth will be larger because one needs to incorporate more distant points to calibrate the kernel. To incorporate a spatially varying weighting method, we employ an adaptive bandwidth using nearest neighbor weighting with a bi-square decay function.

[5]Whenever data are spatially situated, thorny issues surrounding scale and aggregation crop up. At what level of data, or scale (e.g., county, precinct, tract, etc.), should the analysis be conducted? How much or how little should the data be aggregated? The particular problem is the dependence of results on levels of aggregation. We can at least bypass issues arising from the ecological inference problem because our aim is not an individual-level study of participatory behavior, but, rather, a study of how aggregate and geographic elements define landscapes conducive to participation. A relative of the ecological inference problem, the modifiable areal unit problem (MAUP), also presents itself (Openshaw 1984). We are especially mindful that there is no easy answer to the question of what the proper level of aggregation should be in a particular study as well as for the need to establish a means for identifying the operational scale of particular geographic phenomena. While it is difficult to identify the operational scale of a particular phenomenon, one tactic, and the one we employ here, has been explicitly to design zones or units of aggregation that are meaningful entities of the particular phenomenon (Alvanides, Openshaw, and Macgill 2001; Cho, Baer, and Darmofal 2009; Coombes, Green, and Openshaw 1986). While the new units of aggregation remain arbitrary, their validity is based on a substantive and theoretical understanding of a particular application.

[6]One might choose different units than the ones we chose and the results may then differ. This issue surrounds any type of geographical analysis. This issue does not render geographic analyses useless, but it does require that one interpret the results with these assumptions in mind.

Coefficient Variability and Ordinary Least Squares Results

To establish a baseline for our analysis, we begin, not with a GWR, but with a standard OLS regression. These OLS results are presented in Tables 1 and 2. Table 1 lists the results for donors while Table 2 presents the results for volunteers. In a standard OLS analysis, the impact of any one of our independent variables is fixed across the entire state of Texas. In Table 1, the dependent variable is a log transformation with an offset of 1 for the number of donors. We used a log transformation because of skewness in the dependent variables. The number of donors in each precinct ranges from 0 to 102. The dependent variable in Table 2 is a log transformation with an offset of 1 for the number of volunteers. The total number of contributors in each precinct ranges from 0 to 57.

The OLS results indicate both similarities and differences in the geography of donor and volunteer emergence. For example, donors and volunteers emerge in larger numbers in more densely populated areas, in higher income precincts, in precincts that have had more competitive elections, where there are younger voters, as well as in areas with highly active Republican primary voters. Some differences emerge as well. Some variables have an influence on donor activity only (household size). Some are related only to volunteerism (minority presence). Some affect both, but in opposite directions (age distribution). In many ways, these results make sense and one might forego further analysis at this point and begin to delve into the meaning and implications of these results.

Our sense and theoretical expectation, however, is that the next step should be to examine the spatial stationarity of these coefficients. In both Tables 1 and 2, a set of descriptive statistics for the coefficients from a geographically weighted regression is displayed. Since the global OLS values are simply spatial averages that can hide a lot of information, we examine these summary statistics to gain a sense of how much spatial variation underlies the global OLS coefficients. These statistics give us a prima facie case for pursuing a geographically weighted regression path in analyzing our data.[7] While we expect the local parameter estimates to vary, we expect them to vary roughly

[7]One may test the stationarity of coefficients more formally through Monte Carlo experiments by comparing the coefficient under the assumption that the global model holds and the coefficient obtained from randomly rearranging the data spatially. This method, however, is computationally intensive and prohibitive in our application here. One run took about a day, so 250 replications for a test

TABLE 1 Global OLS Regression Results and GWR Coefficient Ranges for Donors

	OLS Estimates	GWR Min	GWR Mean	GWR Median	GWR Max
Intercept	−0.2336*	−0.5045	−0.1181	−0.1424	0.1943
	(0.0564)				
Population Density	0.0166*	0.0094	0.0190	0.0168	0.0571
	(0.0020)				
Percent Minority	0.0002	−0.0040	−0.0011	−0.0009	0.0012
	(0.0003)				
Percent High Income	0.0412*	0.0303	0.0411	0.0450	0.0642
	(0.0014)				
Average Household Size	0.0009*	−0.0025	0.0037	0.0008	0.0237
	(0.0004)				
% Republican for Governor	0.0034*	−0.0007	0.0028	0.0031	0.0043
	(0.0005)				
Competitiveness	0.0228*	0.0142	0.0203	0.0172	0.0324
	(0.0013)				
Percent Elderly	0.0084*	0.0007	0.0065	0.0067	0.0150
	(0.0012)				
Percent Young	0.0031*	−0.0023	0.0020	0.0009	0.0085
	(0.0013)				
Republican Stronghold	0.0113*	0.0021	0.0154	0.0178	0.0244
	(0.0010)				
N	8,390				
R^2	0.190				
AIC	14606.76		14265.86		

*p < 0.05.
Standard errors in parentheses.

