Estimating Spatial Autocorrelation Between Election Result and Census Demographic Distributions within Subset of Hennepin County, Minnesota

Nick Rochon
Department of Resource Analysis, Saint Mary's University of Minnesota, Minneapolis, MN 55404

Keywords: Spatial Autocorrelation, Spatial Cluster, Local Moran's I, Voting Pattern, Census Demographics, Spatial Analysis

Abstract

Voting patterns are increasingly defined by their geographical distribution and tested for evidence of spatial autocorrelation, otherwise known as spatial clusters. Moran's I is a common spatial statistic used to estimate the degree of spatial autocorrelation under an imposed spatial weights matrix. This study aims to estimate the degree of spatial autocorrelation between the 2020 presidential primary election results and US Census demographic distributions within a subset of Hennepin County, MN which include the cities of Minnetonka, Hopkins and St. Louis Park. Spatial and non-spatial data sets were downloaded from publicly available websites and transformed to attribute census data to voting precincts within the study area. A bivariate spatial analysis was completed using GeoDa software (open-source) and based on "rook" contiguity. Final results of this study observed positive spatial autocorrelation among race, age, household structure and median house income estimates when compared to Democratic voting percentages. Moreover, the results provided strong evidence of spatial clustering for half of the tested variable pairs within a ninety-five percent confidence interval and assumes there to be a significant spatial component to the systematic structure of their geographic distributions as a result of this analysis.

Introduction

Voting patterns in the United States are traditionally considered to be divided along urban and rural axes (Morrill, Knopp, and Brown, 2007) and strengthened by the social, economic and cultural differences that exist between geographically distinct voter groups (McKee and Teigen, 2009). Political research often combines elections data with census demographics to make ecological inference on voting behavior, and considers spatial context to provide new insight into the political geography of the voting population.

Background

Spatial statistics is a practical application for examining the intersection between election and census data. Providing a spatial framework to conventional correlation and regression methods, spatial statistics considers both composition and context of geographic data in estimating spatial autocorrelation (Haining, 2009). The term spatial autocorrelation estimates the degree of similarity, positive or negative, between nearby observations

Rochon. N. 2020. Estimating Spatial Autocorrelation Between Election Result and Census Demographic Distributions within Subset of Hennepin County, Minnesota. Volume 23, Papers in Resource Analysis. 12 pp. Saint Mary's University of Minnesota University Central Services Press. Winona, MN. Retrieved (date) http://www.gis.smumn.edu

defined by a geographical proximity (Hubert, Golledge and Costanza, 1981). Today, political election research assumes voting patterns are not independent of spatial effect, and therefore, exhibit some degree of spatial autocorrelation (O'Laughlin, 2008), similar to other social phenomena such as disease outbreak (Rogerson and Yamada, 2004) and crime density (Jeong, Moon, and Heo, 2009).

Project Value

Political election research has demonstrated the effect of spatial autocorrelation on election results and participation levels in the United States (Burnett and Lacombe, 2012), England and Wales (Cutts and Webber, 2007), France (Saib, 2017), Portugal (Caleiro and Guerreiro, 2005) and Indonesia (Yandri, 2017). Moreover, election research has shown positive spatial autocorrelation to exist between election results and demographic variables (Klos, 2008). The concept and understanding of spatial autocorrelation plays a crucial role in developing spatial models throughout multiple fields of academic research, including political election research. The use of georeferenced data continues to increase in efforts to understand ecological phenomena, while most empirical research recognizes the importance of spatial autocorrelation in testing hypotheses on spatial relationships, estimating the degree of spatial effects and distance decay and understanding how spatial geometry might influence the realization of a variable and other valuable information (Getis, 2008).

The purpose of this study is to estimate the degree of spatial autocorrelation between recent presidential primary results and census demographics estimated by the US Census Bureau as late as 2018. In doing so, this study contributes to the existing literature in spatial research with new assessment on the current election cycle as well as provide insight into the spatial relationship between individual demographic variables and partisan support at the local level.

Study Area

The study area (Figure 1) is composed of forty-five voting precincts and thirty-two census tracts within the cities of Minnetonka, Hopkins and St. Louis Park, Minnesota. Combined together this area covers roughly forty-four square miles and includes a total estimated population of slightly more than one-hundred and twenty-one thousand people according to the US Census Bureau. Each of the cities included in this study are considered moderately liberal and have voted in majority for the Democratic candidate in all of the previous seven presidential elections since 1992, according to the Office of the Minnesota Secretary of State.

