# 11 –Spatial Autoregressive Models with GeoDaSpace

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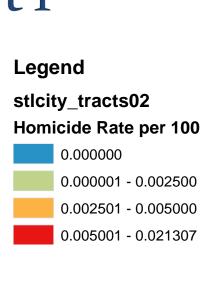
### Outline

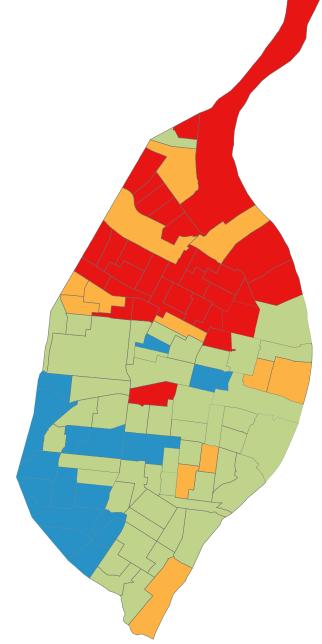
- Spatial Heterogeneity vs. Spatial Dependency
- Higher Ordered Spatial Regression
- GeoDa vs. GeoDaSpace
- Overview of GeoDaSpace
- Lab

# Spatial Heterogeneity vs. Spatial Dependency

### A nuanced discussion – Part 1

- One way to think about spatial heterogeneity and spatial dependency is to ask yourself:
  - (a) Is the intensity of occurrence of an event equally distributed across the landscape?
  - (b) Does the intensity at one location influence the intensity at neighboring locations?

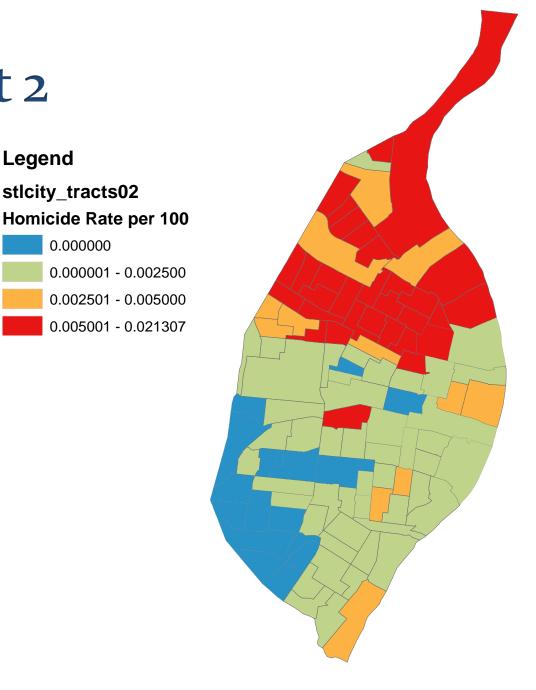




### A nuanced discussion – Part 2

If the answered is "yes" to the first question we are dealing with spatial heterogeneity

If the answered is "yes" to the second question we are dealing with spatial dependency.



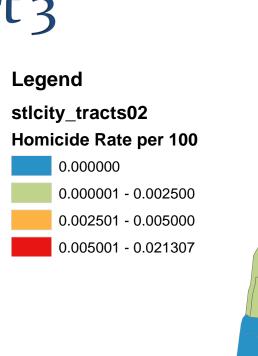
Legend

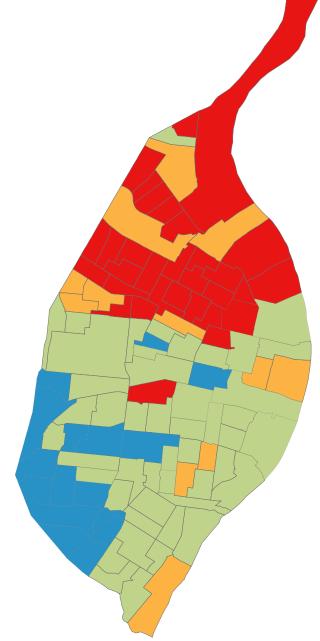
stlcity\_tracts02

0.000000

### A nuanced discussion – Part 3

- Heterogeneity can be related to spatial structure or the spatial process generating data
- We need to challenge the assumption that regression coefficients are fixed throughout the sample





Structural Instability

Heteroscedasticity

Two types of heterogeneity

# Spatial Regime Models

### Spatial fixed effects models

- The spatial regime model is suitable in certain instances in which the assumption of a fixed relation between the explanatory variables and the dependent variable across the study is not tenable.
- Spatial Heterogeneity may be present, in the form of different intercepts and/or slopes in the regression equation for subsets of the data.
- This is often referred to as structural instability or structural change in the academic literature.
- If this is the case, we may want to include additional variables in the SAR models. When the different subsets in the data correspond to regions or spatial clusters, it is called spatial regimes model.