within the bounds of the global confidence intervals, diverging occasionally by chance. For our data, however, the fluctuation is much greater than would be expected by chance. For each of the parameter estimates in Table 1, the lowest proportion of GWR estimates outside ±2 standard errors is 0.297. The mean proportion is 0.348—far greater than one would expect to occur by chance. For the parameter estimates in Table 2, the lowest proportion of GWR estimates outside ±2 standard errors is 0.460. The mean proportion is 0.548. The minimum and maximum values given in the table are thus in good company and not outliers. The median values give us a sense of whether the coefficient distributions are skewed to the right or left. Together, these summary statistics provide evidence that pursuing a geographically weighted regression that attempts to untangle the apparent spatial nonstationarity in the parameter estimates is a reasonable course. We also note that the AIC for the GWR models (for both the donor and volunteer models) is lower than the respective AIC for the OLS models, providing further justification for pursuing the additional detail involved in the GWR model.[8]

statistic would take the better part of a year to complete. One may also employ a Leung test (Leung, Mei, and Zhang 2000a, 2000b), which is analytical in nature, but this test has proven to be as computationally intensive as the Monte Carlo approach in practice. Accordingly, we opted to avoid these tests, giving up the formality of a test statistic for nonstationarity, relying instead on a display of the range over which the coefficients fall. In any case, both are exploratory steps. At worst, we have pursued an unnecessary GWR analysis, but the GWR results and fit that follow show us that the GWR analysis does indeed add much substantive richness.

[8]The AIC is computed according to equation (2.33) in Fotheringham, Brunsdon, and Charlton (2002). We do note that there are some differences between this AIC and the one provided in Hurvich, Simonoff, and Tsai (1998) on which it is based. While these differences are important, they did not affect the relative positioning of the AIC values for our OLS and GWR models. We also recognize but do not delve into issues affecting inference arising from how one should compute the effective degrees of freedom in GWR models.

Table 2 Global OLS Regression Results and GWR Coefficient Ranges for Volunteers

	OLS Estimates	GWR Min	GWR Mean	GWR Median	GWR Max
Intercept	0.2070*	−0.1681	0.2851	0.1681	0.8461
	(0.0435)				
Population Density	0.0125*	0.0060	0.0132	0.0098	0.0459
	(0.0015)				
Percent Minority	−0.0035*	−0.0100	−0.0042	−0.0032	−0.0007
	(0.0003)				
Percent High Income	0.0159*	0.0101	0.0155	0.0146	0.0422
	(0.0011)				
Average Household Size	0.0006	−0.0047	0.0013	0.0006	0.0174
	(0.0003)				
% Republican for Governor	−0.0001	−0.0061	−0.0004	0.0007	0.0031
	(0.0004)				
Competitiveness	0.0148*	0.0083	0.0142	0.0126	0.0258
	(0.0010)				
Percent Elderly	−0.0068*	−0.0158	−0.0081	−0.0094	0.0031
	(0.0009)				
Percent Young	0.0082*	0.0021	0.0076	0.0076	0.0125
	(0.0010)				
Republican Stronghold	0.0044*	−0.0015	0.0061	0.0065	0.0154
	(0.0013)				
N	8,390				
R^2	0.147				
AIC	10263.94		9823.4		

*p < 0.05.
Standard errors in parentheses.

Geographically Weighted Regression Results

Since the GWR results are difficult to summarize given the distinct coefficient estimates for each geographic location, maps are essential for depicting the fluctuation in parameter estimates. The ranges of GWR coefficients across the state for population density, income, and competitiveness are shown in Figures 2–4, respectively. The top map in each set (using the red color scheme) shows the coefficient range when volunteerism is the dependent variable while the bottom map (using the green color scheme) displays the coefficient range when the dependent variable is contributors. The five classifications depicted in the map legends are determined by optimizing within-class homogeneity in the data.[9]

Inspection of the maps in Figure 2 indicates the substantial geographic similarities in the way in which population density affects the number of donors and volunteers. Our general theoretical expectation was that greater density would be related to more volunteers and donors because campaigns find it efficient to spend much of their time in metropolitan areas rather than more sparsely populated locations. We can see from the map that volunteer emergence was usually positively related to greater population density, though less so throughout much of North and East Texas, as well as Houston and South Texas. The

[9]Some might argue that simplicity would dictate a preference for an OLS analysis rather than an analysis that requires maps to depict results. We agree that simplicity and parsimony are important considerations in statistical modeling. At the same time, we believe that other methods may also provide insight. To be clear, we hardly advocate the use of GWR in all analyses. There are many instances where GWR is not especially helpful. Statistical modeling involves making reasonable modeling decisions. For the particular application here, we found GWR to be useful and insightful given the wide variation exhibited in the local parameters across the region of interest, the increase in the goodness-of-fit, and our theoretical expectations. The GWR analysis illuminated aspects of the data and model specification that would otherwise be difficult to uncover.

