Is Commute stressing? A spatial analysis between commuting to work and depression

Abstract

Depression is one of the most prevailing mental health problem is US with an estimated 6.7% of the adults under its impact. However nearly two thirds of them do not actively seek nor receive proper treatment, which calls for investigation in risk factors and management for more accurate prediction and prevention. Previous studies mainly focused their attention on biological, socio-economic, cognitive dimensions and built-environment, leaving a gap of systematic research into physical activity especially for commute's effect on depression diagnosis. The goal of this article is to examine the relationship between commuting to work and depression. Research units are the county level of adults in the United States. Commuting time to work is the main independent variables to measure the commuting to work feature. Number of depressive days in the past 30 days is the dependent variable. Cross-sectional data from American Community Survey(ACS) and County Health Rankings (CHR) data in 2014 are merged according to their FIPS county identity. Ordinal Least Square (OLS) , spatial diagnosis , spatial lag regression ,and geographically weighted regression are used analyze the data. The study hopes to find the link between commuting to work and depression while explore insight of the causal mechanism.

Introduction

According to World Health Organization, depression is the most prevailing mental health problem which identified as the leading cause of (WHO,2014). In the United States, an estimated 15.7 million people aged 18 and above had experience depression episode in 2013 taking up 6.7% of the total American adults(ADAA,2014). The prognosis of depression is inadequate while the death rate of depression is 21%(Cole & Dendukuri, 2003). Therefore, to understand the risk factors of the depression would be of great use, shedding light to the prevention and prediction of the depressive diagnosis. Previous studies have identified risk factors mainly from four dimensions: biological aspect(Kauffman et al., 1997), cognitive perspective (Dobson & Dozois, 2011), socio-economic environment(Eaton et al., 2001) and built-environment (Galea et al., 2005). However, few studies introduced commuting activity aspect into the depression risk factor investigation. In Ohta's study, the increase in duration of commuting time by either walking or cycling is correlated with better mental health in men(Ohta et al., 2007). In a recent study, higher density of auto commuters relative to land area, serving as an indicator of chronic noise exposure, is found associated with more depressive symptoms(Coutts et al.,2016). Commuting aspect was partly mention in separate studies focusing on neighborhood or physical activities . Further investigation into comprehensively understanding of commuting effects on depression syndrome is absent. Therefore , this study would work on building a risk factor model for depression , emphasizing the commuting to work effect on depression.

As the commuting is a big concept, I choose the commuting time to work as the indicator. My main research question is that : Is there a relationship between commuting and depression symptom? If so, what is the direction? How strong is the correlation? What is the mechanism of commuting's effect on depression? Is there any interactions between independent variables?

The observational data of County Health Rankings data and American Community Survey(ACS) in 2014 would be utilized along with US national GIS map. Ordinal Least Squares(OLS) regression and Spatial lag regression model would be used to test the statistical relationship between commuting and depression.

Literature Review

Some epidemiologic studies looks into biological risk factors correlated with depression. Even though there was a study claiming that the depression is moderately to highly heritable(Rice, Harold, & Thapar, 2002), other genome studies have not found robust correlation between specific genes and depression((Lopez-Leon et al., 2008; Shaikh et al., 2008; Shyn et al., 2009; Sullivan et al., 2009). Gender difference that women are more vulnerable to depression has been examined in many existing literature(Hankin &Abramson, 2001; Nole & Girgus, 1994). Generic racial differences such as non-white may consist of diverse ratio of depression rate(Weich et al.,2002).

Socio-economic environment risk factors are well-developed in the existing literature. Sociological factors including child maltreatment (Chapman et al., 2004; Widom, DuMont, & Czaja, 2007), parental divorce and negative family relationships(Gilman et al., 2003; Repetti et al., 2002), weak social capital(McKenzie et al.,2002) were examined with significant correlation with depression. Unemployed (Weich et al.,2002) and poverty would both (Brooks-Gunn & Duncan, 1997; McLeod & Shanahan, 1996;) render higher risk of depression. There is also a growing volume of neighborhood effect on depression studies assessing the neighborhood characteristics such as racial composition, neighborhood poverty (Julien et al., 2012; Paczkowski and Galea, 2010; Beard et al., 2009; Galea et al., 2007; Leventhal, Tama & Jeanne, 2003), and neighborhood health service (Caracci, 2006; Galea et al.,2005).

Apart from genetic and socio-economic dimensions, the built environment investigations are incrementally developing in urban depression (Kim, 2008; Mair et al., 2008). Walkability of neighborhood infrastructure(e.g.parks) and community physical designs (e.g. sidewalk) could also affect the urban residence mental health through bridging their socialization channels and providing physical activity places(Leyden, 2003; De Toit et al., 2007; Cohen et al., 2008; Rogers et al., 2011; Ding et al., 2011). Green space coverage increase can also improve mental health by reducing stress(Bedimo-Rung et al., 2005). Insufficient daylight of housing and air pollution in urban areas may produce mental illness like depression(Evans & Gary W, 2003). Dwelling characteristics such as floor or residence and house structure are tested to be significantly associated with the prevalence of depression (Weich et al., 2002).

