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Emanating Political Participation: Untangling the Spatial Structure Behind Participation

WENDY K. TAM CHO AND THOMAS J. RUDOLPH*

This is an analysis of the spatial structure of political participation in the United States using spatial econometric techniques and newly available geo-coded data. The results provide strong evidence that political participation is geographically clustered, and that this clustering cannot be explained entirely by social network involvement, individual-level characteristics, such as race, income, education, cognitive forms of political engagement, or by aggregate-level factors such as racial diversity, income inequality, mobilization or mean education level. The analysis suggests that the spatial structure of participation is consistent with a diffusion process that occurs independently from citizens' involvement in social networks.

Political participation is the critical link between a nation's citizenry and the governing process; it 'provides the mechanism by which citizens can communicate information about their interests, preferences, and needs and generate pressure to respond.'[1] Motivated by concerns about the potential consequences of participatory biases, scholars have devoted considerable attention to the question of why some citizens are habitually more likely to participate than others. The literature has identified a recurring set of *individual-level* attributes (for example, education, income, age, political interest, political information, political efficacy and civic engagement) that are associated with higher levels of participation.[2] Increasingly, scholars are also underscoring the important role that *context* plays in shaping political participation.[3]

Moreover, there is a growing recognition that political participation is spatially or geographically clustered.[4] Simply put, individuals are more likely to participate if those around them are likely to participate. Nonetheless, while few contest the assertion that context is politically consequential, there is less consensus about the mechanisms through

* Department of Political Science and National Center for Supercomputing Applications at the University of Illinois at Urbana-Champaign; and Department of Political Science at the University of Illinois at Urbana-Champaign, respectively. The authors wish to thank Luc Anselin, Zachary Elkins, Brian Gaines, Jim Gimpel, Jude Hays, Jim Kuklinski and Stephen Weatherford for helpful comments.

[1] Sidney Verba, Kay Lehman Schlozman and Henry E. Brady, *Voice and Equality: Civic Voluntarism in American Politics (*Cambridge, Mass.: Harvard University Press, 1995), p. 1.

[2] Steven J. Rosenstone and John Mark Hansen, *Mobilization, Participation, and Democracy in America* (New York: Macmillan, 1993); Verba, Schlozman and Brady, *Voice and Equality*.

[3] Robert Huckfeldt, *Politics in Context: Assimilation and Conflict in Urban Neighborhoods* (New York: Agathon, 1986); Robert Huckfeldt and John Sprague, *Citizens, Politics, and Social Communication: Information and Influence in an Election Campaign* (New York: Cambridge University Press, 1995); James G. Gimpel, *Separate Destinations: Migration, Immigration, and the Politics of Places* (Ann Arbor: University of Michigan Press, 1999); Scott D. McClurg, 'Social Networks and Political Participation: The Role of Social Interaction in Explaining Political Participation', *Political Research Quarterly*, 56 (2003), 449–64; Diana Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation', *American Journal of Political Science*, 46 (2002), 838–55.

[4] Robert Huckfeldt, Eric Plutzer and John Sprague, 'The Alternative Contexts of Political Behavior: Churches, Neighborhoods, and Individuals', *Journal of Politics*, 55 (1993), 365–81; Carol Kohfeld and John Sprague, 'Racial Context and Voting Behavior in One-party Urban Political Systems', *Political Geography*, 14 (1995), 543–69; Gimpel, *Separate Destinations*.

which context matters. Why do individuals' participatory tendencies tend to reflect those of their surrounding environment? What accounts for this spatial structure underlying political participation? Exploiting recent advances in spatial econometrics, we offer new theoretical insight into these important questions and provide a more nuanced understanding of the spatial and contextual components of participation.

The spatial structure of political participation is potentially explained by a number of alternative theoretical accounts. A self-selection process, in which similarly situated or like-minded individuals choose to live near each other, is a possible explanation. A second possibility is that spatial patterns result from elite-driven processes in which political elites target certain geographical regions for mobilization. A third, and perhaps the leading theory of contextual effects is rooted in the social interaction thesis that holds that the more citizens interact within their social environment, the more likely they are to be exposed to environmental norms of participation and, consequently, to participate accordingly.[5] A fourth and, in our view, underappreciated theory of contextual effects may be termed casual observation. Under this account, spatial proximity shapes behaviour through low-intensity neighbourhood cues that occur outside the realm of voluntary or explicit forms of social interaction.

In the analyses to follow, we examine the spatial structure of political participation in the United States by combining spatial econometric methods with a geo-coded dataset. These techniques enable us, for the first time, to adjudicate between these alternative accounts of the spatial structure of participation. Our results extend the extant literature in three ways. First, we provide strong evidence that political participation is geographically clustered. Secondly, and more innovatively, our results show that this clustering cannot be explained entirely by social network interaction, individual-level characteristics (such as race, income, education, political efficacy), or aggregate-level factors (such as mobilization, racial diversity, income inequality, mean education level). Finally, our results suggest that the spatial structure of participation is consistent with a diffusion process that begins at a core and spreads or propagates itself to neighbouring areas. This diffusion process works independently from citizens' involvement in social networks and points to the critical role that low-intensity neighbourhood cues play in explaining the spatial structure of participation.

