The Political Geography of Inequality:

The Impact of Income Inequality on the Spatial Structures of Electoral Dominance.
I. Introduction

Since the 1970s, the United States has struggled with a middle-class problem. Rooted in what Bluestone and Harrison (1982) dubbed “The Great U-Turn,” the U.S. economy has departed from the union-backed manufacturing of the 1950s and 60s, and typical middle-class jobs have declined as new labor structures have emerged to fill their place (Nielsen and Alderson 1997; Piore and Sabel 1984; Bluestone and Harrison 1982; 1988). The new technologies of the 1990s and 2000s – in a process known as skill-biased technological change (SBTC) – have segmented labor markets, meaning that “decent” jobs¹ now require highly-educated, highly-skilled applicants (Gordon 2016; Berman, Bound, and Machin 1997; Card and DiNardo 2002; Bound and Johnson 1992). Members of what Florida (2002) refers to as the “creative class” are the beneficiaries of this change, while those left behind by the New Economy struggle to make ends meet by working minimum-wage service-sector jobs. Another consequence has been a bimodal labor market, with growth only at the highest and lowest quintiles (Wright and Dwyer 2003). Prospects of reversing this trend are bleak, as high capital returns allow the wealthy to grow increasingly rich compared to workers, while overall economic growth across developed nations slows (Piketty and Saez 2001; Piketty 2014).

Making matters worse in the United States, political polarization has mirrored the rise of economic polarization. The Republican and Democratic parties are growing further and further apart on the ideological spectrum, and prominent scholars believe these phenomena to be linked – that economic polarization leads to political polarization (McCarty, Poole, and Rosenthal 2006; Bartels 2008). The best-known framework for addressing these phenomena is the classic Meltzer-Richards model, which contends that the poorest Americans vote for the party with a redistributive

¹ Wright and Dwyer (2003), for example, rank jobs into five-categories based on earning potential. The find that the strongest growth during the 1990s can be found in the top-quintile and bottom-quintile – corresponding to jobs with the highest and lowest earning potentials. Thus, “decent” jobs are increasingly found in the upper-quintile of the income distribution.
platform, and the wealthiest Americans vote oppositely (Meltzer and Richards 1981). This paper refers to this precept – and the branch of political economy research that it has birthed – as economic-interest theory. Most national-level theories linking economic and political polarization have been built on the core assumption that “high-income voters increasingly identify with the Republican Party and vote for Republican Presidential candidates. Low-income voters are increasingly in the Democratic camp” (McCarty, Poole, and Rosenthal 2006, 71). Bartels (2008, 84) agreed, concluding from national survey data that economic issues are more important to voters than cultural issues, but primarily for a single demographic: “Among white voters in all three income groups, the two issues most strongly associated with presidential vote choices are government spending and services and defense spending.” These studies, alongside the Meltzer-Richards model, have inclined many theorists to accept the economic-interest model, but the racially conditional conclusion of Bartels (2008) suggests that this prevailing view remains imperfect. While the economic-interest theory focuses on the national level, the divide between Red and Blue America is often measured along state, county, and district lines. Close examination is needed to discern if economic patterns reflect political patterns across these spatial units.

This paper will consider whether scholars touting economic-interest theory have failed to ask an important geographical question: does increasing economic polarization predict political polarization across the entire United States? According to the Meltzer-Richards model, the variation should be uniform, and counties with a specific level of economic polarization should show the same political behavior, no matter their location. As yet no comprehensive study has examined whether economic polarization and political polarization coincide spatially, and this analysis seeks to address that understudied dimension. The Electoral College is a spatial mechanism; it attempts to represent the territoriality of the vote. There is a risk that, as electoral dominance becomes structurally entrenched, the pattern by which swaths of states and counties across the United States
contribute their votes in the Electoral College to certain parties is taken as a forgone conclusion. The expectation is that this will cause an increasingly small number of competitive districts to determine elections, driving the current political polarization in the United States. My paper attempts to factor geographical variation into these analyses of electoral dominance.

II. Literature Review

Three books – all based in regime-change theory – have helped advance the Meltzer-Richards model. Together they confront the central question of whether inequality and democracy are compatible. Acemoglu and Robinson (2012) argue that at low-to-moderate levels of inequality democracy is favorable to elites, and taxation balances with their ability to amass wealth. If inequality becomes high, elites will protect their advantage by supporting authoritarian regimes to prevent a populist coup or to maintain control of capital-generating assets. Boix (2003) contends that relatively high inequality is a natural state for democracies but agrees that when redistributive pressures (cost of toleration) grow too great, elites pour resources into measures that disenfranchise the lowest-income voters (cost of repression), in order to achieve a favorable equilibrium. These actions may also be taken by others in an expanded category of elites. For example, Ansell and Samuels (2014, 34) note that “the middle class is, historically speaking, almost never located in the actual middle of the income distribution. It is found in the upper two deciles of a country’s income distribution.”

Directly tied to this elite-centric equilibrium is the well-studied conclusion that low-income voters tend to vote at a lower rate than their higher-earning counterparts (Rosenstone 1982; Geys 2006). Furthermore, in the U.S., political responsiveness to low- and middle-income voters tends to be low (Gilens 2012; Bartels 2008). Political responsiveness is instead limited to top-decile earners, as implied by Ansell and Samuels. Moreover, under this model, when income inequality is high

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2 See Appendix A for a list of states with voter suppression laws.
voters avoid “safety net” redistributive measures such as unemployment benefits, instead preferring universal benefits that redistribute broadly, such as social security. This targets redistribution toward improving their own livelihoods rather than those of the lowest-income earners (Moene and Wallerstein 2001). Generally, “it is safer to assume that: (1) the median member of the working class is located above the median voter, and (2) members of the working class favor redistribution to themselves [SIC], but not to the poor,” (Ansell and Samuels 2014, 42).

These findings offer insight into where the Meltzer-Richards model fails. Employed low- and middle-income voters have a clear reason to shy away from certain redistributive measures, as targeted policies such as unemployment insurance are not in their immediate economic self-interest. Furthermore, low political responsiveness may cause low-income voters not to vote at all, and when combined with political disenfranchisement, the voting base for the Democratic Party proposed by this model begins to crumble. However, these conclusions do not entirely refute the economic-interest theory; they merely indicate that research based on the Meltzer-Richards model may be conceptually unsound.

