Contagion Effects and Ethnic Contribution Networks

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Many political behavior theories explicitly incorporate the idea that context matters in politics. Nonetheless, the concept of spatial dependence—in particular, that behavior in geographic units is somehow related to and affected by behavior in neighboring areas—is not extensively explored. The study of campaign finance is no exception. Research in this area concentrates on the attributes of the individual donor, leaving context underexplored. Concepts such as contribution networks, for instance, are not rigorously tested. This article reexamines the impact of conventional socio-demographic covariates on campaign donation behavior by ethnic contributors and explicitly models spatial effects. The spatial analysis reveals that patterns of campaign donations are geographically clustered (exhibiting both spatial dependence, implying a neighborhood effect, and spatial heterogeneity, implying a regional effect), and that this clustering cannot be explained completely by socio-economic and demographic variables. While socio-demographic characteristics are important components of the dynamic underlying campaign contributions, there is also evidence consistent with a contagion effect whereby ethnic contribution networks are fueling funds to candidate coffers.

Context matters in politics. Politics, after all, is not a set of unrelated individual actions, but is instead an interrelated set of social phenomena. A corollary of this claim is that people are influenced by the context in which they find themselves. Indeed, it is not hard to imagine a plethora of circumstances under which colleagues and neighbors would be influential in the formation and solidification of political beliefs or would be the impetus behind the emergence of some type of political action. Although people can and do maintain relationships that span large distances, it is clear that one of the great sources of enduring and influential interactions is physical proximity. Despite easily-formed theories for spatial effects, the concept of "space"—in particular, that the behavior of people is somehow related to and affected by the behavior of those who reside in close proximity—has received too little attention in political science. The lack of inquiry seems especially strange since many classes of theories in political behavior focus on context and geography. Indeed, this discussion and these theories have spanned and evolved over many decades (Key 1949; Berelson, Lazarsfeld, and McPhee 1954; Putnam 1966; Huckfeldt 1979; Eulau 1986; Huckfeldt and Sprague 1987; 1992; Putnam 2000).

There is a line of research that has focused on various spatial dimensions, social networks, and neighborhood effects. For example, Putnam (1966), Huckfeldt, Plutzer, and Sprague (1993), Huckfeldt (1979) have conducted many studies on social interaction. Weatherford (1982) and Crenson (1978) have focused on the idea of social networks. The role of geography is clear in Baybeck (2001), Tir and Diehl (2002), and Baybeck and Huckfeldt (2002). As well, the policy diffusion literature has looked closely at the idea of how policy innovations adopted in one state may spread to neighboring states (see, e.g., Walker 1969; Gray 1973; Berry and Berry 1992). Finally, Johnston et al. (1997, 1998, 2000, 2001) have, on many occasions, examined the role of spatial context in British elections. All of these works emphasize the role of spatial context and the role of simple geography, though in a manner that is somewhat different than the methods employed here.

This article takes advantage of recent and significant advances in geographic information systems (GIS) and the proliferation of research methodologies and tools for spatial analysis. The confluence of these two factors has created conditions that are ripe for spatial analyses of political data, allowing us to broaden our examination and

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conceptualization of the spatial realm in politics, and to do so in a more systematic and expansive manner. There have been some significant studies utilizing these spatial methodologies in relating political phenomena to geography, especially in the field of conflict studies (see, e.g., Kirby and Ward (1987), Starr (2001), and O'Loughlin (1987). Most and Starr (1980, 1982, 1983, 1984) and Starr and Most (1976, 1978, 1983), in particular, have conducted a number of studies along these dimensions). There have also been some studies in American politics (see, e.g., Gimpel 1999; Rom, Peterson, and Scheve 1998; Saavedra 1998; Sui and Hugill 2002; Kohfeld and Sprague 2002; and Darmofal 2002) as well as comparative politics (see, e.g., Agnew 1987; Brustein 1990; O'Loughlin, Flint, and Anselin 1994; Shin 2001; O'Loughlin 2002; and Shin and Agnew 2002). This piece joins these articles in incorporating and emphasizing the role of geography and context by utilizing spatial econometric techniques to explain political phenomena, with a focus on individual political behavior and American politics.

Another important component behind the increasing ability to examine spatial phenomena is the growing availability of geo-coded data. The primary advantage that accrues from analyzing the spatial dimension is that we can move away from theories that incorporate only individual decision-making, whether across time or in a singular incident, in an isolated realm. That is, the individual need no longer be seen as an atomistic actor. Instead, we can consider theoretical frameworks that place the individual's actions in the context of his "neighborhood," where behavior can be compared to and observed in relation to the behavior of others in close proximity.

Perhaps not surprisingly, spatial analyses are important for both substantive as well as statistical reasons, and these two dimensions are inextricably linked in this context. On the substantive front, spatial models allow us to examine critically theories about the political behavior of individuals in the proper context. Aspatial models omit this spatial component and thus allow one to examine the individual primarily as an atomistic actor only. Statistically, if spatial processes underlie the behavior of interest but are not accounted for in the model, inferences will be inaccurate and coefficient estimates may be biased. 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). 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.

Given that many spatial theories have been proposed (but not tested or tested in limited settings only), the increasing availability of geo-coded data, and the statistical issues that arise, rigorous testing of spatial effects is a natural next step. This article examines spatial effects in the context of campaign contributions. I begin by positing why this form of political behavior may be particularly susceptible to spatial effects. Next, I describe the data gathering and merging process. The contributions data are from the Federal Election Commission (FEC). These data are merged to U.S. Census zip code data. I then present spatial models of campaign donations for 10 separate years. Finally, I conclude by discussing the impact of spatial as well as some aspatial effects, such as time and demographics, on the campaign contribution dynamic.

Spatial and Aspatial Theories of Campaign Donations

Although the idea that the patterns behind campaign contributions have a spatial component has scarcely been tested empirically, the reasoning behind why contributions would exhibit a spatial pattern is not lacking. Some of these reasons are spatial (i.e., attributable to geography), while others are aspatial (i.e., attributable to nongeographic components such as income). For instance, one reason why campaign donations would exhibit a spatial pattern is that campaigns are strategic but have limited resources, and so attempt to allocate these resources wisely. This may mean that a candidate will focus on specific media markets, bombarding the campaign battlegrounds while leaving air time in another part of the country relatively barren. Because this courting is geographically definable, donations may appear to be rolling in in geographic clusters rather than emerging as random, independent events across the United States.

As well, candidates may appeal to specific electoral groups. For instance, it is well known that minority groups (especially blacks and Latinos) tend to favor Democratic candidates. To the extent that these ethnic groups are segregated, whether voluntarily or not, geographic clustering of behavior may again appear. Similarly, Asian Americans tend to reside in clusters. If a candidate is especially attractive to or adept at courting minorities, his set of campaign donations will appear to have some spatial structure, even though the mechanism creating that structure is not a spatial process per se, but is, rather, connected to the dispersion of the minority population.

Alternatively, simple proximity to others exhibiting a certain type of behavior may also be a factor. Social networks may develop in response to "mobilization" so that active solicitation of donations by a candidate has spillover effects via the formation of networks (Putnam 2000; Weatherford 1982). Campbell et al. (1960) identify two factors, community identification and perceived community standards, that serve as the basis for an explanation of community influence. An idea behind this literature is that the initial impetus may be an individual action or a neighborhood fundraiser that then, through social interaction, diffuses to neighboring areas and emerges as a spatial pattern.

Lastly, since money is involved in campaign donations and financial donations are not obligatory, income level always emerges as an obvious explanatory variable. Indeed, research on the origins of campaign donations often focus on socioeconomic factors such as age, education, and income. Verba, Schlozman, and Brady (1995) single out income as "overwhelmingly, the dominant factor" in political contributions. According to their analysis, "[e]ducation, vocabulary, and civic skills play no role" (1995, 361). Gierzynski (2000) concurs, stating that "a look at individual contributors reveals a disproportionate representation of those of higher socioeconomic status" (107). The Brown, Powell, and Wilcox study found that contributors "are generally white, male, well-educated, affluent, and active in contributing at several levels of government" (1995, 49). Rosenstone and Hansen find that education is the most crucial resource in defining participation levels in various political acts with one exception, "[i]ncome—not education—is the most crucial resource for donations of money to political campaigns" (1993, 136).