We begin by discussing competing theories of contextual effects and contrasting their empirical predictions. We then propose an alternative analytical strategy for understanding the spatial structure of political participation. After introducing our data and describing our modelling techniques, we present the results of a spatial autoregressive participation model. 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.

MECHANISMS OF CONTEXTUAL INFLUENCE

Self-Selection

Residential segregation whether by race or economic status is an unfortunate but common reality.[6] Whether driven by discrimination, economic constraints or in-group

[5] Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

[6] Douglas S. Massey and Nancy Denton, *American Apartheid: Segregation and the Making of the Underclass* (Cambridge, Mass.: Harvard University Press, 1993); Douglas S. Massey and Eric Fong, 'Segregation and Neighborhood Quality: Blacks, Asians and Hispanics in the San Francisco Metropolitan Area', *Social Forces*, 69 (1990), 15–32.

pride, many Americans choose to reside near those of similar social status. This self-selection process must be considered as one possible explanation of the spatial dependence of political participation. The reason is that certain individual-level factors that help to determine residential choice, particularly income and race, are also important predictors of participation.[7] If people are, in effect, choosing to live near those with similar participatory tendencies, then what appear to be contextual effects may actually be the result of citizens choosing 'reinforcing social environments'.[8]

The self-selection thesis suggests that contextual effects arise from a self-sorting mechanism in which people make residential decisions based on individual-level criteria. This implies that whatever spatial dependence exists between individuals is due to that same set of criteria and creates a set of expectations concerning the spatial structure of political participation. In particular, the spatial dependence that is created by self-selecting behaviour should be concentrated in one of two types of variables. The first is in the individual-level traits that would cause the clustering we observe. The second is in our social interaction variables, since like-minded individuals tend to have more interaction with each other. If we do observe additional spatial dependence after taking these selection criteria into account, then self-selection may be part of the story but does not define the mechanism through which context shapes participation.

Elite-driven Processes

Mobilization has long been recognized as an important determinant of political participation. Partisan elites often attempt to mobilize citizens by selectively targeting certain types of people, since individuals who have been contacted by a party are far more likely to participate in political activities than those who have not been contacted.[9] Moreover, it is simplest to do such targeting geographically through media markets or within the confines of areal boundaries. Campaigns employ a similar strategy, often targeting battlegrounds or places with multiple or highly contested campaigns.[10] Highly contested races and the bulk of campaign activity are, with rare exception, geographically clustered. As a result, any spatial dependence in individuals' participatory tendencies may be driven by mobilization. If contextual effects are solely mediated by mobilization, then we should not expect to observe any spatial dependence between individuals' likelihood of participating after taking mobilization into account.

Social Interaction

At the core of the social interaction 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.[11] On the supply side, social networks are believed to provide an inexpensive means of acquiring political information. Such networks, however, are assumed to be

[7] Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*.
[8] Robert Huckfeldt, *Politics in Context: Assimilation and Conflict in Urban Neighborhoods* (New York: Agathon, 1986).
[9] Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*.
[10] Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*.
[11] Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*.

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.[12] 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.[13] As this social learning process continues over time, citizens' participatory tendencies should gradually meld with those of their social environment.

The social interaction thesis enjoys considerable empirical support. From a macro-level perspective, some have found that the likelihood of citizen participation is influenced by the social, economic and racial composition of the neighbourhood or city in which he or she resides.[14] From a micro-level perspective, others have emphasized the role of discussion networks in structuring citizens' political participation.[15] This literature has shown that individuals' participatory tendencies are related to several properties of the social network in which they are involved, including its size, politicization and heterogeneity.[16] Moreover, McClurg reports that social network involvement also has indirect effects by conditioning the impact of individuals' resources and personal characteristics on their likelihood of participating.[17] As noted by Mutz, both macro-level and micro-level approaches point to social interaction as the principal mechanism through which context shapes individual behaviour.[18] The social interaction thesis thus carries distinct implications for the spatial structure of political participation. If contextual effects are mediated primarily through social interaction, then we should observe little or no evidence of spatial patterning in individuals' participatory tendencies once their social network involvement is taken into account.

Casual Observation

Much of the literature presumes that contextual influences on participation are mediated through explicit forms of social interaction such as involvement in voluntary associations or discussion networks. Organized social networks, however, are but one forum through

[12] Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*; John D. Sprague, 'Is There a Micro Theory Consistent with Contextual Analysis?' in Elinor Ostrom, ed., *Strategies of Political Inquiry* (London: Sage, 1982), pp. 99–121.

[13] Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*.

[14] Robert Huckfeldt, 'Political Participation and the Neighborhood Social Context', *American Journal of Political Science*, 23 (1979), 579–92; Huckfeldt, *Politics in Context*; Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*; J. Eric Oliver, *Democracy in Suburbia* (Princeton, N.J.: Princeton University Press, 2001).