However, investigation of commuting effects on depression are fragmented mentioned in some studies. Transportation situation such as high way density plays a catalyzing role in urban depression for such as the stress generating noise from highly dense highways (Lederbogen et al., 2011). The increase in duration of commuting time by either walking or cycling is correlated with better mental health in men(Ohta et al., 2007). Coutts and his co-workers(2016) found that higher density of auto commuters relative to land area, serving as an indicator of chronic noise exposure, is found associated with more depressive symptoms. There is a gap of comprehensively understanding of commuting effects on depression syndrome. Therefore, this study would try to examine the effect of commuting to work on depression symptoms while building a risk factor model for depression with OLS and Spatial lag model.

In terms of methodology, most of the urban depression risk factor research took the form of observational studies. Cross-sectional surveys were most frequently conducted (Chen et al., 2015; Gruebner et al., 2015; Frank et al., 2006; Weich et al.,2002;Levy et al.n 1974) while longitudinal surveys with 10 years follow-up was also employed(Stafford et al.,2008). Experimental method was applied as part of the Moving to Opportunity government program which examine the higher neighborhood poverty would correlated with higher urban mental health problems(Leventhal et al., 2003). A number of articles utilized literature reviews to analyze risk factors for urban depression (Julien et al, 2012; Dunn et al., 2011;Gershon et al., 2005; Evans & Gary, 2003; Jackson & Laura E, 2003; Parr & Hester, 1997). For data analysis, Ordinal Least Squares(OLS) regression is the most common method in examining the correlation between risk factors and urban depression(Mueller et al., 2016;Duncan,2013; Ling et al, 2010). Multilevel linear regression and logit regression models were also popular(Stafford et al.,2008). Nearest neighbor methods (Bethell, 1999) and quadrat analysis (Moor et al., 1999;Levy , Leo & Allen .,1974) were employed in spatial analysis for mental health. Exploratory techniques (Moscone, Francesco & Martin et al., 2005) from spatial analysis such as spatial simultaneous autoregressive models are rarely applied due to the geographical data availability (Duncan, 2013). GIS technique in transportation spatial analysis (Gruebner et al., 2015; Chapleau et al., 2005) was lack application in urban depression related issues.

The previous studies of risks factors for depression have following key limitations.The data of variables was collected through survey where many self-reported questions were used to measure the targeted risk factor. The objectivity of data collected would introduce measurement bias into the study. In addition, individual level investigations with consistent matching of geographical information is inadequate. Most of the analysis were taking the mean values of residence units or even broader level units. Boundaries between spatial units lack formal standardization. This would blur the precision of correlation between true factors and urban depression. Spatial regression techniques were seldom used which would benefit the geographical features of risk factors' analysis. Furthermore, there is a gap of literature in commuting effect on depression. Commuting time and transportation related density features were mentioned in existing research but the comprehensive understanding of the mechanism remains inadequate.

Therefore, the purpose of this paper is to examine the relationship between features in commuting such as commuting time to work, and depression symptom distribution. Besides commuting feature, demographical features and socio-economic features would also be evaluated as control variables.

Theory

Psychological theories for depression have been developed in various aspects such as cognitive theory (Hildebrand, 2015; Hankin & Lyn, 2001) , social support theory (Dobson et al., 2011) and behavior(environment avoidance) theory(Carvalho, John and Derek, 2011). Theories for commuting and transportation effect on depression is scarce even though many studies have delved into commuting factors correlated to stress and work performance.

Transactional stress models, developed by Lazarus(1966) , is a widely adapted theory model for commuting stress studies. The transactional stress model 's basic idea is that it is the stressful incidents that bring about uncertainty and loss of control contributes to the mental stress and worse physical performance. There are two dimensions to the stressor framework, the first is the personal perception of potential threat such as traffic congestion during commuting to work; the second is the coping resources including socio-economic and demographic status. These two d dimensions constitute for the personal-environmental transactions framework.

Referring to the transactional stress model, I would use commuting time to work as factor for the personal stressful incident dimension, in the meantime, socio-economic and demographic factors would also be controlled in the model.

Data and Methodology

The County Health Rankings (CHR) data and American Community Survey(ACS) data are the data sources of this study. As the data are cross-sectional in nature, I am using CHR and ACS data in 2014 as training data set. A Cartographic Boundary Shapefile of the United Sates at the county level was taken from the United States Census Bureau website so as to visualize and spatial analyze the data.

The County Health Rankings is run by the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. The data is compiled using a population health model with many factors involved from a diverse data sources such as Behavioral Risk Factor Surveillance System(BRFSS) and Centers for Disease Control and Prevention(CDC). Entities with Federal Information Processing Standard (FIPS) county code are merged and standardized with scientifically-informed weights.

The American Community Survey(ACS) surveys about demographic, job, education, housing and other topics of people in the United States and report survey data on a yearly basis with geographical code. This data set allows not only OLS regression among variables but also spatial regression analysis. The full implementation of the ACS started in 2005 with 2.9 million sample of housing unit addresses, whereby the sampled housing unit addresses increased to 3.3 million in 2011. The sample of ACS each year is systematically divided into 12 months for interviewing with main and supplemental sampling[1].