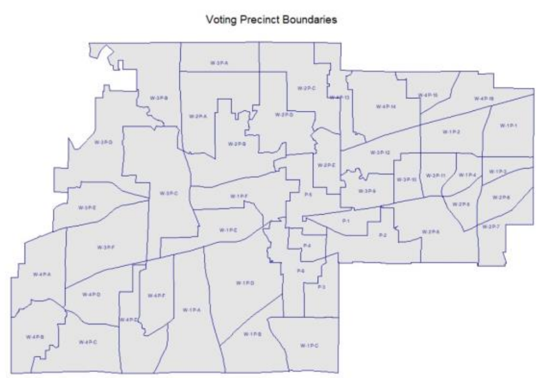

Figure 1. Study area defined by voting precinct boundaries as of the current election cycle for Minnetonka, Hopkins and St. Louis Park, Minnesota.

In the most recent presidential primary election, an average of at least ninety-three percent of city residents voted for Democratic candidates as compared to their Republican counterparts across all voting precincts in the study area. Considering historical election results, this area exhibits strong partisan support for Democratic presidential candidates. As such, it provides a good example to examine relationships between voting patterns and census demographics in an effort to better understand how each variable distribution relates to one another across space. Additionally, this study chose voting precincts and census tracts as the scales of measurement since both are relatively similar in size (but not shape) and are the smallest spatial units with readily available election and demographic data. Limiting the margin of error associated with aggregate data was also considered when selecting these data sets.

Project Overview

A bivariate spatial analysis was conducted to estimate the degree of spatial autocorrelation using publicly available elections and census data. This research examined the percent of Democratic support per voting precinct in comparison to demographic variables assigned to individual voting precincts listed below:

- Percent non-white
- Percent under 60 years old
- Percent female
- Percent below med. household income
- Percent with veteran status
- Percent with disability status
- Percent non-family household
- Percent with home internet access

Race, age, gender and economic variables are commonly studied in the literature and similarly tested in previous research (Klos, 2008). The remaining four variables were readily available at the census tract level and included to expand on existing knowledge of voting behavior and demographics. The intended output includes a summary table of the results, cluster maps to illustrate where positive spatial autocorrelation exists and associated scatter plots to measure the strength and direction of this relationship. The nature of this study was to explore where election results might relate to demographic variables within a spatial model. It is the hypothesis of this study that positive spatial autocorrelation exists between the observed voting pattern and census demographic distributions in the study area where:

H_0 – Observed distributions of Democratic support and census demographics occur randomly between one another

H_1 – Observed distributions of Democratic support and census demographics occur non-randomly between one another

The success of this study relies on accurate data collection, transformation and analysis of the final results. A detailed methodology is described in the following section and includes data sources and techniques for spatial statistical analysis. Remaining sections include a summary of the final results, discussion on the implications of this study and concluding remarks for future research.

Methodology

All of the data used in this study is made publicly available online and available for download or by request. Study area boundaries, election results and census demographics were acquired from multiple sources, prepared and transformed using Excel, R (an open-source statistical computing and graphics language) and GeoDa software (Dr. Luc Anselin's open source spatial analysis tool). None of the data was edited or changed in any way except for the purpose of re-defining the spatial data boundaries to the study area and rendering election results and census demographic variables as percentages. All data captured in this study was retained in aggregate form and therefore does not present the potential for data privacy concerns.

Data Collection and Preparation

Voting precinct boundaries and census tract boundaries (Figure 2) were downloaded from Hennepin County's GIS Open Data website as shapefiles representing the legal definitions from 2012 and 2010, respectively. Using R the shapefiles were stored as spatial data frames using the *sf* (simple feature) package and converted to the standard WGS84 coordinate system for global positioning systems (GPS) based on guidelines provided by the National Geospatial-Intelligence Agency (NGA) for commercial and open-source data sets.

Next, state primary election results from 2020 were obtained from the Minnesota Secretary of State's Office website for selected voting precincts within the defined study area. Vote totals by precinct were downloaded into Excel and used to calculate partisan support with basic cell equations – sum vote totals for each political party (as columns) and divide by the vote total for each voting precinct (as rows). Partisan support was rendered as a percentage and read into R using the *readxl* package as a tabular data frame.