[15] Christopher B. Kenny, 'Political Participation and Effects from the Social Environment', *American Journal of Political Science*, 36 (1992), 259–67; Jan E. Leighley, 'Social Interaction and Contextual Influences on Political Participation', *American Politics Quarterly*, 18 (1990), 459–75; McClurg, 'Social Networks and Political Participation'; Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

[16] Ronald La Due Lake and Robert Huckfeldt, 'Social Capital, Social Networks, and Political Participation', *Political Psychology*, 19 (1998), 567–84; Leighley, 'Social Interaction and Contextual Influences on Political Participation'; McClurg, 'Social Networks and Political Participation'; Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

[17] McClurg, 'Social Networks and Political Participation'.

[18] Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

which social interaction may shape individual behaviour. Indeed, as noted by Huckfeldt and Sprague, '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.'[19] Geographic contexts may also facilitate contextual influence by regularly providing opportunities for indirect, perhaps even involuntary, social interaction through what has been called 'the slow drip of everyday life'.[20] Although it does involve some degree of interaction with one's environment, this subtle mechanism of involuntary influence might be more appropriately termed casual observation. Casual observation exposes citizens to meaningful information through low-intensity neighbourhood cues such as the display of yard signs, bumper stickers, or simple observations and biases created by how neighbours dress and behave, what types of cars they drive, or how well their garden is groomed. Such low-intensity cues may influence behaviour by subtly communicating information about the prevailing norms and sentiments within a community. In particular, they may provide signals about a local community's political culture and ethic[21] or the nature and distribution of political preferences within that community.[22] The distinction between contextual effects rooted in social networks and those rooted in casual observation is conspicuous and important. In the latter process, the influence of environmental cues is 'independent of intimacy – indeed it may not even be verbally transmitted but it is entirely reasonable that citizens may heed'.[23]

For casual observation to serve as an important mechanism of contextual influence, individuals must demonstrate some political awareness of their geographic context that is independent of their involvement in social networks. Importantly, recent research demonstrates that citizens are able accurately to infer information about their neighbours' political and economic standing without any explicit interaction at all.[24] This implies that citizens are able to glean information from low-intensity environmental cues that do not depend on explicit interaction and that are not limited to the more obvious social involvements that have attracted greater scholarly attention.[25] That casual observation potentially plays such an instrumental role in explaining the spatial structure of political participation should not be surprising given the importance of 'weak ties' in the diffusion of new information.[26]

The casual observation thesis creates clear expectations regarding the spatial dependency of political participation. Minimally, it implies that geographic context, in the form of spatial proximity, will influence an individual's likelihood of participating. Citizens' participatory tendencies should be influenced by those of people who live near them. Beyond simple proximity, however, the casual observation thesis anticipates that the influence of geography will persist even after controlling for all potential contextual

[19] Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*, p. 10.

[20] Brady Baybeck and Scott D. McClurg, 'What Do They Know and How Do They Know It? An Examination of Citizen Awareness of Context', *American Politics Research*, 33 (2005), 492–520.

[21] Bernard R. Berelson, Paul F. Lazarsfeld and William N. McPhee, *Voting: A Study of Opinion Formation in a Presidential Campaign* (Chicago: University of Chicago Press, 1954).

[22] David E. Campbell, 'Community Heterogeneity and Participation' (paper presented at the annual meeting of the Midwest Political Science Association, 2004).

[23] Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*, p. 16.

[24] Baybeck and McClurg, 'What Do They Know and How Do They Know It?'

[25] Robert D. Putnam, *Bowling Alone: The Collapse and Revival of American Community* (New York: Simon and Schuster, 2000).

[26] Mark S. Granovetter, 'The Strength of Weak Ties', *American Journal of Sociology*, 78 (1973), 1360–80.

influences. Participatory norms are expected to spread not through explicit social interaction, but through the diffusion of low-intensity cues.

DATA AND MEASUREMENT

To determine how political participation is spatially structured, we must be able to locate individuals in 'space'. Geo-coded datasets are in short supply, though becoming much more prevalent. Privacy concerns often restrict the release of any identifying information on respondents. Even when such geographic information is available, national samples do not typically provide enough respondents in each contextual unit to permit analysts to obtain reliable estimates of context-specific effects. Contextual datasets allow inferences to be made about the effects of geographic context but are often drawn from a single city or metropolitan area, which may limit their generalizability.[27] We overcome these difficulties by using the Social Capital Benchmark Survey (SCBS), a recently available dataset consisting of representative samples gathered from a diverse set of American communities. The SCBS contains representative samples taken from forty-one subnational units, usually specific cities, counties or metropolitan areas.[28] The large number of cities and respondents within those cities allows us reliably to estimate contextual effects by supplying an ample number of respondents across and within contextual units. To establish uniformity of geographic and political boundaries across community sampling units in the SCBS data, we follow a set of procedures recommended by Rahn and Rudolph.[29] First, we use the geo-coded information in the data to separate respondents by 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' (US Census Bureau). Places are, in effect, municipalities with well-defined political and geographic boundaries. Secondly, we also constrain our dataset 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 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. These restrictions produce a dataset consisting of over 5,000 individuals across thirty-two cities and eighteen states, covering every region of the nation.[30]

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

[27] For an exception, see Oliver, *Democracy in Suburbia*.