Socioeconomic variables, especially income, are, then, our chief candidates for aspatial explanatory variables that might be producing the spatial patterning that we observe. Certainly, education and income levels are found in clusters throughout the U.S. Whether the sociodemographic variables are the sources of spatial patterning or if the patterns can be attributed to a more pure spatial process (such as a neighborhood effect) will be the focus of the modeling to follow, but it should be clear that there are many reasons why the campaign finance data may be spatially clustered.

In short, there are many theories behind the dynamic of campaign contributions, both with spatial and aspatial roots that would result in clear spatial patterning. Notably, spatial explanations do not take away from the aspatial findings that have been proposed previously, since both sets of findings can be true simultaneously. There can be a spatial component that complements the nonspatial components. Alternatively, we may find that the spatial explanations comprise a greater proportion of the overall explanation than we had previously thought, i.e., the nonspatial components become less significant or even disappear when viewed in light of the spatial components. In the past, the nonspatial theories have received more attention but not necessarily rightly or justifiably so. The bias results more from a paucity of research in the spatial realm than from a lack of theories.

The immediate goal here is to gain insight into how and why contribution patterns appear as they do across the country. Is there some type of spatial or time-related pattern to the data or are these levels of political behavior solely attributable to decision making that occurs outside simple geography. If the decision-making process is mostly a function of individual traits, then in a unit-level analysis of donation levels, covariates such as partisanship or income levels might be significant predictors, but the spatial parameters should not be significant in the model specifications that control for these covariates. On the other hand, if the contribution dynamic is primarily a diffusion process, driven by network or neighborhood effects, then the spatial lag will be significant, while the socioeconomic indicators will not be significant.

It may also be the case that the patterns can be explained by elite political mobilization, driven perhaps by candidate appearances. Since this analysis does not incorporate a variable such as candidate appearances, if the spatial patterning were the result of this 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 should provide evidence for or against a mobilization theory. Alternatively, and perhaps most likely, the effect may be a combination of the (measured and unmeasured) spatial and aspatial sets of variables. So, there may be "neighborhood effects" as well as effects that are more directly and narrowly connected to individual characteristics and elite tactics. It is important to note here that the specific *mechanism* that produces the spatial patterns is unknown and not determinable via the spatial analyses that are employed here. What we can uncover are patterns that are consistent with the specific mechanisms that produce the contribution patterns that we observe.

The focus of this study is on ethnic contribution networks, specifically, Asian American contribution networks. Akin to the literature on campaign finance behavior, little is known about ethnic contribution networks. In the minority realm, as in the nonminority realm, research has focused on individual-level decision making. For Asian Americans, the impetus behind the contribution dynamic also has roots in socioeconomic factors. One large difference is the importance of ethnic cues and ethnic candidates (Cho 2001, 2002). These factors are, again, based on individual traits, not on social context or contribution networks. In this sense, the research presented here complements and augments the vast literature that has amassed on political behavior and minority political behavior. Individual effects are considered, but alongside the context in which individuals find themselves.

Data Analysis

The data for this project are from the FEC (1980–1998). The database includes contributions to candidates for federal office as well as PACs and party organizations. The specific data for this article include a subset of these data: all contributions from Asian American donors.[1] The Asian American group is perhaps the only group that can be reasonably identified solely by name and so the only group that can be extracted reliably from the FEC data.[2] Since this smaller data set is still quite large (over 65,000 observations), there is not much lost in asymptotics.[3]

An important feature of the FEC data is that they are objective whereas surveys rely on self-reported accounts, which may limit the generalizability of the analysis.[4] There are two main drawbacks to the course taken here. First, the analysis is conducted at the level of a geographic unit rather than at the individual level. This does not take away from the spatial component and the ability to evaluate spatial effects, but only the inferences that we can gather about individuals. Second, because the FEC data are not rich in variables as surveys often are, we can observe and model the spatial patterning of contributions, but an extensive study of contributor motives is not possible.

To perform a spatial analysis, one needs data units that are geographic. Accordingly, the unit of aggregation here is the zip code, and all of the FEC data have been aggregated to the zip code level. The zip code level was chosen because the it is the lowest level of aggregation for which we can obtain data from both the Census and the FEC.[5] In this analysis, the dependent variable is the amount in contributions received from Asian ethnic groups (Chinese, Japanese, Korean, and Vietnamese).[6] The independent variables are from the U.S. Census (Census STF3b file), and have been merged to the FEC data. The independent variables include several measures of socioeconomic status, including income, education, and age. The income variable is the median income in the zip code, measured in $10,000s. The education variable is a 7-category variable that measures the mean educational attainment. The age variable is a 5-category variable that measures the mean age in the zip code. Also available from the census is total population in a zip code[7] and the percentage of the zip code that various groups (such as Asian Americans, blacks, and Latinos) comprise.

Indicators of Spatial Autocorrelation

The first step in a spatial analysis is to determine whether there is any spatial autocorrelation in the data at all.

[1]The full collection of FEC individual contribution reports (1980–1998) is very large, approximately 6 million records. The database was parsed using Asian name dictionaries (both first and last names).

[2]Since the FEC do not include any demographic variables, it is difficult to place many identifying characteristics on the individual donors. While it would be extremely interesting to contrast these findings on Asian Americans with whites, or blacks, or Latinos, such an analysis is not feasible with the FEC data, as none of these three groups can be reliably identified in the data.

[3]This smaller data set makes this problem manageable. Analyzing the entire FEC data set is not feasible at this point because of computing limitations associated with the massive size of the entire data set and the computational intensive nature of spatial analyses (Smirnov and Anselin 2001).

[4]Surveys, often the best sources of individual-level data, are of limited usefulness here, since they conflict markedly in their accounts of campaign contribution levels (Cho 2002). Another major drawback of surveys for the current task is that geographic identifiers are rarely available.

[5]The observations are not individual contributors. While zip codes for individuals are also available, the number of observations is a limiting factor. The greater problem, however, is that the FEC provides no demographic variables for individuals. The census, on the other hand, collects a large number of variables at the zip code level. Thus, the zip code level is an appropriate aggregation level because it is the lowest level of aggregation for which there is extensive data available for estimating the models and theories of interest.

[6]The pan-ethnic identity is certainly one of great contention (Espiritu 1992; Tam 1995), and so the use of the umbrella category always needs to be broached with caution. Many have argued that the pan-ethnic group rises to the occasion in contexts where they are treated by others as a homogeneous group (Espiritu 1992; Lien 2001). In these instances, they join together to fight a common cause or misconception where they have a joint stake. The case of campaign donations and the 1996 campaign finance scandal surrounding Asian donations is certainly a case in point, and so the use of a pan-ethnic category here is justifiable. To the extent that the pan-ethnic identity is not appropriate, the results that follow are conservative estimates of the possible diffusion processes at play. These processes are likely to be even stronger if we were to examine just one ethnic group as diffusion effects are more likely within a single ethnic group rather than across the often internally heterogeneous Asian American group.

[7]Total population is available, but to ensure some consistency in the range of variables, the population variable in the spatial models is population in 1000s of people.