Census demographic data was downloaded from the US Census Bureau's online website. Each demographic variable was captured in the 2018 American Community Survey and was the most recent data available provided by the US Census Bureau. Census tracts were used as the spatial unit of measurement since most meaningful demographic variables are not recorded and/or publicly available at smaller scales of measurement (i.e. census block groups or census blocks). A single table was downloaded into Excel and transposed to include percent estimates for each demographic variable (as columns) per census tract (as rows) within the study area. The table was also read into R and stored as a tabular data frame.

Spatial and Non-Spatial Data Transformation

Most often election and census boundaries do not conform to one another since they are collected by different governing agencies with separate needs and intentions for the data (Amos, McDonald and Watkins, 2017). According to Dr. Michael McDonald of the Public Mapping Project (2001), there are three acceptable methods for merging election and census geography: 1) geospatially join the data based on largest area, 2) geocode voter registration from corresponding voting districts to census geography, or 3) assign geography by voting district (VTD) identifiers provided to the US Census Bureau.

At the time of this study, VTD identifiers were not included within census demographic data sets provided by the US Census Bureau at the census tract level. And while this study attempted to define census tract boundaries by geocoded voter registration data, it was not an accurate method for summarizing the data sets since multiple census tracts can and do exist within a single voting precinct and this relationship must be one to one, not

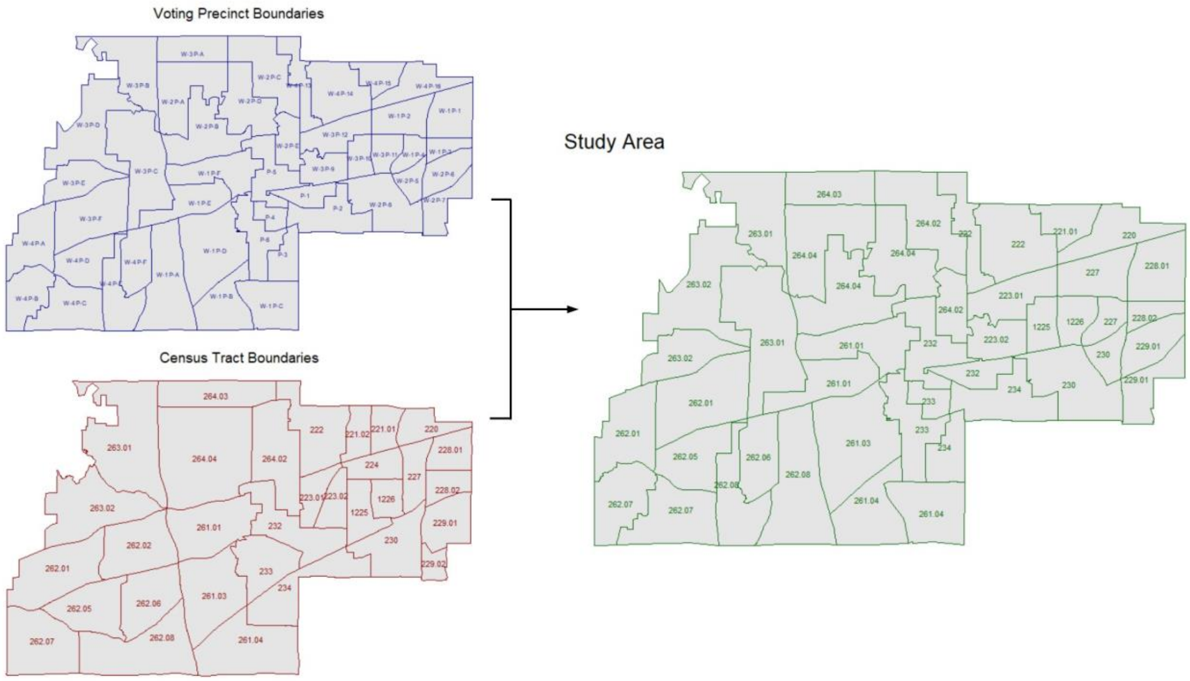

Figure 2. Resulting spatial layer (green) following the spatial join process of attributing census tract identifiers (red) to voting precinct boundaries (blue) based on largest areal overlap.

one to many. Election and census data were therefore merged based on largest areal overlap using the *sf* package in R (Figure 2). It is important to note four census tracts did not constitute a majority of any of the voting precincts and were therefore removed from the spatial layer and final analysis: tracts 221.02, 224, 229.02 and 262.02.

Finally, the non-spatial election results and census demographics were merged to this spatial data frame shown in Figure 2 and exported as a shapefile to be used for spatial statistical analysis. The shapefile contained a total of forty-five discrete voting precinct boundaries, each defined by one of twenty-eight census tracts and attributed with the percent Democrat vote and percent demographic variable distributions. This shapefile was used as the basis for statistical analysis outlined in the following section.