[28] The SCBS data were collected by telephone interview in July–November 2000.

[29] Wendy M. Rahn and Thomas J. Rudolph, 'A Tale of Political Trust in American Cities', *Public Opinion Quarterly*, 69 (2005), 530–60.

[30] 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.

project, or (4) participated in any demonstrations, protests, boycotts or marches. Our participation index thus ranges on a scale from 0 to 4.[31]

To test the social interaction thesis, we require individual-level measures of social network involvement. While the SCBS does not include information about individuals' discussion 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 *macher* index, which was created through a principal components analysis of four indicators: (1) a count of respondents' involvement in eighteen social groups, (2) whether they had served as an officer or on a committee in one of those groups, (3) frequency of attending club meetings, and (4) frequency of attending public meetings. We also capture the effects of social network involvement by including a measure of informal social connectedness, Putnam's *schmoozer* index.[32] In the SCBS, the *schmoozer* index was calculated as the mean standardized response to five questions concerning the frequency with which respondents (1) play cards or board games with others, (2) visit relatives, (3) have friends over to their home, (4) socialize with fellow workers outside the workplace, and (5) hang out with friends at a park, shopping mall or other public place. Whether social interaction and connectedness take place in formal or informal settings, we expect them to increase the likelihood of participation because they reduce information costs, create social incentives to participate and increase the likelihood that a participant will be targeted for mobilization.[33] A principal issue in our analysis, however, is not whether social network involvement influences the likelihood of participation, but whether it explains the spatial structure of participation.

In addition to social network involvement, the spatial structure of participation may be driven by self-selection, elite-driven processes, or casual observation. To account for self-selection and elite-driven processes, we control for several determinants of participation that might also be linked to decisions concerning residential choice and mobilization. At the individual level, our model controls for education, income, age, race, gender, interpersonal trust and multiple measures of political engagement, such as political interest, political information, political efficacy and ideological strength.[34] At the aggregate level, we control for cities' level of education, racial diversity, income inequality and for whether a gubernatorial election was ongoing at the time of interview.[35] To capture

[31] The mean of the variable is 1.14, and the standard deviation is 1.12. In our analysis, we rescale this variable from 0 to 1. Absent from our measure of political participation is voter turnout. Our decision to exclude turnout was based primarily on measurement grounds. The instruments measuring petition, rally, march and project all asked whether respondents had engaged in such activities during the last twelve months. Since the 2000 SCBS was a pre-election survey, the turnout instrument had a very different time horizon, asking respondents whether they had voted four years prior in 1996. Additionally, some work suggests that the determinants of turnout are not always identical to those of other forms of participation. See Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*; Verba, Schlozman and Brady, *Voice and Equality*.

[32] Putnam, *Bowling Alone*; Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*.

[33] Putnam, *Bowling Alone*.

[34] Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*; Verba, Schlozman and Brady, *Voice and Equality*.

[35] Alberto Alesina and Eliana La Ferrara, 'Participation in Heterogeneous Communities', *Quarterly Journal of Economics*, 115 (2000), 847–904; Huckfeldt, *Politics in Context*; Oliver, *Democracy in Suburbia*; Rosenstone and Hansen, *Mobilization, Participation, and Democracy in America*.

the effect of low-intensity cues, we examine the spatial parameters of our model, a process we describe in detail in the following sections.

SPATIAL MODELLING 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 as to why context might matter and how the link between context and participation should be conceptualized. We have categorized these theories into four sets: self-selection, elite-driven processes, social interaction and casual observation. Notably, the lack of consensus in the literature does not revolve around the existence of a spatial effect, but in how to distinguish the various explanations that underlie these effects. The ability to measure and interpret the forces that simultaneously define these spatial effects is a key element lacking in the literature. Studies tend to focus on one explanation to the detriment of understanding the interaction between the various spatial roots of participation, and in so doing, suffer from the likely ill effects of confusing one source with another. Although different methodologies and measures have been proposed and used, spatial econometric methods and tools have yet to be fully fused and utilized with these queries that are classic applications for spatial econometric techniques.[36]

Given the geographic location of our observations, spatial models allow us to scrutinize 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?[37] Is this spatial autocorrelation linked to measured or unmeasured covariates or is the patterning characteristic of diffusion 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 behaviour of interest but are not accounted for in the model, an omitted variables problem will result. Consequently, ordinary least squares (OLS) estimates of a non-spatial model may result in inaccurate inferences and biased and inconsistent coefficient estimates.[38] Hence, even if one were not