Because the Meltzer-Richards equilibrium does not fully capture real-world dynamics, a number of scholars have found evidence against the economic-interest theories based on it. This excerpt from Iverson and Soskice (2015, 21) summarizes a common counterargument:

In the case of the United States, McCarty et al. (2006) find that while inequality is rising, Republican identification is also increasing, contrary to the expectation of the Meltzer–Richard model, but consistent with a story where declining relative standing of the poor, deunionization, and disintegration of social networks undermine political information in the lower half of the distribution.

Many authors contend that examining economic-interest alone ignores important sociological theories that also help to explain rising political polarization. Often referred to as the “Culture Wars” theory, its numerous adherents contend that political polarization derives from growing cultural and social differences between the two parties’ core constituents (Hunter 1991;
Fiorina, Abrams, and Pope 2006). Fiorina and Abrams (2008, 568) provide a succinct summary of this argument:

The culture-war narrative grew out of arguments about conflicting moral visions or “worldviews.” Wuthnow (1989) and especially Hunter (1991) argued that Americans increasingly were dividing into two values camps: the culturally orthodox, who hold a traditional, religious, absolutist view of morality, and the culturally progressive, who hold modern, secular, relativistic view of morality. In turn, such differing value systems provide fertile ground for political polarization and underlie battles about specific cultural issues such as abortion, gay rights, and now stem cell research.

But Fiorina and Abrams (2008, 584) conclude that “the literature indicates that the American public as a whole is no more polarized today than it was a generation ago, whether we focus on general ideological orientations or positions on specific issues.” Instead, they posit a new mechanism driving recent polarization: elites are becoming highly polarized in the current high-inequality climate, and the masses are forced to choose among polarized elites. Also, as Hetherington (2001, 28) argues: “Greater ideological polarization in Congress has clarified public perceptions of party ideology, which has produced a more partisan electorate.”

This shift has created an atmosphere ripe for entrenched patterns of party identification across the United States. Partisanship is intrinsically linked to political polarization, but mechanisms determining partisanship do not rely solely on economic-interest theory, and this nuance is crucial. While the “Culture Wars” argument has become mired in its focus on religious issues, the social and cultural factors it emphasizes may still be a powerful predictors of voting behavior. Partisanship reflects a social, affective tie to a particular party, and it drives individuals to cast their ballot on behalf of their party rather than economic-interest solely defined as redistribution. For example, while affluent voters turn out in higher numbers, strong party identification also increases voter turnout (Dimock et al. 2014). As partisanship increases, the weight of cultural, moral, and even economic issues at the ballot box declines (Ellis 2006).
A contributing factor to polarization, partisanship increasingly appears to have strong spatial dependencies. Bill Bishop, a journalist who has examined political polarization carefully, put forward a theory of political polarization in his 2008 book, The Big Sort. Drawing from the work of a variety of prominent political scientists, he suggests that like-minded people are simply moving to the same places in the United States, congregating in enclaves that reinforce political orientation. Those in the highly-educated “creative class” are moving to cities and the coast, and they tend to be politically liberal. Meanwhile, as liberal voters leave for urban areas, the concentration of conservatives in rural areas and small-towns increases. In other words, whether actively or by default, like-minded people are clustering in specific geographic locations, delineated along party lines and shared values that serve to create structural divisions between consistent Democratic or Republican voting areas.

Recent research fortifies Bishop’s hypothesis. A 2014 Pew Research Center report on political polarization found that 76 percent of “consistently conservative” voters preferred rural areas and small towns, while 46 percent of “consistently liberal” voters preferred to live in cities (45). The authors also found that 50 percent of consistently conservative voters agreed with the statement that “It’s important to me to live in a place where most people share my political views,” (Dimock et al. 2014, 13).

Spatially-dependent behavior, moreover, is not solely a political phenomenon. Prominent research supports the idea that economies also cluster and that their effects bleed across census boundaries. For example, Durlauf (2004) argues that “neighborhood” is as much an economic as a political or geographic construct. Means of production are known to cluster geographically, but industries such as R&D, high-technology, and skilled labor also create agglomeration economies due to spillover effects (Anselin, Varga, and Acs 1997; Audretsch and Feldman 1996; Rosenthal and Strange 2004). Yet spatial effects are often ignored by current economic-centric theories, decreasing these theories’ compatibility with real-world circumstances. Consider the border dividing Kansas
City, Missouri from Kansas City, Kansas – a completely arbitrary division separating a single urban area into two different legal and political entities. Current analyses treat these communities as distinct from one another, but this ignores their geographic proximity and economic similarity. Between being founded on the simplistic Meltzer-Richards model, the competing social theories, and lack of attention to spatially dependent processes, there is little reason to believe that economic-interest theory, in its current form, is sufficiently explanatory to justify broad application.

III. A Spatial Argument

Available literature suggests that it is not economic polarization alone but a potent mix of elite, party, and geographic polarization that drives political divergence in the United States, with the least-studied element being the geographic component. Questions it raises, such as “Where in the United States is political polarization highest?” and “Where is electoral dominance making certain counties structurally uncompetitive?” require analyses. Moreover, there is ample evidence that both economics and politics show spatial dependence. Accordingly, this paper will use spatial econometrics to test the presence of real-world correlations between these phenomena, as should be predicted by economic-interest theory. If political structures are creating electorally dominant areas – which reinforce the electoral importance of highly polarized areas – then the economic behavior should be uniform in these electorally dominant areas. For the current branch of economic-interest theory to be true, clusters of low-inequality counties should predict Republican-dominated areas, and clusters of high-inequality counties should predict Democratic-dominated areas as suggested by the Meltzer-Richards model, independent of economic variation.

My argument is that for the economic-interest model to be true, any political polarization found in a given U.S. county must be the product of income inequality specific to that county, but also in neighboring counties. Traditional OLS regression treats each county as an isolated entity, but
spatial analysis adds explanatory weight based on the economic and political behavior of geographical “neighbors,” which can be defined as shared borders or proximity. This added factor accounts for economic trends such as agglomeration, spillover, and neighborhood effects. It also accounts for the social affective ties of partisanship: two rural counties separated by a census line are weighted to reflect shared economic and political conditions. Counties are not isolated units, economically or politically, and spatial analysis allows us to treat counties as part of a continuum of the broader economic, political, and geographic landscape of the United States.

