Untangling the Spatial Structure of Political Participation

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Abstract

This article analyzes the spatial structure of political participation in the United States using spatial econometric techniques and newly available geocoded data. Our results provide strong evidence that political participation is geographically clustered, and, moreover, that this clustering cannot be explained entirely by social networks or other individual-level characteristics such as race, income, education, or political engagement. The analysis suggests that the spatial structure of participation is consistent with a diffusion process that occurs independently from citizens' involvement in social networks.

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Political participation is a concept whose theoretical import for democratic societies requires little elaboration. Participation provides an opportunity for citizens to exercise their political voice by expressing their policy preferences. Participation is also central to the electoral process because it enables citizens to act on their preferences and to influence the selection of elected officials. The communication of citizen preferences, whether directly through legislators' rational anticipation or mediated through electoral turnover, is the engine that drives representation (Mansbridge 2003; Stimson, MacKuen, and Erikson 1995). Participation is the critical link between the citizenry and the governing process; "[p]olitical participation provides the mechanism by which citizens can communicate information about their interests, preferences, and needs and generate pressure to respond" (Verba, Schlozman, and Brady 1995, 1).

Motivated by concerns about participatory bias in the political system, scholars have frequently investigated the question of why some citizens are habitually more likely to participate than others. Such work has identified a recurring set of individual-level attributes (e.g., education, income, age, political interest, political information, political efficacy, partisan strength, and involvement with social or civic organizations) that are positively associated with higher levels of participation (Nagler 1991; Rosenstone and Hansen 1993; Verba, Schlozman, and Brady 1995).

Political scientists have become increasingly interested in exploring the role that context plays in shaping political behavior. Following in the tradition of Key (1949), Durkheim (1951), and Berelson, Lazarsfeld, and McPhee (1954), scholars have rediscovered the importance of context in shaping, for example, policy diffusion (Rom, Peterson, and Scheve 1998; Saavedra 2000), policy attitudes (Grogger and Weatherford 1995), campaign contributions (Cho

2003), voting behavior (Zuckerman 2004), and political participation (Gimpel 1999; Gimpel and Schuknecht 2003; McClurg 2003).[1]

Many participation studies have adopted an aggregate-level approach to conceptualize context in terms of a geographic unit such as a neighborhood or city. Such work demonstrates that the likelihood of citizen participation is influenced by the social composition of the neighborhood or city in which one resides (Huckfeldt 1979, 1986; Huckfeldt and Sprague 1995; Oliver 2001). Embracing a more micro-level perspective, other studies have conceptualized context in terms of an individual's social networks. This literature shows that an individual's likelihood of participating is related to the size, frequency, politicization, and heterogeneity of his discussion network, as well as to the participatory activities of those in this network (Huckfeldt and Sprague 1995; Kenny 1992; Leighley 1990; McClurg 2003; Mutz 2002). As Mutz (2002) observes, both macro- and micro-level accounts point to social interaction as the principal mechanism through which context shapes individual behavior. The social interaction thesis holds that the more citizens interact within their social environment, whether defined in geographic or informational terms, the more likely they are to be exposed to the environmental norms of participation and, consequently, to participate accordingly.

We join this lively literature by examining the spatial structure of political participation in the United States through an important but underexplored venue. In particular, we exploit recent advances in spatial econometrics to provide a more nuanced understanding of the spatial and contextual components of participation. The combination of statistical spatial methods and our large geo-coded data set gives us a unique and advantageous vantage point. Our findings extend the extant literature in three ways. First, we provide strong evidence that political participation is geographically clustered. Second, while others have established the

[1] In contrast, the "individualist" school suggests that contextual effects on political behavior should disappear once appropriate individual-level factors are controlled for (see e.g. Kelley and McAllister 1985). As we will later see, however, our analysis calls into question the assumptions underlying the "individualist" argument.

link between participation and social network or socio-economic factors, our results show that this clustering cannot be explained entirely by social network interaction or by other potentially relevant individual-level characteristics such as race, income, education, and cognitive measures of political engagement. Finally, our results suggest that the spatial structure of political participation is consistent with a diffusion process that occurs independently from citizens' involvement in social networks. Our analysis further indicates that this process is likely related to low-intensity neighborhood cues rather than to a series of alternative contextual accounts.

We begin by reviewing the social interaction theory of contextual effects and discussing the strengths and limitations of previous empirical applications. We then propose an alternative analytical strategy for understanding the spatial structure of political participation. After introducing our data and describing our modeling techniques, we present the results of a spatial autoregressive model (in the form of a spatial lag model) of participation. We conclude with a discussion of our principal findings, how they fit in and extend the literature, and an assessment of their theoretical and methodological implications.

1 The Social Interaction Theory of Contextual Effects

The leading micro-level theories of contextual effects are rooted in social interaction. Central to this social interactionist thesis is the supply and demand of political information. On the demand side, the theory is premised upon the belief that individuals value political information but that they, operating as cognitive misers, wish to obtain such information on the cheap (Huckfeldt and Sprague 1995). On the supply side, social networks are believed to provide an inexpensive means of acquiring political information. Such networks, however, are assumed to be informationally biased; that is, they are expected to provide information with an unbalanced perspective. It is through social interaction within this biased environment that individuals are believed to acquire and process much of their political information (Huckfeldt and Sprague 1995; Sprague 1982). Social interaction thus triggers a social learning process in which citizens are exposed to the prevailing sentiments of their social network. Views that are consonant with those of the social network are met with positive reinforcement while dissonant views are subject to negative reinforcement (Huckfeldt and Sprague 1995). As this social learning process continues, we expect citizens' preferences to gradually come to resemble those of their larger social network.