FIGURE 2 Volunteers and Donors: Population Density

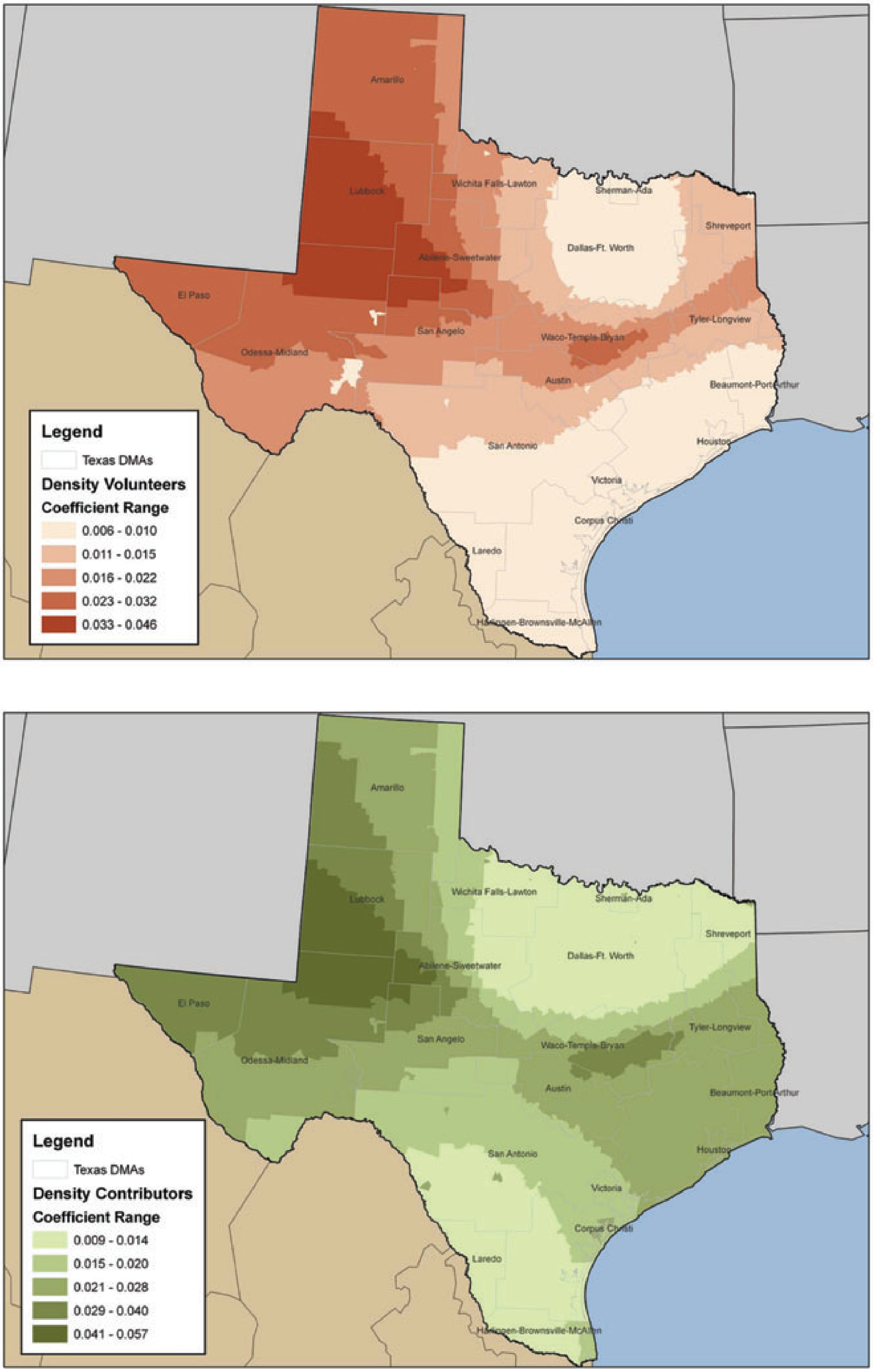


FIGURE 3 Volunteers and Donors: High Income

