Spatial analysis of changes in the unemployment rate: A county-level analysis of the New England states

Zachary A. Smith
Saint Leo University

ABSTRACT

This research project examines the spatial dependence of unemployment rates during a period of economic uncertainty occurring at a tract level of analysis in the New England States. The spatial components used to describe spatial dependence in unemployment rates are physical, ethnic, and occupational distances. The researcher identified statistically significant levels of spatial dependence using each of the distance metrics ($\alpha = .10$); however, the economic and statistical significance of the physical distance metric dominates the other two spatial variables (*p* value of less than .001 and an R^2 value of .3367). Furthermore, in this project, the researcher was able to improve the coefficient of determination for the final model used to estimate changes in unemployment rates from .201 to .694 by adding spatially dependent variables to the traditional independent socioeconomic variables in a multivariate regression analysis.

Keywords*:* Unemployment Rates, Spatial Dependence, Physical Distance, Ethnic Distance, Occupational Distance

INTRODUCTION

Following the research of Conely and Topa (2002), this project attempts to estimate social interaction effects and use the estimates of these parameters to understand how social interaction effects influenced changes in the unemployment rate as the U.S. Economy entered into a recessionary climate in 2008. To accomplish this task the researcher used three different socioeconomic distances (i.e. geographic, ethnic, and occupational) as well as traditional economic variables believed to have some explanatory power over potential changes in county-level unemployment rates. This paper finds that these socioeconomic distances have significant explanatory power over the changes in the unemployment rates for the 67 counties included in this study.

To explore the social characteristics that might be associated with changes in the unemployment rate during a period of economic uncertainty, the researcher had to identify both a time prior to the decline in the general economy (i.e. a peak in the business cycle) and a low point (i.e. a trough in the business cycle). To accomplish this, the researcher reviewed the changes in the Gross Domestic Product (GDP) leading up to the most recent recession, which occurred in the last quarter of 2008. From 2006 to 2008, the unemployment rate and the percentage change in the GDP of the U.S. had been negatively correlated and seemed to display substantial dependence—see Figure 1.

It has been established that the unemployment rate is a lagging indicator of economic activity; therefore, it will presumably take a number of periods for changes in GDP to affect the labor market. The consumer has a substantial influence over this relationship, as consumers' demand less producers will respond by supplying less. Producers will supply fewer goods and services to deal with a lower demand, thus, will require less labor. Hence, the researcher should be able to describe changes in the unemployment rate using current and lagged GDP data.

Table 1 shows the relationship between the Unemployment Rate and GDP data using various lags of the change in U.S. GDP from 2006 to 2008. It is evident, at least using this time horizon, that the relationship between lagged GDP and the unemployment rate is significant. This model generates an R^2 of .98 at lag five. The researcher carried this exercise out to determine when the study should start and when the study should end—the researcher has determined that the study should be run from the first quarter of 2006 to the fourth quarter of 2008 to capture the change in unemployment rate from the peak of the cycle to the trough.

LITERATURE REVIEW

Akerlof, G. (1980) stated, in an analysis of social customs and their influence on unemployment, that "a custom, once established, will persist, provided that the disobedience of the custom results in sufficient loss of reputation, and provided that the cost of disobedience is sufficiently high" (p. 751). Moreover, Akerlof, G. (1980), concludes that "a custom, that is fairly costless to follow will, once established, continue to be followed because persons lose direct utility by disobeying the underlying social code and also because, according to the model, disobedience of social customs will result in loss of reputation" (p. 772). The general idea presented in Akerlof, G. (1980), has a profound influence on how researchers can think about social interaction effects and their influence on the actions of policy makers, individual agents, and in the aggregate at a county level of analysis. Customs permeate our culture and whether researchers are analyzing individual or county level interactions, the customs that have been established regionally or based upon an individual's ethnic or occupational affiliations cause a clustering of like individuals amongst various socio-economic groupings.

Customs, and an individual's likeliness to obey these customs, influence their behavior and therefore, their choices by influencing the perceived utility of a perspective outcome based upon potential negative externalities that arise from disobeying an established custom. Akerlof, G. (1997) explains that social externalities arise from social interactions and posits that an agent's choice to maximize their expected outcome may be influenced by their social affiliations with other agents in a particular locality; furthermore, that "group interactions are an important influence on individual decisions; [therefore,] the analysis of social programs must include an evaluation of an intervention's impact on group interactions and not just the direct affects of the program" (Akerlof, G., 1997, p. 1023). Ioannides and Topa (2010), likened this concept of social interactions and the implicit effect that social interactions or groupings have on behavior by explaining that "social interdependencies emerge naturally if individuals share a common resource or social space in a way that is not paid for but still generates constraints on individual action" (p. 244). Therefore, our social position, whether it is geographic or socio-economic, has a profound effect on an individual's perceived economic outcomes.

Conley and Topa (2002) use this general argument to analyze whether the social economic distance between two agents influences their ability to obtain employment. The authors accomplish this by constructing physical, ethnic, and occupational distances between the various tracts in Chicago and examine whether the distances between two tracts have explanatory power over their respective unemployment levels. However, Conley and Topa (2002) question whether the Census Tract Level is the appropriate scale of analysis to use to evaluate social interaction effects; specifically, whether "most actions take place at lower levels of agglomeration" (p. 25). Akerlof, G. (1997) echoed this question and stated "that the community is endogenously defined in terms of peoples' sense of location. What may appear as a community to an outside reformer…may be too large a unit in which to encompass the social interactions involved in social exchange" (p. 1023). This research project questions these two statements and examines whether researchers might be able to examine the effects of these social interactions using a county level of analysis during a period of economic uncertainty.