Accordingly, we want to test the null hypothesis of spatial randomness against the alternative hypothesis of spatial autocorrelation. Spatial autocorrelation occurs when values of a certain variable are systematically related to their geographic locations. That is, there is some relationship between the levels of donations in neighboring area. Evidence of such a relationship would support the spatial theories. If the spatial autocorrelation statistic is statistically significant, however, further analysis needs to be conducted to determine the source of the autocorrelation. The Moran's I statistic (Moran 1948; Cliff and Ord 1973) is the most commonly employed method of assessing the significance and/or degree of spatial autocorrelation in the data (Cliff and Ord 1981). A positive and significant Moran's I indicates spatial clustering of contribution amounts. Specifically, the Moran's I statistic is

$$I = \frac{\sum_i \sum_j w_{ij}(y_i - \mu)(y_j - \mu)}{\sum_i (y_i - \mu)^2},$$

where w_{ij} is an element of a row-standardized spatial weights matrix, y is the contribution amount, and μ is the average contribution amount in the sample. The Moran's I statistic can be thought of as a counterpart to the familiar Durbin-Watson statistic used to detect autocorrelation in time-series data. Spatial autocorrelation occurs when the similarity of values of interest is related to the locations of the units, i.e.

$$\mathrm{Cov}(y_i, y_j) = E(y_i y_j) - E(y_i)E(y_j) \neq 0, \quad \forall\, i \neq j.$$

If spatial autocorrelation is present in the data, models that do not explicitly account for spatial effects are inadequate for adjudicating between spatial and nonspatial theories. If spatial randomness is rejected, the next recourse is to explore the processes that may have generated the observed spatial patterns.

We can see from Table 1 that the global Moran's I statistic is highly significant for every year of the FEC data.[8] However, note that even if the pattern seems to be spatially clustered, the pattern of contributions may, in fact, be spatially random, driven simply from clustering of demographic traits such as income. So far, we have only observed spatial patterns. We cannot yet make any claims about why these patterns occur, because we have not conducted any analysis of this type. We have simply surmised that the pattern of contributions, without controlling for any variables, is not random.[9] We will explore the source of the spatial dependence in the spatial regression models to follow.

Table 1 Global Moran's I Statistic

Year	Moran's I	Z-value	p-value
1980	0.2845	21.79	0.00
1982	0.1398	8.35	0.00
1984	0.1981	14.39	0.00
1986	0.0411	3.49	0.00
1988	0.1739	24.06	0.00
1990	0.3749	50.98	0.00
1992	0.2599	50.10	0.00
1994	0.2196	35.28	0.00
1996	0.1795	35.51	0.00
1998	0.2612	47.27	0.00

We can obtain a more detailed look at spatial autocorrelation by examining the local indicators of spatial autocorrelation (LISA) statistics (Anselin 1995). This local Moran statistic is closely related to the global Moran's I statistic. Specifically, the local Moran's I statistic is

$$I_i = \frac{z_i}{\sum z_i^2} \sum_j w_{ij} z_j \tag{1}$$

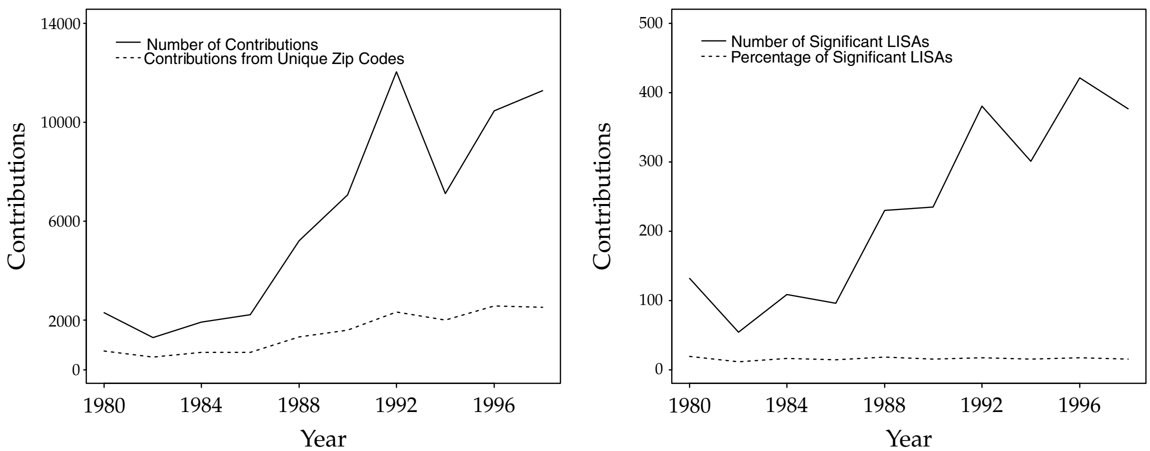
where z is the mean-deviated contribution amounts given by Asian Americans. Inference is based on a conditional randomization approach.[10] The average of the local Moran's I statistics is equal to the global Moran's I, to a factor of proportionality. Examining the local autocorrelation statistics allows us to identify observations that are "extreme contributions" to the global statistic by noting which values are, say, 2 or more standard deviations from the mean. These local indicators allow us, moreover, to

[8]The weights matrix is based on an inverse distance measure where the distance band is 50 miles. That is, the spatial lag for each zip code can be seen as the weighted average (with the w_{ij} being the weights) of its geographically-defined neighbors (those zip codes that fall within the distance band). The distance is measured from the centroid. Different weights matrices (but the same specification, as described above) are computed for each year, so the connectivity structure differs from year to year, where the change is dependent on the specific contributions in that year. In the 1998 data, the minimum number of neighbors is 0. Fifty-one observations have no neighbors. The maximum number of neighbors is 253. Only one observation has this many neighbors. The average number of neighbors is 86. The specification of the weights matrix is important in any spatial analysis. Accordingly, here, different specifications for the weights matrix were examined. For instance, a distance band of 100 miles was also employed. The results were basically identical to those that resulted from using the 50-mile band. K-nearest neighbor and contiguity definitions were briefly explored, but were not used, as it is difficult to reconcile these specifications with a substantive story or theory.

[9]Note as well that because the Moran's I statistic is sensitive to other forms of specification errors such as non-normality and heteroskedasticity (Anselin and Rey 1991), these results should be examined further. Both of these characteristics can affect the sensitivity of the results.

[10]Significance was based on a permutation approach with the number of permutations set at 999.

FIGURE 1 LISA Statistics and Rise in Contribution Activity
The plot on the left shows the rise in the sheer number of contributions and the rise in the number of sites where contributions originate. The plot on the right shows a rise in the number of significant LISA statistics each year and the relatively stable percentage of significant LISA statistics.



identify areas of interest that may have nonrandomly distributed values (high or low) in relation to their neighboring values. Rejection of the null hypothesis here indicates local clustering (either a high value surrounded by high values or a low value surrounded by low values) or local spatial outliers (a high value surrounded by low values or a low value surrounded by high values). Figures A-1–A-10 display plots of the LISA statistics for each of the years listed in Table 1.[11] The black dots indicate areas with significant LISA statistics. The grey dots indicate areas with insignificant LISA statistics.

Two observations are immediately obvious from this set of plots. The first observation is that the number of sites where contributions originate generally increases every two-year cycle. An examination of the data indicate that the sheer number of contributions generally increases every election cycle as well. We can see this graphically in the plot on the left in Figure 1. So, as a group, Asian Americans are becoming increasingly active in this form of political participation. The number of contributors is rising and their geographical diversity is growing. Second, more observations have significant LISA statistics at the end of the time cycle than at the beginning. In other words, with each passing election cycle, more observations are correlated with their neighboring values, giving one more reason to explore possible diffusion effects. We can see this graphically in the plot on the right of Figure 1.

[11]Alaska and Hawaii are included in the analysis, though not in the plots. The omission from the plots is purely a matter of aesthetics.

The dotted line in this plot indicates that despite the clear rise in both the sheer number of significant observations and the clear upward swing of the numeric base of correlated values, the percentage of all LISA statistics that are significant in a given year does not change dramatically over time.

If we make the leap to assume that the spatial autocorrelation is more likely to originate from donors who have resided in the U.S. for a longer period of time, because they have simply had more opportunities to integrate into a neighborhood structure, the patterns in the LISA statistics might implicate some themes in the literature. For instance, there may be evidence for the idea that newly arrived immigrants behave uniquely relative to those who have resided in the U.S. longer because their incentives and cost structure differ significantly (Cho 1999; Wong 2000). Relatedly, others have argued that one's stake in the political system and thus one's level of political participation rises concurrently with the amount of time an immigrant is in the U.S. (Uhlaner, Cain, and Kiewiet 1989). For Asian Americans, then, the continuous rapid flow of immigrants serves to supply a constant set of new immigrants to the mix as well as to expand the base of potential contributors. The rising number of significant LISA statistics imply that these contributors are spatially related. This phenomenal growth shows no sign of yielding. The flow of Asian immigrants into the U.S. has been nothing short of dramatic in the last few decades. The growth in the number of contributors has almost kept this same phenomenal pace.