Analysis

Local Moran's I Statistic and Spatial Weights Matrix

The most common approach to explore spatial autocorrelation among geographic data is Moran's I statistic and local indicators of spatial association (LISA) (Matkan, Shahri and Mirzaie, 2013). Moran's I is a global index which measures the likelihood of spatial autocorrelation on a scale of -1 to 1 or the tendency of the data to be systematically dispersed versus clustered. A Moran's I value of 0 represents no autocorrelation or perfect randomness in the data.

Global Moran's I is useful in estimating spatial autocorrelation using one statistic to summarize the spatial patterns, however it is less useful in determining where spatial clusters or outliers might exist within the data since it assumes the underlying global pattern is generally homogeneous (Ord and Getis, 1995; Anselin, 2003). Local Moran's I decomposes global indicators and focuses on specific locations within the data to identify how they might be similar or dissimilar to neighboring locations and can therefore explicate where spatial clusters and outliers exist outside of the global pattern (Anselin, 1993). Using local Moran's I each location is attributed with its own correlation coefficient. In this way, local Moran's I accounts for pockets of spatial heterogeneity in the data and is the preferred method for statistical analysis of spatial data.

A bivariate local Moran's I is a continuation of the univariate Moran's I and is estimated as follows:

$$I = \frac{N}{\sum\sum w_{ij}} \frac{\sum\sum w_{ij}\,(x_i - \bar{x})\big(y_j - \bar{y}\big)}{\sum(y_i - \bar{y})^2}$$

The above formula represents *I* as the bivariate Moran's I statistic and is an estimate of the relationship between the value of an original variable at location *i* (x_i) and the average of all neighboring values for another variable *j* (y_j) or its spatial lag. This study defines *N* geographic units as individual voting precincts within the study area. A spatial weights matrix was created to assign spatial contiguity to the data based on the "rook" function (Klos, 2008).

In this way, the spatial weights matrix reduces the amount of interaction of voting precincts and constrains the number of neighbors to only those voting precincts which share a border. Each variable and its neighbors are multiplied by the spatial weight and then divided by the sample variance. The result of this statistic yields the degree of linear association (positive or negative) between variable pairs at neighboring locations (Anselin, Syabri and Smirnov, 2002). The strength of the interaction is equal to the combined effect of the coefficient and row-standardized weights (Anselin, 2003). Of the forty-five voting precincts included in the study area, an average of 4.44 neighbors were estimated per voting precinct with a standard deviation of 1.50, according to the spatial weights connectivity histogram in Figure 3.

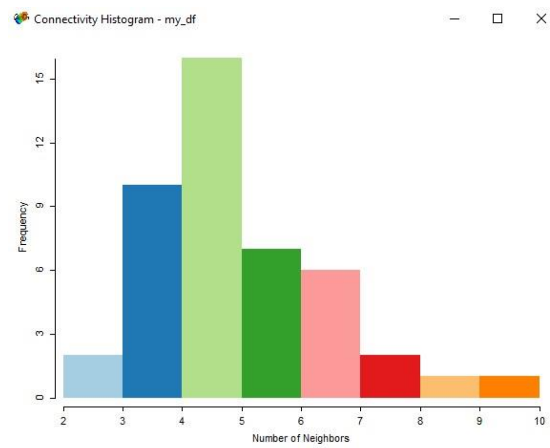

Figure 3. Connectivity histogram generated from the "rook" spatial weights matrix using GeoDa software. This output shows the distribution of defined neighbors per voting precinct.

Spatial Analysis Using GeoDa Software

The spatial analysis was completed using the bivariate local Moran's I statistic provided within GeoDa software. The final shapefile containing voting precinct boundaries and election and census demographic attributes was loaded into the GeoDa interface and tested for spatial autocorrelation between variable pairs under the Space – Bivariate Local Moran's I menu function.

A bivariate local Moran's I statistic estimates the degree of spatial autocorrelation between variable pairs, including an original variable and a spatial lag variable at each voting precinct within the study area. As a result, the spatial analysis was conducted twice for each variable pair – once with the percent Democrat vote as the original variable and individual demographic variable as the spatial lag; and again, with individual demographic variable as the original variable and the percent Democrat vote as the spatial lag variable.