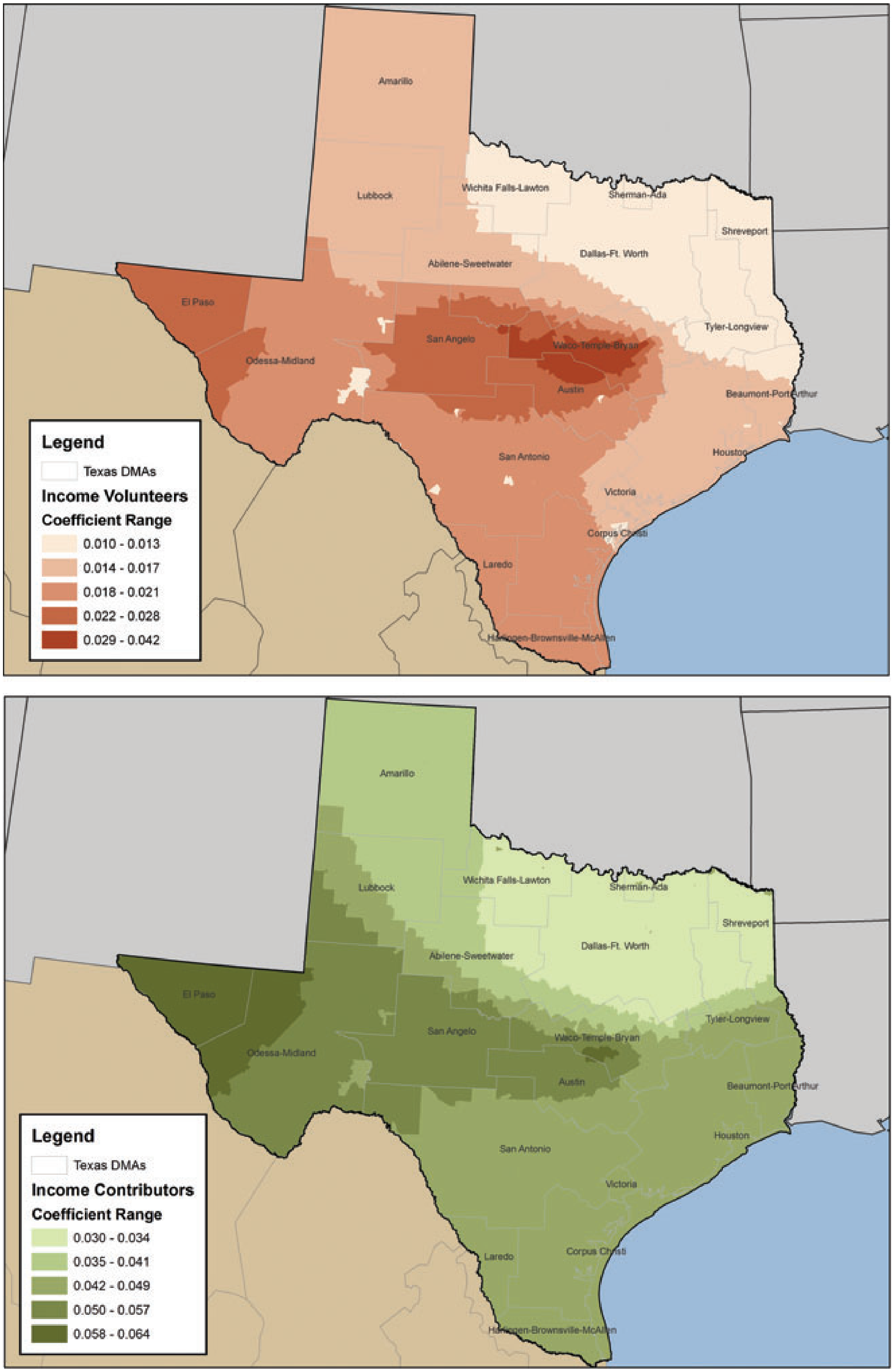
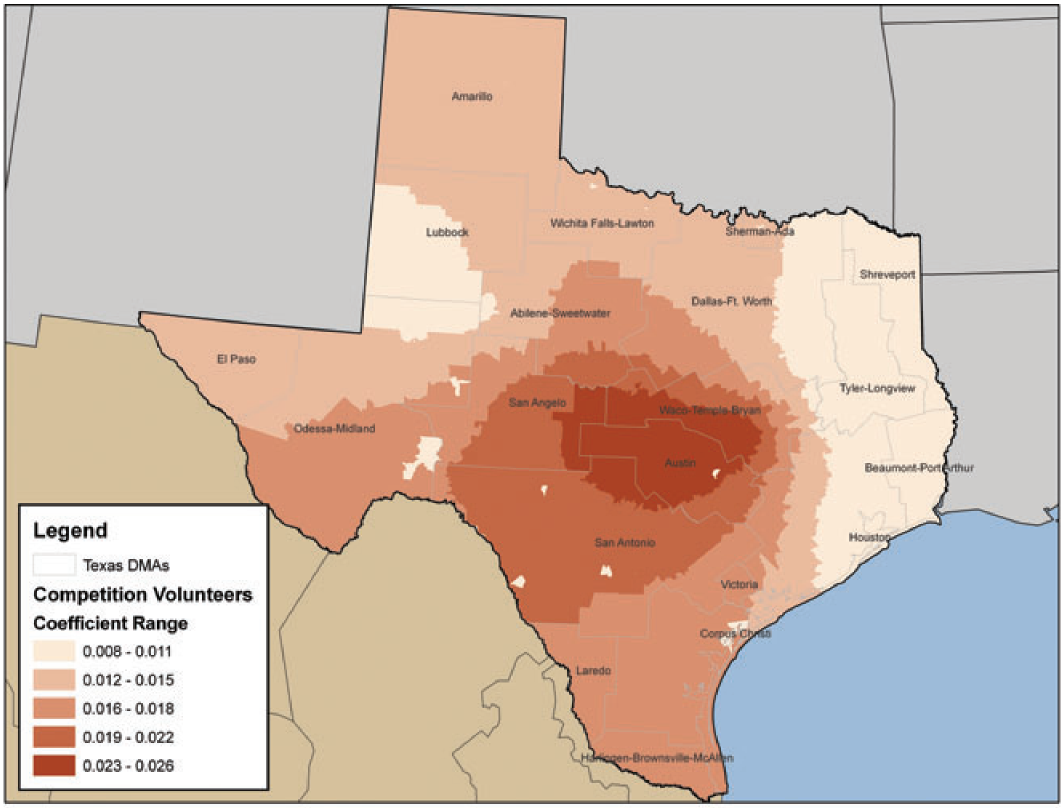
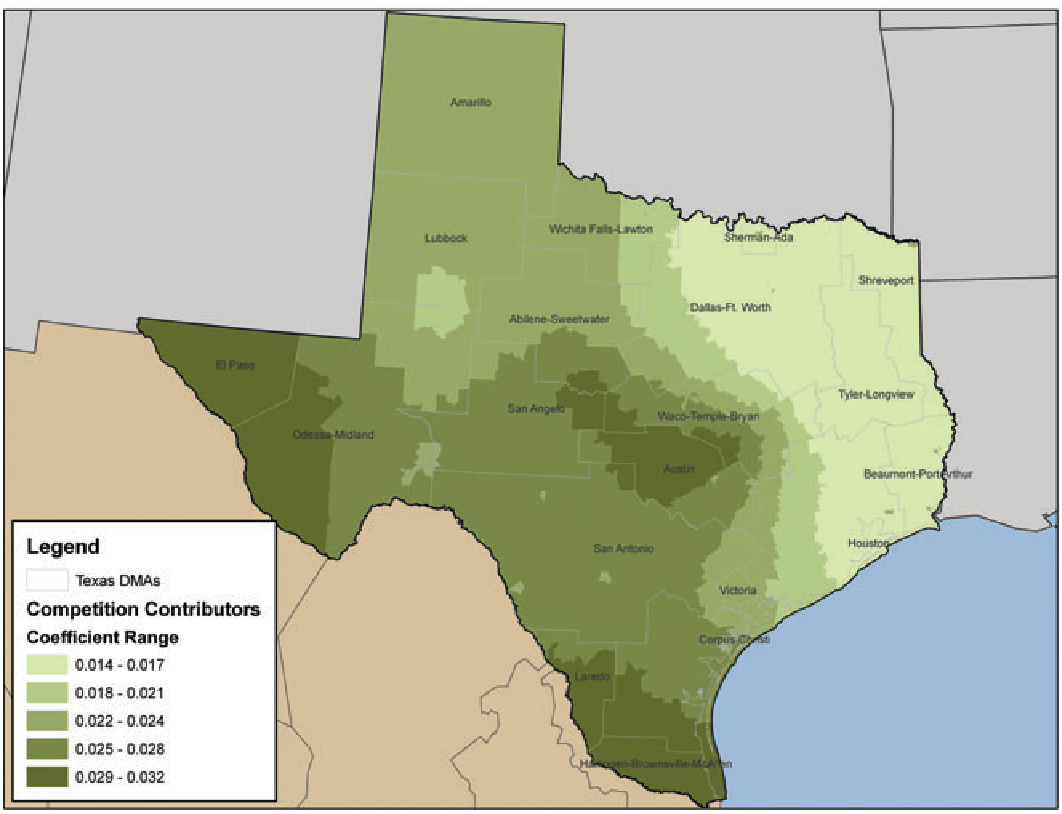