# Higher Ordered Spatial Regression

### Review of SAR Models – Baseline Models

Spatial Lag

$$y = B_0 + \rho W y + X \beta + \varepsilon$$

Spatial Error

$$y = B_0 + X\beta + \lambda W\varepsilon + \xi$$

### Higher Ordered Models

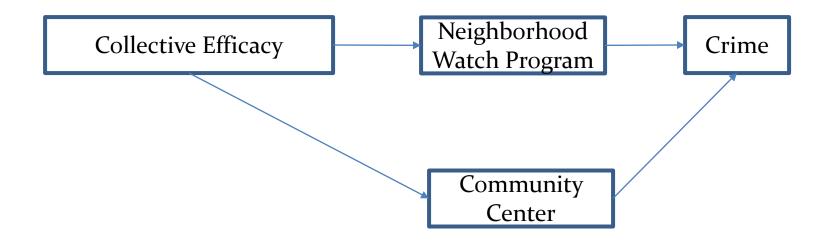
Spatial Lag

$$y = B_0 + \rho Wy + X\beta + Y\gamma + \varepsilon$$

Where  $Y\gamma$  is an endogenous variable

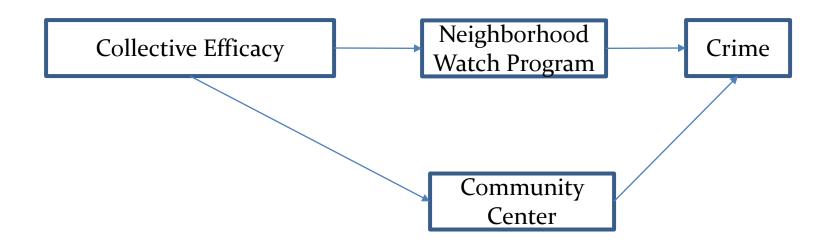
### Let's define some terms

- What is an endogenous variable?
  - One can think of an endogenous variables as been determined or influenced by "other" variables. We typically call the these "other" variables are called exogenous variables



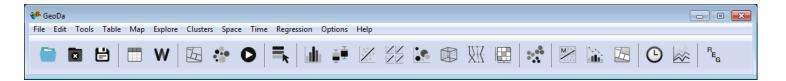
### Let's define some terms

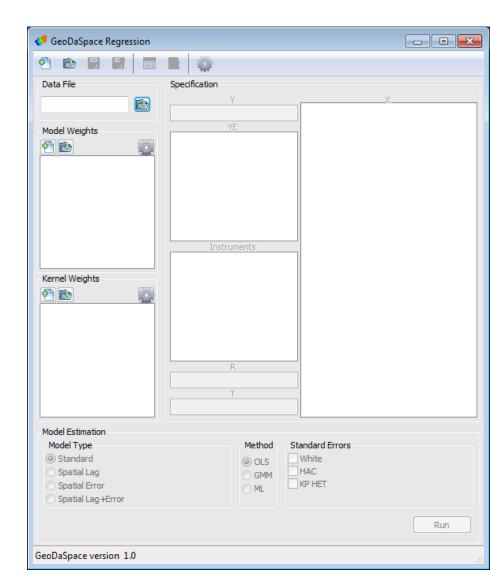
- What is an instrumental variable?
  - An instrumental variable does not have a direct correlation with the dependent variable
  - However, an instrumental variable does have a direct correlation with an independent variable which has a correlation with the dependent variable.