1.1 Social Networks

The social interactionist thesis enjoys considerable empirical support. Given the importance of information exchange under the social interactionist framework, much of the recent literature has sought to examine the degree of congruence between an individual's political attitudes and behavior with those of others in his social networks (particularly those with whom they are known to discuss politics). Weatherford (1982) was among the first to use surveys to generate information about citizens' personal political networks. By gathering information about the characteristics of individuals' political discussants, Weatherford (1982) was able to establish the characteristics of a local social network in which the exchange of political information actually occurs. More importantly, he demonstrates that several properties of these political networks have a profound influence on a citizen's political attitudes. In particular, an individual's attitude concerning social liberalism, economic liberalism, and presidential approval are all shown to be a function of the politicization, partisan composition, and homogeneity of his local political networks.

The political consequences of interaction within social networks are not limited to the domain of public opinion. Recent work suggests that social interaction may lead to contextual influences on political participation as well. Leighley (1990) reports that one is more likely to contact an elected official, to engage in campaign activities such as attending a political meeting or working for a candidate, and to engage in cooperative political activities such as signing a petition or joining a national organization as the number of discussants in one's network increases. Discussant conflict, as measured by the heterogeneity of one's social network, increases the likelihood of contacting, campaign activities, and voting, but is unrelated to cooperative activities. Politicization of the discussion network increases the likelihood of contacting and cooperative activities, but decreases the likelihood of voting and campaign activities. Leighley's (1990) findings suggest that even after controlling for a wide range of individual-level attributes, the properties of one's discussion network are still significantly related to multiple measures of political participation. In addition, McClurg (2003) finds that not only does social network interaction influence participation levels directly, it does so indirectly by conditioning the effects of individuals' resources and personal characteristics on political participation.

Mutz's (2002) recent analysis of "cross-cutting" networks sheds additional light on the consequences of social networks for political participation. Using a discussant generator to obtain data about actual exposure to cross-cutting political communication within one's social networks, Mutz (2002) reports that political participation may actually be lower among those who are embedded in heterogeneous networks, particularly in cases involving confrontational participation. Moreover, her results help to explain the process through which such heterogeneity depresses participation. Exposure to cross-cutting messages reduces the likelihood of citizen participation, she argues, by creating greater ambivalence and by increasing the perception that political action may disrupt otherwise comfortable social relationships.

1.2 Social Context

Recent empirical examinations of the social interactionist thesis have emphasized the role of discussion networks in structuring citizens' political participation (Kenny 1992; Leighley

1990; McClurg 2003; Mutz 2002; Weatherford 1982). Such studies are well positioned to show whether explicit interaction between intimates in a social network leads to contextual influences on individual behavior. Social networks, however, are but one forum through which social interaction may shape individual behavior. Social contexts, such as the neighborhood in which one lives, may also serve as a source of contextual influence by regularly providing opportunities for indirect, perhaps even involuntary, social interaction. As noted by Huckfeldt and Sprague, the distinction between contextual effects rooted in social networks and those rooted in social contexts is conspicuous and important; "it would be a gross error to believe that social interaction is politically relevant only when it occurs among intimates who interact on a voluntary basis" (1995, 10). Whether the manifestation is the display of yard signs, bumper stickers, campaign buttons, or other readily observable means, social contexts may be every bit as much of a source of information as are social networks; "[t]he influence of such information is independent of intimacy—indeed it may not even be verbally transmitted—but it is entirely reasonable that citizens may heed" (Huckfeldt and Sprague 1995, 16). Moreover, one recent study reports that citizens are able to accurately infer information about their neighbors' political and economic standing without any explicit interaction at all (Baybeck and McClurg 2004). This implies that citizens glean information from low-intensity environmental cues that do not depend on explicit interaction and are not limited to the more obvious social involvements that have attracted greater scholarly attention.

1.3 Harmonizing Divergent Themes

To be sure, we do not imply that the theoretical distinction between social contexts and social networks is lost on those who study discussion networks (Kenny 1992; Mutz 2002). Kenny (1992), for example, describes them as potentially complementary yet distinct elements of social structure. The problem is not that the literature has failed to make clear theoretical distinctions between social contexts and social networks, but, rather, that it has too often focused on analyzing the effects of one form of contextual influence to the detriment of the other. The result of these diverging but complementary tracks of research is two parallel streams of literature that focus either on social networks (Kenny 1992; Leighley 1990; McClurg 2003; Mutz 2002; Weatherford 1982) or on social context (Huckfeldt 1979, 1986; Oliver 2001), but rarely intersect (see Huckfeldt and Sprague 1995). In the analyses to follow, we propose an alternative modeling strategy for assessing the social structure of political participation. Our spatial modeling approach allows us to examine the extent to which participation is spatially structured independent of social network involvement and other individual-level attributes. In this way, we bridge the literature by examining social context within a model that also examines the effects of social networking and considering how these two divergent themes intersect.