Independent Variable

There following are the main independent variables for measuring the public transportation dimension.

Commuting time to work. The time spent on public transportation would be roughly counted through this variable whose data comes from ACS. And the time would be recorded in minutes. Mean commuting time of each county level area would be utilized to run in the OLS regression and Spatial regression models.

[1] American Community Survey(ACS) Sample Size Definitions https://www.census.gov/programs-surveys/acs/methodology/sample-size-and-data-quality/sample-size-definitions.html

Controlled Variables

Education. Socio-economic factors would greatly impact mental health(Williams et al., 1997; Adler et al., 1994). As educational level is significantly associate with income and socio-economic status(Nocon et al., 2007), I would take years of received education as a proxy of socio-economic measurement and a control variable.

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Population density. According to Levy's study, population density has strong correlation with health problems(Levy et al., 1974). Therefore I am adding the population density as a control variable here. The population density data comes from ACS survey data that records the population density per square mile of land area in 2014.

Sexratio. Gender of the samples would be taken as controlled variable because empirical evidences showing that women are more vulnerable than men to suffer depression (Hankin et al., 2001). The ACS data have gender information of the respondent which is calculated into male per 100 female ratio in the county level.

Age. The demographic variable age should be controlled as the depression syndrome does not distribute randomly in different age of people(Duncan et al., 2013). I am using the mean age of the county level from ACS data in 2014.

Race. Observable studies had shown ethical/racial differences in depression symptoms(DR Williams et al., 1997). As the racial distribution in US is not random and have spatial cluster features, I would control for the race variable. The data comes from ACS 2014 data. The continuous variable takes the value of the percentage of black people in the county level population.

Dependent Variables

Depressive days. The dependent variable is measured based on the self-report survey question: " Thinking about your mental health, which includes stress, depression , and problems with emotions, for how many days during the past 30 days was your mental health not good?". The individual level survey was conducted by The Behavioral Risk Factor Surveillance System(BRFSS) which is a state-based random digit dial(RDD) telephone survey including more than 400,000 annual respondents since 2011. The County Health Rankings weighted the data and averaged the number of depressive days into county level.

Data Analysis method

Ordinal Least Square (OLS) spatial diagnosis ,spatial lag regression model, and geographically weighted regression will be applied to analyzing the data. Data cleaning and regression running will be processed using R programming. Spatial analysis software such as QGIS and Geoda will be applied to spatial lag regression and data visualization.

To date, my data resource has many limitations. Firstly, the level of variable matching between different datasets is encountering problem of macro level matching. It would only be county level which can not generate micro level correlations between commuting and depression. Secondly, the cross-sectional nature of the data would not be able to produce temporal trend outcomes. Thirdly, multicollinearity may occur due to the interaction or correlations between independent and control variables, such as the commuting time to work and neighborhood poverty. National Longitudinal Survey of Youth (NLSY)(1979-2012) with census tract level of depression data using Center for Epidemiologic Studies Depression (CES-D) Scale scoring will be accessible after few months request. Once I have the NLSY data, I would be able to develop the results with more precise modelling. Ideally, a self-conducted survey at individual level would be the best choice, however not feasible at present due to censor and funding limitation.

Results

(1) Data description

In this study, county level of data from ACS and CHR in 2014 are extracted and merged by FIPS county code. The depression is measured by the depressive days for the past 30 days and weighted at the county level. Independent variable commuting time to work comes from ACS 2014 estimate data set that record the mean commuting time to work at county level in US. Table 1 summarizes the information about the independent variable, dependent variable as well as control variables.

The total number of county level samples of our data is 3107. In US, people have an average of 2.94 days of depressive emotions for the past 30 day before the BRFSS survey. The mean commuting time to works is 23 minutes and the average poverty rate per county is 12.23% which are not low. An average of 20% of the population receives bachelors degree or higher which shows that the higher education coverage is pretty high in US. The ratio of black people is too high so we will delete the column data of this variable.

Table 1. Descriptive Statistic Table for Variables

Statistic	N	Mean	St. Dev.	Min	Max
depression	3,107	2.943	1.653	0.000	10.100
populationdensity	3,107	261.410	1,733.733	0	69,468
blackpercent	3,107	83.970	16.045	10	100
commute	3,107	23.313	5.410	10	44
sexratio	3,107	100.651	11.634	68	273
age	3,107	40.972	5.261	21	65
education	3,107	20.439	9.024	2	79
poverty	3,107	12.234	5.731	0.000	44.300

(2) Visual Inspection

Whether a feature is spatially random distributed can be easily inspected from visualization. The Figure 1 mapped the county level depressive days in US.