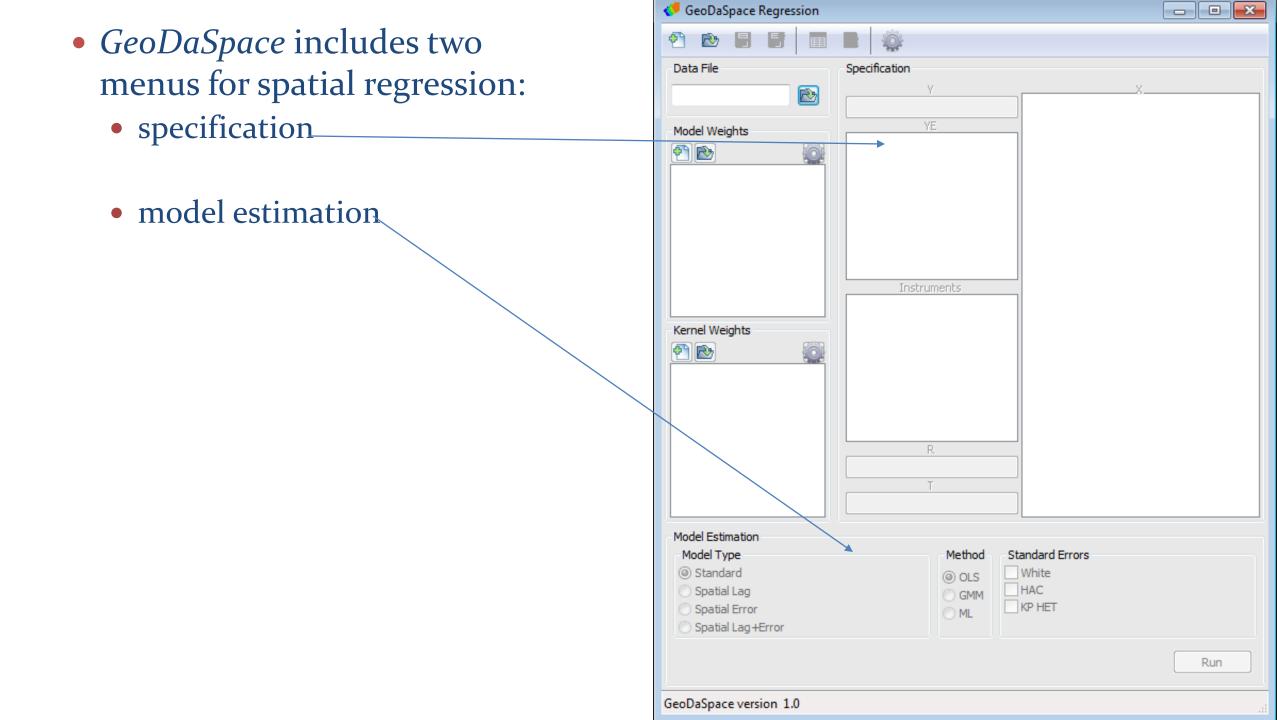


## GeoDa vs GeoDaSpace

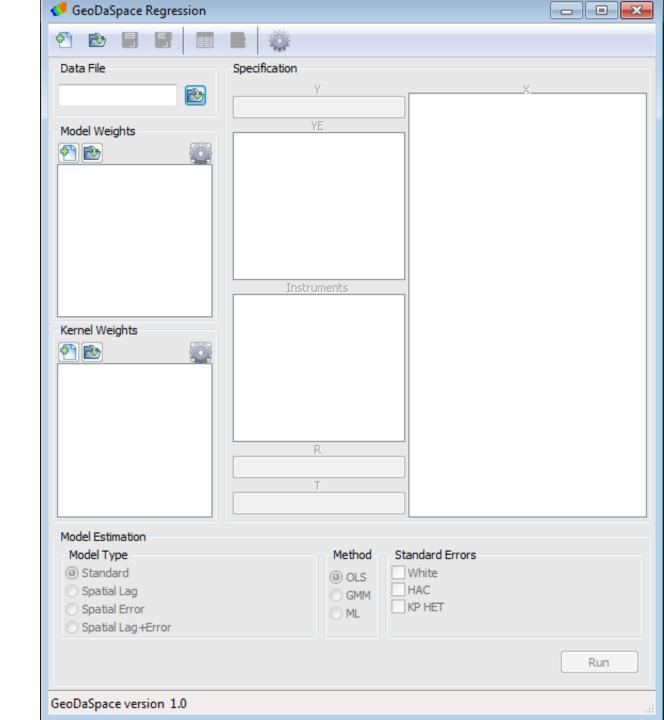
### GeoDa vs GeoDaSpace







- The design of *GeoDaSpace* **does not** consist of an interactive environment combining maps with statistical graphs, using a technology of dynamically linked windows.
- *GeoDaSpace* is geared to the higher order analysis of discrete geospatial data
  - characterized by their location in space either as points (point coordinates) or polygon (polygon boundary coordinates).