FIGURE 4 Volunteers and Donors: Competitiveness





most pronounced positive effects of population concentration appear in West Texas and the Panhandle, with a notable effect in the Waco media market, and specifically around the Temple-Killeen area (top map in Figure 2).[10]

Population density has a greater impact on contributors than it does volunteers, on average, although the impact on contributors is more variable across the state (bottom map in Figure 2). For every 1,000-person increase in people per square mile, the number of volunteers jumped by as much as 99.5%, and as little as 1.8%, with an average effect of 6.7%. The range for contributors was 2.5% to 298%, with a typical impact of 3.7%. Two differences worth noting are the very low coefficient values for contributors in the North Texas region (generally the Sherman-Ada, Wichita Falls, and Dallas-Fort Worth media markets) as well as the high coefficient values in the Lubbock-Amarillo and Odessa-Midland areas. Perhaps unexpectedly, the emergence of volunteers and donors is variably connected to population concentration. For instance, North Texas should be productive of more participants and West Texas somewhat fewer—though in repeated contacts, campaign officials emphasized the serious underperformance of North Texas. This variable effect nicely illustrates the value of GWR in unpacking the global estimate of population's impact that obscures these important differences.

Like the effect of population density, the impact of income is variable across the state. Figure 3 illustrates the variability of the high income (percent earning $200,000 or more) coefficients for donor and volunteer emergence. Volunteerism is responsive to high income most clearly in the Waco and Austin media markets, and is hardly responsive in North Texas, East Texas, the Houston metro area, and the Panhandle. A 1% increase in a precinct's affluence produces between a 2.7% and 67% gain in the number of volunteers. An interesting observation is that the variance in the number of high-income neighborhoods has an inverse relationship with the size of the coefficient in the local area. This is consistent with our theory that homogeneity, which can manifest itself in a myriad of ways, tends to spur participation.

For contributors (the bottom map in Figure 3), the total number rises from about 20% to over 400% for every 1% increase in high-income earners. El Paso and West Texas stand out as locations particularly influenced by the presence of affluence. Campaign officials we interviewed expressed concern about the poor performance of the North Texas region as far as donations are concerned, in spite of the impressive affluence of Dallas and its suburbs. Going into the 2010 contest, this area is widely considered to be weak in its enthusiasm for the governor's reelection, and this sentiment appears to be reflected in our maps from 2006.