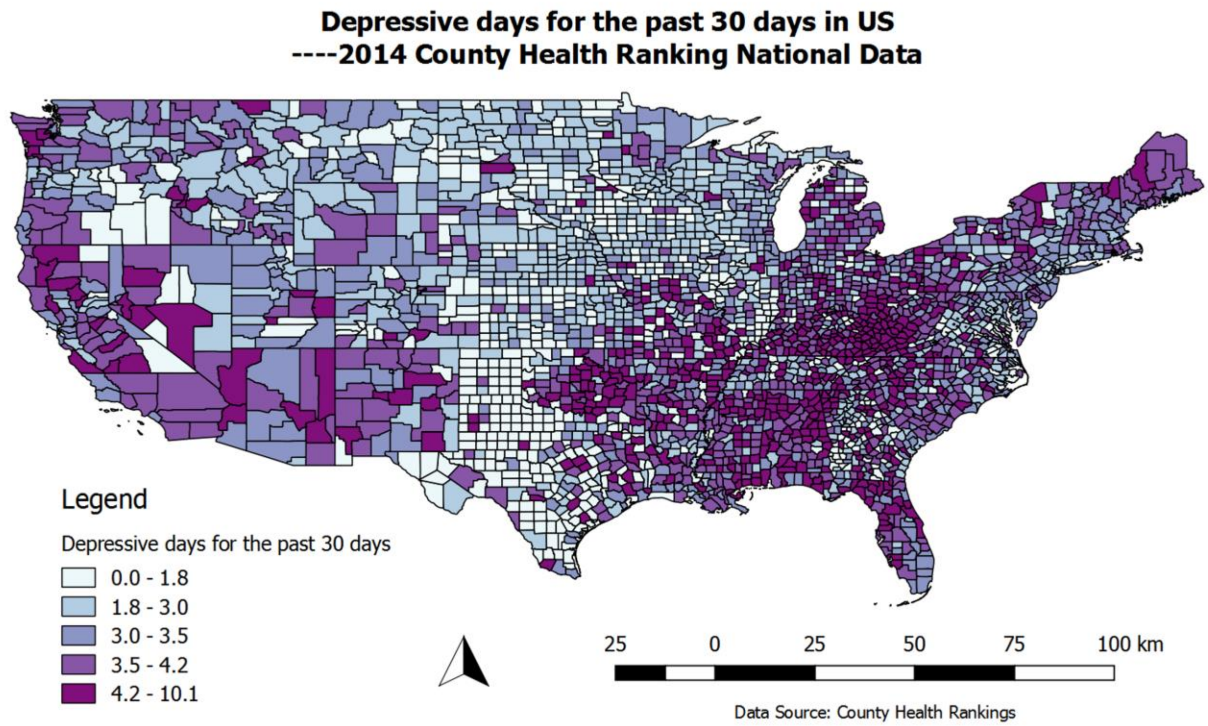

Figure 1. Depressive days for the past 30 days at county level in US

From figure 1 we can see that the east and west part of US , roughly speaking, have higher depressive days than the middle.

(3) Moran's I test

To statistically examine the spatial dependency we observed from the distribution map, I ran the Moran's I test with 1st Order Queen and 2nd Order Queen weight matrix. The results are shown in Figure 2 in scatter plots.

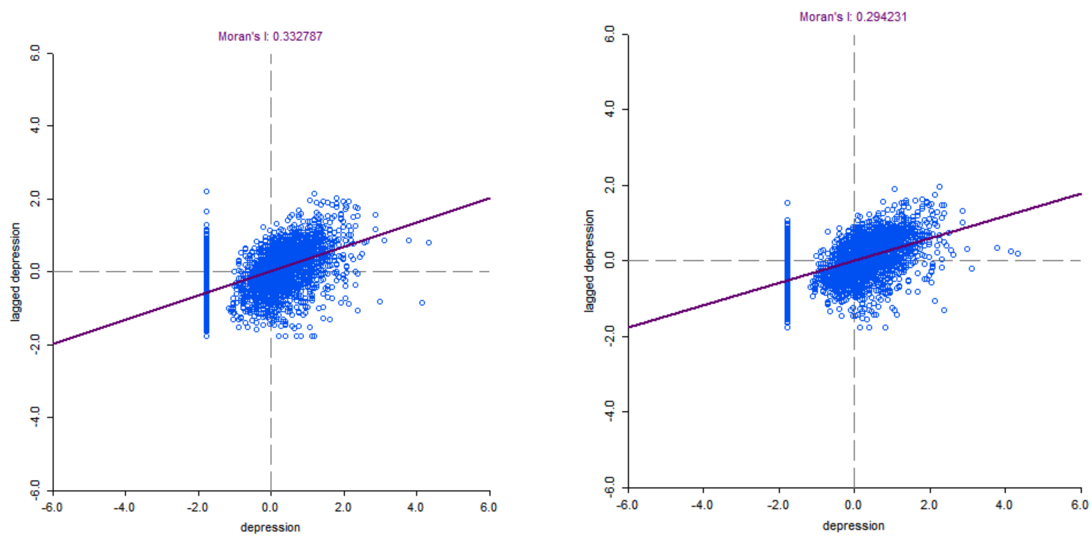

Figure 2. Scatter Plots of First and Second Order of Queen Contiguity

The pseudo p-values of both Moran's I index are both 0.001 with statistical significance. The significant Moran's I of depressive days demonstrates the existence of spatial dependence of the dependent variable--- depressive days. The location of significant spatial clusters of depressive days is visualized in Figure3 using 1st Order Queen.