2 Data and Measurement

To determine whether political participation is spatially structured when not allied with social network involvement, we must have both a measure of social context as well as social networks in our data. We can create a measure of social context if we are able to geocode the data. That is, if we have geographic identifiers (e.g., precinct, tract, FIPS code) for every individual, we can locate that individual in "space," thus creating a measure of social context. Such data sets tend to be few and far between for a variety of reasons. First, while nationally representative samples can provide detailed information about citizens' social networks, they generally do not allow reliable inferences to be made about the effects of social context (Kenny 1992; Leighley 1990; Mutz 2002; Weatherford 1982). Privacy concerns often restrict the release of any identifying information on the respondents. Even when such geographic information is available, these national samples often are not sufficiently concentrated to allow us to obtain context-specific estimates of neighborhood effects. There simply are not enough respondents in each geographic unit to permit reasonable estimation to proceed. Contextual data sets allow inferences to be made about the effects of social context but are typically drawn from a single city or metropolitan area such as Buffalo, NY (Huckfeldt 1979) or South Bend, IN (Huckfeldt and Sprague 1995),[2] so the generalizability of these results to the broader population is somewhat tenuous.

2.1 Social Capital Benchmark Survey

To overcome these data challenges, we make use of the Social Capital Benchmark Survey (SCBS), a recently available data set consisting of representative samples gathered from a diverse set of American communities. The SCBS contains representative samples taken from 41 subnational units, usually specific cities, counties, or metropolitan areas.[3] The large number of cities and the large number of neighboring respondents within those cities allows us to make reliable estimates of contextual effects. Given the lack of uniformity in the geographic and political boundaries across community sampling units, we follow a set of procedures recommended by Rahn and Rudolph (2002) for analyzing the SCBS data. First, we use the geo-coded information in the data to separate respondents on the basis of the specific "place" in which they live. Places are defined as "a concentration of population either legally bounded as an incorporated place, or identified by the Census Designated Place (CDP)" with a "legal description of borough, city, town, or village" (U.S. Census Bureau). Places are, in effect, municipalities with well-defined political and geographic boundaries. Second, we also constrain our data set to places with at least forty respondents to ensure a minimum threshold of respondents within each community sample. We also restrict our analysis to cities with a population of 100,000

[2] For an exception, see Oliver (2001)

[3] The SCBS data were collected by telephone interview from July–November 2000.

or more to maintain greater consistency in the size of geographical units. Our results are thus more indicative of spatial effects in relatively large American cities than in cities generally. This final population-size restriction creates a data set consisting of 6,540 individuals across 32 cities and 18 states, covering every region of the nation.[4]

2.2 Measurement and Variables

The dependent variable in our analysis is political participation, which we construct as an additive index based on individuals' responses to four questions. Specifically, respondents were asked to indicate whether, during the last twelve months, they had (1) signed a petition, (2) attended a political meeting, or rally, (3) worked on a community project, or (4) participated in any demonstrations, protests, boycotts, or marches. Our participation index thus ranges on a scale from 0 to 4, with a mean value of 1.14 and a standard deviation of 1.12. Absent from our measure of political participation is voter turnout. We exclude turnout in the present analysis for two reasons. First, the determinants of voter turnout are frequently not identical to those of other forms of participation (Rosenstone and Hansen 1993; Verba, Schlozman, and Brady 1995). Second, the measure of self-reported turnout in the SCBS is less than ideal. Because it was administered between July and November of 2000, the SCBS cannot ask about turnout in the 2000 election and is forced instead to inquire about whether respondents voted four years earlier in the 1996 presidential election.[5]

As noted above, our analysis requires individual-level measures of social network involvement. While the SCBS does not include information about individuals' involvement in dis-

[4] A complete listing of these cities is reported in the Appendix. While each city contains a random sample of voting age adults, it should be noted that the cities themselves do not constitute a representative sample of all American cities. Fortunately, however, the SCBS data also contain a nationally representative baseline survey. A comparison of the marginals from our 32-city sample with those of the national sample indicates that our sample is representative for the variables under analysis.

[5] In future work, we plan to investigate the spatial structure of voter turnout, but this unique form of participation is omitted here for simplicity, clarity, and focus.

cussion networks per se, it does include an extensive battery of items concerning their formal and informal social interactions. To capture the effects of social network involvement, we first include a measure of organized or formal social interactions. Specifically, we utilize Putnam's (2000) *macher* index. As described by Putnam (2000), the word *macher* is a Yiddish term used to refer to people who are highly involved in formal organizations and who "make things happen in the community." In the SCBS, the *macher* index is the result of a principal components analysis that includes

1. involvement in 17 types of organized social groups,
2. service as an officer on a committee,
3. frequency of attending club meetings, and
4. frequency of attending public meetings.

Secondly, we include a measure of the individual's informal social interactions, Putnam's (2000) *schmoozer* index. Putnam (2000) reserves the term *schmoozer* to describe those with high levels of informal social connectedness. In the SCBS, the *schmoozer* index is based on a principal components analysis of the regularity with which individuals

1. play cards or board game with others,
2. visit with relatives,
3. have friends over to their home,
4. socialize with coworkers outside the workplace, and
5. hang out with friends at a park, shopping mall, or other public place.

Whether social interaction and connectedness takes place in formal or informal settings, we expect it to increase the likelihood of political participation because it reduces information costs for citizens, creates social incentives to participate, and increases the likelihood that one will be targeted for mobilization (Rosenstone and Hansen 1993).[6] Indeed, a number of studies in the burgeoning social capital literature link such forms of social interaction to higher levels of political participation (Putnam 2000).