[36] 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 J. Johnston, *Econometric Models* (New York: McGraw-Hill, 1984). However, issues related to spatial autocorrelation are absent from many commonly cited basic texts (see, e.g., G. Judge, R. C. Hill, W. E. Griffiths, H. Lutkepohl and T. C. Lee, *Introduction to the Theory and Practice of Econometrics* (New York: Wiley, 1982); William H. Greene, *Econometric Analysis*, 2nd edn (New York: Macmillan, 1993); and D. J. Poirier, *Intermediate Statistics and Econometrics: A Comparative Approach* (Cambridge, Mass.: MIT Press, 1995)) and advanced econometric texts (see, e.g., T. B. Fomby, R. C. Hill and S. R. Johnson, *Advanced Econometric Methods* (New York: Springer-Verlag, 1984); T. Amemiya, *Advanced Econometrics* (Cambridge, Mass.: Harvard University Press, 1985); G. Judge, W. E. Griffiths, R. C. Hill, H. Lutkepohl and T. C. Lee, *The Theory and Practice of Econometrics*, 2nd edn, (New York: Wiley, 1985); and R. Davidson and J. G. MacKinnon, *Estimation and Inference in Econometrics* (New York: Oxford University Press, 1993)).

[37] 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, $\mathrm{Cov}(y_i, y_j) = \mathrm{E}(y_i, y_j) - \mathrm{E}(y_i)\,\mathrm{E}(y_j) \neq 0$, for $i \neq j$, where y_i and y_j are observations on a random variable at locations i and j in space.

[38] Luc Anselin, *Spatial Econometrics: Methods and Models* (Dordrecht: Kluwer Academic Publishers, 1988).

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 the light of the spatial components. If the decision-making process is mostly a function of individual traits or a process such as self-selection, 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. By contrast, if the participation dynamic is primarily a diffusion process, driven by network or neighbourhood effects, then the spatial parameter will be significant, while the other indicators will not.

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. Certainly, these variables may have a 'spatial' component in that their values are often clustered in space. For instance, neighbourhoods can often be described by income levels. 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. The source, instead, is likely to be linked to other factors such as self-selection or social interaction. However, 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 neighbouring values.

Spatially autoregressive models often take the form of a spatial lag or a spatial error model, though many applications do not fit neatly in one of these two boxes.[39] Spatial lag models are most appropriate when the spatial patterning is a function of the neighbouring observations. Spatial error models 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.[40] Alternatively, when the spatial error structure is ignored, simple inefficiency is apparent in the estimates but the standard errors are biased.[41]

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, then there is evidence that

[39] L. Anselin, A. K. Bera, R. Florax and M. J. Yoon, 'Simple Diagnostic Tests for Spatial Dependence', *Regional Science and Urban Economics*, 26 (1996), 77–104.

[40] Anselin, *Spatial Econometrics*; Luc Anselin, 'What is Special about Spatial Data?' in Daniel A. Griffith, ed., *Spatial Statistics: Past, Present, and Future* (Ann Arbor, Mich.: Institute of Mathematical Geography, 1990), pp. 63–77.

[41] Luc Anselin and Daniel Griffith, 'Do Spatial Effects Really Matter in Regression Analysis?' *Papers, Regional Science Association*, 65 (1988), 11–34.

neighbours (as defined by the analysis) somehow drive the behaviour.[42] If we have controlled for individual-level factors, social interaction and elite mobilization in the spatial lag model, then low-intensity cues that are spread through neighbourhoods in an obvious but understated fashion are likely to be factors.

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.[43] 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

$$y = \rho Wy + X\beta + \varepsilon,$$

where W is an $N \times N$ spatial weights matrix, ρ is the spatial autoregressive coefficient, ε is the error term, and X and β 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 neighbours. We defined an individual's neighbour as anyone living within a two-mile radius of that individual.[44] 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.[45] 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. The explicit inclusion of the spatial lag term implies that the influence of a 'neighbour's' (as defined by the weights matrix) participation level is not an artefact of measured and unmeasured independent variables, but that the level of participation of one's neighbours affects one's own likelihood of participation.[46]

[42] Luc Anselin and Anil K. Bera, 'Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics,' in Aman Ullah and David E. A. Giles, *Handbook of Applied Economic Statistics* (New York: Marcel Dekker, 1998), pp. 237–85. Note that the specific *mechanism* that produces the spatial patterns is unknown and not determinable via spatial analyses. What we can uncover are patterns 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 casual links/mechanisms.

[43] 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 A. K. Bera and M. J. Yoon, 'Specification Testing with Misspecified Alternatives', *Econometric Theory*, 9 (1993), 649–58; Anselin *et al.*, 'Simple Diagnostic Tests for Spatial Dependence'. On the non-robust forms, see also P. Burridge, 'On the Cliff–Ord Test for Spatial Autocorrelation', *Journal of the Royal Statistical Society, Series B*, 42 (1980), 107–8. Bera and McKenzie discuss the invariance of the non-robust diagnostics to different alternatives (see A. K. Bera and C. R. McKenzie, 'Alternative Forms and Properties of the Score Test', *Journal of Applied Statistics*, 13 (1986), 13–25).