IV. Methodology

The Meltzer-Richards model predicts that voting patterns will fluctuate according to levels of inequality. As a test of the contrasting economic-interest theory, I used county-level data to compare income inequality with margin of victory to see if these variables coincide spatially. For measuring income inequality I used two indicators. The first is a ratio of income inequality taken from data available through the Economic Policy Institute, compiled and published by Sommelier, Price and Wazeter (2016). This ratio compares the average income of the top 1 percent of income earners in each county with the average income of the bottom 99 percent of earners. The second indicator of income inequality is a GINI index compiled by the U.S. Census Bureau for each county.

3 This measure follows in the footsteps of Piketty and Saez (2001) and Piketty (2014) to study income inequality at the county level across the United States. Using IRS reports for household income, dataset guarantees that the incomes of commuters are measured in the same county that their ballot is cast, and therefore provides a spatially-sensitive and well-researched variable with which to measure income inequality.

4 The GINI index and inequality ratio are measuring slightly different patterns of inequality. The GINI index, a more traditional indicator of income inequality, measures distribution and concentration of inequality. The inequality ratio, by comparison, is better suited to study the raw magnitude of income inequality. To clarify, the bottom 99% in the vast majority of counties earn between $30,000 and $60,000 in yearly household income. This will only change the ratio by a factor of two, at most. By comparison, the top 1% generally range from $250,000 to as much as $5,000,000 (excluding outliers of up to $20,000,000), which contributes as much as a factor of twenty. For this reason, the inequality ratio helps to measure the raw magnitude separating the poorest and wealthiest voters in each county. The GINI index compares the concentration. A classic example is if 20% of a county’s population acquires 60% of the income earnings, it would correspond roughly to a GINI coefficient of (0.4), a relatively high value. This indicates the concentration and distribution of inequality across the population. See Appendix B for the GINI coefficient equation and further clarification.
I measured electoral dominance using margin of victory in the 2012 presidential election.\textsuperscript{5} Values for margin of victory that have a negative sign correspond to a Democratic win, whereas those with a positive sign reflect a Republican victory.\textsuperscript{6} The larger the value, whether positive or negative, the greater the margin of victory. The goal of this approach was to introduce a spatial covariate into analyses in which geography has often been ignored. Electoral dominance is measured using presidential election data because: 1) voter turnout tends to be highest during presidential elections; 2) votes cast for a presidential candidate reflect a clearer binary choice between redistributive and non-redistributive platforms, 3) congressional elections are subject to down-ballot effects caused by voters' focus on the presidential ticket; and 4) electoral returns for Senate and House races are reported only by electoral districts, for which almost no measures of economic polarization exist. In addition, no major third-party candidate ran in the 2012 election, and the economic policies put forth by Barack Obama and Mitt Romney provided reasonably clear distinctions between redistributive and non-redistributive positions.\textsuperscript{7}

While counties in Hawaii and Alaska can be compared to each other, the neighboring system at the core of spatial analysis prevents them from being easily compared to counties in the contiguous forty-eight states. Also, Alaska is the sole state in the CQ dataset that reports election data only at the electoral-district rather than county level. The following analyses were therefore limited to contiguous U.S. states.

The first analysis involves simple multivariate OLS regression using county-level data to determine the extent to which income inequality accounts for variation in political polarization,

\textsuperscript{5} Voting data for each county is taken from the \textit{CQ Voting and Elections Collection}.
\textsuperscript{6} In the subsequent analysis, the sign of the margin of victory causes Democratic clusters to be \textit{Low} and Republican clusters to be considered \textit{High}.
\textsuperscript{7} In his prior term, the incumbent President Obama passed the Affordable Care Act (ACA), eponymously nicknamed \textit{Obamacare}. This piece of signature redistributive legislation clearly signaled his redistributive stance. Romney and the Republican Party platform during pressed for dismantling the ACA. Furthermore, during the 2012 election, Romney was for measures such as privatizing social security, while Obama opposed such measures, (according to the Republican and Democratic Party Platforms for 2012 election).
without controlling for spatial effects. The second set of tests applies spatial autocorrelation to check for spatial dependence in each variable. If the variables proved to be spatially-dependent, I applied a geographically-weighted (GW) regression to account for spatial correlation. The OLS regressions were then compared to the geographically-weighted regressions to assess the relative importance of spatial phenomena. To mitigate demographic effects, I used U.S. Census data to control for racial and educational patterns in each county. The model also included an estimated voter turnout rate and an estimated population density. Ideally, these allow for control of possible social influences that may also be spatially dependent.

V. The Experiment

Spatial analysis is predicated on the First Law of Geography as stated by Waldo Tobler (1970, 236): "Everything is related to everything else, but near things are more related than distant things." In order to account for this relationship, analyses began by creating a weight matrix that indicates neighbors, (denoted in the matrix as a 1 for a neighboring county, and a 0 otherwise). The resulting matrix was then incorporated into subsequent calculations to improve the predictive

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 2 2 2 2 2
2 1 1 1 2
2 1 0 1 2
2 1 1 1 2
2 2 2 2 2
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*Figure 1: For a given county "0", the queen contiguity reflects that any shared borders or vertices indicate a neighbor. 1st order contiguity is indicated by a "1" and 2nd order contiguity is indicated by a "2".*
capacity of the model. For all analyses in this paper, I used a queen contiguity spatial weight matrix including 1st and 2nd order contiguity (Anselin 1988, 1993).\textsuperscript{8} Figure 1 illustrates this approach.