This study is interested in voting precincts which exhibit positive spatial autocorrelation (high-high or low-low) between demographic and voting percentage distributions per voting precinct. GeoDa software illustrates positive spatial autocorrelation using dark red (high-high) and dark blue (low-low) colors. These highlighted areas therefore represent spatial clusters where the distribution of the original and spatial lag variables is positively correlated to one another and provide evidence in support of the alternative hypothesis (H_1) which estimates that these distributions are not likely to occur randomly. Areas highlighted in light red (high-low) and light blue (low-high) represent spatial outliers, or negative spatial autocorrelation, and are not an interest of this study.

The estimated spatial clusters were calculated based on a spatially random reference distribution of 9,999 permutations to assess for statistical significance with a minimum standard p-value < 0.05. These areas are therefore supported by a ninety-five percent confidence interval of exhibiting positive spatial autocorrelation under random conditions.

Results

Following the bivariate spatial analysis outlined in the previous section, the final results of this study identify which demographic variables are positively correlated to the observed voting pattern and where these similarities are spatially clustered. Table 1 summarizes the relationship between each variable pair and includes the average percent for individually observed spatial clusters as well as the percent increase or percent decrease from the total average of the entire data set.

In the end, four demographic variables were identified to be positively spatially autocorrelated, either (low-low) or (high-high), when compared to the percent Democrat vote across the study area. These include percent non-white, percent under the age of sixty-five, percent below median household income and percent non-family households. While the remaining four demographic variables – percent female, percent with veteran status, percent with disability status and percent with home internet access – did not exhibit clustering as a result of the spatial analysis.

Many of the demographic variables shared clusters defined by the same voting precincts. These include W-3 P-E, W-3 P-F, W-4 P-A and W-4 P-B which similarly exhibited positive (low-low) spatial autocorrelation among percent non-white, percent below median household income and percent non-family household demographics. Additionally, voting precinct W-3 P-9 exhibited positive (high-high) spatial autocorrelation among percent non-white, percent below median household income and percent non-family household demographics. It is important to note that W-3 P-F and W-4 P-A were both defined by census tract 262.01 as a result of the spatial join process; therefore, these were represented by the same underlying demographics.

Resulting spatial clusters illustrate areas that contain either above high or below low estimates of partisan support and demographic variables as well as

Table 1. Cluster Mean Values, Difference (+/-) from Global Mean and Cluster Pattern/Locations of Spatial Autocorrelation among Voting Precincts.

Demographic Variable	**Cluster Vote Mean**	**+/- Total Mean**	**Cluster Demographic Mean**	**+/- Total Mean**	**Cluster Pattern**	**Clustering Voting Pre-cincts**
Percent Below Med. HH Income	95.0%	+1.7%	65.1%	+18.4%	High-High	W-3 P-9
	90.2%	-3.1%	29.8%	-16.9%	Low-Low	W-3 P-E, W-3 P-F, W-4 P-A, W-4 P-D
Percent Non-Family HH	95.2%	+1.9%	53.6%	+8.0%	High-High	W-1 P-4, W-2 P-5, W-2 P-6, W-3 P-9, W-3 P-12
	89.6%	-3.7%	23.7%	-21.9%	Low-Low	W-3 P-E, W-3 P-F, W-4 P-A, W-4 P-B, W-4 P-D
Percent Non-White	95.0%	+1.6%	21.3%	+4.2%	High-High	W-3 P-9
	90.1%	-3.2%	6.9%	-10.2%	Low-Low	W-3 P-E, W-3 P-F, W-4 P-A, W-4 P-B, W-4 P-D, W-4 P-E
Percent Under 65 Years	95.4%	+2.1%	91.1%	+7.9%	High-High	W-1 P-4, W-2 P-8, W-4 P-16
	90.6%	-2.7%	81.5%	-1.7%	Low-Low	W-1 P-A
Percent Female	93.32%	N/A	51.2%	N/A	No clus-ters	N/A
Percent Veteran Status	93.32%	N/A	6.0%	N/A	No clus-ters	N/A
Percent Disability Status	93.32%	N/A	9.6%	N/A	No clus-ters	N/A
Percent Home Internet Access	93.32%	N/A	88.1%	N/A	No clus-ters	N/A

The bottom four demographic variables paired with voting percentages did not exhibit positive spatial autocorrelation or clustering as a result of this analysis. With no clusters identified for these variables there is no way to compare location-specific distributions from the global data set and are therefore described as "N/A" in the above table.

neighbors which also contain relatively similar estimates for the corresponding variable pair. The percent non-family household and percent non-white demographic variables displayed the greatest evidence of spatial clustering, with each containing ten and seven spatially autocorrelated clusters of voting precincts between tested variable pairs, respectively. While the percent below median household income and the percent under the age of sixty-five each contained spatial clusters of five and four voting precincts, respectively.