[44] Our weights matrix was created using a distance-based definition for neighbours. 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 neighbour 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 analyse the effects of geographic distance both within and across cities.

[45] J. K. Ord, 'Estimation Methods for Models of Spatial Interaction', *Journal of the American Statistical Association*, 70 (1975), 120–6; Anselin, *Spatial Econometrics.*

[46] In our analysis, social context is clearly defined as residential location. To be sure, individuals have varied social experiences that are not limited by place of residence. Other social focal points may be at work or school. Obviously, our measure of social context does not capture these interactions, and we do not pretend that it does. Rather, our findings should be understood in the context of social interactions guided by residential location.

EMPIRICAL RESULTS

The results of our spatial analyses are reported in Table 1. As we might expect, the political engagement variables are significant and positive. Substantively, these coefficients indicate that participation rates are higher among the politically interested, the politically efficacious, and the politically informed, so those who are more politically engaged are more likely 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 resource variables, the variables measuring race and gender, or the aggregate-level factors. Confirming previous research, individual education level, interpersonal trust and the mean education level in the area of residence are important determinants of political participation. Organized social involvement appears to be particularly influential.

Our main consideration, however, is not to confirm or disprove previous findings, but to gain insight into how various factors combine and interact to produce the spatial structure that is so obviously apparent in political participation. Is the unmistakable spatial structure simply a manifestation of individual self-selection, elite mobilization, or is social interaction the main consideration? Though these factors have been examined individually, there has been little effort to understand the spatial phenomena as a whole or to untangle the visible spatial autocorrelation into its component parts. Does the spatial structuring simply emanate from within individuals or do neighbours radiate their behaviour and significantly influence one another?

Our analysis focuses on our spatial model that explicitly accounts for multiple possible roots of spatial autocorrelation. Consider the spatial lag parameter, which is an indicator of 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.[47] Despite controlling for a number of individual-level factors, Table 1 shows that the spatial lag parameter remains positive and significant, implying that an individual's likelihood of participating in politics is positively related to the participation level of his neighbours. More importantly, this result also implies that the spatial autocorrelation we observe is distinct 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 and aggregate-level factors.

Given that similarly situated people often reside in close proximity to one another (the self-selection thesis), our independent variables are likely to account for considerable spatial autocorrelation, and so this result is far from intuitive. Even after we account for similar characteristics, the extent of the spatial structure in political participation has not

[47] It is important to note that a spatial lag is not directly analogous to a time series lag. It seems intuitive and appealing to equate spatial autocorrelation with time series autocorrelation, but the spatial econometric literature is clear that this analogy is misleading and wrong (see Anselin, *Spatial Econometrics*, for an extensive discussion on this precise point). Instead, the differences are significant. Spatial autocorrelation is more complex because the nature of the dependence is multidirectional and multidimensional. In time-series data, events that occurred earlier in time affect those that occur later in time (uni-dimensional). The reverse is not true. In spatial analyses, neighbours affect each other and so the autocorrelation is two-dimensional. In addition, spatial autocorrelation can be viewed as multi-directional since each observation simultaneously affects multiple neighbours. The multi-directional and multi-dimensional nature of spatial data complicates the nature of dependence considerably and so spatial techniques are not and could not be a straightforward extension of time-series methods. This will become obvious in the main text when we further elaborate on the interpretation of the spatial lag and the spatial lag model.

TABLE 1 *Spatial Lag Model of Political Participation*

	Coefficient (SE)	Impact
Intercept	− 0.215 (0.111)	
Political Engagement		
Political Interest	0.200* (0.019)	22.0%
Political Information	0.058* (0.015)	8.7%
Ideological Strength	0.015 (0.008)	
Political Efficacy	0.042* (0.007)	12.1%
Resources		
Education	0.011* (0.003)	7.1%
Income	0.007 (0.004)	
Age	− 0.002* (0.000)	− 11.1%
Race and Gender		
Black	− 0.003 (0.016)	
Hispanic	− 0.007 (0.019)	
Asian	− 0.087* (0.028)	
Other	0.035 (0.028)	
Female	0.020 (0.011)	
Social Capital		
Organized Involvement	0.174* (0.006)	61.4%
Informal Involvement	0.028* (0.009)	6.4%
Interpersonal Trust	0.034* (0.012)	5.8%
Aggregate-Level Factors		
Income Inequality	0.150 (0.223)	
Percentage Black	− 0.087 (0.052)	
Gubernatorial Election	− 0.016 (0.014)	
Mean Education	0.038* (0.017)	5.7%
Spatial lag (ρ)	0.06*	
LM test for residual autocorrelation	0.007	
Log likelihood	− 2,610.24	
Number of cases	5,381	

Source: Social Capital Benchmark Survey (2000).
Note: Impact scores are calculated using one standard deviation shocks.
$*p < 0.05$.

been depleted. Moreover, consistent with the work of Mutz, McClurg, Leighley and others, social involvement and social networking are plainly components of the social context abstraction.[48] However, while the social interaction variables are related to political participation, these effects also do not deplete the spatial structure evident in participatory behaviour. Also, the aggregate-level factors describing similar social context and elite mobilization explain but a small part of why we observe similar behaviour among

[48] Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'; McClurg, 'Social Networks and Political Participation'; Leighley, 'Social Interaction and Contextual Influences on Political Participation.'

neighbours. Instead, after accounting for all of these factors, there is still significant spatial autocorrelation as indicated by the spatial lag parameter.