This matrix links counties to others that directly border the target county and then to those that border the target-contiguous neighbors. I chose this approach because: 1) in counties east of the Mississippi River, second-order neighbor counties may be as few as thirty miles from the geographic center—a short commute; 2) western counties tend to be much larger, so fixed Euclidean-distance weights often excludes obvious neighbors; and 3) as cities and economic hubs are rarely found in the geographic center of a county, this system provides a clear upper-bound for possible spatial correlation. The overall goal of this weighting system is to provide sufficient room to differentiate explanatory power arising from economic and political forces at the county level. For an example of how the spatial weight matrix is applied, Equation 1 shows how the global Moran’s I statistic is calculated, where \( n \) is the number of observations, \( S_o \) is the sum of the weighted neighbor values, \( x_i \) is the variable of interest found in the current areal unit, \( x_j \) is the variable of interest in the neighboring areal unit, and \( w_{ij} \) is an element in the matrix of spatial weights.

\[
I_t = \left( \frac{n}{S_0} \right) \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n} x_i^2} \quad \text{Equation 1}
\]

Values for the statistic range from -1 to 1, with -1 being perfectly dispersed, 0 being no spatial dependence, and 1 being highly clustered. Assessing clustering patterns allows for a more dynamic understanding of key phenomena, detailing where predictor variables are highly spatially dependent. Anselin (1988; 1993) describes this statistic as the cornerstone of evaluating spatially-dependent relationships.

\textsuperscript{8} Three island counties had no neighbors. In this case, I manually assigned neighbors corresponding to their nearest neighbors, allowing for complete spatial analysis of all counties in the contiguous United States.
VI. National Level Results

The following sections show experimental results at the national level. Given that theory strongly suggests that economic and political behavior clusters, it is reasonable to test for spatial dependence. Figures 2 and 3 describe the spatial behavior of these key variables. Fig. 2 shows bivariate Moran’s I scatterplots and statistics – contrasting economic polarization variables with margin of victory – which assess bivariate clustering patterns (Anselin 1993; 1995). Matching theoretical predictions, there is significant evidence (Moran’s I statistics of 0.499889 and 0.52923 for the LnRatio and Gini models, respectively) that these phenomena spatially cluster and therefore require subsequent spatial lag and spatial error-correction regressions beyond normal OLS models. The suggestion is that economic polarization found in neighboring counties may predict the electoral dominance in a target county.

A second test can be applied to discern patterns of spatial clustering. For this, local indicators of spatial association (LISA) cluster maps provide a visual interpretation of clustering patterns. These maps are best suited for assessing local clustering patterns, but I apply them to the national (global) model to give a visual representation of economic and political patterns across the United States. In Fig. 3, the LISA cluster maps detail where the independent and dependent variables show significant levels of univariate clustering across the United States (Anselin 1995).

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9 For the entirety of this paper, the variable labels are as follows: *LnRatio* refers to the natural log of the income inequality ratio. *MoV* refers to the margin of victory during the 2012 election. *Gini* refers to the GINI index for a given county. *HighSchool* refers to the percentage of a county’s population who have only a high school degree of less (calculated using estimates from the U.S. Census for the population over 25 who have completed a high school degree or less, divided by the total population over 25 in each county). *Turnout* is the measure of voter turnout (calculated using a U.S. census estimate for the voting-age-population of each county, divided by the total number of votes cast according to the CQ election returns). *NonWhitePc* refers to the non-white percentage of the population (calculated from U.S. census estimates for white-only, non-Hispanic or Latino, divided by the total population of each county. Finally, *PopDensity* refers to the population density of each county (calculated as the total population divided by the land area for each county in square miles). All data for the control variables was collect for the year 2012, using the U.S. Census Bureau’s American Population Survey (APS) 5-year estimates for 2012.
Figure 4 illustrates results of bivariate regressions of the two measures of economic polarization against the margin of victory measured in each county. Each set of regressions begins with the OLS model, then progresses to a spatial lag model, and ends with a spatial error-correction model (Anselin 2003). The spatial lag model uses the measured value for each variable, weighted by the spatial matrix. The spatial error-correction model, by comparison, analyzes the relationship between the residuals of the spatially-weighted variables, again weighted by the spatial matrix to assess the residuals found in neighboring counties. The aim of the bivariate models is to clearly assess the relationship between economic and electoral dominance geographically, before controls are included.

Figure 5 shows results from multivariate models at the national level. Again, the models begin with simple multivariate OLS regressions and proceed to the two GW models for the LnRatio and Gini variables, separately. These models also include the control variables and provide a comprehensive analysis of possible factors driving electoral dominance across the spatial dimension.

Looking at the simple OLS models for the natural log of the income inequality ratio (LnRatio) against the margin of victory (MoV), the model describes results that, while statistically significant, explain little variance (R-square = 0.005424). The GINI index (Gini) fairs only slightly better at providing explanatory power (R-square = 0.055812) Moreover, the Jarque-Bera test across the bivariate model suggests that substantial problems of multicollinearity exist between the independent and dependent variables across both simple bivariate regressions, and both measures of income inequality also show unacceptable levels of heteroscedasticity.

The LISA clustering maps and Moran’s I statistics show significant spatially-dependent variance. The interrelated spatial processes between counties – both political and economic – may thus be causing abnormality in the distribution of the variables, so heteroscedasticity may in fact be
caused at least in part by neglecting the role of spatial dependence. Therefore, it is reasonable to proceed to the GW regressions.

To compare the spatial regressions, the Akaike info criterion (AIC) and log-likelihood (LLH) criterion are compared in place of pseudo r-square and p-values. Notably, the LLH values increase and the AIC values decrease for both the spatial lag and spatial error-correction models as compared to the OLS models, suggesting a better fit. However, the change is almost negligible from the Gini spatial lag model to the spatial error-correction model, and the AIC increases while the LLH decreases for the LnRatio bivariate model, corresponding to a slightly poorer fit. In the Breusch-Pagan test across all bivariate models – simple and spatial – there is a high-probability of heteroscedasticity. A few possible explanations for this include: 1) the spatial dependence isn’t entirely eliminated, leaving lingering patterns of spatial heteroscedasticity; 2) misspecification error exists among the variables, as the multicollinearity and heteroscedasticity results in the simple models first indicate. Normally, due to the diagnostic issues, I would not continue past the bivariate models; however, I proceeded to multivariate analyses to illustrate the importance of the spatial dimension. I began with the LnRatio models and progressed through the simple OLS, spatial lag, and spatial error-correction models. Again, the models significantly improved from simple to spatial analysis, as measured by the AIC and LLH values. The same held true for the Gini models. Notably, the introduction of control variables altered the LnRatio models, with LnRatio losing significance in the spatial error-correction model entirely. However, it would be incorrect to dismiss the