Social network involvement has been shown to be a significant factor even after one has accounted for the standard socio-economic indicators such as age, income, education as well as individual resources (Rosenstone and Hansen 1993; Verba, Schlozman, and Brady 1995). We aim to expand our understanding of the dynamic underlying political participation by further probing the abstraction behind contextual effects. Our spatial model controls for SES factors, social network involvement, race, gender, and multiple indicators of political engagement, such as political interest, political information, political efficacy, and ideological strength. Each of these indicators is expected to be positively associated with participation. Finally, we also control for level of interpersonal or social trust.

3 Spatial Modeling and Political Participation

It is clear from the extant literature that social context and spatial analyses are important for substantive reasons in the study of political participation. Theories abound for why context might matter and how the link between context and participation should be conceptualized. In addition to the social interaction thesis discussed above, another explanation of contextual effects involves the issue of political mobilization. According to this account, political elites target certain geographical units for mobilization based on the socio-demographic profiles of

[6]Such interactions are expected to be particularly consequential for participation when they involve the exchange of political information (Baybeck and McClurg 2004).

the voters. Alternatively, some scholars attribute contextual effects to a self-selection process in which similarly situated or like-minded individuals choose to live near each other. Yet another account is, of course, that these are true contextual effects arising from low-intensity environmental cues that may or may not be connected to social interaction. Indeed, the lack of consistency in the literature does not revolve around a debate about the existence of a spatial effect, but in how one might measure and interpret these spatial effects. Several different methodologies and measures have been proposed and used in these analyses. Somewhat surprisingly, spatial econometric methods and tools have yet to be fully fused and utilized with these queries that are clearly classic applications for spatial econometric techniques.[7]

Given the geographic location of our observations, spatial models allow us to examine rigorously the spatial patterning in the data. Is there spatial autocorrelation, i.e. are observations that are close in proximity somehow more closely related to each other than they are to observations that are not in close proximity?[8] Is this spatial autocorrelation linked to measured or unmeasured covariates? Or is the patterning characteristic of diffusion or contagion processes? These questions lie at the heart of the participation literature. Notably, even aside from the substantive reasons, spatial models are important for statistical reasons as well. Statistically, if spatial processes underlie the behavior of interest but are not accounted for in the model, an omitted variables problem will result. Consequently, OLS estimates of a nonspatial model

[7] Perhaps part of the reason is that although econometric texts commonly discuss issues related to autocorrelation on the time dimension, the spatial dimension has been much more neglected. Accordingly, spatial methods have not as quickly been adopted as part of the "standard" toolbox. An exception is Johnston (1984). However, issues related to spatial autocorrelation are absent from many commonly cited basic (e.g., Judge et al. (1982), Greene (1993), Poirier (1995)) and advanced econometric texts (e.g., Fomby et al. (1984), Amemiya (1985), Judge et al. (1995), Davidson and MacKinnon (1993)).

[8] Spatial autocorrelation is essentially the coincidence of value similarity with locational similarity. Spatial autocorrelation may appear in the form of positive spatial autocorrelation (high values for a random variable are clustered in space and low values are similarly clustered) or negative spatial autocorrelation (the values at various locations tend to be surrounded by dissimilar values). The existence of spatial autocorrelation is more formally defined by the moment condition,

$$\mathrm{Cov}(y_i, y_j) = \mathrm{E}(y_i, y_j) - \mathrm{E}(y_i)\,\mathrm{E}(y_j) \neq 0 \qquad \text{for } i \neq j$$

where y_i and y_j are observations on a random variable at locations i and j in space.

will result in inaccurate inferences and biased and inconsistent coefficient estimates (Anselin 1988). Hence, even if one were not interested specifically in the "spatial effect," but only in the aspatial effects, omitting the possibility of a spatial aspect from the model may affect the interpretation of the results, spatial and otherwise.

To be sure, spatial explanations do not take away from the aspatial findings that have linked the participation impetus to individual characteristics or traits, since both sets of findings can be true simultaneously. We may find, however, that the spatial explanations comprise a greater proportion of the overall explanation than we had previously thought, i.e., the non-spatial effects decline in magnitude or even disappear when viewed in light of the spatial components. If the decision-making process is mostly a function of individual traits, then in a unit-level analysis of participation rates, individual-level covariates might be significant predictors, and the spatial parameters would not be significant in the model specifications that control for these covariates. On the other hand, if the participation dynamic is primarily a diffusion process, driven by network or neighborhood effects, then the spatial parameter will be significant, while the other indicators will not be significant.

These spatially autoregressive models can be described as one of two varieties, a spatial lag model or a spatial error model, though many applications do not fit neatly in one of these two boxes (Anselin, Bera, Florax, and Yoon 1996). Spatial lag models are most appropriate when the spatial patterning is a function of the neighboring observations. Spatial error models, on the other hand, imply that the spatial patterning is the result of unmeasured covariates. Diagnostics are used to determine whether the data more closely follow a spatial lag or a spatial error specification. Erroneously ignoring spatial dependence (in the form of a spatial lag) may create bias and inconsistency in the same way that we understand the omitted variable problem to affect OLS estimates (Anselin 1988, 1990). Alternatively, when the spatial error structure is ignored, simple inefficiency is apparent in the estimates but the standard errors are biased (Anselin and Griffith 1988).