As Conley and Topa (2002) discussed, developing "a better understanding of the likely components of socio-economic distance will greatly facilitate the estimation of social interaction effects" (p. 304). This paper builds on the research conducted by Conley and Topa (2002), focusing specifically on applying the socio-economic distances that they used to estimate the social interactions effects at a tract-level of analysis in the city of Chicago and applies them at a county-level analysis in the New England States. Based upon a *strength of position* as well as a basic argument for and against the maintaining strong social ties Ioannides and Loury (2004) illustrated how these social interactions could cause a *sorting* of individuals into various networks. Applying the sentiment of Conely et al. (2002) to Ioannides et al. (2004), the researcher can reasonably test for evidence of *clustering* behavior among people with similar preferences and tastes at a county level of analysis.

According to Conley and Topa (2002), employees find employment approximately 50% of the time through social networks (p. 304). Ioannides and Loury (2004) also found that the following four elements are critical factors that should be explored to understand how job networks influence labor market outcomes: (a) employer, (b) relational, (c) contact, and (d) worker heterogeneity (p. 1061—see Table 2 for a categorization of the variables used in this study). This research project's basic model has components of three of the four critical factors that Ioannides and Loury (2004) have indicated effect labor-market outcomes (i.e. relational, contact, and worker heterogeneity)—the researcher did not add employer-related factors in this analysis. Ioannides et al. (2004) indicated that “contact and relational heterogeneity respectively denote variations in the resource endowments of one’s associates and the social relationships that allow individuals to claim access to resources possessed by their associates” (p. 1061); whereas, worker heterogeneity refers to differences in worker productivity or other characteristics (Ioannides et al., p. 1061). Both types if heterogeneity seems to possess substantial explanatory power over socio-economic interactions and outcomes.

This studies main goal is to determine whether researchers could use spatially dependent variables to improve a model’s ability to forecast changes in the unemployment rate of a particular county as the U.S. Economy’s business cycle went from peak to trough from the first quarter of 2006 to the fourth quarter of 2008. According to Topa (2001), agents’ choices and payoffs are affected by other agents’ actions, not just indirectly through markets, but also directly through imitation, learning, social pressure, information sharing, or other non-market externalities…It is also assumed that agent[s] interact locally, with a set of neighbors defined by an economic or social distance” (p. 261). The researcher believes that this analysis will find that as the geographic, ethnic, and occupational distances between two agents increase, their actions will become increasingly dissimilar; moreover, that neighboring county’s unemployment rates will influence a particular county’s unemployment rate. The researcher will use the concept of spatial dependence, and tests constructed to identify spatial dependence, to identify if and where social interaction effects occur and the extent of these interaction effects.

DATA

For this project, the researcher collected data from a variety of sources. For the traditional economic variables, the researcher used the U.S. Census Bureau’s *American FactFinder Fact Sheet* (URL: http://factfinder.census.gov) to obtain 3-year estimates, from 2006-2008, for the following variables: (a) The percentage of the population 25 years and over, (b) The percentage of the population that is a high school graduate or higher, (c) The percentage of the population that has a Bachelor’s Degree or higher, (d) Per capita income, (e) The percent of families below poverty level, and (f) The percent of individuals below the poverty level. The researcher used information from U.S. Census Bureau’s American FactFinder website, listed above, to obtain information pertaining to the ethnic composition of a particular county. Estimates of the counties occupational breakdown by NAICS code was taken from the U.S. Census Bureau 2002 economic census (URL: http://www.census.gov/econ/census02/data/nc/NC001.HTM). Unemployment data was found on the Bureau of Labor Statistic’s website: ww.bls.gov. Finally, the researcher obtained the latitude and longitudinal coordinates to determine the physical distance between two counties.

METHODOLOGY

This study expands the research conducted by to Conley and Topa (2002), in which they found significant levels of physical, ethnic, and occupational dependence occurring in their analysis of unemployment rates at a tract level of analysis in the City of Chicago. The researcher builds on their study by examining the following research questions using a county level of analysis.

Research Question 1: Is there evidence of spatial dependence in the spatial lags of physical, ethnic, and occupational distances?

Research Question 2: How well do the spatial lags of physical, ethnic, and occupational distances explain the changes in unemployment rates during a period of economic uncertainty?

Research Question 3: How well do variables traditionally used explain unemployment rates predict changes in unemployment rates during a period of economic uncertainty?

Research Question 4: Can researchers use a mixture of traditional variables and spatially lagged variables to improve the predictive power of a regression analysis to predict changes in unemployment rates during a period of economic uncertainty?

The following sections provide an answer to these research questions.

This paper's attempt to explain what factors may have caused changes in the unemployment rate during the recent economic downturn relied on both spatially dependent and traditional independent variables. The traditional independent variables are: (a) The log of the average per capita income, (b) The percent of families living below the poverty rate, (c) The percent of individuals living below the poverty rate, (d) The percent of individuals that have a high school education or higher, (e) The percent of individuals that have greater than a bachelor's degree, and (f) The percent of the population that are 16 years or older. The spatially dependent variables are as follows, the spatial lag of the difference in the unemployment rate during the economic downturn with respect to: (a) Physical Distance, (b) Ethnic Distance, and (c) Occupational Distance. The complete model is presented below:

$$\hat{y}_i = \alpha_i + \rho W_1 y_i + \varphi W_2 y_i + \delta W_3 y_i + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \beta_3 x_{3,i} + \beta_4 x_{4,i} + \beta_5 x_{5,i} + \beta_6 x_{6,i} + \varepsilon$$