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10 To mitigate these heteroscedasticity errors, I first attempted to cull unreasonable outliers from the dataset. Teton, WY, for example, had the highest income inequality ratio of all counties in the United States in; however, this ratio was 1.5x higher than the ratio found in Teton, WY during the 2011 and 2013 years, possibly a statistical aberration. Additionally, several counties with populations below 2000 people in the United States had extremely high ratios. Therefore, I set these counties to their average inequality ratio for their respective states. I also took the natural log to achieve a normal distribution. While significantly normalized the data, the heteroscedasticity remained. Similarly, despite a normal distribution for the GINI index, and being compiled using the 5-year American Public Survey estimate (from the U.S. Census Bureau), the multicollinearity and heteroscedasticity remained in the OLS regressions. I chose not to cull outliers from this dataset, as the 5-year estimate showed less aberrations like those seen in the case of Teton, WY for the income inequality ratio.
Figure 2: Bivariate Moran's I Statistics for MoV vs. LnRatio and MoV vs. Gini:

Figure 3: Univariate LISA Cluster maps for the independent and dependent variables:

High-High: corresponds to a county with a high \( x \) measurement, whose neighbors generally also have a high measure of \( x \).

Low-Low: corresponds to a county with a low \( x \) measurement, whose neighbors generally also have a low measure of \( x \).

Low-High: corresponds to a county with a low \( x \) measurement, whose neighbors generally have a high measure of \( x \).

High-Low: corresponds to a county with a high \( x \) measurement, whose neighbors generally have a low measure of \( x \).

Top Row:

- a) MoV (Romney = + margin; Obama. = - margin)
- b) Ln(Ratio)

Bottom Row:

- c) Gini Index
Figure 4: Univariate Regression Result – OLS and GW Models

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**DIAGNOSTICS**

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<th>SL (2)</th>
<th>SL (5)</th>
<th>SE (3)</th>
<th>SE (6)</th>
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<td>Koenker-Basset Test</td>
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<td>White Test</td>
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<tr>
<td>Log-Likelihood</td>
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<td>2220.7***</td>
<td>2361.2***</td>
<td>2505.3***</td>
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<td></td>
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<tr>
<td>Log-Likelihood (Spatial Dependence)</td>
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</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
### Figure 5: Multivariate Regression Results – OLS and GW Models

Dependent Variable: MoV  
Mean dependent Var: 21.651  
Number of Observations: 3109  
S.D. dependent Var: 29.9716

<table>
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<th>Variable</th>
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<th>(2)SL</th>
<th>(3)SE</th>
<th>(4)OLS</th>
<th>(5)SL</th>
<th>(6)SE</th>
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<td>Constant</td>
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<td>W_MoV</td>
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<td>0.9525***</td>
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<td>(0.0107)</td>
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<td>(0.0107)</td>
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<td>LnRatio</td>
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<td></td>
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<td>(0.712)</td>
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<tr>
<td></td>
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<td>(14.02)</td>
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<td>(8.191)</td>
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<td>34.829***</td>
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<td>NonWhite</td>
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<td>PopDensity</td>
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<td>Lambda</td>
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<td>(0.0083)</td>
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<td>0.654567</td>
<td>0.806335</td>
<td>0.308723</td>
<td>0.665015</td>
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<td>Akaike Info Criterion</td>
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<td>Log-Likelihood</td>
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**DIAGNOSTICS**

<table>
<thead>
<tr>
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<th>Breusch-Pagan Test</th>
<th>Koenker-Bassett Test</th>
<th>White Test</th>
<th>Log-Likelihood (Spatial Dependence)</th>
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<td>409.84***</td>
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<td>14.066***</td>
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<td>183.42***</td>
<td>232.42***</td>
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<td>2044.1***</td>
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<td></td>
<td>215.25***</td>
<td>232.42***</td>
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<td>3771.6***</td>
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**Note:**  *p<0.1; **p<0.05; ***p<0.01*
economic-interest model due to this outcome. One problem is that ominous diagnostic results from the bivariate models regarding evidence of heteroscedasticity and multicollinearity lingered across all models. This suggests that the problems are not resolved in the multivariate models, and including control variables may only worsen the situation. The improved fit suggests that spatially-dependent processes are present, but the results of the bivariate and multivariate regressions cannot be considered robust.

Given these limitations of OLS and GW regressions, this analysis cannot completely explain trends at the national level. However, to further pursue the central question, the next section examines four states—California, Texas, Florida, and Wisconsin—for local clustering patterns. The threatening diagnostic results warn against another series of regressions at the state level, so I opted to assess the local spatial patterns by examining the LISA cluster maps across these states, as well as the local Moran’s I statistic for each state.

VII. State Level Results

A primary barrier to the widespread application of spatial analysis involves limitations to global analysis. For example, with nearly 3109 counties in the contiguous landmass of the U.S., results indicating statistical significance can appear without the presence of meaningful actual effects. This is further compounded by using local-level indicators (such as LISA maps) to explain global trends. Moreover, two spatial factors are likely to affect the global model: 1) spatial drift, which is caused in this case by the larger geographic size of Western counties; and 2) non-stationary spatial effects, which may be present due to the fact that theoretical conditions of inequality and political patterns are thought to be increasing in some areas and decreasing in others (Anselin 1995, 2003). Many bivariate spatial statistics are susceptible to these problems, and it is for this reason that I limited the remaining analysis to a local scale.
Each of the four states mentioned above provides a different example of the relationship between economic polarization and electoral dominance. Counties within states tend to be of more uniform area, hopefully reducing error caused by spatial drift, and the univariate analysis will minimize the introduction of bivariate non-stationary spatial process. California and Texas are both large, diverse states that tend to anchor the Democratic and Republican parties, respectively, while Florida and Wisconsin are places where neither party wins consistently. However, geographical and other differences between these latter two – the German-settled, Rust-Belt Wisconsin versus the Southern, Hispanic-influenced Florida – allow for significant variation among social control variables. Additionally, these analyses did not involve regressions or bivariate statistics but only included univariate calculations for LISA cluster maps and Moran’s I statistics. This allows for a visual comparison of clustering patterns of electoral dominance against patterns of economic polarization and the control variables. Hopefully, the results will provide insight into the structures of electoral dominance and inequality at a local scale, controlling for the bivariate diagnostic problems. The subsequent four figures (Fig. 6, Fig. 7, Fig. 8, and Fig. 9) contain local Moran’s I statistics and LISA cluster maps for each state, including all variables used in the GW regressions.