Due to limitations on space and organization, not all graphics are included for each of the test variable pairs within this study. As an example, Figure 4 illustrates the geographical distribution of the estimated positive (high-high) spatial autocorrelation between percent Democrat vote and percent non-family households. Figure 5 illustrates the direction and strength of this relationship using a scatter plot to estimate the local Moran's I coefficient and linear regression along an x- and y-axis. In this example, it is perceived that below average and above average observations are geographically distinct from one another and can be represented by a statistically significant positive relationship based on the local Moran's I coefficient.

A summative assessment of these results and how they relate to previous research is discussed in the following section. Study limitations, new discoveries and opportunities for future research are also included.

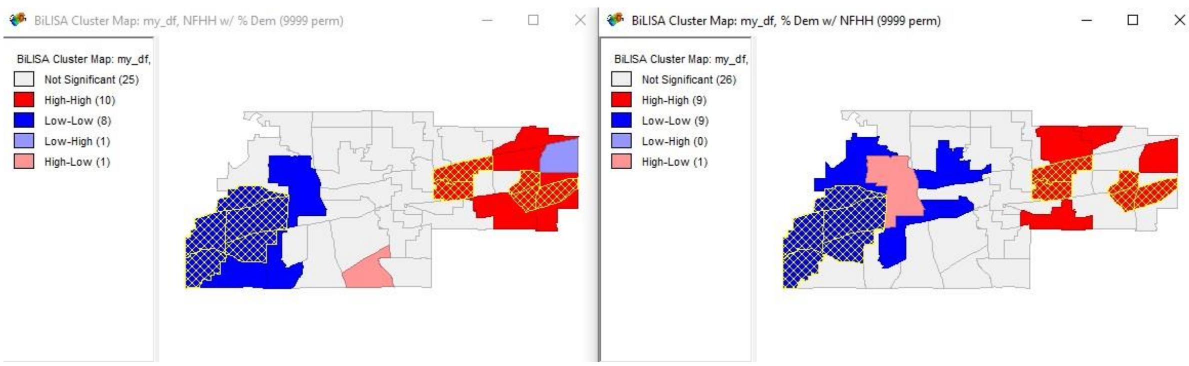

Figure 4. Cluster maps showing positive spatial autocorrelation between percent non-family households (NFHH) and percent Democratic support (% Dem). Areas in dark blue represent voting precincts with significantly lower estimates of non-family households and less Democratic support compared to respective mean values, while areas in dark red represent significantly higher estimates of non-family households and greater Democratic support compared to the mean. Voting precincts highlighted in yellow constitute the spatial clusters estimated by the bivariate local Moran's I coefficient.