$\hat{y}_i$:	Estimated Difference in Unemployment Rates
α_i:	Intercept term
$\rho W_1 y_i$:	Spatial Lag of the Difference in the Unemployment Rate in respect to 'Travel Distance (Auto)'
$\varphi W_2 y_i$:	Spatial Lag of the Difference in the Unemployment Rate in respect to 'Ethnic Distance'
$\delta W_3 y_i$:	Spatial Lag of the Difference in the Unemployment Rate in respect to 'Occupational Distance'
β_1:	The beta coefficient for the log of the average Per Capita Income
β_2:	The beta coefficient for the % of families living below the poverty rate
β_3:	The beta coefficient for the % of individuals living below the poverty rate
β_4:	The beta coefficient for the % of individuals that have a high school education or higher
β_5:	The beta coefficient for the % of individuals that have greater than a bachelor's degree
β_6:	The beta coefficient for the % of the population that are 16 years or older
ε:	Error Term

Spatial Components

This research project used three different spatial components. The first, is based upon physical distance and it takes two forms: (a) the neighbor effects or 'boundary sharing' and (b) travel distance or how far, in terms of geographic miles, one county resides in comparison to another (typically, the researchers used the mid-points of the counties to run this calculation). The second neighborhood effect explored in this study is ethnic distance. When researchers examine the ethnic distance between two counties, they are evaluating how similar counties are to one another with respect to their population's ethnic breakdown and from this an ethnic distance is calculated. The final distance metric that was calculated in this study was the occupational distance between counties. The occupational component is similar to the ethnic component, in that it compares the occupational breakdown found in one country against another and estimates their distance in terms of 'likeness' or 'similarity'. The following sections provide an explanation of how each of these metrics was calculated.

Physical Distance

Physical distance is the easiest distance metric to explain. Everyone has had experiences traveling and whether measured in time or distance traveled, there is a cost associated with their travel. The distance traveled can be thought of as a cost associated with the activity that provoked them to travel. This study takes this concept and applies it to county-level interactions by first stating that if a county shares a boundary with an adjoining county (first spatial lag of geographic distance), that county is more likely to interact with the adjoining county than it is likely to interact with counties that do not share a boundary. Next, this project analyses how quickly the neighbor's influence on the county of interest deteriorates as the distance between the two counties increases. By using this strategy to analyze the neighborhood effects, researchers can show how quickly the spatial dependence between two counties deteriorates and at what point the dependence between the two counties becomes insignificant.

Ethnic Distance

It has been shown that people with similar ethnic backgrounds are more likely to associate with each other (see Ioannides & Loury, 2004, p. 166), when compared against people with different ethnic backgrounds. Furthermore, if the community that an individual agent resides has a greater proportion of agents that possess a similar ethnic background, those agents are likely to have a greater chance of uncovering employment opportunities through networking in those groups than they would otherwise (Conley & Topa, 2000, p. 10 and Ioannides et al., 2004). This research project posits that counties that have similar ethnic structures will have similar unemployment rates, all other things equal; so, theoretically, spatial dependence is likely to exist between counties that have similar ethnic compositions. A modified formula taken from Conley and Topa (2002) that the researcher used to calculate ethnic distance is as follows:

$$ed_{i,j} = \sum_{k=1}^{7} \sqrt{(e_{i,k} - e_{j,k})^2} \qquad \text{Equation 2}$$

$ed_{i,j}$: Ethnic distance between agent i and j
e_k: % Ethnicity of agent i
e_j % Ethnicity of agent j through k

After the researcher calculated the ethnic distance between each of the counties included in the study, the distances between counties were used to construct the weight matrices. The ethnic distance variable indicates how far each counties ethnic structure was from each of the other counties in the sample. Using this structure to construct the spatial lag ethnic distance, the most weight would be given to the county that is least like the target county, in terms of ethnic composition; therefore, the Moran's I, the test for spatial dependence, should turn out to be negative if there is spatial dependence.

Occupational Distance

According to Conley and Topa (2002), individuals with similar occupational backgrounds are "more likely to convey useful information about job openings, or generate referrals" to the currently unemployed (p. 310). This research project projects this general statement on a county of individuals and makes inferences about the benefits of these kinds of relationships using the following calculation (Conley et al., 2002, p. 311):

$$\mathrm{OD}_{i,j} = \sum_{k=1}^{12} \sqrt{\left(o_{i,k} - o_{j,k}\right)^2} \qquad \text{Equation 3}$$

$od_{i,j}$: Occupational distance between agent i and j
o_i : Number of people employed in occupation k
o_j Number of people employed in occupation i at location j

The occupational distance variables used in this study share the same properties as the ethnic distance variables. That is, if the researcher was to use the raw distance, the county with the greatest distance from the county of interest would generate the greatest weight in the weight matrices; therefore, the coefficients are expected to be negative.

Spatial Lag Model

To determine whether a specific variable is spatially dependent, researchers need to calculate the 'spatial lag of the variable of interest'. In all three of the spatial dependence calculations used in this project, the researcher will have to determine a way to define a neighborhood. Typically, the distances between two counties would be used to construct a connectivity matrix (*C*), which is an *n* x *n* matrix, where n^{th} is each county contained in the sample (the exception to this approach is using the raw distance score to construct the weight matrix using travel distance, which can be seen in Tables 4b and 4c). If county *i* and county *j* are considered neighbors, within the matrix, the row-column match between counties *i* and *j* will take on a value of one (or in the case of ethic and occupational distance a distance score will be calculated base upon the aforementioned distance metrics); otherwise, this row-column match will take on a value of zero.