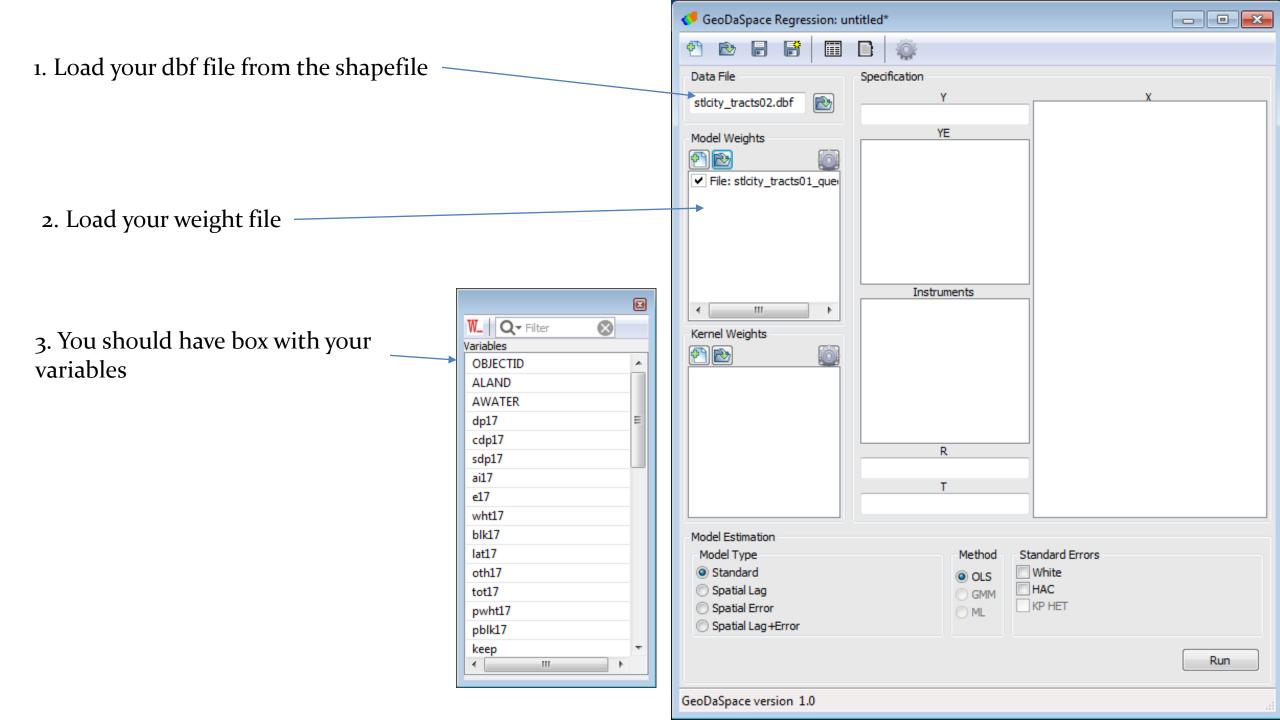
Spatial weight matrices

Spatial data

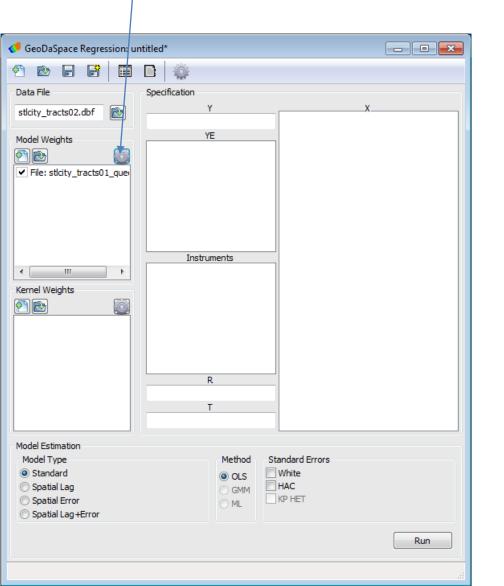
Spatial regression

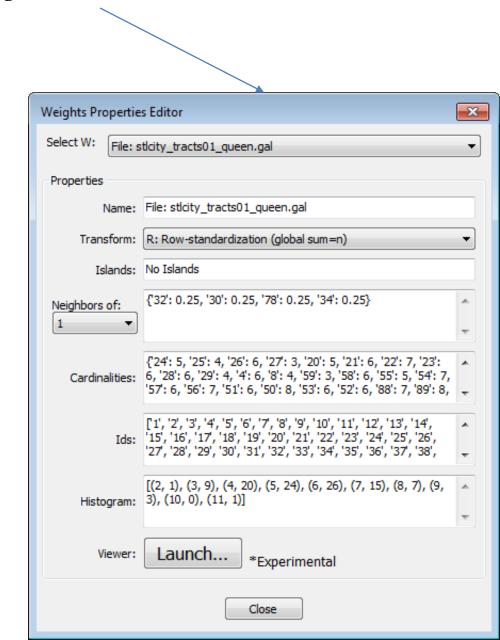
GeoDaSpace

# Working with GeoDaSpace

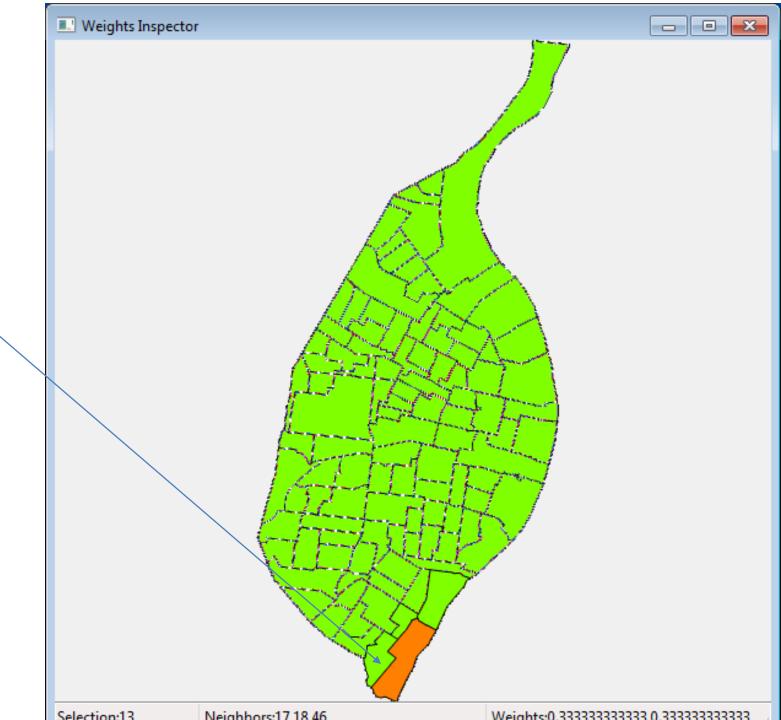


4. Select the "setting" buttons in the Model Weights box, and you should get this box

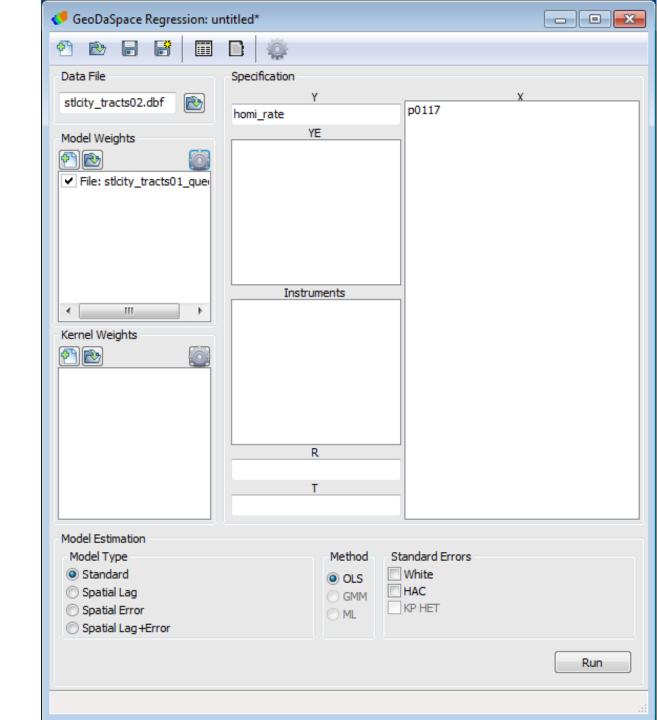




5. Link the dbf to the shapefile and you view the weight file and how it constructed the weight matrix.

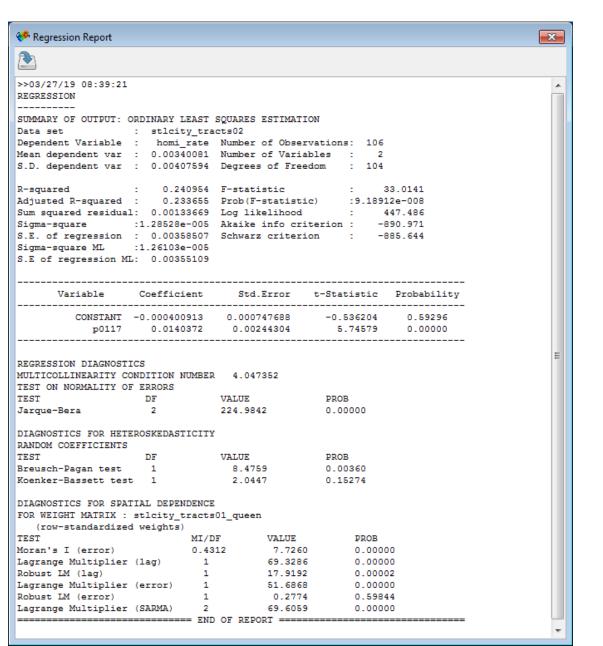


6. Let's replicate the results from GeoDa



## OLS

#### Results from GeoDa

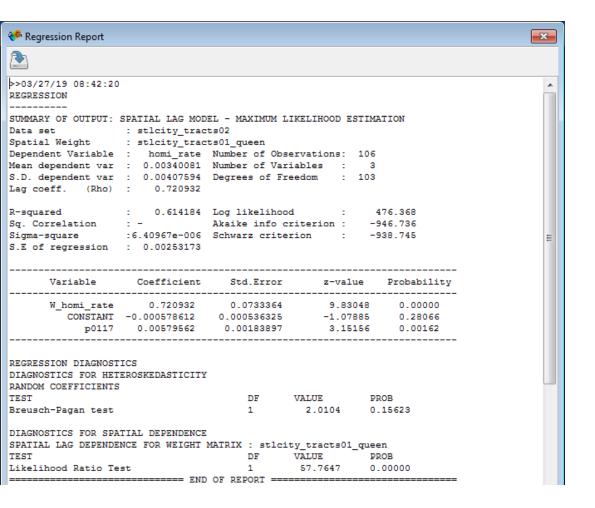


#### Results from GeoDaSpace

P 🖎 🔒 😝 🗕 +				
REGRESSION				
SUMMARY OF OUTPUT: ORD	~			
 )ata set :s	stlcity tracts02.d			
Weights matrix : F	ile: stlcity trac	ts01 queen.gal		
Dependent Variable :	homi rate	Number	r of Observations	3: 106
Mean dependent var :	0.0034	Number	r of Variables	: 2
S.D. dependent var :	0.0041	Degree	es of Freedom	: 104
R-squared :				
Adjusted R-squared :	0.2337			
Sum squared residual:	0.001	F-stat	tistic	: 33.0141
Sigma-square :	0.000	Prob(1	F-statistic)	: 9.189e-08
S.E. of regression :	0.004	Log 1:	ikelihood	: 447.486
Sigma-square ML :		Akaike	e info criterion	: -890.971
S.E of regression ML:	0.0036		rz criterion	
	Coefficient	Std.Error	t-Statistic	Probability
	-0.0004009			
	-0.0004009 0.0140372			
		0.0007477 0.0024430		
CONSTANT p0117 REGRESSION DIAGNOSTICS MULTICOLLINEARITY CONI	) OITION NUMBER	0.0007477 0.0024430		
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E	S DITION NUMBER CRRORS	0.0007477 0.0024430 	-0.5362041 5.7457892	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E	S DITION NUMBER CRRORS	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E	S DITION NUMBER CRRORS	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E	DITION NUMBER CRRORS DF 2	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E TEST Jarque-Bera DIAGNOSTICS FOR HETERO	OITION NUMBER CRORS DF 2 OSKEDASTICITY	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E TEST Jarque-Bera DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS TEST	OITION NUMBER CRORS DF 2 OSKEDASTICITY	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E TEST Jarque-Bera DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS	OITION NUMBER CRRORS  DF 2 OSKEDASTICITY  DF 1	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND TEST ON NORMALITY OF E TEST Jarque-Bera DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS TEST Breusch-Pagan test	CRRORS  DF 2  SKEDASTICITY  DF 1	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND  FEST ON NORMALITY OF E FEST  Jarque-Bera  DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS  FEST  Breusch-Pagan test Koenker-Bassett test	CRRORS  DF 2  SKEDASTICITY  DF 1	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND  REST ON NORMALITY OF E TEST  Jarque-Bera  DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS TEST  Breusch-Pagan test Koenker-Bassett test  DIAGNOSTICS FOR SPATIA TEST	DITION NUMBER CRRORS DF 2 DSKEDASTICITY DF 1 1 L DEPENDENCE MI/DF	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY CONDITION  TEST ON NORMALITY OF E TEST  Jarque-Bera  DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS TEST  Breusch-Pagan test Koenker-Bassett test  DIAGNOSTICS FOR SPATIA TEST  Lagrange Multiplier (1	CRRORS  DF 2  SKEDASTICITY  DF 1 1 1  AL DEPENDENCE MI/DF .ag) 1	0.0007477 0.0024430 	-0.5362041 5.7457892 	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY CONFIEST Jarque-Bera DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS FEST Breusch-Pagan test Koenker-Bassett test DIAGNOSTICS FOR SPATIA TEST Lagrange Multiplier (1	CRRORS  DF 2  SKEDASTICITY  DF 1 1 1  AL DEPENDENCE MI/DF .ag) 1	0.0007477 0.0024430 	-0.5362041 5.7457892 PROB 0.0000 PROB 0.0036 0.1527 PROB 0.0000	
CONSTANT p0117  REGRESSION DIAGNOSTICS MULTICOLLINEARITY COND  REST ON NORMALITY OF E TEST  Jarque-Bera  DIAGNOSTICS FOR HETERO RANDOM COEFFICIENTS TEST  Breusch-Pagan test Koenker-Bassett test  DIAGNOSTICS FOR SPATIA TEST	CRRORS  DF 2  SKEDASTICITY  DF 1 1 1  AL DEPENDENCE MI/DF .ag) 1	0.0007477 0.0024430 4.047 VALUE 224.984 VALUE 8.476 2.045 VALUE 69.329	-0.5362041 5.7457892 	