Spatial models are much like traditional models, but with an added spatial component. Building a model of political participation, then, would begin with the tried-and-true socio-economic variables (age, income, education, etc.). Certainly, many of these variables have a "spatial" component in that these variables are often clustered in space. For instance, neighborhoods can often be described by income levels. Moreover, it may very well be that after accounting for these individual-level characteristics, there is no remaining spatial patterning that can be distinguished from the spatial patterning in these covariates. In this case, there is no true spatial effect. On the other hand, if, after accounting for a whole host of variables, spatial autocorrelation remains, then the source of this spatial patterning must either result from unmeasured covariates or be a function of neighboring values.

If the spatial patterning were the result of an unmeasured variable, the spatial error model would be a relevant spatial specification, and the fit of the spatial error model or evidence of remaining spatial error dependence after fitting a spatial lag model should provide evidence for or against theories involving unmeasured variables. If the diagnostics indicate that a spatial lag model is a more appropriate specification, and the results from a spatial lag model indicated no remaining spatial error structure, then there is evidence that neighbors (as defined by the analysis) somehow drives the behavior (Anselin and Bera 1998). It is important to note here that the specific *mechanism* that produces the spatial patterns is unknown and not determinable via spatial analyses. What we can uncover are patterns that are consistent with the specific mechanisms that produce the participation patterns that we observe. This is not unlike traditional regression analyses that are also unable to establish causal links/mechanisms.

In our data analysis, the robust Lagrange Multiplier diagnostics indicated that the spatial lag specification was appropriate, and so we focus our discussion on the spatial lag model.[9] In the spatial lag model, an otherwise routine regression has an additional regressor that takes the form of a spatially lagged dependent variable, Wy. That is, the spatial lag model would take the form

$$y = \rho\, Wy + X\boldsymbol{\beta} + \epsilon, \tag{1}$$

where W is an $N \times N$ spatial weights matrix, ρ is the spatial autoregressive coefficient, ϵ is the error term, and X and $\boldsymbol{\beta}$ have the usual interpretation in a regression model. The spatial lag can be seen as the weighted average (with the w_{ij} being the weights) of its geographically-defined neighbors.[10] In this model specification, because the lag term is correlated with the error term, OLS should not be used, since it will be both biased and inconsistent (Ord 1975, Anselin 1988). Instead, the spatial lag model should be estimated via a maximum likelihood or instrumental variables formulation. The spatial lag model is most consistent with contagion theories and diffusion processes, since it provides evidence against spatial patterning due to unmeasured covariates. The explicit inclusion of the spatial lag term implies that the influence of a "neighbor's" (as defined by the weights matrix) participation level is not an artifact of measured and unmeasured independent variables, but that the level of participation of one's neighbors affects one's own likelihood of participation.[11]

[9]The general decision rule for specification in a spatial model begins with an examination of the non-robust forms of the Lagrange Multiplier tests for the spatial error and spatial lag. Both of these may be significant. In this case, one then examines the robust forms of these Lagrange Multiplier tests and bases the specification choice (either lag or error) on the robust tests. For a discussion of the robust diagnostics, see Bera and Yoon (1993) and Anselin, Bera, Florax, and Yoon (1996). On the non-robust forms, one may also see Burridge (1980). Bera and McKenzie (1986) discuss the invariance of the non-robust diagnostics to different alternatives.

[10]Our weights matrix was created using a distance-based definition for neighbors. We are able to locate individuals in "space" because our data identify the census tract in which the individual resides. We defined an individual's neighbor as anyone living within a two-mile radius of that individual. This calculation was made from the centroid of a census tract to the centroid of other census tracts. Importantly, this allows us to analyze the effects of geographic distance both within and across cities.

[11]The evidence of a diffusion or contagion effect is indirect. The spatial regression models cannot identify the specific mechanism that produces the spatial effects. Instead, the value added is that if the observed phenomenon

4 Empirical Results

The results from our spatial analyses are reported in Table 1. Column 1 lists the results from the spatial lag model without either one of Putnam's social capital measures, formal or informal. The model in column 2 includes the measure of organized involvement, but not the measure of informal involvement. The model in column 3 omits the organized involvement variable, but includes the informal involvement variable. Lastly, the model in column 4 includes both of Putnam's social capital measures.

[Table 1 about Here]

As we might expect, the political engagement variables are all highly significant and positive across the models in all four columns. Substantively, these coefficients indicate that participation rates are higher among the politically interested, the politically efficacious, the politically informed, and those who are more ideologically extreme. In short, the more politically engaged one is, the more likely one is to participate. This confirms a long line of research and is not earth-shattering news. As well, there are few surprises in the estimated relationship between participation and the three resource variables or the five variables measuring race and gender. Confirming previous research, education, income, and interpersonal trust are particularly influential determinants of political participation.

Our main consideration, however, is not to confirm or disprove previous findings, but to fine-tune the conceptualization of social context in studies of political participation. In our models, then, apart from the political engagement, resource, and individual characteristics, we are more interested in the effects of the two social involvement variables and the effects of the spatial lag

were actually characterized by a diffusion process, then we would expect to see these spatial imprints emerge. The discovery of spatial effects, then, behooves future research to place some emphasis on uncovering the mechanisms that would produce diffusion. Note that this situation is not unlike other regression models where the evidence for the casual mechanism is also indirect.

parameter. Consider first the effects of social involvement. The coefficients for both organized involvement and informal involvement are both positive and statistically significant. Whether it is organized or informal, social involvement clearly contributes positively to participation. Notably, the coefficient representing organized social involvement is substantially larger than the coefficient representing informal social involvement. By comparing across data columns, we also note that the inclusion of the organized social involvement variable appears to improve the fit of the model much more than the addition of the informal social involvement variable. Collectively, these two patterns suggest that political participation is more strongly related to one's involvement in organized social groups than to informal forms of social involvement. However, both types of involvement are significant as we can see from the Log Likelihood values that indicate that the model which fits best among these four is the model with both of Putnam's social capital measures. Consistent with the work of Mutz (2002), McClurg (2003), Leighley (1990), and others, social involvement and social networking are plainly components of the social context abstraction.