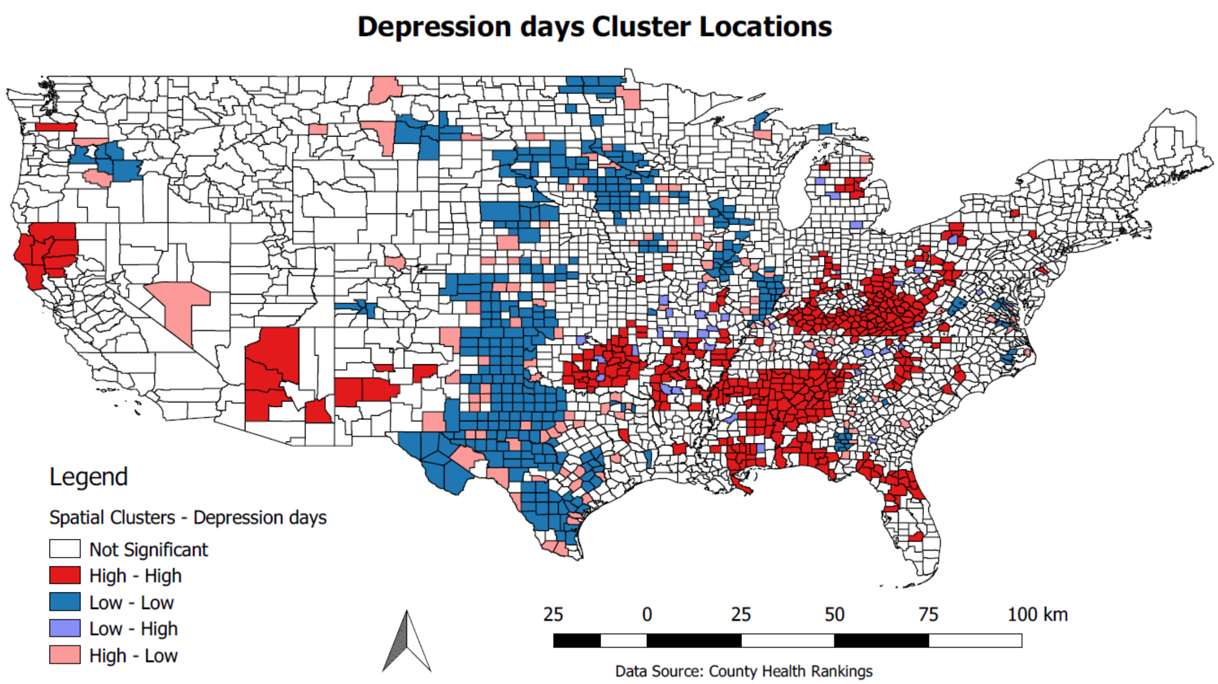

Figure 3. Locations of Significant Spatial Clusters of Depressive days(1st Order Queen)

From Figure 3 we can see the locations of clusters(red = higher percentage of depressive days; blue = lower percentage of depressive days). Looking at the Figure 3, we can see that the higher depressive clusters locate in the west and middle east of the US ; lower depressive clusters locate in the middle of US territory.

As the significance for 1st and 2nd Queen are at the same level, I would use the 1st Order Queen contiguity as the weight matrix for the OLS diagnostics.

(4) OLS diagnosis

Table 2. Diagnostics for Spatial Dependence for First Queen Weight Matrix

DIAGNOSTICS FOR SPATIAL DEPENDENCE
FOR WEIGHT MATRIX : W1
(row-standardized weights)

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.2424	22.7325	0.00000
Lagrange Multiplier (lag)	1	603.8714	0.00000
Robust LM (lag)	1	108.3008	0.00000
Lagrange Multiplier (error)	1	507.9253	0.00000
Robust LM (error)	1	12.3546	0.00044
Lagrange Multiplier (SARMA)	2	616.2260	0.00000

From Table 2, the LM lag and error tests indicate that both lag and error dependence is prevalent (for their p-values are 0.00000). Controlling for the spatial error dependence, the lag dependence is still statistically significant(p-value = 0.00000) however the error dependence lost its significance(p-value = 0.2394) after controlling for lag dependence. Therefore, the spatial lag regression model would be suitable for examining the spatial dependence.

(5) Spatial lag regression

Before going into details about the spatial lag regression result, I would like to compare the log likelihood and AIC of the OLS regression model and the spatial lag model. The results of OLS regression model of the variables in this research are summarized in Table 3. The results of Spatial Lag regression model of the variables in this research are summarized in Table 4. There is an increase in log likelihood from -5827.63(for OLS) to -5592.88(for spatial lag), indicating an improvement of fit in the spatial lag model. Meanwhile, the AIC decreases from 11711.5(for OLS) to 11201, also suggesting an improvement of the spatial lag regression model for adding a spatial lagged dependent variable.