These nonconstant effects are also evident for local political competition. Volunteerism is most sensitive to political competition in Central Texas, and particularly in parcels lying within the Austin, Waco, and San Antonio media markets (top figure in Figure 4), areas that witnessed an especially vigorous congressional campaign for the 17th district seat held by Democratic incumbent Chet Edwards. Local competition stimulates volunteers the least in East Texas along the Louisiana border, where Democrats have some notable strongholds, as well as the Lubbock and Odessa-Midland areas of West Texas, where Republicans commonly enjoy lopsided majorities. In the latter regions, Republicans even in relatively divided precincts may feel safe and unthreatened. In the former region, they may feel browbeaten and defeated.

Sometimes regional party factionalism mutes the grassroots and donor support for a statewide candidate. Campaign staff specifically noted that the governor had been criticized by Republican state legislators in East Texas (Tyler, Longview, Marshall), attributing some of the lukewarm support there to his lack of popularity among GOP elites.

Potential contributors are also apparently sensitive to local competitive winds, with the biggest effects around Austin, and throughout West Texas. Local competition has a stronger global impact on donors than on volunteers, but East Texas and North Texas are sore spots for campaign participants of both types. In far West Texas and the Panhandle region, contributors responded well to local competition, but volunteers were less responsive by comparison. Distance from the geographic origin of most campaign activity understandably discourages those in far-flung locations from participating as volunteers, while encouraging check-writing as a more meaningful form of involvement beyond voting.

Discussion

General, global patterns are interesting, but they are simply spatial averages and often mask a great deal of regional variation that may result from a wide variety of possible sources. In our study of participation here, our hypotheses, that various factors affecting volunteer and donor emergence would vary spatially, was plainly borne out

[10]One might be inclined to think that the locations where the coefficients are larger are tied to greater variation in population density, while less variation results in a more modest effect, but this is not the case. Population density varies less across precincts in West Texas and the Panhandle than it does in North Texas (Dallas-Fort Worth and vicinity) or in the South.

in the analysis. This evidence of spatially varying effects behooves us to ask why space matters. Is the problem with making global statements about political behavior that our model was not sufficiently well specified? For instance, if particular local parameter estimates were always high in urban areas and low in rural areas, then the suggestion is that the model would be served well by the addition of a variable that taps ruralness. Our coefficient patterns were not quite this simple, but there were definite connections to the sociocultural landscape of the study area, as well as the designated market areas (see Figure 1) that define media markets and shape campaign media outreach. An ANOVA shows that the patterns of variability in various coefficients are fairly well explained by reference to both the sociocultural regions as well as the DMAs. Interestingly, not all of the Texas media markets were needed to explain the bulk of the variation. The 10 sociocultural regions proved to explain about as much of the variation (with greater parsimony) in the regression coefficients as the 20 media market regions. Our GWR analysis, then, can be seen as a model-building procedure where the goal is to find a model specification for which there is no significant spatial nonstationarity. In this sense, it is not "space" that matters, but determining why regions develop their unique identities. In our application here, the model suggested by the pattern of GWR coefficients is somewhat complex with the interaction of a different set of regional variables for different individual characteristics. Nonetheless, these interactions would decrease the spatial heterogeneity that we currently observe and might illuminate why geography is relevant.

At the same time, the fit was not perfect for any of these area-based explanatory schemes. The patterns we observe cannot be entirely explained by reference to media market boundaries, the Perry campaign's 40 most highly targeted counties, or the broad sociocultural regions of the state, as understood by students of the Lone Star State's political history and development. Some degree of the coefficient variation remains unexplained. This residual significant "spatial effect" may be the result of unmeasured or omitted variables. In this sense, again, it is not "space" per se that matters, but variables that define why the study area would be partitioned into distinct regions. GWR, in this case, allows us to account for these omitted effects by incorporating the ability to identify locally varying parameter estimates. GWR is also helpful in this situation because the maps displaying the parameter variation may offer clues as to why there is any patterning at all. Perhaps these geographically defined patterns point to a need to accumulate additional local knowledge in future research efforts on this subject. In this way, GWR is helpful in identifying the nature of misspecification in individual-level effects, improving our understanding of the participatory behavior.

The patterns we observe reflect the admixture of partisan, ethnic, and socioeconomic characteristics of voters in response to periodic election-oriented stimuli. The features of this amalgamation can be seen partly in the way that the rising and falling of the regression coefficients across our maps correspond to local extremes in the variation of key explanatory variables.

It may also remain the case that even with a "proper specification," local behavior is intrinsically different, giving rise to the argument that it is actually space that matters and that space is not simply a surrogate for other variables. This argument harkens back to complex but traditional arguments about model specification. What is less controversial about our analysis here is that because coefficients vary spatially, standard analyses produce misleading results that imply a global process governing behavior. Instead, our focus on local structures sheds light on the mechanisms behind the participation impetus and confirms our theoretical expectations that squarely place sociological and ecological forces within the participation equation. The coefficient patterns and their interesting variation and interaction with individual characteristics would have been difficult to detect using standard statistical tools. Unearthing these spatial patterns requires a spatially sensitive tool such as geographically weighted regression.