Next, the researcher took this connectivity matrix (*C*) and transformed it to a row-normalized connectivity weight matrix (*W*) where each row sums up to one by dividing each c_i of the binary connectivity matrix *C* by the total number of links $\sum c_{i\cdot}$ (Ward, M. and Gleditsch, K., 2008, pg. 18). Furthermore, Ward et al. (2008) explained that researchers can use the scalar $y_i^s = c_{i\cdot} * y$, the spatial lag of *y* on itself, using the *W* to describe the connectedness of each neighboring observation of unit *i* to estimate the spatial dependence embedded in the sample (p. 18); therefore, the spatial lag of *y* is the average of all of the neighbors of *y* in lag *i*. This study applies the spatially lagged model to explain the dependence between the county of interest and its spatial lag. When researchers use a spatially lagged model, they are assuming, according to Ward and Gleditsch (2008) that "they believe that the values of y in one unit i are directly influenced by the values of y found in i's 'neighbors'" (p. 35). The reader can compare this model with spatial error model, in which, according to Ward et al. (2008), researchers treat the spatial correlation as a nuisance that should be eliminated—this nuisance will lead to estimation problems (p. 65). This project assumes that there is information embedded in 'neighborhood' that will have significant explanatory power over what happens in the county of interest. This paper uses the Moran *I* statistic to proxy for spatial dependence; formally, this metric can be calculated using the following formula (Ward and Gleditsch, 2008, p. 23):

$$I = \frac{n \sum_i \sum_{j \neq i} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_i \sum_{j \neq i} w_{ij})} \qquad \text{Equation 4}$$

RESULTS

This section evaluates: (a) Moran's tests for spatial dependence using different lags and weighting structures for each of the distance metrics used in this study, (b) Models that estimate the change in unemployment rates using traditional and spatially dependent variables, and (c) A final model using traditional and spatial components to estimate the changes in unemployment rates. The section will start by reporting the results of the spatial dependence between the percentage change in the unemployment rates and the physical, ethnic, and occupational distances between counties. Next, the researcher presents the results of an OLS regression using the traditional independent variables outlined in previous sections. The researcher then estimated the spatial dependence found in each of the spatially dependent variables indentified in this study. Finally, the variables are combined and an OLS regression is run to determine what mix of spatially dependent and traditional variables generated the best estimation of the changes in unemployment rates experienced in a period of economic uncertainty.

Physical Distance

For this portion of the analysis, the researcher used three different weighting schemes; Table 4 presents the results. It is evident that Weighting Scheme 2, produces the most significant results using the first neighbor strategy (i.e. lag 1), but a thorough examination of both Weighting Schemes 1 and 2, would portray what Conley and Topa (2002) conveyed in their paper, which is that "spatial correlation decays roughly monotonically with distance" (p. 325). The researcher presents evidence of this by graphing the Moran's *I* on the upper distance limit of each respective lag, as seen in Figure 2. In Figure 2, the spatial dependence between the change in the unemployment rates and physical distance goes from a very strong relationship when neighbors reside within 20 miles of the target county, diminishes quite rapidly as they move from 20 to 60 miles, and then deteriorates and becomes insignificant from 60 to 80 miles.

The researcher chose to use the 2nd weighting scheme, bordering county, because the spatial dependence found using this method was the most significant; however, the strength of the spatial dependence was very similar to specifying 'a neighborhood' as counties within 20 miles of the county of interest. To carry out this analysis the researcher constructed a connectivity matrix (*C*) using the criteria set for weighting scheme 2, lag 1 (i.e. the counties must share a border) in Table 4b. The spatial dependence between the percentage change in the unemployment rates and geographic distance (identified by the Moran *I* test statistic) is .5803 and significant using an α of less than .001. As the researcher altered the connectivity matrix, moved to the second lag (i.e. separated the counties by another county and required both counties share a border with the county that separates them), the spatial dependence between the percentage change in the unemployment rates and geographic distance deteriorates to .1930 and is insignificant using an alpha of less than .10. Since the spatial dependence is no longer significant at Lag 2, the researcher will create the spatial lag used in the OLS regression analysis, by constructing the connectivity matrix using the first lag of the second weighting scheme.

Ethnic Distance

To determine whether changes in unemployment rates exhibited spatial dependence in terms of ethnic distance, the researcher constructed two different weighting schemes and displayed the results of these test for spatial dependence in Table 4b. The researcher based the first weighting scheme, percentage cohorts, upon the first physical distance-weighting scheme in Table 4a. If the distance between two counties was smaller than 90% of the distances between the other counties in the sample, then this particular relationship would be examined in the 00 – 10 percent lag (if smaller than 80 percent of the distances in the population, the relationship would be evaluated in the 00 - 20 lag). The researcher initially assumed that if a county's ethnic composition is similar to another, changes in their unemployment rates might also be similar—and, spatial dependence would be evident in the sample. This did not happen; weighting structure 1 produced no economically or statistically significant results, in terms of spatial dependence.

Since the percentage distance weighting used in Weighing Scheme 1 failed to produce any significant results the researcher ran a Moran test using the raw ethnic distances calculated by Equation 2. The results were not significant using an α of .05, but there is a weak statistical relationship between the change of unemployment rates and ethnic distances that is statistically significant using an α of .10. Since this, the raw ethnic distance weighting procedure, is relatively easy to describe and recreate the researcher has chosen to use this weighting procedure to run the regression analyses.