Table 3. OLS Regression Results

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REGRESSION
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SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set            :  final11
Dependent Variable  :  depression  Number of Observations: 3109
Mean dependent var  :     2.94185  Number of Variables   :    7
S.D. dependent var  :     1.65342  Degrees of Freedom    : 3102

R-squared           :    0.090350  F-statistic           :     51.3505
Adjusted R-squared  :    0.088591  Prob(F-statistic)     :           0
Sum squared residual:     7731.47  Log likelihood        :    -5827.63
Sigma-square        :     2.49241  Akaike info criterion :     11669.3
S.E. of regression  :     1.57874  Schwarz criterion     :     11711.5
Sigma-square ML     :      2.4868
S.E of regression ML:     1.57696

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------------
          CONSTANT       3.16764       0.428111       7.39911      0.00000
        traveltime     0.0502906     0.00532121       9.45099      0.00000
          sexratio    -0.0129619     0.00242126      -5.35336      0.00000
           meanage    -0.0230516     0.00576652      -3.99749      0.00007
            popden  -2.16175e-005  1.72269e-005      -1.25487       0.20963
           poverty     0.0599023     0.00606756       9.87255      0.00000
               edu    0.00604585     0.00393934       1.53474      0.12495
-----------------------------------------------------------------------------
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Table 4. Spatial Lag Regression Results

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REGRESSION
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SUMMARY OF OUTPUT: SPATIAL LAG MODEL - MAXIMUM LIKELIHOOD ESTIMATION
Data set            : final11
Spatial Weight      : w1
Dependent Variable  :  depression  Number of Observations: 3109
Mean dependent var  :     2.94185  Number of Variables   :    8
S.D. dependent var  :     1.65342  Degrees of Freedom    : 3101
Lag coeff.   (Rho)  :    0.488664

R-squared           :    0.254821  Log likelihood        :    -5592.88
Sq. Correlation     : -            Akaike info criterion :     11201.8
Sigma-square        :     2.03717  Schwarz criterion     :     11250.1
S.E of regression   :     1.42729

-----------------------------------------------------------------------------
       Variable      Coefficient      Std.Error       z-value    Probability
-----------------------------------------------------------------------------
      W_depression      0.488664      0.0215325       22.6943      0.00000
          CONSTANT       2.46014       0.391548        6.2831      0.00000
        traveltime     0.0180448     0.00486172       3.71162      0.00021
          sexratio   -0.00765779     0.00219022      -3.49636      0.00047
           meanage    -0.0265757     0.00522911      -5.08225      0.00000
            popden  -7.66173e-006  1.55763e-005     -0.491883       0.62280
           poverty     0.0350633     0.00555049       6.31716      0.00000
               edu    0.00184223      0.0035616      0.517247      0.60498
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From Table 4 we can see that, the autoregressive coefficient of the spatial lag for the errors is 0.48 with statistical significance. Controlling for the spatial lag for the errors, the remaining variables in the regression stays significant except the education. The coefficient of the spatial lag for the traveltime variable is positive indicating that longer commuting time would on average result in higher depressive days with statistical significance. Utilizing spatial lag model , I examined the spatial autocorrelation of the OLS regression model and optimized the model with more properly tailored inferences.