Consider next the effects of the spatial lag parameter. Recall that the spatial lag parameter is an indicator for whether the spatial structure of participation is primarily driven by a diffusion process or alternatively, can be attributed to the spatial structure embedded within the independent variables. Despite controlling for a number of individual-level factors, Table 1 shows that the spatial lag parameter remains positive and highly significant in all model specifications. This implies that an individual's likelihood of participating in politics is strongly and positively related to the participation level of his neighbors. More importantly, this result also implies that the spatial autocorrelation we observe sits apart from the spatial clustering associated with any of the covariates in our model. In other words, the spatial structure of political participation is independent of any spatial structure evident in citizens' social involvement, political engagement, socio-economic attributes, race, and gender. Given that similarly situated people often reside in close proximity to one another, our independent variables likely account for considerable spatial autocorrelation, and so this result is far from intuitive. Even after we account for the fact that high income/education/resource etc. individuals behave similarly to other similarly situated individuals, the extent of the spatial structuring has not been depleted.

An important consideration in interpreting these models is the Lagrange Multiplier test for residual autocorrelation.[12] This statistic measures whether, after incorporating the spatial lag variable in the model, the residuals from the spatial lag model still indicate that some spatial structure remains in the data. If it does, then there would be evidence that some of the remaining spatial structure is the result of unmeasured variables. In our models, the Lagrange Multiplier test statistic for residual autocorrelation is insignificant in all instances, indicating that the spatial autocorrelation is sufficiently accounted for by the spatial lag variable. In other words, we have evidence that the spatial autocorrelation in the data is the result of the influence of the behavior of one's neighbors. We emphasize that it is not the result of a failure to capture the effects of some unmeasured variables that might be spatially clustered.

What unmeasured variables are potentially relevant when analyzing the spatial structure of political participation? One leading possibility would be city-level factors. City-level factors are inherently geographically clustered. Moreover, a growing body of literature suggests that citizen participation is a function of city-level attributes, such as racial heterogeneity, income inequality, and size of city (Alesina and LaFerrara 2000; Costa and Kahn 2003; Oliver 2001). While our results do *not* imply that such factors have no influence on citizen participation, they do suggest that such factors are not responsible for the *spatial autocorrelation* observed in our data. Political mobilization would also fall into this category, as would media markets,

[12]For a discussion of this test statistic, see Anselin and Bera (1998).

electoral competition, and any unmeasured variable that is not perfectly correlated with distance between neighbors.[13] In this way, the insignificance of the Lagrange Multiplier test for residual autocorrelation is perhaps one of our most important findings because it allows us to rule out many competing mechanisms as the source of the spatial patterning in political participation.[14]

Our primary interest here is in detangling the spatial component of political participation, and not in developing a theory on how all components, spatial and otherwise, affect participation. Since the Lagrange Multiplier statistic testing for residual spatial autocorrelation is not significant in our spatial lag specification, the implication is that the *spatial* effects in our data are not the result of omitted variables in our model specification.[15] Hence, there is no need to explore other context-level indicators to persuade us that our model is well-specified in the spatial sense. While we may not have included all variables that affect political participation,

[13] The spatial patterning in the data is also unlikely to be the result of self-selection in residency for two reasons. First, self-selection is typically thought to be based on socio-demographic factors, something our model controls for directly. Second, some may argue that similarly situated people (on the SES continuum) are more likely to interact. We also control for social interaction.

[14] Note that this is not the one-directional Lagrange Multiplier test that is designed to test a single specification assuming correct specification for the remainder of the model. That test would result in unwanted "power" due to the presence of local lag dependence. Instead, in our specification, we have already noted the presence of a significant spatial lag effect. Accordingly, valid statistical inference needs to take this lag dependence into account when testing for error dependence. The specification of this Lagrange Multiplier statistic tests for error misspecification in a model with a lag term present, based on the residuals of a maximum likelihood estimation of the spatial lag model. For details of this test, see Anselin and Bera (1998). The insignificant test statistic provides evidence that we have sufficiently accounted for the spatial autocorrelation with the spatial lag term. In other words, the error term (a measure of the effects of variables omitted from the model) contains no remaining spatial autocorrelation and so we have evidence that the spatial autocorrelation in the data is not the result of unmeasured variables, but is sufficiently captured by the spatial lag term.

[15] More formally, we are testing the null hypothesis $H_0 : \lambda = 0$ (where λ is the spatial error term) in the presence of ρ (the spatial lag term). We base this test on the residuals of a maximum likelihood estimation of the spatial lag model. The resulting statistic is

$$\mathrm{RS}_{\lambda|\rho} = \frac{\hat{d}_\rho^2}{T_{22} = (T_{21A})^2 \, \widehat{\mathrm{Var}}(\hat{\rho})}$$

where W_1 and W_2 are the spatial weights matrices associated with the spatially lagged dependent variable and the spatial autoregressive disturbances, respectively (here, assumed to be the same), the "hat" denotes quantities that are evaluated at the maximum likelihood estimates of the model $Y = \rho W_1 y + X\beta + \xi$, $T_{21A} = \mathrm{tr}[W_2 W_1 A^{-1} + W_2' W_1 A^{-1}]$, $T_{22} = \mathrm{tr}[(W' + W)W)]$, and $A = I = \hat{\rho} W_1$.

we have evidence that the *spatial component* of political participation is not a result of included or omitted variables in our model. Instead, it is linked to the behavior of one's neighbors.