Occupational Distance

Initially, for the analysis of occupational distance, the researcher started out using a weighting structure similar to the one used to estimate the spatial dependence between the change in unemployment rates and physical distance (i.e. Table 4b); again, the researcher is attempting to determine if spatial dependence decreases monotonically as the occupational distance between counties increases. This analysis found no evidence of this. Conley and Topa (2002) stated that, both distance metrics (i.e. ethnic and occupational) had strong and negative spatial dependence when the distance grew substantially large between the two counties; therefore, if this project is not able to identify spatial dependence using small occupational distances, it may be useful to try to use greater occupational distances. The results of the Moran tests for these lags are presented in Table 4c at distances of greater than 30, greater than 40, and greater than 50 percent. The results do not seem to support the findings Conley et al. (2002) that strong and negative spatial dependence occurs when the distance grows substantially large between the two counties, because there was an insignificant, but negative (which supports Conley et al.) relationship at distances that are greater than the bottom 80% of the population. Since the relationship between occupational distance and changes in the unemployment rates seems to be complex, the researcher chose the simplest weighting scheme to describe the spatial dependence using this metric, Weighting Scheme 1 – Raw Distance. Using this weighting scheme the researcher found that spatial dependence is statistically significant using an α of .10.

Using Spatial Variables to Predict Changes in the Unemployment Rate

After choosing weighting structures that coincide with evidence of spatial dependence presented in the previous sections, the researcher was interested in examining how useful and significant each of the spatial lags were in explaining changes in the unemployment rates. Table 5a presents the results of this stage of the analysis. All of the spatial lags based upon different distances (i.e. physical, ethnic, and occupational) generated statistically significant results using an α of .10, but it is obvious that the explanatory power embedded in the spatial lag, using physical distance as the distance metric, far exceeds that of the other distances. As the researcher added the two other spatial lags (i.e. based upon ethnic and occupational distance) to the physical distance variable and attempted to explain changes in the unemployment rates, the R^2 value increases from .337 to .345. It seems obvious and is verified by conducting an *F* test (*F* statistic - .4089) that the addition of these two spatially lagged variables offers very little additional explanatory power that is not already included in the spatial lag of the physical distance.

Using Traditional Variables to Explain Changes in Unemployment Rates

In this section, the researcher determined to what extent changes in the traditional independent variables explained changes in unemployment rates. The traditional variables used in this study were: (a) The log of the average per capita income, (b) The percent of families living below the poverty rate, (c) The percent of individuals living below the poverty rate, (d) The percent of individuals that have a high school education or higher, (e) The percent of individuals that have greater than a bachelor's degree, and (f) The percent of the population that are 16 years or older. In this round of the analysis, five counties were dropped from the study, because the researcher could not obtain the data necessary to run a regression analysis including all of the independent variables; the counties dropped from the analysis were: (a) Essex, (b) Grand Isle, (c) Piscataquis, (d) Nantucket, and (e) Dukes.

The results of the regression analysis using traditional explanatory variables are presented in Table 5b; the results were statistically significant using an α of less than .05. The traditional dependent variables that displayed statistically significant explanatory power over changes in the unemployment rates during a period of economic uncertainty were: (a) Per Capita Income, (b) Family-Level Poverty, and (c) Education—obtaining a high school diploma or greater. The results seem to coincide with some more general assumptions about employability: Typically, people with (a) higher per capita incomes, (b) whose family lives above the poverty line, and (c) have a greater than a high school education are more likely to have marketable skills when compared against those who do not.

Regression Analysis

This section will present the final model and explain the relationship between the percentage change in unemployment and the explanatory variables. This process will be completed in five steps: (a) Construct an OLS regression analysis using only the physical lag of the change in unemployment rates, (b) Include the remaining spatial components, (c) Use the spatial lag of the change in unemployment rates based on physical distance and include the traditional independent variables, (d) Add the remaining spatial lags to the preceding regression, and (e) Omit the outliers from previous regression—see Table 5c for the regression results. Again, it is necessary to state that five counties used to estimate the spatial dependence were not included in the latter stage of the analysis because the data need to estimate the parameters for the traditional independent variables were unavailable, these counties were: (a) Essex, (b) Grand Isle, (c) Piscataquis, (d) Nantucket, and (e) Dukes.

Table 5c provides the results of the regression analyses and summarizes the general findings. In Model 1, the researcher relied solely on the explanatory power of the spatial lag of physical distance to explain changes in the unemployment rates. Again, the spatial lag of unemployment rates base upon physical distance has substantial explanatory power over the changes in unemployment rates experienced using a county level of analysis from 2006 to 2008. The second iteration of this model, the addition of our spatial lags of ethnic and occupational distance to the physical distance metric, improved the model's explanatory marginally, but it seems that the spatial lag of physical distance dominates the other two spatial components. In Model 3, the researcher included only the spatial lag of physical distance and the traditional explanatory variables to attempt to explain the changes in unemployment rates during this period, again the results improve marginally. Finally, in Models 4 and 5, the researcher added both the traditional and spatially lagged components to this analysis and omitted the outliers in the spatially lagged ethnicity variables and, again, marginally improved the models predictive power.