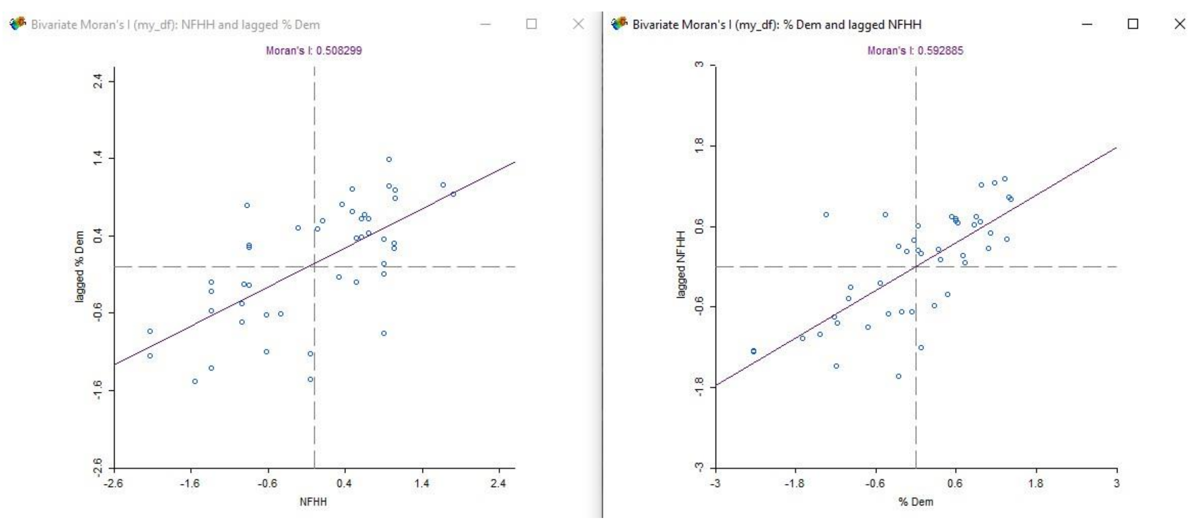

Figure 5. Scatter plot showing the strength and direction of the same variable pair included in the above cluster maps. The value along the x-axis is defined as the original variable, while the value along the y-axis is the spatial lag variable. Spatial clustering occurs around the voting precincts pointed within the upper right-hand quadrant of each scatter plot.

Discussion

The goal of this study was to explore the spatial relationship between state primary elections data and census demographics. The results estimate that four of the eight demographic variables were, in fact, positively spatially autocorrelated to Democratic support within a ninety-five percent confidence interval. Local Moran's I explicates the relationship between election results and census demographics and provides strong evidence of spatial clustering between the voting pattern and census demographic distributions and can therefore reject, in part, the null hypothesis that these distributions occur randomly.

Literary Support and Divergence

The results of this study are supported by existing literature which observed positive spatial autocorrelation among general voting behaviors under geographical concentration (Kim, Elliot and Wang, 2003; Seabrook, 2009; Saib, 2017). Spatial clustering of voting and demographic distributions converge with results from Klos (2008) in which race, age, and median household income trends were similarly observed to correlate with regional voting patterns at the local level. Assuming that these patterns are not independent of spatial effect under random conditions, the results of this study are also defended by the general understanding that political behavior often exhibits some degree of spatial autocorrelation due to the geographic forces that are inherent to the data set (O'Laughlin, 2008).

It is difficult to interpret the demographic variables that were not spatially clustered since there is seemingly no consistent relationship to partisan support in the study area. Under the local Moran's I statistic, these demographics are inconsistent in their distributions depending on the original and spatial lag variable assignment. The spatial structure of these variables are therefore estimated to exist in a completely random distribution in comparison to one another from this analysis and do not provide much room for inference or interpretation beyond this understanding.

Demographic variables like veteran and disability status and home internet access are not commonly discussed in the existing literature and very well could be unrelated to voting patterns in general. It is also possible that these variables would test differently under a different spatial weights matrix or confidence interval. That said, gender is thoroughly discussed in the literature, but whether due to little variation among the female population per voting precinct in the study area or an insignificant estimation under the imposed ninety-five percent confidence interval, gender was not observed to have a positive correlation to the observed voting pattern in this study.

Study Limitations

As spatial analysis continues to contribute to political science research and theory, it is important to understand the limitations and meaning of this type of analysis. While this study does not claim that certain demographic distributions lead to partisan support, or the inverse for that matter, the results of this study do indicate areas with observed similarities between half of the tested variables centered around neighboring voting precincts. In the same vein, results from this analysis do not provide reasons for why spatial clustering exists – they simply speak to what was observed under random conditions and whether the apparent similarity (or dissimilarity) in values for a feature and its neighbors is statistically significant or not. Given the scope of this study, it is impossible to determine all of the factors that contribute to the geographic distribution of voting patterns and census demographics; however, local Moran's I does well to estimate the spatial relationship between these variable pairs under the assumption that their geographical reference point is not irrelevant (O'Laughlin, 2008).

Spatially correlated clusters were most commonly observed along the southwest and east regions of the study area, which could be relevant if these areas are comprised of similar neighborhood types or population groups. While only some of the voting precincts were identified as statistically significant, there still exists a degree of similarity from neighboring precincts not identified in the cluster maps as the result the spatial analysis method (Anselin, 2003).

Among the limitations associated with this study, the use of census demographics creates the problem of ecological inference (Shively, 1969), or inferring individual behaviors from aggregate data. That said, this practice is common among political science research and mitigated by the use of data recorded at the census tract-level as opposed to less granular estimates. Another limitation stems from the spatial join process which resulted in losing a total of four census tract identifiers. Due to common differences between census and election geometries, study results are not entirely representative of the study area and would be more accurate if all voting precincts were attributed to a single, unique census tract.

Future Research

Future research is necessary to further substantiate the presence of spatial autocorrelation among voting pattern and demographic trends. A more comprehensive spatial analysis would resolve many of the limitations associated with this study and expand on existing research with data from future election cycles and the 2020 Census project. Ongoing efforts to relate election and census spatial boundaries will also provide new techniques for comparing these data sets in future studies.