For the purposes of this paper, California serves as an excellent testing ground for some of the economic clustering theories suggested by current literature. It supports large, thriving “high-tech” clusters in places like Silicon Valley and San Francisco, but also stands as one of Democrats’ firm bulwark states in presidential elections. This case of structural Democratic dominance at the state level should offer insight into the validity of economic-interest theory. The margin of victory in California clearly clusters around the Bay area (Democratic) and Northern California (Republican) with a Moran’s I statistic of 0.3274. Notably, the LnRatio matches the MoV cluster patterns very closely, and in the direction expected – with high-inequality corresponding to Democratic voting patterns, and vice versa. Although the GINI index shows a high inequality cluster in the Bay area as
well, it does not show any significant clustering in the northern counties. Instead, the index suggests strong clustering in the eastern part of the state. Among control variables, education shows low levels of overlapping clusters and does not predict the lopsided Republican cluster in the northern counties. Interestingly, both the non-white population and particularly the population density found in California counties seem to correspond well with political clustering, but the non-white population does not seem to generate the same Democratic patterns in the southern part of the state. Finally, turnout percentage is shown to be dismal in the southern part of the state, but it does not neatly correspond to Democratic or Republican clusters, as suggested by the revised equilibrium.

In the national-level studies, Texas was shown to display strong clustering patterns across both variables, at least using the LISA statistic. Theoretically, it offers the antithesis of the California case. Texas is a large, populous state with large minority populations, yet it votes consistently Red, which makes it a valuable case study. Looking first at MoV, it is apparent that political clustering is shown to be strongest in the Panhandle, West Texas, and border counties. With a high Moran’s I statistic (0.5852), Texas is also the most polarized of all four states in terms of political clustering. This is not the case for either measure of economic polarization, though. The Moran’s I statistics for both LnRatio and Gini are shown to be relatively low, (0.0968) and (0.1200) respectively. Moreover, these two variables show sporadic overlap with the large, clear MoV clusters. In this case, LnRatio contradicts the Meltzer-Richards model in the clusters that do overlap, with low-inequality mapping to Democratic clusters. The GINI index coincides slightly better, predicting a small Democratic cluster in the south and a Republican cluster in the north. Of the control variables, low-education and high-minority clusters appear to correspond to the strongly Democratic clusters found in West Texas and the border counties. The high value for Moran’s I statistic (0.5965) for the non-white
### Figure 6: Local Moran’s I statistics and LISA cluster maps for each variable – California.

<table>
<thead>
<tr>
<th>Variable</th>
<th>MoV</th>
<th>Ln(Ratio)</th>
<th>Gini</th>
<th>HighSchool or Less (%)</th>
<th>NonWhite (%)</th>
<th>PopDensity (1/mile²)</th>
<th>Turnout (%)</th>
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<tr>
<td>Local Moran's I Statistic</td>
<td>0.3274</td>
<td>0.2229</td>
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<td>0.3892</td>
<td>0.1055</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</tbody>
</table>

#### LISA Cluster Map:
- Not Significant
- High-High
- Low-Low
- Low-High
- High-Low

### Figure 7: Local Moran’s I statistics and LISA cluster maps for each variable – Texas.

<table>
<thead>
<tr>
<th>Variable</th>
<th>MoV</th>
<th>Ln(Ratio)</th>
<th>Gini</th>
<th>High School or Less (%)</th>
<th>NonWhite (%)</th>
<th>High School or Less (%)</th>
<th>Turnout (%)</th>
</tr>
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<td>Local Moran's I Statistic</td>
<td>0.5852</td>
<td>0.0968</td>
<td>0.12</td>
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<td>0.5965</td>
<td>0.1183</td>
<td>0.0727</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

#### LISA Cluster Map:
- Not Significant
- High-High
- Low-Low
- Low-High
- High-Low

### Notes:
- Top Row: a) MoV (Rep (+), Dem(-)) b) Ln(Ratio) c) Gini Index d) HighSchool Edu. (%) e) Non-white Pop. (%) f) Pop-density (per Sq. Mi) g) Turnout (%)
### Figure 8: Local Moran’s I statistics and LISA cluster maps for each variable – Florida.

<table>
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<tr>
<th>Variable</th>
<th>MoV</th>
<th>Ln(Ratio)</th>
<th>Gini</th>
<th>HighSchool or Less (%)</th>
<th>NonWhite (%)</th>
<th>PopDensity (1/mile²)</th>
<th>Turnout (%)</th>
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</thead>
<tbody>
<tr>
<td>Local Moran’s I Statistic</td>
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<td>0.2379</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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</tbody>
</table>

LISA Cluster Map:
- Not Significant
- High-High
- Low-Low
- Low-High
- High-Low

### Figure 9: Local Moran’s I statistics and LISA cluster maps for each variable – Wisconsin.

<table>
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<th>Variable</th>
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<th>Gini</th>
<th>HighSchool or Less (%)</th>
<th>NonWhite (%)</th>
<th>PopDensity (1/mile²)</th>
<th>Turnout (%)</th>
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<tr>
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<td>No</td>
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<td>Yes</td>
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</tbody>
</table>

LISA Cluster Map:
- Not Significant
- High-High
- Low-Low
- Low-High
- High-Low

Top Row:
- a) MoV (Rep +), Dem(-)
- b) Ln(Ratio)
- c) Gini Index
- d) HighSchool Edu. (%)

Bottom Row:
- e) Non-white Pop. (%)
- f) Pop-density (per Sq. Mi)
- g) Turnout (%)
population stands out as being particularly salient to the Democratic clusters, but it doesn’t
correspond strongly to Republican-dominant counties. Population-density overlaps with the
Panhandle’s Republican cluster and may begin to explain the divide between West Texas and South
Texas Democrats. Turnout with a Moran’s I of (0.0727) shows little clustering pattern, and only
overlaps with the southern Democratic cluster.