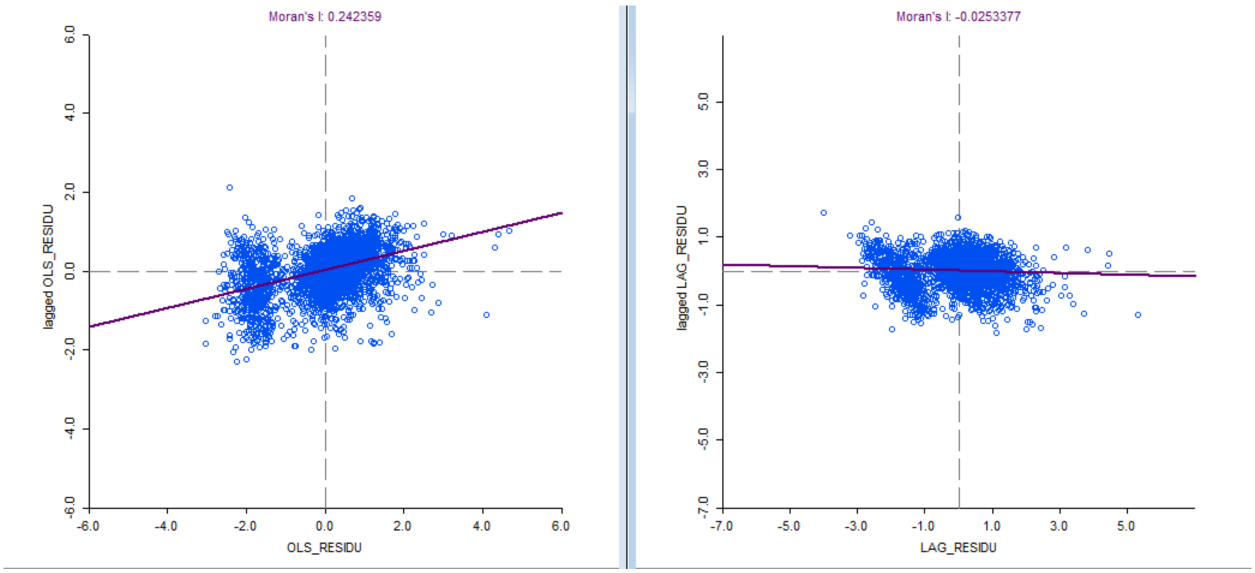

Figure 4. Moran's I test for Residuals of OLS and Spatial Lag Regression

The Figure 4 exhibits the Moran's I test for OLS residuals and Spatial Lag residuals. The OLS residuals had significant positive spatial dependence(Moran's I: 0.2424, p-value = 0.001). The spatial lag residuals showed negative spatial dependence(Moran's I: -0.0253, p-value = 0.01), but the absolute value of the relationship was much smaller than that of the OLS residuals, indicating that the spatial lag residuals were closer to being randomly distributed. After visualizing the OLS residuals and Spatial Lag residuals(Figure 5). we can observed that the spatial lag residuals did have more randomly distributed pattern than the OLS.

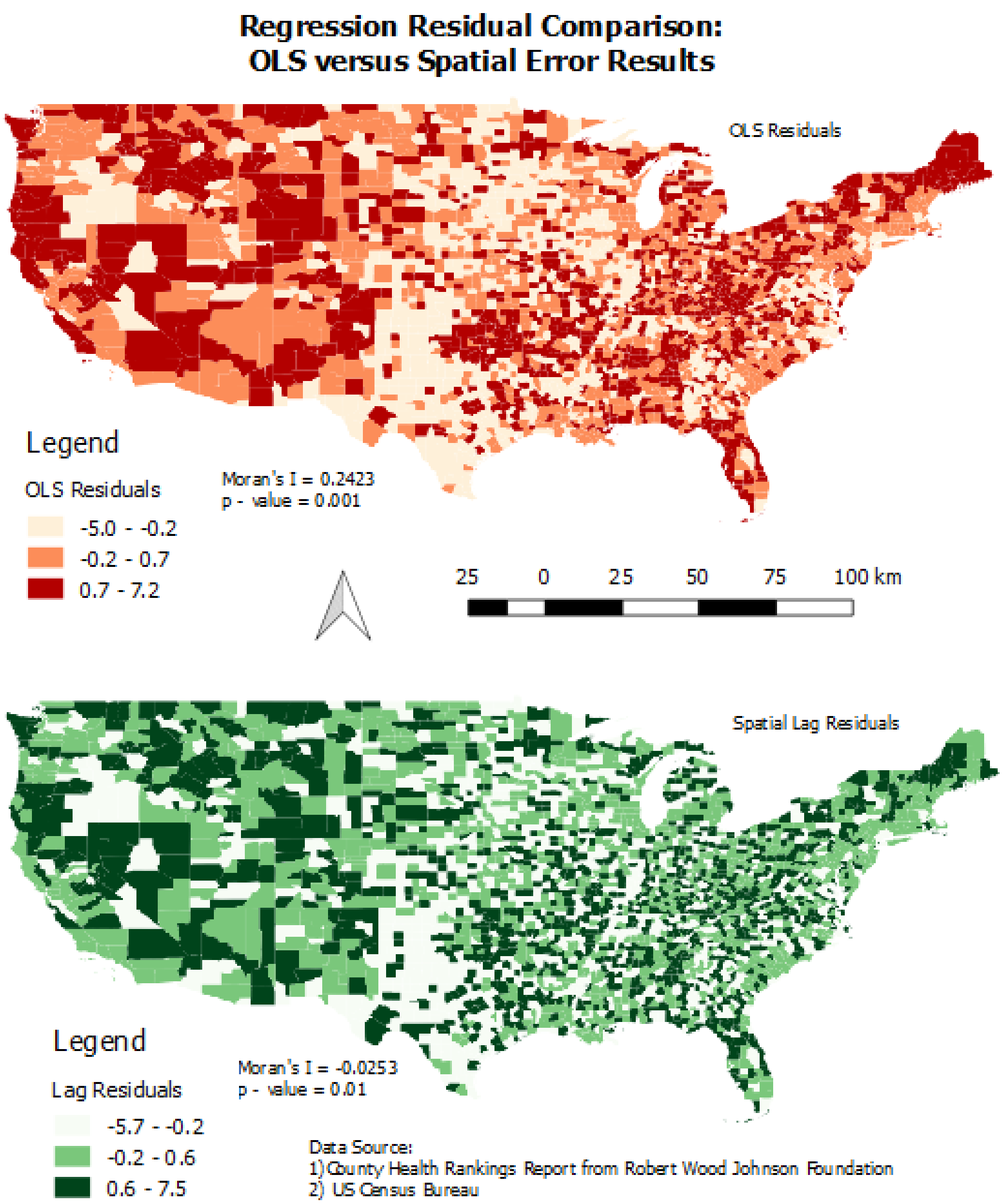

Figure 5. Regression Residuals Comparison

Geographically weighted regression in R is also used to test the non-stationarity in the data. The results are visualized in Figure 6. The spatially dependent Local R-square is larger in the west part of the US as well as the middle parts of the eastern US. There exist larger proportion of positive effect of commuting time on depression while some middles parts are clustered for negative effects. Figure 6 further justifies the use of spatial analysis is better than a global model in this case.