An important consideration in interpreting our model is the Lagrange Multiplier test for residual autocorrelation.[49] This statistic measures whether, after incorporating the spatial lag variable in the model, the residuals from the spatial lag model still indicate that 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 (extremely so with a p-value of 0.93), indicating that the spatial autocorrelation in the data is sufficiently accounted for by the spatial lag variable.[50] In other words, we have strong evidence that the spatial autocorrelation in the data is the result of the influence of the behaviour of neighbours, and that our model is well-specified with respect to the spatial components of participation.

There are, of course, omitted contextual variables that might potentially influence individuals' likelihood of participation, such as electoral competition or media markets. However, the insignificance of the Lagrange Multiplier test statistic for residual spatial autocorrelation implies any such variables omitted from our model while possibly explaining additional variance in participation rates, do not account for any remaining spatial dependence in the data. 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.[51] 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, we have evidence that the spatial component of political participation is not a result of included or omitted variables in our model but is, instead, linked to the behaviour of neighbours.

Our results 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 seem intuitive. Our evidence that this spatial structure is consistent with

[49] For a discussion of this test statistic, see Anselin and Bera, 'Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics'.

[50] 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: $RS_{\lambda|\rho} = \widehat{d_\rho^2} / [T_{22} - (T_{21A})^2 Var(\hat{\rho})]$, 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 $A = \hat{\rho} W_1$.

[51] 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, 'Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics'. 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.

a diffusion process may also strike some as intuitive. However, what is certainly neither intuitive nor obvious is that this diffusion process exists independently of our measures of citizens' social involvement, political engagement, interpersonal trust, resources, race and gender. Strikingly, although many of our independent variables are spatially clustered, the spatial clustering in our explanatory variables does not fully account for the spatial structure of participation. Even more notably, the spatial clustering of any unmeasured variable 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. Clearly, these results help us disentangle the conceptualization of social context in studies of political participation.[52]

What is the nature of this diffusion process? Since we have ruled out many obvious suspects (such as racial diversity, income inequality, mean education levels, political mobilization, media markets, individual-level attributes, social interaction, etc.), low-intensity cues that do not rely on explicit social interaction emerge as the primary suspect. 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.

DISCUSSION

Political participation is a concept whose theoretical import for democratic societies requires little elaboration. As a critical mechanism for the communication of citizen preferences, participation is, in many respects, the engine that drives representation. A particularly rich literature has sought to identify and explain the individual-level determinants of participation. The literature on the contextual components is certainly far from exploratory but in comparison can be described as being in much earlier stages of research. One aspect that resonates with this claim is the manner in which spatial context has been explored. In particular, while the extant literature has occasionally explored alternative mechanisms of contextual influence, it has seldom done so within the same study. Studies of individual attributes, in contrast, never explore the effects of, say, education, in isolation without simultaneously exploring other individual attributes such as age, income or political engagement, to name a few. In fact, research that focused on one element to the complete exclusion of other possible roots would be considered shortsighted and inadequate. Similarly, contextual studies need to move away from examining one source of spatial similarity and into a richer modelling scheme that is able to yield deeper and broader insights into this phenomenon. By exploiting the analytical advantages of spatial econometrics, our analysis generates new substantive insights by simultaneously exploring competing mechanisms of contextual influence. Our results can be separated into three streams.

[52] The lack of significant remaining spatial autocorrelation is satisfactory by traditional standards to allow us to conclude that any spatial structure has been modelled by the inclusion of the proper covariates and the spatial lag. We do note, however, that while our specification is clearly satisfactory in this regard, it may not be the only satisfactory specification. See Lance A. Waller and Carol A. Gotway, *Applied Spatial Statistics for Public Health Data* (New York: Wiley, 2004), chap. 9. Certainly this is akin to modelling in any regard, spatial or otherwise.

First, our results provide strong evidence that participation is geographically clustered. In other words, citizens' participatory behaviour is heavily influenced by the participatory behaviour of those who live in close proximity to them. While this finding is consistent with some previous research,[53] it is by no means intuitive. Indeed, the 'individualist' school suggests that contextual effects on political behaviour should disappear once appropriate individual-level variables are controlled for.[54] Implicit in the individualist perspective is the presumption that contextual influences on political behaviour can, in the end, be explained solely in terms of what psychologists call individual differences. While our results certainly suggest that individual-level factors such as cognitive engagement, political information and education are important, these factors do not tell the whole story. Given the importance of organizational, social and spatial factors in shaping participation, our results suggest that scholars should focus on the sociological as well as the psychological determinants of participation. Moreover, given recent increases in residential mobility and decreases in geographically-based forms of social involvement,[55] the finding that spatial proximity influences citizens' participatory behaviour is plainly striking.