Florida provides another useful case comparison: a populous, diverse state that is plugged
into the high-tech economy but does not display electoral dominance at the state level. In contrast to
Texas and California, Florida offers a relatively polarized example. The political clusters in Florida
are located at the upper and lower areas of the state. The Moran’s I statistic (0.2551) shows less
MoV clustering than Texas or California but still implies that even within a polarized state,
Democratic- and Republican-dominant counties tend to cluster. Complicating the picture is the fact
that High-Low and Low-High counties are intermingled in the north and south, suggesting greater
dispersion in the clusters.\textsuperscript{11} \textit{LnRatio} seem to correspond moderately to political clusters, but less
neatly than might be predicted by the Meltzer-Richards model. In addition, the clustering patterns
do not seem to be particularly strong. What is important is that the GINI coefficient is not
significant at all in this model, suggesting little explanatory power in this case. Regarding social
variables, the non-white population seems to cluster neatly with the Democratic voting cluster at the
southern tip of Florida, and the two High-Low counties seen in the northern counties correspond to
two of the Low-High clusters MoV counties present. Low high-school educational attainment also
seems to display important clustering in the northern counties, overlapping with a subset of the
highly-Republican cluster. Population density shows that low-population clusters may lead to

\textsuperscript{11} High-Low indicates that it shows a positive margin of victory (Republican-dominant) while surrounded by counties
with a negative margin of victory (Democratic-dominant), and vice-versa for Low-High. See the Fig. 3 caption for further
clarification.

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Republican voting patterns, similar to the clusters found in the Texas Panhandle, although the overlap does not seem to be as consistent.

Wisconsin provides the final case: a competitive state in the Rust-Belt – smaller and less diverse than the previous states, and one deeply affected by the loss of manufacturing jobs. Additionally, Wisconsin went Blue in the 2012 presidential and U.S. senate elections, despite the governor’s office and both houses of the state legislature shifting strongly to Republicans in 2010. Looking first at the Moran’s I statistic, the independent and dependent variables show less clustering than in any other state. Neither the GINI index nor LnRatio show significant clustering patterns, and the low clustering patterns for MoV corresponds to less electoral dominance across the state. The control variables do not offer much additional information. Educational attainment (high-school education or less) shows almost no clustering at all (0.099), and the non-white population clusters are not significant. The two control variables that do show clustering patterns, population-density and turnout, imperfectly correspond to the Republican cluster, and this coincidence may simply be a phenomenon specific to the Milwaukee-Chicago corridor.

VIII. Discussion

Unfortunately, results at the national level were inconclusive regarding the relationship between income inequality and electoral dominance. Multicollinearity and heteroscedasticity issues persist throughout all models—simple and spatial, univariate and multivariate—and since spatial factors are likely to further exacerbate these misspecifications due to the spatial weighting process, the problems cannot be readily dismissed. Still, though national-level regression results are inconclusive in testing the relationship between economic polarization and electoral dominance, the results from global Moran’s I concretely indicate that there is an important spatial component to political behavior.
Tests at the state level provide more insight into how these spatially-dependent phenomena operate at the local level. In electorally dominant states – California and Texas – there is a noticeable difference in how economic-interest theory can be applied. In California, the income inequality ratio predicts electoral dominance in the directions prescribed by the Meltzer-Richards model, whereas in Texas the income inequality ratio fails to coincide with major political clusters and the GINI index may hold more explanatory power. However, in both states low population-density and a high white population (reciprocal of the non-white population) are seen to correspond to Republican-dominant clusters. The non-white population also seems to coincide moderately with the highly-Democratic clusters.

In the two more polarized states – Florida and Wisconsin – there is a noticeable drop in political clustering patterns, particularly in Wisconsin. What is also interesting is that in Florida the GINI index is not significant, and in Wisconsin neither the GINI nor inequality ratios are significant. The income inequality ratio remains significant in Florida, but more dispersed patterns of political clustering emerge. This may suggest that as inequality decreases, electoral dominance decreases, and polarization increases.

One important implication from the state cases is that political and economic behavior are spatially dependent, as all of the variables included in the analysis show some spatial clustering patterns. Also, the explanatory power of social variables such as minority population, voter turnout, and population-density should not be ignored. While education levels can arguably be lumped into the economic-interest models, these other three control variables show significant co-clustering patterns in key states, often corresponding to the expected direction of correlation as well. There is evidence that economic interest remains an important component to understanding political polarization; however, from the clustering patterns for income inequality across all of these states, the economic-interest theory needs to be heavily qualified spatially.
An argument may be made from this evidence that certain types of inequality can produce different voting patterns, based on sporadic overlap of the GINI index (concentrated inequality) and the inequality ratio (magnitude of inequality). For example, the Bay Area in California is shown to be a highly-educated, diverse Democratic stronghold with concentrated, high-magnitude income inequality, which reflects “creative class” polarization suggested by the literature.\(^{12}\) The southern tip of Florida also shares the clustering characteristics, and counties like Miami-Dade may be susceptible to similar equilibrium forces. Perhaps bimodal growth and SBTC are creating new structures of inequality that differ from less urban areas.

In Texas, however, contrasting patterns appear, perhaps hewing closer to the revised Meltzer-Richards equilibrium. Low inequality in the Panhandle seems to predict a Republican-dominant cluster. The white-population percentage, and low population density also appear significant to this lopsided political behavior. Moreover, in contrast to California, South Texas exhibits a cluster of low-education, “traditional” inequality (measured by the GINI index), non-white population, and low-turnout, corresponding roughly to a small cluster of counties with a low-magnitude inequality ratio. It is possible that areas without significant “creative class” growth are seeing agrarian rentier-style inequality, rather than inequality arising as a product of SBTC labor structures. Though inconclusive, this argument may begin to integrate economic-interest theory with spatial analysis to ask the question: Is economic polarization structurally different in areas plugged into the New Economy?