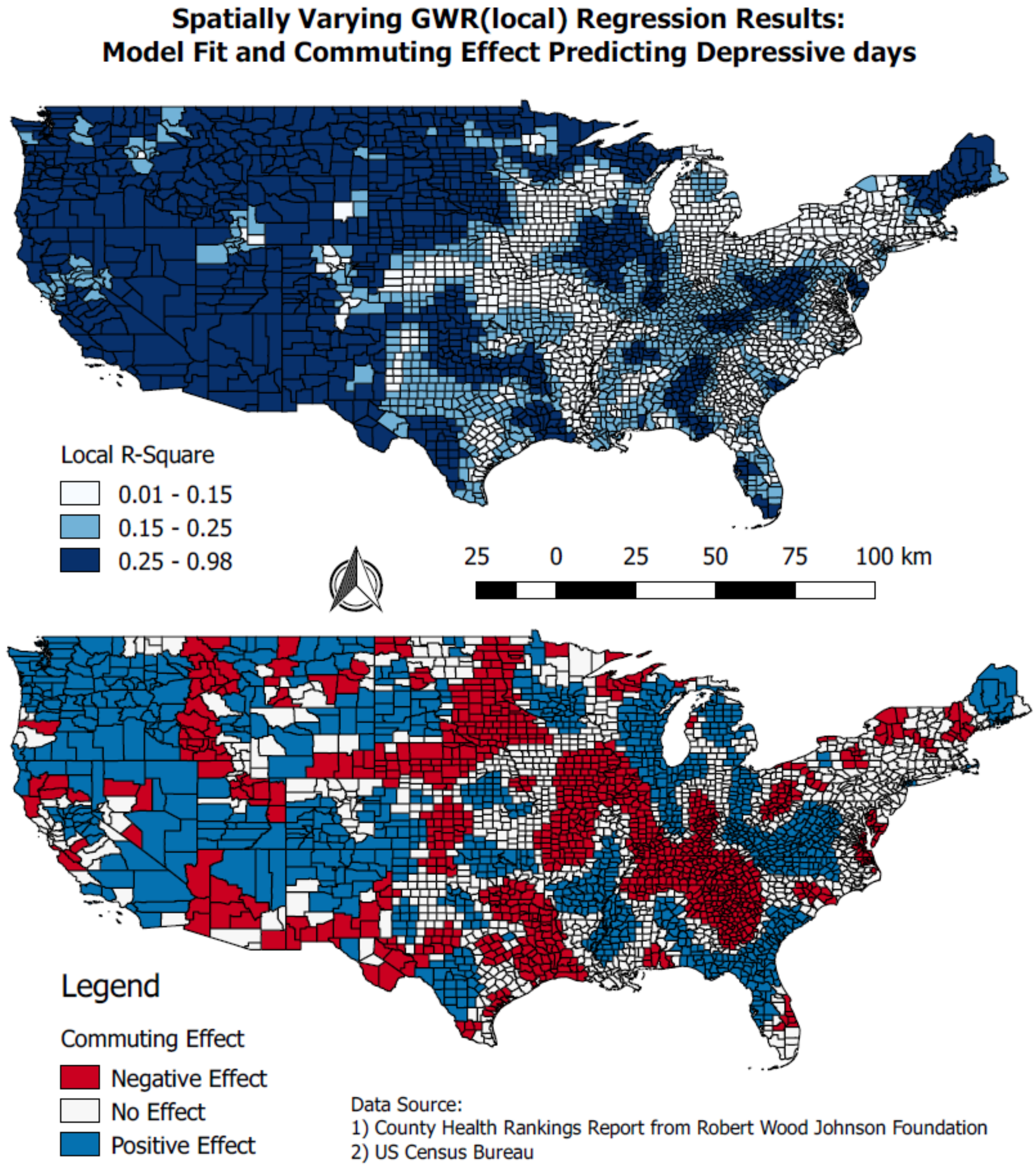

Figure 6. Geographically Weighted Local Variations in the Commuting Effect on Depressive Days

After running the OLS regression and Spatial Lag regression , we have drawn the conclusion that the commuting time to work has statistical significant correlation with depressive days, controlling for other socio-economic and demographic variables. The longer commuting time to work would generally result in longer depressive days. However, this effect has spatial dependence. Western part of US is more fit for the positive correlation inference than the eastern part. Therefore, after taking the spatial lagged factor in to the regression into consideration, the coefficient of the traveltime decreased from 0.05 to 0.01.

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