It is clear from these census figures and the plots in Figure 1 that campaign finance is an increasingly pertinent arena for those interested in the political behavior of the most rapidly growing group in the U.S. With the passing of each election cycle, a growing number and a broader geographic mix of Asian Americans are engaging in this form of political participation. Perhaps more importantly, and more indicative of the sophistication behind this form of behavior, the spatial patterns imply that the web that underlies this form of behavior is growing in size as well as complexity.

Spatial Models

Given that we have significant spatial autocorrelation in our data, both on a global scale as well as a more local scale, as indicated by the Moran's I statistic and the large number of significant LISA statistics every year, the next step is to determine whether these spatial effects are true spatial effects, or if they are spurious, in the sense that they can be attributed entirely to patterns in other variables such as income or education. If we control for all of these other factors and the spatial variable remains significant, then we have evidence that the pattern is consistent with a "neighborhood effect"(via a spatially lagged dependent variable), or perhaps an elite mobilization effect (via an unmeasured mobilization variable), but not an effect that is solely attributable to socioeconomic characteristics of these areas. In other words, if contribution amounts are determined solely by the structural factors included in the model as independent variables, no remaining spatial patterning of contribution amounts beyond those resulting from socio-demographic similarity of geographically-proximate areas should remain.

For the national data, the spatial dependence that appears in the contributions data may be modeled as a spatial lag model.[12] The robust Lagrange Multiplier diagnostics for each of the years, excluding 1986, indicate that the spatial lag route would be profitable. 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 neighbors. 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. The explicit inclusion of the spatial lag term implies that the influence of a "neighbor's" (as defined by the weights matrix) contribution amount is not an artifact of measured and unmeasured independent variables, but that the contribution amounts in neighboring areas actually increases the likelihood of campaign contributions in its neighbors. Note that 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 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.

[12]The specification of the spatial model is, of course, chosen after examining the data and various diagnostics. The other large class of models involves modeling the spatial dependence as a spatial error model. In the spatial error model, the dependence is incorporated into the error structure so that $E[\varepsilon_i \varepsilon_j] \neq 0$, i.e. the off-diagonal elements of the error covariance matrix are non-zero and incorporate the structure of the spatial dependence. In this case, OLS is unbiased but is not efficient. So, the estimate of standard errors will be biased. The spatial error model would evaluate the extent to which the spatial patterns of campaign contributions not explained by the measured independent variables can be accounted for by clustering of error terms. In other words, the spatial error model captures the spatial effects of unmeasured independent variables. A satisfactory spatial error model implies that a spatially-lagged dependent variable is not necessary for explaining the observed spatial patterns. Instead, the patterns are explained by geographic patterning of measured and unmeasured independent variables. Whether a spatial lag or a spatial error formulation is employed is a decision that is based on diagnostics. In this particular study, the diagnostics indicated that no spatial effects remained in the 1986 national data after controlling for other covariates. The spatial effects were not detected in the model even though the Moran's I statistic for the 1986 data was significant. This is not unusual, as the Moran's I statistic is very sensitive to various forms of specification errors such as non-normality and heteroskedasticity (Anselin and Rey 1991). A little exploration into these data indicate the presence of both non-normality and heteroskedasticity. For the other years, the robust Lagrange Multiplier diagnostic for the spatial lag was significant. Somewhat atypically, the robust Lagrange Multiplier diagnostics for spatial error was also significant in some of the years (1988–1998 for the national data, and 1990, 1992, and 1998 for the western region data). Because the robust Lagrange Multiplier lag test statistic is larger than the robust Lagrange Multiplier error test statistic, a spatial lag model was pursued. Attempts to explore sources of spatial heterogeneity in the data helped to resolve this issue for some of the data, but not these aforementioned years.

These data also exhibit qualities consistent with spatial heterogeneity as indicated by spatial Chow tests on the overall coefficient stability across regimes. In particular, we can see from Table 2 that a spatial Chow test indicates that observations in the West differed significantly from observations in other states for each election cycle beginning in 1988. Given the evidence of distinct spatial regimes, a disaggregated modeling strategy is pursued for these data. That is, we analyze separate models for each region and examine each of these models separately for evidence of spatial dependence. In addition, spatial Chow tests for the non-western states also indicate that the states in the Northeast are significantly different from the other non-western states for each of the years from 1988–1998, except 1990. These pockets of distinctive behavior are not surprising given our substantive inclinations about the Asian American group. The bulk of the Asian American population resides in the West, and proportionally, the West bears more than its share of campaign contributors. The Northeast bears many of these same qualities, but to a lesser degree.

The models for the entire nation are reported in Table 2.[13] The models for the other regions are displayed in Tables 3 and 4. Spatial lag models are indicated by a value for the spatial lag variable, while spatial error models are indicated by a value for the spatial error variable.[14] In each of the tables, the column heading is the year indicator. The dependent variable is the amount in contributions received from Asian donors, and observations are zip codes.[15]

The results vary somewhat from year to year, but some consistent themes are evident as well. One implication of these patterns of change and stability is that the logic behind Asian American contributions is evolving, not static in this twenty-year time period. Although one might prefer and expect an overarching story, the lack of a single story throughout this time period is not unusual and should not necessarily be expected given the phenomenal growth and compositional change that has characterized this time period for the Asian American group. Asian Americans have been arriving in droves only since the late 1960s, after the Immigration and Nationality Act of 1965 eliminated racial quotas. One can hardly expect in some 15–30 years that they would have established deepset grooves of political behavior in an American system that was, until just recently, largely foreign to them. Integrating into the political mainstream certainly does not occur instantaneously (see e.g., Reedy 1991 and Glazer and Moynihan 1972), and so we should not expect that a group's political presence would appear instantaneously with its physical presence. Moreover, we would expect the establishment of a pattern of political behavior to follow later yet.

The theme of change is one that has been uncovered by previous studies (Tam 1995; Wong 2000; Lien 2001). Indeed, as will see, several themes of the Asian American political behavior literature will be uncovered again, while some will appear to have changed. The difference is that spatial effects are explicitly considered here. The interplay between spatial effects and the traditional individual-level variables affects the results. In some instances, the effects will be evident simultaneously. In others, one effect may dominant the others or negatively impact the others.

Strikingly, the early patterns of contributions do not seem to be related to income. The lack of relationship here is surprising given the strong relationship between an individual's income level and campaign contributions that has been uncovered by more than one study (Rosenstone and Hansen 1993; Verba, Scholzman, and Brady 1995; Brown, Powell, and Wilcox 1995; Gierzynski 2000). In these data, the relationship between income and

[13]As previously discussed, non-normality and heteroskedasticity affect the estimation (Anselin and Rey 1991). Because the Koenker-Basset diagnostic for heteroskedasticity indicated that heteroskedasticity might be an issue for the 1980, and 1990–1998 national data, the model for these years is computed via instrumental variables (2SLS) with a groupwise heteroskedasticity variable. In the presence of a high degree of non-normality and especially for large data sets, 2SLS is the preferred strategy over the asymptotically more efficient maximum likelihood approach. The groupwise heteroskedasticity variable is a region variable (Northeast, South, Midwest, Central South, Mountain states, California, Hawaii, and the rest of the West). Inclusion of this variable alleviated the problem with heteroskedasticity in all of the years except 1990 and 1992. That is, the Koenker-Basset diagnostic does not indicate a problem with heteroskedasticity once this region variable is included.