These patterns are important both in understanding the theoretical underpinning of participation as well as in the practical realm of politics where this more nuanced view of the data stands to expose potentially damaging regional weaknesses in a campaign's outreach. The practical application of geographically weighted regression to the campaign context could rescue regression-related methods from the weakness of overgenerality that commonly limits their analytic utility for decision making. Strategic decisions depend not just on a singular estimates of impact for a vast area, but also on what is happening in places that local experts know differ widely from one another but for a mix of reasons that are not always obvious. Clearly a political campaign cannot expect the same yield everywhere out of the same appeal, whether that appeal is for donors, volunteers, or voters. Indeed, we cannot expect the same yield out of the same appeal even when individual characteristics of the communication targets are highly similar.

In summary, quantitative generalization should not be blind to important patterns in statistical relationships that display wide variance locally. In the study of many political phenomena, significant local variation is very likely the rule rather than the exception, behooving analysts to consider the possibility, at a minimum. Geographically weighted regression has permitted us to accommodate the heterogeneity in the contextual processes that generates the flow of volunteers and contributors into a political campaign at a fine level of granularity. In doing so, we have underscored the importance of accumulating greater information about local context and its role in conditioning political behavior.

References

Alesina, Alberto, and Eliana LaFerrara. 2000. "Participation in Heterogeneous Communities." *Quarterly Journal of Economics* 112(3): 847–904.

Alvanides, Seraphim, Stan Openshaw, and James Macgill. 2001. "Zone Design as a Spatial Analysis Tool." In *Modeling Scale in Geographical Information Science*, ed. Nicholas J. Tate and Peter M. Atkinson. Chichester, UK: Wiley and Sons, 141–58.

Campbell, David E. 2006. *Why We Vote: How Schools and Communities Shape Our Civic Life*. Princeton, NJ: Princeton University Press.

Campbell, Donald T., and Julian C. Stanley. 1963. *Experimental and Quasi-Experimental Designs for Research*. Boston: Houghton Mifflin.

Cho, Wendy K. Tam. 2003. "Contagion Effects and Ethnic Contribution Networks." *American Journal of Political Science* 47(2): 368–87.

Cho, Wendy K. Tam, Neil Baer, and David Darmofal. 2009. "Environmental Determinants of Racial Attitudes Redux." Working Paper, University of Illinois at Urbana-Champaign.

Cook, Thomas D., and Donald T. Campbell. 1979. *Quasi-Experimentation: Design and Analysis Issues for Field Settings*. Boston: Houghton Mifflin.

Coombes, M. G., A. E. Green, and S. Openshaw. 1986. "An Efficient Algorithm to Generate Official Statistical Reporting Areas: The Case of the 1984 Travel-to-Work Areas Revision in Britain." *Journal of the Operational Research Society* 10: 943–53.

Cox, Kevin. 1969. "The Voting Decision in a Spatial Context." In *Progress in Human Geography: International Reviews of Current Research*, ed. Christopher Board, Richard J. Chorley, Peter Haggett, and David R. Stoddart. Vol. 1. London: Edward Arnold, 81–117.

Dawes, Robyn, and Richard H. Thaler. 1998. "Anomalies: Cooperation." *Journal of Economic Perspectives* 2(3): 187–97.

Eagles, Munroe. 1995. "Class versus Community? Social Identities and Political Mobilization." In *Spatial and Contextual Models in Political Research*, ed. Munroe Eagles. London: Taylor and Francis, 211–33.

Eagles, Munroe, and Stephen Erfle. 1989. "Community Cohesion and Voter Turnout in English Parliamentary Constituencies." *British Journal of Political Science* 19(1): 115–25.

Finifter, Ada W. 1974. "The Friendship Group as a Protective Environment for Political Deviants." *American Political Science Review* 68(2): 607–25.

Fotheringham, A. Stewart, Chris Brunsdon, and Martin Charlton. 2002. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. London: John Wiley & Sons.

Giles, Michael W., and Kaenan Hertz. 1994. "Racial Threat and Partisan Identification." *American Political Science Review* 88(2): 317–26.

Gimpel, James G., Karen M. Kaufmann, and Shanna Pearson-Merkowitz. 2007. "The Battleground vs. the Blackout States: The Behavioral Implications of Modern Presidential Campaigns." *Journal of Politics* 69(3): 786–97.

Gimpel, James G., J. Celeste Lay, and Jason E. Schuknecht. 2003. *Cultivating Democracy: Civic Environments and Political Socialization in America*. Washington, DC: Brookings Institution Press.

Gimpel, James G., Frances E. Lee, and Joshua Kaminski. 2006. "The Political Geography of Campaign Contributions in American Politics." *Journal of Politics* 68(3): 626–39.

Gosnell, Harold F. 1948. *Democracy: The Threshold of Freedom*. New York: Ronald Press.

Herrnson, Paul S. 2004. *Congressional Elections: Campaigning at Home and in Washington*. Washington, DC: CQ Press.