# Spatial Lag

#### Results from GeoDa



#### Results from GeoDaSpace

Data set	:stlci	ty_tracts02.d	lbf			
Weights matrix	:File:	stlcity_trac	ts01_queen.gal			
Dependent Variable	: ho	mi_rate	Number	r of Observation	ıs:	106
Mean dependent var	:	0.0034	Number	r of Variables	:	3
S.D. dependent var	:	0.0041	Degree	es of Freedom	:	103
Pseudo R-squared	:	0.6235				
Spatial Pseudo R-sq	uared:	0.4008				
Sigma-square ML	:	0.000	Log li	ikelihood	:	476.368
S.E of regression	:	0.003	Akaike	e info criterior	:	-946.736
			Schwar	rz criterion	:	-938.745
Variabl			Std.Error	z-Statistic		Probability
CONSTAN	 Г		0.0005363	-1.0788828		0.2806400
W_homi_rat	2	0.7209334	0.0733390	9.8301534		0.0000000
p011	7	0.0057956	0.0018389	3.1516165		0.0016237

# Spatial Error

#### Results from GeoDa

Regression Report

#### >>03/27/19 08:45:08 REGRESSION SUMMARY OF OUTPUT: SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION : stlcity tracts02 Spatial Weight : stlcity tracts01 queen Dependent Variable : homi\_rate Number of Observations: 106 Mean dependent var : 0.003401 Number of Variables S.D. dependent var : 0.004076 Degrees of Freedom Lag coeff. (Lambda) : 0.769312 : 0.602553 R-squared (BUSE) R-squared Sq. Correlation Log likelihood : 473.454778 Sigma-square :6.60291e-006 Akaike info criterion : -942.91 S.E of regression : 0.00256961 Schwarz criterion Variable Coefficient Std.Error Probability z-value 1.99731 0.04579 CONSTANT 0.00245817 0.00123074 p0117 0.00438642 0.00226379 1.93764 0.05267 0.0696768 11.0411 REGRESSION DIAGNOSTICS DIAGNOSTICS FOR HETEROSKEDASTICITY RANDOM COEFFICIENTS PROB 1.6470 0.19936 Breusch-Pagan test DIAGNOSTICS FOR SPATIAL DEPENDENCE SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : stlcity\_tracts01\_queen VALUE Likelihood Ratio Test 51.9385 0.00000

×

#### Results from GeoDaSpace

SUMMARY OF OUIPUI:	MAXI	MUM LIKELIHOOD SE	PATIAL ERROR (MI	THOD = FULL)		
ata set	:st	lcity_tracts02.db	of			
Weights matrix	:Fi	.le: stlcity_tract	:s01_queen.gal			
Dependent Variable	:	homi_rate	Number	r of Observation	ıs:	100
Mean dependent var	:	0.0034	Number	r of Variables	:	2
D. dependent var	:	0.0041	Degree	es of Freedom	:	104
seudo R-squared	:	0.2410				
igma-square ML	:	0.000	Log 1:	ikelihood	:	473.45
.E of regression	:	0.003	Akaik	e info criterion	1 :	-942.91
			Schwar	rz criterion	:	-937.58
Variabl	 e	Coefficient	Std.Error	z-Statistic		Probability
CONSTAN	 Т	0.0024582	0.0012307	1.9973160		0.0457909
lambd	a	0.7693111	0.0696769	11.0411133		0.000000
p011	7	0.0043864	0.0022638	1.9376453		0.052666

# An Higher Ordered Model

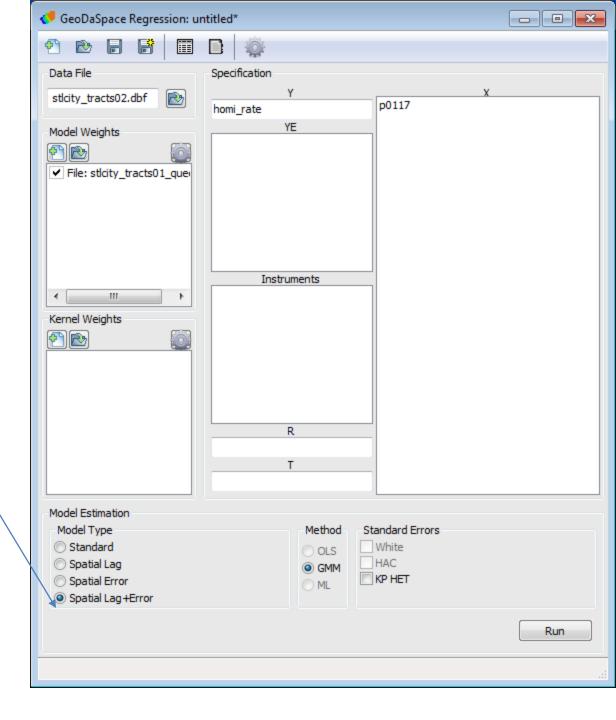
### Spatial Lag and Spatial Error Model

$$y = B_0 + \rho W y + X \beta + \varepsilon$$

Where

$$\varepsilon =$$

$$\lambda W \varepsilon + \varepsilon$$



#### REGRESSION

\_\_\_\_\_

SUMMARY OF OUTPUT: SPATIALLY WEIGHTED TWO STAGE LEAST SQUARES (HOM)