[14]For the West, the Koenker-Basset diagnostic for heteroskedasticity indicated that heteroskedasticity might be an issue in these data for the years 1988–1998. Hence, the model for these years was computed via instrumental variables with a groupwise heteroskedasticity variable. In this case, the groupwise heteroskedasticity variable separated the regions of California (Bay Area, Los Angeles area, Central Valley, and the remaining parts of California), and the rest of the western region (Oregon, Washington, Hawaii, and Alaska). Inclusion of this variable alleviated the problem with heteroskedasticity in all of the models. In 1990, and 1998, the data indicate that a spatial error model may be appropriate, but the spatial error model diagnostics indicate additional spatial lag dependence, and the spatial lag models had slightly better fit statistics, and so Table 3 reports the spatial lag results. For the Northeast, each model was computed via instrumental variables with a groupwise heteroskedasticity variable. In the other regions, only the 1992 and 1996 data had indications of heteroskedasticity. The other models were computed via maximum likelihood.

[15]Only zip codes where some money originated from Asian Americans are included. The other zip codes are essentially "islands," and so there is no "neighboring behavior" to observe or analyze.

TABLE 2 Spatial Lag Models. Dependent Variable: Contribution Amount from Asian Americans at the Zip Code Level

	1980	1982	1984	1986	1988	1990	1992	1994	1996	1998
Constant	25.14	−2481.55	−3014.99	−7372.14**	−564.30	−1622.47**	−2865.79**	−2021.39**	−3853.76**	−1833.75**
	(418.09)	(2119.21)	(1798.39)	(2266.44)	(756.81)	(721.32)	(915.54)	(766.01)	(951.51)	(669.68)
Population	6.16**	10.17	9.20	42.40**	4.42	19.55**	20.13**	0.15	24.60**	10.96**
	(3.06)	(11.02)	(9.78)	(13.87)	(5.88)	(5.16)	(6.68)	(5.27)	(7.25)	(5.05)
Percent Asian	43.30**	40.01**	65.22**	73.95**	112.93**	68.71**	83.12**	100.87**	124.81**	164.87**
	(8.44)	(14.38)	(13.12)	(16.38)	(15.75)	(14.98)	(12.92)	(15.00)	(18.88)	(20.03)
Age	242.79	1590.89**	1803.25**	1931.35**	553.53**	454.60	979.77**	664.38**	1447.73**	522.42**
	(159.65)	(733.99)	(707.76)	(802.33)	(234.85)	(262.45)	(304.83)	(261.81)	(338.45)	(232.35)
Education	−95.54	−209.69	−86.92	439.88	−116.13	−0.47	36.33	261.54	−80.24	224.68
	(96.57)	(434.86)	(379.02)	(506.12)	(162.93)	(162.30)	(196.48)	(168.58)	(213.84)	(150.52)
Income	40.46	259.37	148.76	444.82**	205.30**	281.94**	348.60**	141.54**	500.78**	153.30**
	(38.00)	(154.13)	(136.19)	(176.11)	(66.04)	(67.81)	(82.49)	(65.67)	(99.39)	(71.34)
Percent Minority	2.76	−4.55	−1.15	26.27	−1.35	3.66	0.71	3.24	5.25	−1.14
	(2.34)	(12.88)	(10.14)	(13.64)	(4.33)	(4.22)	(4.98)	(4.52)	(5.25)	(3.67)
Spatial Lag (r)	0.06**	0.04**	0.03**		0.03**	0.03**	0.03**	0.03**	0.02**	0.03**
	(0.01)	(0.01)	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Spatial Chow Test	6.15	6.88	8.00	9.84	33.86**	84.79**	108.79**	32.87**	27.68**	61.56**
R^2	0.17	0.13	0.14	0.08	0.19	0.33	0.22	0.16	0.14	0.20
N	671	455	657	639	1183	1420	2072	1821	2288	2206

Note: Standard errors in parentheses.
** $p < 0.05$.

TABLE 3 Spatial Lag Models. Dependent Variable: Contribution Amount from Asian Americans at the Zip Code Level (West Only)

	1980	1982	1984	1986	1988	1990	1992	1994	1996	1998
Constant	−269.49	1300.38	1273.46	−5053.18	−5336.42**	−3531.08	−6677.27**	−6443.86**	−3911.88	−9345.54**
	(751.16)	(2339.73)	(1885.05)	(3447.91)	(2213.28)	(2036.34)	(2257.39)	(1930.93)	(2136.92)	(2599.79)
Population	6.38	19.45	19.78	31.31	47.38**	26.87**	33.26	34.32**	56.95**	38.66**
	(6.93)	(14.01)	(12.26)	(21.61)	(15.90)	(13.76)	(17.64)	(13.23)	(15.73)	(17.33)
Percent Asian	40.63**	29.81**	48.12**	42.02**	111.74**	112.45**	214.21**	111.91**	98.17**	167.71**
	(9.71)	(10.59)	(11.29)	(15.61)	(16.98)	(20.68)	(25.57)	(14.62)	(17.49)	(21.41)
Age	−60.94	906.51	1142.12	3532.11**	3267.05**	1461.37	2069.68**	2030.95**	2702.57**	2788.22**
	(294.02)	(708.32)	(683.38)	(1209.70)	(872.03)	(833.55)	(836.89)	(651.67)	(853.53)	(992.76)
Education	119.49	−737.77	−829.18	−805.85	−1181.30**	−354.89	−202.29	226.20	−1142.38**	−38.71
	(180.51)	(543.53)	(433.34)	(751.14)	(524.87)	(494.26)	(510.84)	(449.13)	(538.20)	(617.82)
Income	44.16	141.26	116.14	455.59	914.85**	582.17**	870.44**	421.84**	871.88**	1256.83**
	(90.09)	(168.92)	(150.31)	(268.42)	(205.40)	(206.28)	(244.68)	(168.99)	(239.26)	(257.50)
Percent Minority	−16.79**	−22.42	−33.62**	−18.84	−53.31**	−42.64**	−69.96**	−32.32**	−53.84**	−33.62
	(6.77)	(15.85)	(12.53)	(24.89)	(19.02)	(15.32)	(20.17)	(15.44)	(19.82)	(20.15)
Spatial Lag (r)	0.07**	0.06**	0.06**	0.05**	0.05**	0.05**	0.05**	0.04**	0.05**	0.03**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.21	0.11	0.15	0.07	0.24	0.43	0.30	0.20	0.16	0.27
N	291	229	249	273	458	502	698	606	660	752

Note: Standard errors in parentheses.
$^{**}p < 0.05$.

TABLE 4 Spatial Lag Models. Dependent Variable: Contribution Amount from Asian Americans at the Zip Code Level (Northeast and Other Regions)

	1988	1990	1992	1994	1996	1998
Northeast						
Constant	−17164.50**		−8794.43**	−11076.4**	−23848.30**	−1229.86**
	(3999.68)		(2288.65)	(2477.17)	(4253.9)	(3416.58)
Population	39.58**		51.01**	37.51**	97.78**	41.90**
	(18.12)		(12.35)	(12.74)	(22.67)	(18.77)
Percent Asian	219.16**		130.98**	67.95	390.33**	132.32**
	(49.61)		(35.98)	(35.35)	(67.31)	(53.64)
Age	6134.51**		2458.78**	2770.62**	5860.38**	2546.80
	(1596.74)		(916.52)	(989.90)	(1699.22)	(1431.64)
Education	213.88		332.24	1214.24**	1709.21**	1467.45**
	(646.87)		(416.24)	(475.53)	(860.83)	(624.09)
Income	823.68**		485.95**	138.64	715.05**	224.22
	(233.01)		(153.39)	(171.13)	(311.64)	(230.03)
Percent Minority	16.83		−7.10	−5.38	8.66	−1.88
	(20.03)		(11.89)	(12.47)	(23.08)	(17.22)
Spatial Lag (r)	0.00		0.02**			0.02**
	(0.01)		(0.00)			(0.01)
Spatial Error (l)				0.05**	0.03**	
				(0.00)	(0.01)	
R^2	0.17		0.21	0.14	0.17	0.13
N	401		613	516	651	581
Other Regions						
Constant	18.21	−2626.48**	−2903.96	−461.45	−2247.06	569.54
	(1354.16)	(1202.37)	(2307.06)	(1134.60)	(1618.68)	(879.10)
Population	−1.36	26.81**	0.94	−7.71	−3.58	5.81
	(8.88)	(7.49)	15.60	(8.11)	(11.16)	(6.31)
Percent Asian	59.72	104.70**	12.55	29.98	63.31	110.11**
	(43.94)	(25.17)	52.89	(46.32)	(61.39)	(40.53)
Age	201.20	710.69	402.56	314.01	1016.10	283.07
	(426.22)	(446.67)	(795.24)	(389.48)	(568.06)	(300.91)
Education	141.81	41.52	404.67	228.03	−273.28	−266.73
	(280.91)	(245.46)	(518.80)	(258.08)	(354.28)	(196.41)
Income	100.18	332.26**	474.49**	48.15	698.35**	212.99**
	(108.82)	(96.50)	(214.22)	(104.78)	(156.36)	(89.94)
Percent Minority	0.70	3.03	20.74	7.25	13.68	−2.12
	(7.57)	(6.68)	(6.69)	(13.09)	(8.81)	(4.97)
Spatial Lag (r)	0.05	0.01**	0.03	0.06**	0.05**	0.07**
	(0.03)	(0.00)	(0.03)	(0.02)	(0.02)	(0.01)
R^2	0.05	0.11	0.03	0.03	0.07	0.08
N	324	918	760	701	980	874