Conclusion

Voting patterns and census demographic distributions are not necessarily independent from their geography and do exhibit spatial autocorrelation under a spatial model estimated by bivariate local Moran's I. Spatial analysis is a valuable approach for understanding current political phenomena and patterns of spatial heterogeneity within an evolving electorate in presidential elections. Improved technology and data accuracy is imperative for future research on this topic and will provide new insight and greater transparency into the political process.

References

Amos, B., McDonald, M., and Watkins, R. 2017. When Boundaries Collide: Constructing a National Database of Demographic and Voting Statistics. *Public Opinion Quarterly*, *81*(S1), 385–400.

Anselin, L. 2003. An Introduction to Spatial Autocorrelation Analysis with GeoDa. Spatial Analysis Laboratory. University of Chicago.

Anselin, L., Syabri, I., and Smirnov, O. 2002. Visualizing Multivariate Spatial Correlation with Dynamically Linked

Windows. Spatial Analysis Laboratory. University of Chicago.

Burnett, W., and Lacombe, D. 2012. Accounting for Spatial Autocorrelation in the 2004 Presidential Popular Vote: A Reassessment of the Evidence. *The Review of Regional Studies, Southern Regional Science Association*, *42*(1), 75-89.

Caleiro, A., and Guerreiro, G. 2005. Understanding the election results in Portugal. *Portuguese Economic Journal*, *4*(3), 207–228.

Cutts, D., and Webber, D. 2009. Voting Patterns, Party Spending and Relative Location in England and Wales. *Regional Studies*, *44*(6), 735–760.

Getis, A. 2008. A History of the Concept of Spatial Autocorrelation: A Geographer's Perspective. *Geographical Analysis*, *40*(3), 297–309.

Haining, R. 2009. Spatial Autocorrelation and the Quantitative Revolution. *Geographical Analysis*, *41*(4), 364–374.

Hubert, L. J., and R. G. Golledge, and C. M. Costanza. 1981. "Generalized Procedures for Evaluating Spatial Autocorrelation. *Geographical Analysis 13*, 224– 32.

Jeong, K., Moon, T., and Heo, S. 2009. Analysis of Spatio-temporal Pattern of Urban Crime and Its Influencing Factors. *Journal of the Korean Association of Geographic Information Studies*, *12*(1), 12–25.

Kim, J., Elliot, E., and Wang, D. 2003. A spatial analysis of county-level outcomes in US Presidential elections: 1988–2000. *Electoral Studies*, *22*(4), 741–761.

Klos, J. 2008. Determining spatial correlations between voting behavior and selected demographic variables in a changing electorate. *Middle States Geographer, 41*, 19–26.

McDonald, M. 2001. *About the Data*. Public Mapping Project. http://www.publicmapping.org

McKee, S., and Teigen, M. 2009. Probing the reds and blues: Sectionalism and voter location in the 2000 and 2004 U. S. presidential elections. *Political Geography*, *28*(8), 484–495.

Matkan, A., Shahri, M., and Mirzaie, M. 2013. Bivariate Moran's I and LISA to Explore the Crash Risky Locations in Urban Areas. *N-Aerus Xiv*. 1-12.

Morrill, R., Knopp, L., and Brown, M. 2007. Anomalies in red and blue: Exceptionalism in American electoral geography. Political Geography, 26(5), 525–553.

O'Loughlin, J. 2008. *A Companion to Political Geography*. John Wiley & Sons.

Ord, J. K., and Getis, A. 1995. Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis*, *27*(4), 286–306

Rogerson, P., and Yamada, I. 2004. Monitoring change in spatial patterns of disease: comparing univariate and multivariate cumulative sum approaches. *Statistics in Medicine*, *23*(14), 2195–2214.

Saib, M. 2017. Spatial Autocorrelation in Voting Turnout. *J Biom Biostat 8*, 376.

Seabrook, N. 2009. The Obama Effect: Patterns of Geographic Clustering in the 2004 and 2008 Presidential Elections. *The Forum*, *7*(2), 188–209.

Shively, P. 1969. Ecological Inference: The Use of Aggregate Data to Study Individuals. *The American Political Science Review, 63*(4), 1183-1196.

Yandri, P. 2017. The Political Geography of Voters and Political Participation: Evidence from Local Election in Suburban Indonesia. *Indonesian Journal of Geography*, *49*(1), 57–64.