CONCLUSION

This paper's main goal was to expand the research conducted by Conley and Topa (2002) to determine if the researcher could find evidence of spatial dependence in terms of physical, ethnic, and occupational distances using a county level of analysis. By expanding the unit of measurement from a tract level to a county level, this project questions whether social interaction effects are restricted to lower levels of agglomeration (Conley & Topa, 2002, p. 25) than a tract level of analysis and whether researchers can use a county level of analysis to analyze aggregate social interactions involved in social exchanges (Akerlof, 1997, p. 1023). In contrast to what Conley and Topa (2002) found in their analysis of spatial dependence at a tract level of analysis, in which the researchers found that the social interaction effects attached to physical, occupational, and ethnic distance decreased monotonically with distance, the researcher finds that the social interaction effects attached to physical distance decreases monotonically as distance increases—this is not the case when the researcher evaluated the remaining social interaction effects. The social interaction effects or spatial dependence found using the ethnic and occupational distances, first, does not decrease as distances increase and, second, the coefficients attached to the spatial dependence are negative and statistically significant. This finding has interesting implications, to explain this phenomenon; the researcher needs to alter the way researchers describe county level interactions in terms of ethnic and occupational distances using a county level of analysis.

The spatial lags of ethnic and occupational distances illustrate an interesting structural relationship that is occurring between these counties and is somewhat intuitive. As the occupational and ethnic disparities between counties increase, the explanatory power of these two metrics increases. The interpretation of this finding is that if a county is somewhat similar to another county, in terms of ethnic and occupational structure, these two metrics have little explanatory power over the directional changes in unemployment rates. However, as the counties become increasingly dissimilar, in terms of occupational and ethnic make-up, the strength of these metrics explanatory powers grows and trends toward generating statistically significant spatial dependence between the two counties of interest. The dissimilarity between two counties seems to have a statistically significant influence on changes in their unemployment rates.

Conley and Topa (2002) also found, in their analysis of social interactions at a tract level of analysis is Chicago, that the Ethnic and Occupational Distances dominated the Physical Distance metric in terms of spatial dependence. This study finds that the information embedded in the physical distance metric dominates the other two proxies for social interaction effects; moreover, after conducting a *f* test, the researcher determined that the Ethnic and Occupational Distances did not contribute enough predictive power to be included in a model that uses only spatially dependent variables to explain the changes in unemployment rates during a period of economic uncertainty. Therefore, the information embedded in the Physical Distance metric seems to dominate the social interaction effects inherent in the Ethnic and Occupational Distances.

The final model illustrates how pervasive the effects of spatial lags, especially when examining physical distance, are in terms of describing changes in our dependent variable (i.e. changes in unemployment rates during a period of economic uncertainty). In this analysis, relying solely on traditional independent variables to explain the changes in unemployment rates, the researcher was able to generate a model that was statistically significant; however, the model lacked economic significance. By including the spatial lag of physical distance with the traditional economic variables, the researcher was able to improve the statistical significance of the model from an R^2 of .201 to .659. The addition of the spatial lags of occupational and ethnical distances and the omissions of the outliers enabled the researcher to improve the final model marginally.

The models presented in this paper indicate that there was significant spatial dependence in the changes of unemployment rates occurring at a county level of analysis from 2006 to 2008. The extension of the results found in Conley and Topa (2002) to a county level of analysis have significant social and policy ramifications. For example, governmental agencies could use models similar to these to forecast how aid packages would affect the unemployment rate in a particular area and what potential spill-over effects that aid package would have throughout the system. These same agencies could segment particular regions that are ‘isolated’ in terms of occupational, ethnic, or physical distances and construct aid packages to help to either ‘connect’ those counties (i.e. developing infrastructure, promoting diversity, etc.) or provide aid to those counties if the act of connecting them is cost prohibitive. Finally, to expand the results presented in this analysis, researchers could examine whether there is evidence of spatial dependence using the same socioeconomic distances using: (a) a broader sample space and/or (b) different geographic regions.

REFERENCES

Akerlof, G. A. (1980). A Theory of Social Custom, of Which Unemployment May be One Consequence. *The Quarterly Journal of Economics, 94(4),* pp. 749-775.

Akerlof, G. A. (1997). Social Distance and Social Decisions. *Econometrica, 65(5),* pp. 1005-1027.

Conley, T. G. and Topa, T. G. (2002). Socio-economic distance and spatial patterns in unemployment. *Journal of Applied Econometrics, 17*, p. 303-327.

Ioannides, Y. M. and Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature, 42,* p. 1056-1093.

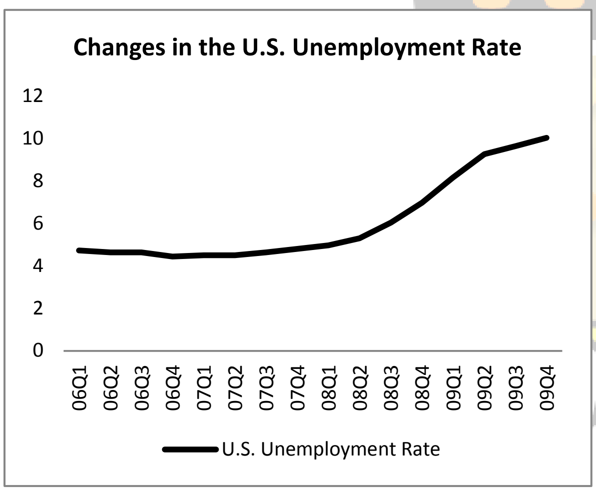
Ioannides, Y.M.and Topa, G. (2010). Neighborhood Effects: Accomplishments and Looking Beyond Them. *Journal of Regional Science, 50(1),* pp. 343-362.

Topa, G. (2001). Social interactions, local spillovers and unemployment. *Review of Economic Studies, 68,* p. 261-295.

Ward, M. D. and Gleditsch, K. S. (2008). *Spatial Regression Models.* Thousand Oaks, CA: Sage Publications, Inc.