Note: Standard errors in parentheses.
** $p < 0.05$.

contributions does not appear to be established until the mid-1980s. Once this pattern emerges, the analysis indicates that it persists. Although this relationship may not concur with the bulk of the literature on campaign finance, one must consider that the population bases for these previous studies have been comprised of primarily native-born Americans. Variation on the native-born/foreign-born dimension in those studies was virtually absent and if present, not a primary concern in the analysis.

These data, in contrast, are rich in variance on the nativity dimension, permitting us to catch a glimpse into the unfolding of the political incorporation dynamic. Hence, while the initial reaction to an insignificant income coefficient is somewhat surprising, some reflection on the context of these data mutes this initial reaction. Despite the oft-heard claim that Asians contribute primarily because of their high income levels (Lew 1987), then, the evidence here implies that the dynamic is considerably more complex. The evidence for a contagion effect is becoming stronger with each passing election, implying that Asian Americans are becoming increasingly sophisticated political actors with more and stronger intragroup ties.[16] As indicated by the significant income coefficient in later years, income levels may partly explain the behavior, but it is certainly not the sole determinant, and not even a significant part of the explanation in the earlier years.

Another strong similarity between the results in the various regions is that the "Percent Asian" variable is significant and generally rising throughout. The only exception is in the "Other Regions," where Asian Americans are also the most sparse. In the rest of the country, however, the main jump in values for this variable, as for the income variable, again occurs in the mid-1980s, where the magnitude of the coefficients makes a clear rise to a new plateau. At this point, activity rises, and the organization of this activity becomes more evident. The basic interpretation of the coefficient on "Percent Asian" is that as the percentage of Asians in a zip code rises, so too do the dollar amounts that are donated by Asians from those areas. Note that this is not simply a function of a larger population base in some areas, since the model controls for differences in population. The effect is over and above the population effect. Hence, Asian Americans are at least as active as others in terms of donating, and far from passive in this form of political behavior. This effect is present even when the income effect is absent, so it is not necessarily related to socioeconomic factors.

On more than one dimension, then, the confluence of a number of factors in the mid-1980s seems to have signaled a silent "new age" for Asian American politics, one that gives credence to the claims that the Asian American group is a "sleeping giant." The giant still appears to be in a state of semi-slumber, but there is evidence that the giant is beginning to stir. Notably, the observed changes in the 1980s coincide with the appearance of the first significant numbers of Asian American candidates for political office.[17] So the period of the 1980s for this group was indeed characterized by change on many political dimensions.

The most notable difference between the results for various regions is that, in all regions except the West, as the percentage of other minority residents rises, there seems to be little to no effect on campaign contributions from Asian Americans. In the West, however, we can see from Table 3 that there is a significant and negative effect. So, on a national scale and in the non-western states, after controlling for other variables, the dollar amounts that flow to candidates neither rises nor falls as the heterogeneity of the minority composition increased. In the West, the dollar amounts from Asian Americans decline in areas that are more ethnically heterogeneous. Hence, while there seems to be some ethnic contribution network at play among Asian Americans, this web of donations does not appear to cast itself more widely to include other ethnic groups on a national scale, and is negatively affected by other ethnic groups in the West. This result accords with much of the ethnic studies literature on political coalitions, namely, that Asian Americans do not generally align themselves with other minority groups to form a broader coalition (Saito 1998; Cho and Cain 2001; Lien 2001). The field of

[16]Note that while the data here are at the zip code level and we are primarily interested in individual behavior, this is not a classic case of the ecological inference problem. The reason is that the dependent variable, the amount in contributions from Asian Americans, we know, is attributable only to the Asian American residents in the zip code areas. We are unsure if the median income of the zip code area is representative of the median income of Asian Americans in the zip code area. However, a zip code area is a relatively small geographic unit, so this should not be a pervasive problem. The issue is how well the variable measures the underlying heterogeneity. Thus, problems that may occur in the analysis and interpretation are all related to the extent that zip codes variables do not adequately capture the underlying heterogeneity. This same caveat applies to the age variable. Other variables like population, percent Asian, and percent minority are less problematic. The percent Asian variable can obviously be attributable only to Asian Americans, and this variable is a basic measure of context. The percent minority variable does not apply only to Asians, but is instead the percentage of the area that is comprised of blacks and Hispanics. However, this variable, like the percent Asian variable, is a measure of context. It gives us an indication of how contribution amounts from Asian Americans vary as a function of context. The population variable allows us to examine how contribution amounts vary as population density changes. Hence, these last three variables are not problematic, as they are measured on a level of interest.

[17]Prior to the 1980s, there were few Asian American candidates. Although there were not a large number of candidates in the 1980s, and many of the candidates who did run were unsuccessful, the rise in numbers was nonetheless significant. During the 1980s, the number of Asian American candidates who ran for office rose to the double digits. This number increased dramatically in the 1990s. See Cho (2002) for a complete list.

campaign finance, where Asian Americans are especially active, does not appear to be an exception.

Interestingly, even after we control for socioeconomic and demographic factors, variables widely recognized to be influential, the spatial lag is still significant. This result holds for every year examined in the entire U.S. (except for 1986) as well as just the western region. The general pattern holds in the other regions as well. In the West, although the patterns among all of the variables is roughly the same, the magnitude of the spatial lag effect is larger and the models generally explain more variance in the data. It is not particularly surprising that the West would exhibit more spatial effects given that it has traditionally hosted and continues to host the bulk of the Asian American populace. The type of ethnic networks that we seek through the analysis pursued here are most likely to occur in locations where Asian Americans have resided the longest. As the length of time increases, there are more opportunities to integrate into the community as well as into the political scene.

Moreover, as the size of the community grows, there are more opportunities and outlets to integrate into the community. Hence, what is surprising is the simple existence of spatial effects that is evident apart from the tried-and-true socioeconomic indicators. Contribution amounts, then, are not generated solely by the non-spatial structural factors that have been identified by earlier research. Given that these effects exist, the relative magnitude of these effects in the West and in the nation align with initial expectations. While some of these spatial lag effects may seem small initially, note that the dependent variable is dollar amounts. In this time span, Asian Americans have contributed millions of dollars. The spatial lag effects, in terms of proportion, has remained largely the same, but the dollar amounts have increased seven-fold, and have regularly exceeded 7 million dollars in the 1990s. Thus, the effect is both substantively and statistically significant.[18] These effects are also likely to be tempered because the Asian American group is considered as a whole here, but ethnic networks are likely to be stronger within the various ethnicities that comprise the larger group.

The autocorrelated geographic patterns that we see in the models with significant spatial lag effects are typical of those patterns we might observe if contagion or diffusion effects were at play. People influencing people, and contributions begetting more contributions. Socioeconomic factors are also at play, but contrary to studies that examine only the atomistic actor outside of the context in which he resides, there is considerable evidence that contextual factors are also at play. The exact manner in which these webs operate is not clear from this analysis. However, we can see the emergence of the idea that candidates can tap into a ethnic contribution network.