The results presented provide strong evidence that the spatial structure of participation is consistent with a theory of diffusion or contagion. Our finding that political participation is spatially structured may strike some readers as unexceptional. Our evidence that this spatial structure is consistent with a diffusion process may also strike some as not exceptionally noteworthy. However, what is clearly exceptional is our demonstration that this diffusion process exists *independently* of citizens' social involvement, political engagement, interpersonal trust, resources, race, and gender. Although many of our independent variables are spatially clustered, the spatial clustering in our explanatory variables does not drive the spatial structure of participation. Even more notably, the spatial clustering of any unmeasured variables is not the culprit driving the display of spatial autocorrelation in participation rates. In short, social context matters independent of variables that are included *or excluded* from our model. Strikingly, these results help us detangle and fine-tune the conceptualization of social context in studies of political participation.

What is the nature of this diffusion process? The answer is the same as the answer to what the spatial lag is actually measuring. As noted above, we can rule out many obvious suspects (e.g. city-level factors, political mobilization, media markets, etc.), but identifying the precise mechanism is a task for future research. One promising possibility is the effect of low-intensity cues that do not rely on explicit social interaction. These cues may well be local sources of socialization that are in the general vicinity, but not specifically associated with an individual's formal or informal networks. So, our spatial lag may be capturing general environmental cues that are not absorbed by Putnam's instrumentation, but are nonetheless powerful influences on political participation. Indeed, even misanthropes are not insulated from the effects of context.

5 Discussion

In recent years, the participation literature has underscored the importance of context as a determinant of citizens' political participation. Such contextual effects have typically been explained either in terms of the contextual composition of one's city or neighborhood or in terms of one's social network involvement. We harmonize these divergent themes in the literature by simultaneously modeling participation as a function of both social context and social network involvement. We confirm some previous studies and find that both social context and social network involvement are importantly related to citizen participation. At the same time, our study expands our understanding of how these two concepts interact and intertwine to define the social context abstraction. Our results can be separated into three streams.

First, our results provide strong evidence that participation is geographically clustered. In other words, citizens' participatory behavior is heavily influenced by the participatory behavior of those who live in close proximity to them. This finding is consistent with previous research that demonstrates a link between social context and political participation (Huckfeldt 1979, 1986; Huckfeldt and Sprague 1995; Oliver 2001). While we are certainly not the first to show that social context influences participation, previous studies have too often been limited by narrow research designs that examine only a single city or metropolitan area and, equally as important, by a failure to account for spatial autocorrelation in the data. Our research remedies both of these deficiencies.

Our finding that citizens' participation is shaped by those around them is, in many ways, also consistent with previous research on the effects of social network involvement. Analysts of social networks have repeatedly shown that the composition of one's network is politically consequential. There is considerable disagreement, however, concerning the directional implications of network composition for participatory behavior. While some studies find that contextual homogeneity increases the likelihood of participation (Mutz 2002), others suggest that contextual homogeneity is inversely related to participation (Leighley 1990). The Moran's I statistic (Moran 1948, 1950a, 1950b) in our analysis was positive and significant, which indicates that participation rates in nearby areas are similar whether the rate is high or low.[16] That the Moran's I statistic is significant implies that our results can be distinguished from spatial randomness where high and low participation rates would be found in close proximity with no distinguishable spatial patterning. It also implies that the directional implications of contextual homogeneity are unlikely to be constant across situational contexts. When an individual is situated in a homogenous context in which participation is high, that individual's likelihood of participating will increase. When an otherwise identical individual is situated in a homogeneous context in which participation is low, that individual's likelihood of participating will decrease. With respect to levels of political participation, then, the directional effects of contextual homogeneity are not uniform and should be expected to vary across situational context. Such variation, we believe, by unifying some of the seemingly discrepant findings in the literature (e.g. Leighley 1990; Mutz 2002), helps us recalibrate the conceptualization of social context.

Secondly, we find that the geographical clustering of participation in our data cannot be attributed to variables that were included (i.e. social network involvement, race, political en-

[16] Moran's I (1950a, 1950b) was originally proposed as a simple test for correlation between nearest neighbors, a generalization of one of his earlier tests (1948). It was a two-dimensional analog of the test of significance of the serial correlation coefficient in univariate time series. Cliff and Ord (1972, 1973) formally presented Moran's I as

$$I = \frac{N}{S_0}\left(\frac{e'We}{e'e}\right)$$

where $e = y = X\boldsymbol{\beta}$ is a vector of OLS residuals, $\boldsymbol{\beta} = (X'X)^{-1}X'y$, W is a matrix of spatial weights, N is the number of observations, and $S_0 = \sum_i \sum_j w_{ij}$ is a standardization factor equal to the sum of the spatial weights. If the weights are row-standardized, Moran's I simplifies to

$$I = \frac{e'We}{e'e}$$

.

gagement, resources, gender) or omitted from our model (i.e. political institutions, ideological heterogeneity, income inequality, or other city-level factors). In arguing that these micro- and macro-level variables do not account for the spatial structure of participation, we do *not* imply that they are unrelated to participation. Clearly, as our own results attest, social network involvement is strongly and positively related to citizen participation. Similarly, there are a growing number of city-level factors that may be associated with levels of citizen participation (see e.g. Alesina and LaFerrara 2000; Costa and Kahn 2003; Oliver 2001). However, the diagnostics from our spatial lag model provide evidence that such factors are not underlying the *spatial* patterns observed in our data. Instead, participation rates are strongly affected by the *participatory behavior* of neighbors, not in terms of other variables that sometimes exhibit geographic clustering.