Our finding that citizens' participation is shaped by those around them speaks to an ongoing debate concerning the effects of contextual homogeneity on participation. While some studies find that contextual homogeneity increases the likelihood of participation,[56] others suggest that it is inversely related to participation.[57] Our Moran's *I* statistic was positive and significant indicating that participation rates in nearby areas are similar whether the rate is high or low.[58] The significant Moran's *I* statistic 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 homogeneous 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

[53] Huckfeldt, 'Political Participation and the Neighborhood Social Context'; Huckfeldt, *Politics in Context*; Huckfeldt and Sprague, *Citizens, Politics, and Social Communication*; Oliver, *Democracy in Suburbia*.

[54] See, e.g., Jonathan Kelley and Ian McAllister, 'Social Context and Electoral Behavior in Britain', *American Journal of Political Science*, 29 (1985), 564–86.

[55] Putnam, *Bowling Alone*.

[56] Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

[57] Leighley, 'Social Interaction and Contextual Influences on Political Participation'.

[58] Moran's *I* was originally proposed as a simple test for correlation between nearest neighbours, a generalization of one of his earlier tests. See P. A. P. Moran, 'The Interpretation of Statistical Maps', *Journal of the Royal Statistical Society, Series B*, 10 (1948), 243–51; P. A. P. Moran, 'The Interpretation of Statistical Maps', *Biometrika*, 37 (1950), 17–23; P. A. P. Moran, 'A Test for the Serial Dependence of Residuals', *Biometrika*, 37 (1950), 178–81. It was a two-dimensional analogue of the test of significance of the serial correlation coefficient in univariate time series. Cliff and Ord formally presented Moran's I as $I = (N/S_0)(e'We/e'e)$, 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 $S_0 = \Sigma_i \Sigma_j w_{ij}$ is a standardization factor equal to the sum of the spatial weights. See A. Cliff and J. K. Ord, 'Testing for Spatial Autocorrelation among Regression Residuals', *Geographic Analysis*, 4 (1972), 267–84; A. Cliff and J. K. Ord, *Spatial Autocorrelation* (London: Pion, 1973). If the weights are row-standardized, Moran's I simplifies to $I = e'We/e'e$.

believe, by unifying some of the seemingly discrepant findings in the literature,[59] helps us reconcile these strands.

Secondly, we find that the geographical clustering of participation in our data cannot be entirely attributed to variables that were included (i.e. social network involvement, race, political engagement, resources, gender, income inequality, racial diversity, elite mobilization and mean education levels) or omitted from our model (i.e. media markets, political institutions or other city-level factors). In arguing that these micro-level and macro-level variables do not account for the spatial structure of participation, we do *not* imply that they are unrelated to participation. As our own results attest, social network involvement is strongly related to participation. Similarly, many city-level factors may be associated with levels of participation.[60] However, the diagnostics from our spatial lag model provide evidence that such factors are not underlying the *spatial* patterns in our data. Instead, participation rates are influenced by the participatory behaviour of neighbours and not simply by other individual-level or aggregate-level variables that sometimes exhibit geographic clustering.

Finally, our results show that the spatial structure of political 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. Rather, our main contribution lies in establishing the nature of this diffusion process and its *independent* existence from our measures of social network involvement and a wide range of other individual-level and aggregate-level attributes. Collectively, our results point to an important role for casual observation in the diffusion of low-intensity environmental cues in explaining the spatial dependency behind political participation. An important implication of this result is that geographical proximity matters in ways that are not sufficiently accounted for by leading theories of contextual effects. Psychologically, our results also imply that the genesis and spread of ideas is not wholly dependent upon explicit 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.

By identifying spatial imprints consistent with a diffusion process, our analysis helps to rule out a number of competing theories concerning the mechanisms of contextual influence. Spatial econometric techniques allow us, for the first time, to paint a much richer and fuller theory of the role of social context in spurring political participation. An intriguing finding centres on the role of casual observation and the diffusion of low-intensity environmental cues in defining spatial dependence. This aspect of political participation is often overlooked in the scholarly literature, but apparently unduly so. Indeed, our results suggest that the quest to understand the emanation and transmission of these cues is central to our understanding of how context and political participation intersect.

[59] See, e.g., Leighley, 'Social Interaction and Contextual Influences on Political Participation'; Mutz, 'The Consequences of Cross-Cutting Networks for Political Participation'.

[60] See, e.g., Alberto Alesina and Eliana La Ferrara, 'Participation in Heterogeneous Communities'; Dora L. Costa and Matthew E. Kahn, 'Civic Engagement and Community Heterogeneity: An Economist's Perspective', *Perspectives on Politics*, 1 (2003), 103–11.

APPENDIX TABLE A1 *Cities Analysed by Population Size*

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