For some of the years in the national data, 1988–1998, diagnostics for the spatial model indicate that some spatial error dependence remains. In the data for the western region, there appears to be some remaining spatial error dependence in a few of the years as well (1990, 1992, 1998). The spatial effects in these years are more complex than in the years where the diagnostics indicate no remaining spatial error dependence. That these years are clustered toward the end of the time period examined appears to indicate again that the complexity underlying the contribution dynamic is growing. In earlier years, the spatial lag was sufficient.[19] Because there are remaining spatial effects in these latter years from some unmeasured variable or variables, it is more difficult to expound on the origins of the spatial patterning. There seems to be some effect that can be captured via a spatial lag (i.e. an effect consistent with a diffusion process), but also some effect that may be, perhaps, consistent with a political mobilization or candidate effect story, where the variable (or variables) that measures these effects are not included or perhaps not available. Exploring these additional sources of spatial patterning and the mechanisms that may be lurking beneath these spatial patterns is an obvious extension of the analysis presented here. In general, fit statistics and diagnostics indicated that the spatial lag model was more appropriate, although some spatial error dependence did remain in several of the years. In the Northeast, the spatial error model was more appropriate for two of the years. The evidence, then, seems more consistent with a contagion effect than a mobilization effort,

[18]Moreover, these estimates are conservative. The spatial effects are likely to be much greater. The data here include all donations. If we were to limit the data to donations just to Democrats or just to Republicans, one can see how the diffusion effect would be expected to be larger. Within-party donations are more likely to beget more donations than to beget donations to the other party. Examining all of the donations, then, likely tempers the observed spatial effects.

[19]These models are still not ideal for several reasons. One reason that has already been mentioned is the difficulty of discerning the various types of spatial effects that may exist (i.e., spatial heterogeneity and spatial lag versus spatial error dependence). Another problem is that the model diagnostics show evidence of non-normality. Finally, the inclusion of the spatial dependence parameter did not eliminate the heterogeneity in every case. The data are limited, however, so the difficulty is exacerbated. The data need to be merged into the FEC data at some level of aggregation. The Census provides many socioeconomic variables, but no political variables, which may be useful here.

though there is some evidence of a mobilization effect as well. In any case, these data are complex on the spatial realm, with manifestations of many forms of spatial effects, from lag dependence to error dependence to spatial heterogeneity.

Conclusion

Donation rates across the country vary. Most of the analysis of these rates, however, have focused on the individual actor, acting within his own realm, making decisions based upon his own personal resources. For instance, past research has suggested that socioeconomic factors figure prominently in the decision to contribute (Sorauf 1988; Rosenstone and Hansen 1993; Verba, Scholzman, and Brady 1995; Brown, Powell, and Wilcox 1995; Gierzynski 2000). In the Asian American context specifically, research suggests that socioeconomic factors are at play, but that ethnic cues are also important. In neither the research on minority nor nonminority groups is there a focus on social context and how that might affect the contribution dynamic.

A central question in this article is whether the individual effects remain even after spatial effects are controlled. If the spatial lag is not significant, then we can explain the clustering of donation rates with covariates that measure individual characteristics. That is, "imitation" or diffusion through social networks cannot explain the clustering. Alternatively, if some clustering effect remains even after the covariates related to individual characteristics are controlled, then a diffusion process is likely to be a factor. As we saw from the analysis, spatial effects remain even after individual effects are controlled, implying that some type of diffusion force prominently underlies the Asian American campaign contribution network. In some of the later years, additional spatial error dependence remains, implying perhaps that some elite mobilization effort or candidate effect is fueling some of the spatial patterning. In either case, these spatial effects do not originate solely from the socioeconomic variables included in the model or completely within the realm of the individual-level explanations offered by previous research. Clearly, context plays a role.

By the end of the time span examined here, the patterns that we would expect to occur among the general populous manifest themselves among Asian Americans. Both the spatial lag as well as the socioeconomic indicators become significant predictors of geographical patterns of contributions. Whether these patterns will endure or how these patterns may morph in the future may be questionable, but the roots of the contextual effects have been laid. From the analysis presented thus far, we can see that the story is partly one of the atomistic actor acting alone, but it is also the story of the individual actor within the context of a more broadly defined neighborhood. In this way, the ethnic contribution network is nothing to balk. While less sophisticated political actors act alone, without a clear understanding of the immense benefits that arise from collective action, there is now evidence that Asian Americans are tending away from the less sophisticated individual-level model, and toward a more complex and involved networked model of behavior.

To be sure, Asian Americans bear some unique qualities as only one group of the polity. Nonetheless, the diffusion story likely underlies all of the campaign finance data and has broader implications for political behavior theories.[20] Certainly the social context literature has already advanced these theories, and so empirical studies will not lag much further behind. Here, limiting the analysis makes it feasible. Although broad and varied theories of network and neighborhood effects are posited without matching empirical verification, this analysis begins to move in a new direction and gives gusto to the adage that context matters.

[20]The limitations in computing power and model complexity, at the moment, hinder a larger study of the entire FEC database.

APPENDIX A: LISA Statistics[21]

FIGURE A-1 LISA Statistics for 1980

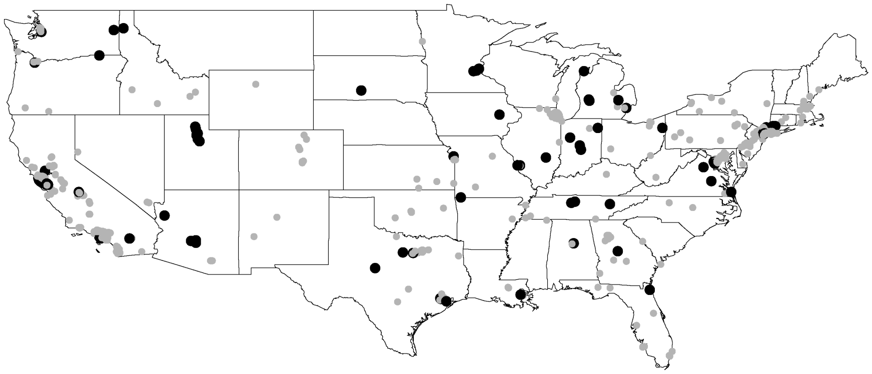
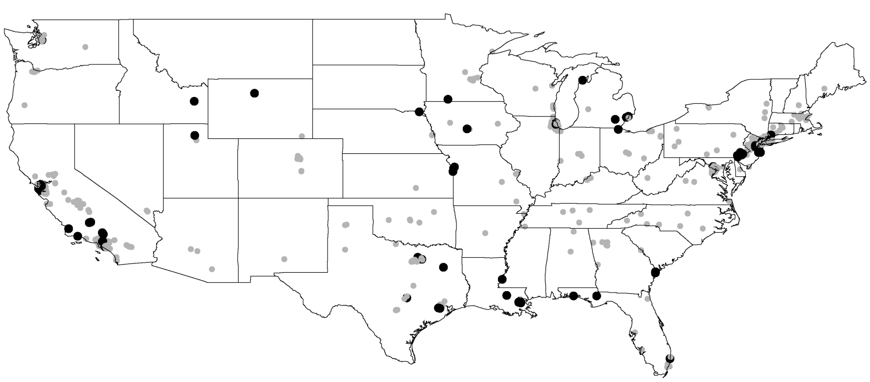


FIGURE A-2 LISA Statistics for 1982

FIGURE A-3 LISA Statistics for 1984



[21]Black dots indicate a zip code with a significant LISA statistic. Grey dots indicate a zip code with an insignificant LISA statistic.