Huang, Yefang, and Yee Leung. 2002. "Analyzing Regional Industrialisation in Jiangsu Province Using Geographically Weighted Regression." *Journal of Geographic Systems* 4: 233–49.

Huckfeldt, R. Robert. 1986. *Politics in Context: Assimilation and Conflict in Urban Neighborhoods*. New York: Agathon Press.

Huckfeldt, Robert, and John Sprague. 1995. *Citizens, Politics and Social Communication: Information and Influence in an Election Campaign*. Cambridge: Cambridge University Press.

Hurvich, Clifford M., Jeffrey S. Simonoff, and Chih-Ling Tsai. 1998. "Smoothing Parameter Selection in Nonparametric Regression Using an Improved Akaike Information Criterion." *Journal of the Royal Statistical Society, Series B* 60: 271–93.

Johnston, Ron J., and Charles J. Pattie. 2006. *Putting Voters in Their Place: Geography and Elections in Great Britain*. Oxford: Oxford University Press.

Johnston, Ron J., and P. J. Taylor. 1979. *Geography of Elections*. Harmondsworth, UK: Penguin Books.

Jordan, Terry G. 1967. "The Imprint of the Upper and Lower South on Mid-Nineteenth-Century Texas." *Annals of the Association of American Geographers* 57(4): 667–90.

Jordan, Terry G. 1978. "Perceptual Regions in Texas." *Geographical Review* 68(3): 293–307.

Key, V. O., Jr. 1949. *Southern Politics in State and Nation*. New York: Knopf.

Key, V. O. 1956. *Politics, Parties and Pressure Groups*. New York: Thomas Y. Crowell.

Knoke, David. 1990. "Networks of Political Action: Toward Theory Construction." *Social Forces* 68(4): 1041–63.

Krassa, Michael A. 1995. "Contextual Conditioning of Political Information: Common Themes from Disparate Data." In *Spatial and Contextual Models in Political Research*, ed. Munroe Eagles. London: Taylor and Francis, 179–94.

Krassa, Michael A., and James H. Kuklinski. 1990. "Informedness, Social Networks and the Potential for Citizen Action." Presented at the annual conference of the American Political Science Association, San Francisco.

Leung, Y., C.-L. Mei, and W.-X. Zhang. 2000a. "Statistical Tests for Spatial Nonstationarity Based on the Geographically Weighted Regression Model." *Environment and Planning A* 32: 9–32.

Leung, Y., C.-L. Mei, and W.-X. Zhang. 2000b. "Testing for Spatial Autocorrelation among the Residuals of the Geographically Weighted Regression." *Environment and Planning A* 32: 871–90.

Lutz, James M. 1991. "Marginality, Major Third Parties and Turnout in England in the 1970s and 1980s: A Re-Analysis and Extension." *Political Studies* 39: 721–26.

Lutz, James M. 1995. "Diffusion of Voting Support: The Radical Party in Italy." In *Spatial and Contextual Models in Political Research*, ed. Munroe Eagles. London: Taylor and Francis, 43–61.

Meinig, Donald W. 1969. *Imperial Texas: An Interpretative Essay in Cultural Geography*. Austin: University of Texas Press.

Mutz, Diana. 2006. *Hearing the Other Side: Deliberative versus Participatory Democracy*. New York: Cambridge University Press.

Openshaw, Stan. 1984. *The Modifiable Areal Unit Problem*. Norwich, UK: Geo Books.

Pantoja, Adrian, and Gary Segura. 2003. "Fear and Loathing in California: Contextual Threat and Political Sophistication among Latino Voters." *Political Behavior* 25(3): 265–86.

Pattie, Charles J., and Ron J. Johnston. 2000. "People Who Talk Together Vote Together: An Exploration of Contextual Effects in Great Britain." *Annals of the Association of American Geographers* 90(1): 41–66.

Rosenstone, Steven J., and John Mark Hansen. 1993. *Mobilization, Participation, and American Democracy*. New York: Macmillan.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. 2002. "Assessing 'Neighborhood Effects': Social Processes and New Directions in Research." *Annual Review of Sociology* 28: 443–78.

Schlozman, Kay L., Sidney Verba, and Henry E. Brady. 1999. "Civic Participation and the Equality Problem." In *Civic Engagement in American Democracy*, ed. Theda Skocpol and Morris Fiorina. Washington, DC: Brookings Institution Press, 427–57.

Shaw, Daron R. 1999. "The Effect of TV Ads and Candidate Appearances on Statewide Presidential Votes, 1988–1996." *American Political Science Review* 93(2): 345–61.

Shaw, Daron R. 2006. *The Race to 270: The Electoral College and the Campaign Strategies of 2000 and 2004*. Chicago: University of Chicago Press.

Shea, Daniel M., and Michael John Burton. 2006. *Campaign Craft: The Strategies, Tactics and Art of Political Campaign Management*. 3rd ed. Westport, CT: Praeger.

Zuckerman, Alan S. 2005. *The Social Logic of Politics: Personal Networks as Contexts for Political Behavior*. Philadelphia: Temple University Press.