\_\_\_\_\_

Data set :stlcity tracts02.dbf

Weights matrix :File: stlcity tracts01 queen.gal

Dependent Variable: homi rate Number of Observations: 106

Mean dependent var : 0.0034 Number of Variables :

S.D. dependent var : 0.0041 Degrees of Freedom : 103

Pseudo R-squared : 0.6329

Spatial Pseudo R-squared: 0.4684

N. of iterations : 1

\_\_\_\_\_\_

Variable	Coefficient	Std.Error	z-Statistic	Probability
CONSTANT	-0.0006033	0.0003979	-1.5159112	0.1295418
W homi rate	0.9106472	0.1314021	6.9302327	0.0000000
p0117	0.0033861	0.0024243	1.3966910	0.1625065
lambda	-0.4582897	0.3759493	-1.2190201	0.2228366

\_\_\_\_\_

Instrumented: W\_homi\_rate

Instruments: W p0117

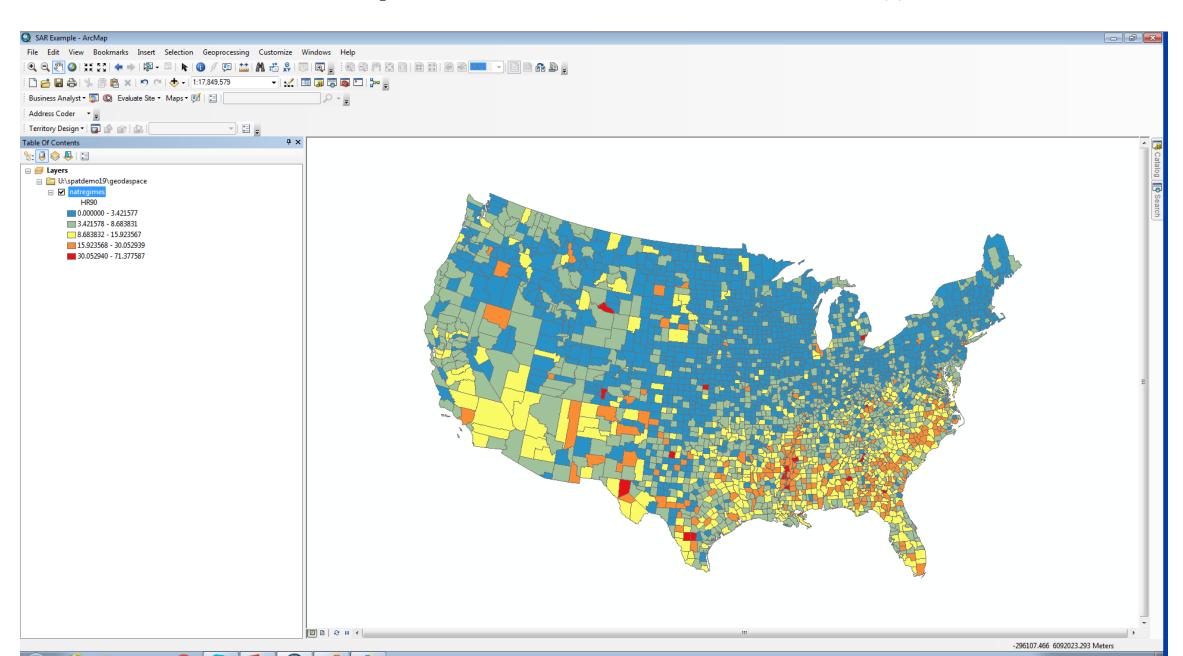
Variable	OLS	SLM	SEM	SLM and SEM	SLM and SEM With KP HET
Poverty	.0140372 (.00244)***	0.00579562 (0.00183897)**	0.00438642 (0.00226379)*	0.0033861 (0.0024243)	0.0033853 (0.4240851)
Constant	-0.0004 (0.0007)	-0.000578612 0.000536325	0.00245817 (0.00123074)	-0.0006033 (0.0003979	-0.0006025 (0.0003500)
ρ		0.720932 (0.0733365) ***		0.9106472 (0.1314021)***	0.9101785 (0.1708339)***
$\lambda$			0.769312 (0.0696768)***	-0.4582897 (-0.4582897)	-0.1473622 (0.4240851)
r-square	0.240954	0.614184	0.602553	0.6329	0.6329
Log likelihood	447.486	476.368	473.454	NA	NA
AIC	-890.971	-946.736	-942.91	NA	NA
Moran's I Residual	.431166***	-0.0570314	-0.0455698	NA	NA
N	106	106	106	106	106
* $\leq$ .05, ** $\leq$ .01, *** $\leq$ .001 Standard Errors in Parentheses					