FIGURE A-4 LISA Statistics for 1986

FIGURE A-5 LISA Statistics for 1988

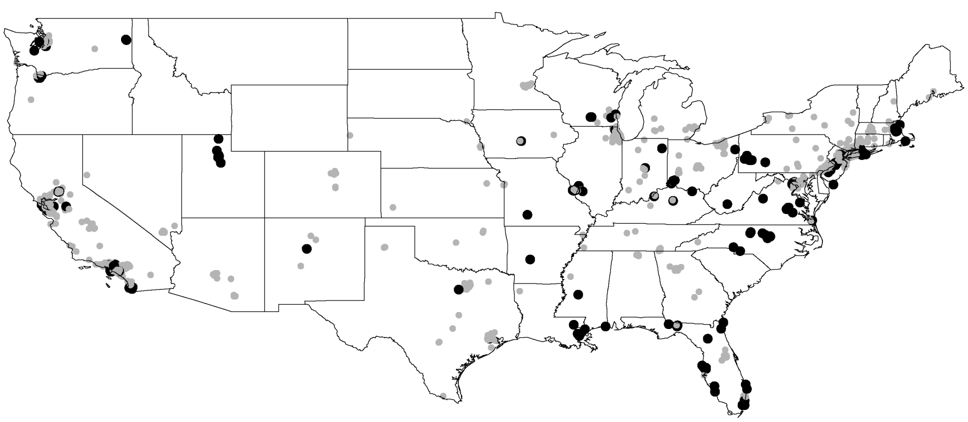


FIGURE A-6 LISA Statistics for 1990

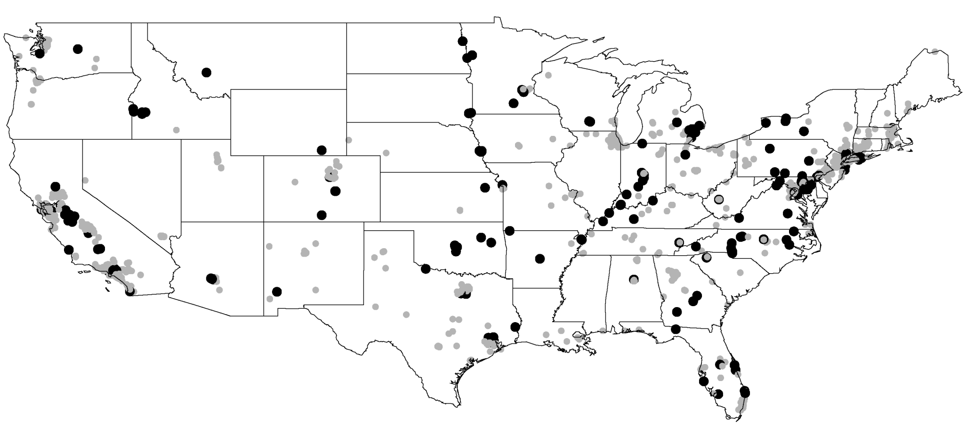


Figure A-7 LISA Statistics for 1992

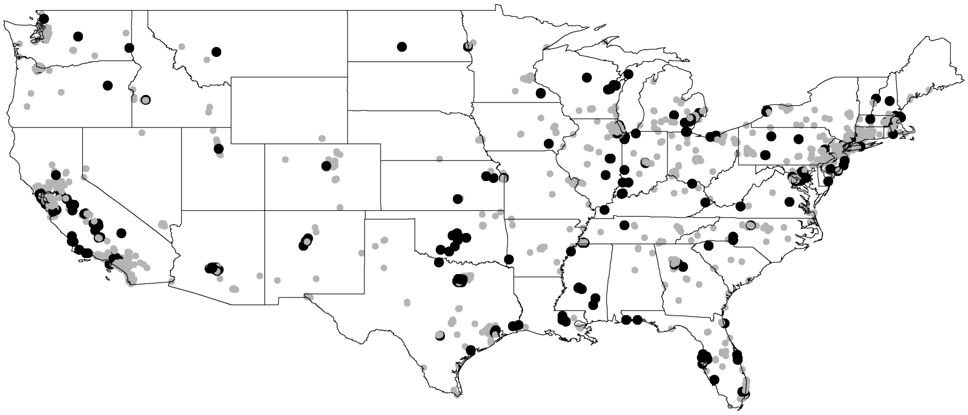


Figure A-8 LISA Statistics for 1994

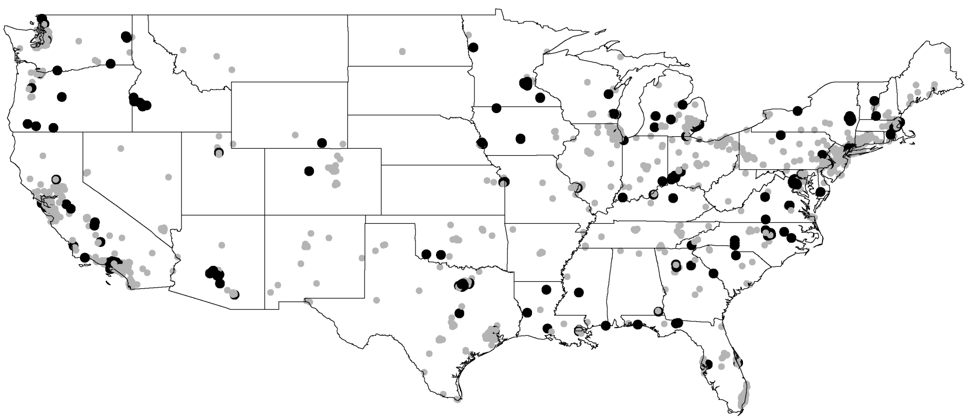


Figure A-9 LISA Statistics for 1996

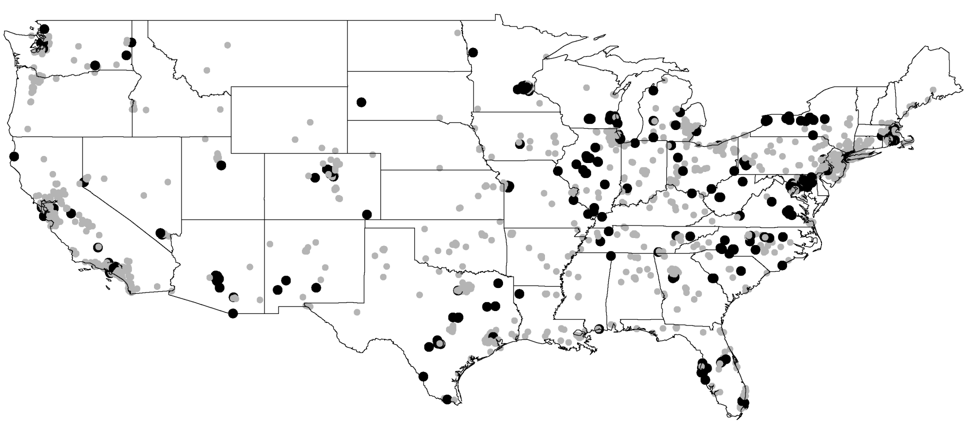
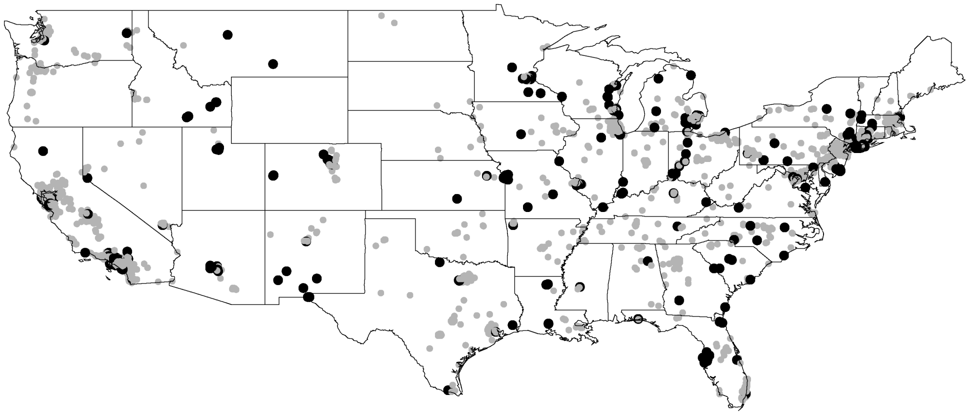


FIGURE A-10 LISA Statistics for 1998



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