**IX. Conclusion**

This paper sought to test economic-interest theory under spatial conditions. While able neither to support nor reject the validity of the theory broadly, the economic and political clustering

\(^{12}\) Please review footnote 4 for the key differences between the GINI coefficient and inequality ratio.
patterns shown at the national and state levels suggest that spatial analysis can indeed improve current models. Clearly, some areas in the state-level analyses show high electoral dominance coinciding with high-economic polarization, and vice-versa. But just as often the variables are not significant or do not overlap with crucial clusters of electoral dominance. Moreover, there is evidence that certain areas are susceptible to different types of inequality, and thus different equilibriums. This may suggest that specific types of inequality, perhaps those created by SBTC change, are creating different structures of electoral dominance in some areas of the United States. In others, the rentier-elites may be the primary cause of inequality rather than bimodal labor structures. In either case, broad application of the simple Meltzer-Richards model across the geographic dimension fails.

Overall, the results caution against excluding spatial factors from any analysis of political behavior. For example, Moran’s I statistics, both local and global, for political polarization are significant across the states and national levels, respectively. Additionally, in electorally dominant states these statistics predict higher clustering patterns, and the coefficient decreases in less polarized states. This alone should push scholars to endorse the spatial analysis as a new lens through which to study how political polarization increases.

Also of note is the fact that social variables used in this model align with the findings of Bishop (2008) and Dimock et al. (2014). Population-density, minority population (and by extension white population) both appear to have significant explanatory power across the state-level cases. For this reason, the paper concludes by stressing the importance of social variables. Economic-interest theory needs to be updated to maintain explanatory power, but social factors appear to matter across the spatial dimension as well.

Further implications are that future studies should attempt to incorporate spatial indicators in survey research. Although spatially-sensitive data is becoming more accessible, political economy
as a field should make an effort to advance this as rapidly and extensively as possible. Additionally, the Meltzer-Richards model shows inconsistent patterns in predicting electoral dominance and political polarization in areas of the United States, and case studies of local spatial analysis may help correct this. In the case of Miami-Dade county and the San Francisco Bay area, economic polarization seems to be heavily influenced by the urban cores. Researchers may need to look at spatially-dependent processes at the city level to assess salient economic and political behavior. Furthermore, economic-interest theory would be well served by incorporating a revised equilibrium model into future research. Lastly, the social variables of population-density and percentage of non-white population appear to coincide with electorally dominant areas. Including these variables into future work is vital, as there may be racialized political and economic factors contributing to electoral dominance.
Bibliography


**Acknowledgements:**

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Appendix A: Voter Suppression Laws effecting the 2012 presidential election by state (quoted directly from the Brennan Center for Justice).

**Restrictions in Effect for 2012 Election**

Fifteen states have passed restrictive voting laws and executive actions that have the potential to impact the 2012 election, representing 203 electoral votes, or 75 percent of the total needed to win the presidency.

**Florida**
- Early voting restriction
- Executive action making it harder to restore voting rights for those with past criminal convictions
- Voter registration drive restrictions are still in place, but the most onerous aspects of the law were blocked by a federal court

**Georgia**
- Early voting restriction
- Georgia also has a photo ID law, which passed in 2005

**Illinois**
- Voter registration drive restriction

**Iowa**
- Executive action making it harder to restore voting rights for those with past criminal convictions

**Kansas**
- Photo ID required to vote

**New Hampshire**
- Voter ID required — non-photo IDs allowed for 2012 election, but photo ID required starting September 1, 2013

**Pennsylvania**
- Photo ID was requested but NOT required to vote, per October 2, 2012 court decision

**Rhode Island**
- Voter ID required — non-photo IDs allowed for 2012 election, but photo ID requested starting January 1, 2014

**South Dakota**
- Law making it harder to restore voting rights for those with past criminal convictions

**Tennessee**
- Photo ID required to vote
- Proof of citizenship required to register
- Early voting restriction

**Texas**
- Voter registration drive restriction
- Texas passed a law requiring a photo ID to vote, but a federal court blocked that law in August — it was NOT in effect in 2012

**Virginia**
- Voter ID required, including non-photo ID

**West Virginia**
- Early voting restriction

**Wisconsin**
- Voter registration restriction
- Wisconsin passed a law requiring photo ID to vote, but two state courts blocked that law — it was NOT in effect in 2012
Appendix B: Additional Equations

Local Moran’s I and LISA Statistics:

The LISA Statistic is effectively a local Moran’s I equation for a single county. These are aggregated into the cluster maps when the county is shown to have a significant Moran’s I measurement:

\[ I_i = \frac{Z_i}{m_2} \sum_j w_{ij} Z_j \]

Where:

\[ m_2 = \frac{\sum Z_i^2}{N} \]

Then:

\[ I = \frac{\sum I_i}{N} \]

Where \( I \) is the local Moran’s I value, \( I_i \) is the value for a given county, \( N \) is the number of neighbors, \( w_{ij} \) are the entries in the spatial weight matrix for the county \( i \) and it’s neighbor \( j \), and \( Z_i \) is the deviation from the mean of the variable of interest, (Anselin 1995).

In the bivariate case, the variable of interest \( Z_i \) (in this case margin of victory) in a county \( i \) is compared with a different variable of interest (income inequality) for \( Z_j \) for a neighbor \( j \).

Spatial Lag and Spatial Error-Correction:

Rather than write the full derivations for these statistics, I encourage readers to read Spatial Externalities, Spatial Multipliers, and Spatial Econometrics, published by Luc Anselin in 2003 for the spatial lag and spatial error-correction calculations found used in the geographically-weighted regressions. These provide comprehensive calculations detailing the full process behind these spatial statistics.

GINI Index:

The Gini Index is calculated as:

\[ G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2 \sum_{i=1}^{n} \sum_{j=1}^{n} x_j} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|}{2n \sum_{i=1}^{n} x_i} \]

Where \( x_i \) is the wealth or income of person \( i \), and there are \( n \) persons, and \( G \) is the GINI coefficient.\(^{13}\) The US Census Bureau uses the household estimates across the population to apply this measure across United States counties and equivalent measures. The coefficient produced ranges from 0 (perfect equality) to 1 (perfect inequality).

\(^{13}\) Equation from Wikipedia: GINI Coefficient.