TABLES & FIGURES

Figure 1: Visual Representation of the relationship between the U.S. Unemployment Rate and the Percent Change in the Gross Domestic Product (GDP)



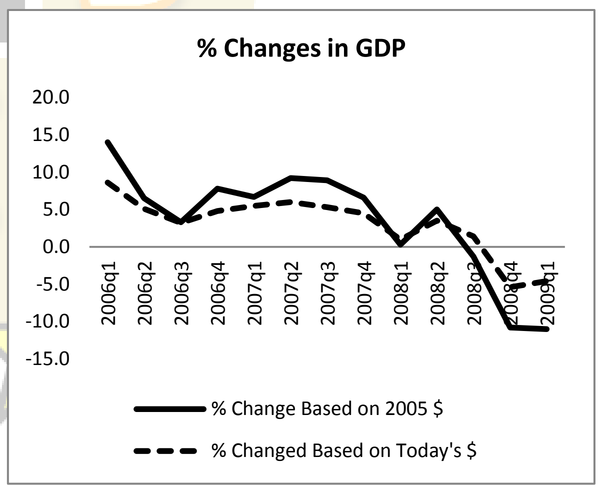


Table 1: An Examination of the Relationship between Unemployment Rates and Gross Domestic Product (GDP)

Table 1: Illustration of the Relationship between the Unemployment Rate and the Percentage Change in GDP During a Period of Economic Uncertainty

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	OLS (6)
τ	-0.374**	-.489	.070	-.034	-.098	-.166*
	(0.143)	(.173)	(.151)	(.094)	(.089)	(.065)
τ-1		.197**	-.162	-.166	-.119	-.073
		(.172)	(.203)	(.124)	(.106)	(.079)
τ-2			-.428**	-.165	-.172^	-.155^
			(.15)	(.123)	(.1)	(.073)
τ-3				-.405***	-.293**	-.292**
				(.094)	(.11)	(.077)
τ-4					-.245**	-.181^
					(.1)	(.086)
τ-5						-.246**
						(.084)
β0	6.361***	6.315***	6.442***	6.632***	6.87***	7.27***
	(0.458)	(.455)	(.382)	(.244)	(.223)	(.205)
R2	0.345	.41	.667	.898	.947	.98
n	15	14	14	13	12	11

Notes: Standard Errors are in parentheses; ^ Significant at 15%; * Significant at 10%; ** Significant at 5%; *** Significant at 1%

Table 2: An Examination of the Relationship between Unemployment Rates and Gross Domestic Product (GDP)

Table 2. County Level Characteristics Used as Descriptor Variables

Sorting Variables	
Relational	Spatial Lag of the Difference in the Unemployment Rate in respect to Ethnic Distance
	Spatial Lag of the Difference in the Unemployment Rate in respect to Occupational Distance
	Percentage of Families Living Below the Poverty Rate
	Percentage of Individuals Living Below the Poverty Rate
Contact	Spatial Lag of the Difference in the Unemployment Rate in Respect to Travel Distance
	Log of Per Capita Income
Worker Heterogeneity	Percentage of Individuals that have a High School Education or Higher
	Percentage of Individuals that have Greater than a Bachelor's Degree
	Percentage of the Population that are 16 Years or Older
Spatial Mismatch	Average commute time to work in minutes

Figure 2: Correlogram—Physical Distance and the Unemployment Rate

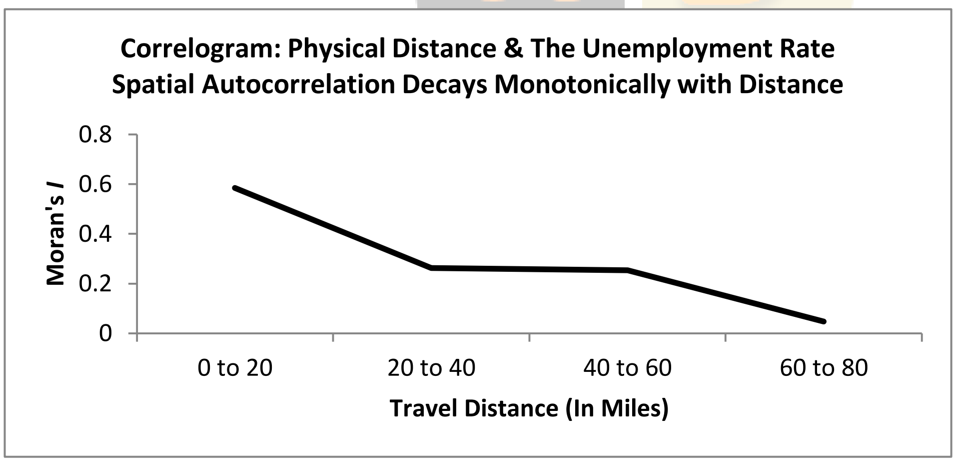


Table 4a: Physical Distance

Table 4a. An Examination of the Spatial Dependence found in our sample using different lags of physical distance

Weighting Scheme #1: Travel Distance				
Range (In Miles)	Moran's *I*	P-Value	R^2	n
00-20	0.5857 (.2813)	0.0594	0.2654	14
20-40	0.2625 (.1056)	0.0156	0.0907	64
40-60	0.2536 (.0862)	0.0041	0.0796	102
60-80	0.0474 (.1056)	0.6543	0.0016	130
Weighting Scheme #2: Bordering County				
Lag #1*	0.5803 (.0101)	0.0000	0.3367	67
Lag #2^	0.1930 (0.1217)	0.1176	0.0373	67
Weighting Scheme #3: Diminishing Effect				
Lag #1^^	0.0229 (0.124)	0.1844	0.0005	67

Notes: * - The first lag consists of counties that share a border with the target county; ^ - The second lag consists of counties that are separate by a county; therefore, they are two counties away. ^^ - To calculate the diminishing effect all counties within the studies are neighbors, but the counties that are closest to one another have more of an impact on the changes of the others unemployment rate. The calculation is as follows: $w_{i,j}= 1/(1+|h|)$, where $h = s_i\text{-}s_j$ *and the* s terms are locations on a map, *h*is the distance between the two locations, and *w* is the weight that the j*th* firm has on the *i*th county.