Lastly, our results show that the spatial structure of participation is consistent with a diffusion or contagion process. Our contribution here lies not in arguing that contextual effects may occur through a diffusion process; others have suggested as much (Huckfeldt and Sprague 1995). Rather, our contribution lies in establishing that this diffusion process exists *independently* from social network involvement and a wide range of other individual-level attributes, allowing us to refine the conceptualization of social context and its link with political participation. The implication of this result is that, with respect to political participation, geographical proximity matters in ways that are not sufficiently accounted for by existing theories of contextual effects and the mechanisms are likely characteristic of diffusion processes. Psychologically, our results also imply that the genesis and spread of ideas is not wholly dependent upon communication with other people. Simply observing those around us, but not communicating with them, may be how we pick up many of our ideas, a point that is often unacknowledged in the literature because adult life seems to revolve so much around social communication.

In many ways, it is impossible to pin down exactly why diffusion occurs. However, our analysis has identified spatial imprints consistent with diffusion and helped us to rule out a number of competing theories for why it might occur and to narrow our search for a mechanism. What has emerged is a leading theory that diffusion works through low-intensity environmental cues. This aspect of political participation is understudied, but apparently unduly so. Rather, this may be the most exciting research path in the quest to understand how context and political participation intersect.

Table 1: **Spatial Lag Models of Political Participation**

	Model 1	**Model 2**	**Model 3**	**Model 4**
Political Engagement				
Political Interest	0.212***	0.154***	0.208***	0.153***
	(0.012)	(0.011)	(0.012)	(0.011)
Political Information	0.057***	0.047***	0.062***	0.049***
	(0.009)	(0.008)	(0.009)	(0.008)
Ideological Strength	0.012***	0.015***	0.018***	0.015***
	(0.005)	(0.004)	(0.004)	(0.004)
Political Efficacy	0.048***	0.028***	0.046***	0.028***
	(0.004)	(0.004)	(0.004)	(0.004)
Resources				
Education	0.019***	0.010***	0.020***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Income	0.012***	0.004*	0.011***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.002***	-0.002***	-0.0009***	-0.002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Race and Gender				
Black	0.024**	0.004	0.033***	0.006
	(0.010)	(0.009)	(0.010)	(0.008)
Hispanic	-0.018	-0.005	-0.002	-0.001
	(0.012)	(0.010)	(0.012)	(0.010)
Asian	-0.056***	-0.027*	-0.044**	-0.024
	(0.017)	(0.016)	(0.017)	(0.016)
Other	0.051***	0.046***	0.051***	0.046***
	(0.018)	(0.016)	(0.017)	(0.016)
Female	0.021***	0.015**	0.019***	0.014**
	(0.007)	(0.006)	(0.007)	(0.006)
Social Capital				
Organized Involvement	—	0.112***	—	0.114***
		(0.003)		(0.003)
Informal Involvement	—	—	0.056***	0.017***
			(0.006)	(0.005)
Interpersonal Trust	0.032***	0.026***	0.030***	0.025***
	(0.008)	(0.007)	(0.007)	(0.007)
Intercept	-0.183***	-0.001	-0.205***	-0.012***
	(0.023)	(0.021)	(0.022)	(0.021)
Spatial Lag (ρ)	0.161***	0.167***	0.158***	0.166***
LM Test for residual autocorrelation	0.391	2.126	0.166	2.092
Log Likelihood	-137.87	431.54	-86.61	436.86
Number of Cases	5296	5296	5296	5296

Source: Social Capital Benchmark Survey (2000).
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$, two-tailed

Table A.1. Cities Analyzed by Population Sizes

Cities	Population Size
Los Angeles, California	3,694,820
Chicago, Illinois	2,896,016
Houston, Texas	1,953,631
Phoenix, Arizona	1,321,045
San Diego, California	1,223,400
Detroit, Michigan	951,270
San Jose, California	894,943
Indianapolis, Indiana	781,870
San Francisco, California	776,733
Boston, Massachusetts	589,141
Seattle, Washington	563,374
Denver, Colorado	554,636
Charlotte, North Carolina	540,828
Cleveland, Ohio	478,403
Atlanta, Georgia	416,474
Mesa, Arizona	396,375
Minneapolis, Minnesota	382,618
Cincinnati, Ohio	331,285
St. Paul, Minnesota	287,151
Birmingham, Alabama	242,820
Baton Rouge, Louisiana	227,818
Greensboro, North Carolina	223,891
Rochester, New York	219,773
Glendale, Arizona	218,812
Fremont, California	204,413
Grand Rapids, Michigan	197,800
Winston-Salem, North Carolina	185,776
Knoxville, Tennessee	173,890
Syracuse, New York	147,306
Sunnyvale, California	131,760
Manchester, New Hampshire	107,006
Santa Clara, California	102,361

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