Table 4b. Ethnic Distance

Table 4b. Moran's *I* tests for spatial dependence of the change in the unemployment rate based upon ethnic distance

Weighting Scheme #1: Percentage Distance				
Percentage	Moran's *I*	*p* value	R^2	*n*
00-10	-0.021 (.062)	.736	.003	37
00-20	.007 (.045)	.881	.0005	47
00-30	.009 (.027)	.745	.002	48
00-40	.071 (.041)	.089	.053	56
00-50	.035 (.05)	.478	.008	65
00-60	.012 (.030)	.703	.002	66
00-70	-.031 (.019)	.103	.041	66
00-80	-.02 (.014)	.153	.032	66
00-90	.007 (.015)	.628	.004	67
Weighting Scheme #2: Raw Ethnic Distance				
Raw Distance	-0.914 (0.509)	0.077	0.047	67

Percent refers to the percent of the population that is included in the calculation of the spatial lag. Identification of significant Moran's *I* statistics using an alpha of .01 and .05, respectively, are denoted with the following identifiers: ^ and *.

Table 4c. Occupational Distance

Table 4c. Moran's *I* tests for spatial dependence of the change in the unemployment rate based upon occupational distance

Percent	Moran's *I*	*p* value	R^2	*n*
Weighting Scheme #1: Raw Distance Score				
Raw Distance	-1.022	0.088	0.044	67
	(-0.591)			
Weighting Scheme #2: Increasing Neighborhood				
Percent	Moran's *I*	*p* value	R^2	*n*
00-10	-0.035	0.623	0.005	54
	(.071)			
00-20	-0.08	0.169	0.032	60
	(.057)			
00-30	-.062	0.056	0.059	62
	(.032)			
00-40	-0.033	0.329	0.015	64
	(.033)			
00-50	-0.071*	0.045	0.060	67
	(.035)			
00-60	-0.082^	0.004	0.118	67
	(.028)			
00-70	-0.035	0.159	0.030	67
	(.021)			
00-80	-0.041*	0.033	0.068	67
	(.019)			
00-90	-.026*	0.025	0.075	67
	(.011)			

Notes: Percent refers to the percent of the population that is included in the calculation of the spatial lag. Identification of significant Moran's *I* statistics using an alpha of .01 and .05, respectively, are denoted with the following identifiers: ^ and *.

Table 5a: Regressions Run Using Spatially Dependent Variables

Table 5a: Regressions Run Using Spatially Dependent Variables

Results of Regressions Using Spatially Dependent Variables to Explain the Variation in Unemployment Rates

	Model 1	Model 2	Model 3	Model 5
Intercept	0.0344	4.056^	4.778^	0.93
	(0.29)	(0.875)	(1.631)	(1.051)
Spatial Lag of Unemployment Based on Physical Distance	0.985^			.919^
	(0.172)			(0.16)
Spatial Lag of Unemployment Based on Ethnic Distance		-1.45^		-0.396
		(0.537)		(0.707)
Spatial Lag of Unemployment Based on Occupational Distance			-1.849	-0.086
			(0.977)	(0.711)
R^2	0.337	0.101	0.052	0.345
N	67	67	67	67

Notes: Significance Levels - * - significant with an α < .05; ^ - significant with an α < .01.

Table 5b: Regression Run Using Traditional Independent Variables

Results of Regression Analysis Using Traditional Independent Variables to Explain Changes in Unemployment Rates	
Intercept	12.26^
	(4.15)
LN(Per Capita Income)	-0.731*
	(0.338)
Poverty (Family)	-0.034*
	(0.016)
Poverty (Individual)	-0.026
	(0.017)
Education (HS or Better)	-2.603^
	(1.125)
Educational (BA or Higher)	0.6222
	(0.683)
16 and older	-0.675
	(0.916)
R^2	.201
N	62

Notes: Significance Levels - * - significant with an α < .05; ^ - significant with an α < .01. The following counties were omitted from this round of the analysis because they did not have traditional independent variable data available: (a) Essex, (b) Grand Isle, (c) Piscataquis, (d) Nantucket, and (e) Dukes

Table 5c: Regressions Run Using Traditional and Spatially Dependent Variables

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-0.393	9.919*	1.225	8.039	10.467
	(.242)	(5.320)	(3.116)	(5.645)	(6.128)
Spatial Lag of Unemployment Based on Physical Distance	1.236^ (0.143)	1.017^ (.177)	1.168^ (.149)	.946^ (.175)	.875^ (.177)
Spatial Lag of Unemployment Based on Ethnic Distance		-0.317 (.552)		-1.328 (.763)	-1.320 (.818)
Spatial Lag of Unemployment Based on Occupational Distance		-5.565 (3.127)		-3.995 (3.197)	-6.29 (3.404)
Traditional Independent Variables	No	No	Yes	Yes	Yes
Omitted Outliers (Ethnicity)	No	No	No	No	Yes
R^2	0.555	.583	.659	.691	.694
N	62	62	62	62	57

Notes: * - Significant with an α of .05; ^ - Significant with an α of .01