### Reflections on SLM and SEM

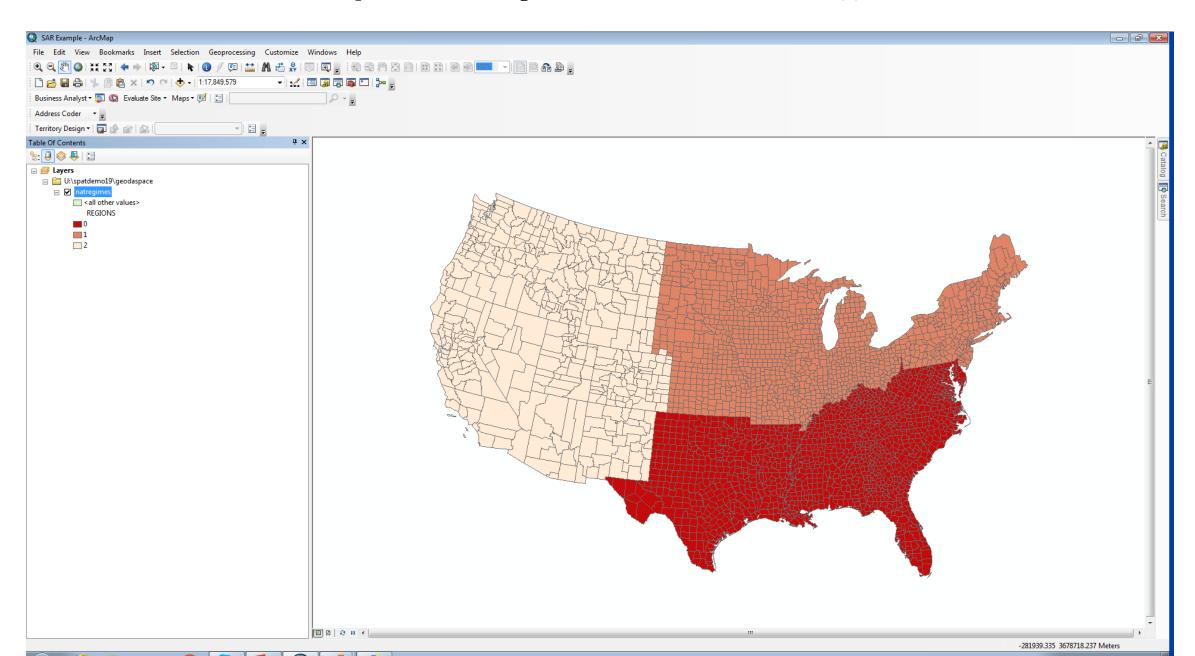
- The joint model is a special case...
  - Spatial Heteroskedasticity is a problem, especially in the error model
  - Spatial Autocorrelation is still a problem, especially in the error model
  - There is no clear preference for the SLM or SEM
- It is possible that both  $\, \rho \,$  and  $\, \lambda \,$  can be significant

# Spatial Regime Models

This is a map of the Homicide Rate for the U.S. Counties for 1990



This is a map of the three regions for the U.S. Counties for 1990



First we want to build a basic OLS model

Where:

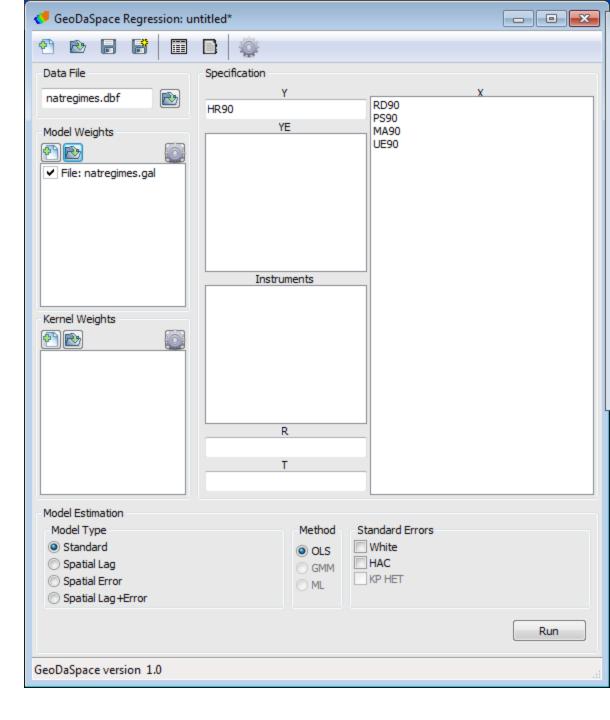
HR90=Homicide Rate

RD90=Resource Deprivation

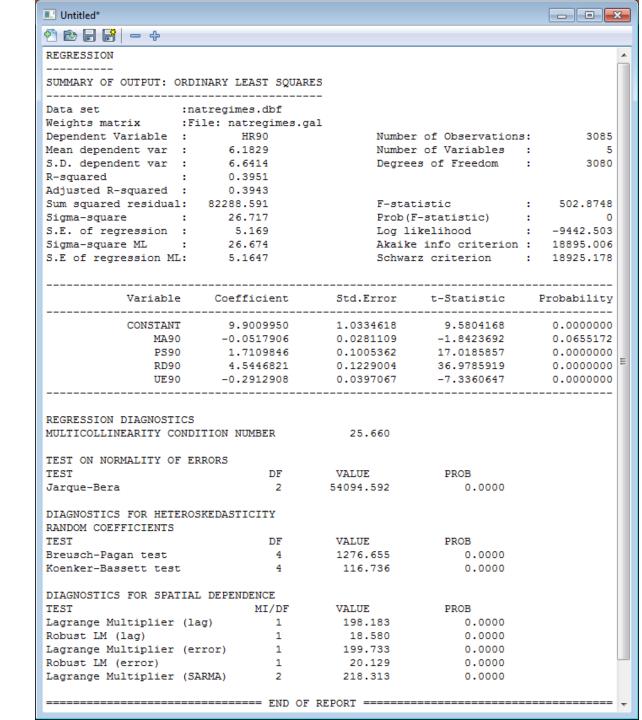
PS90=Population Structure Component

MA90 = Median Age

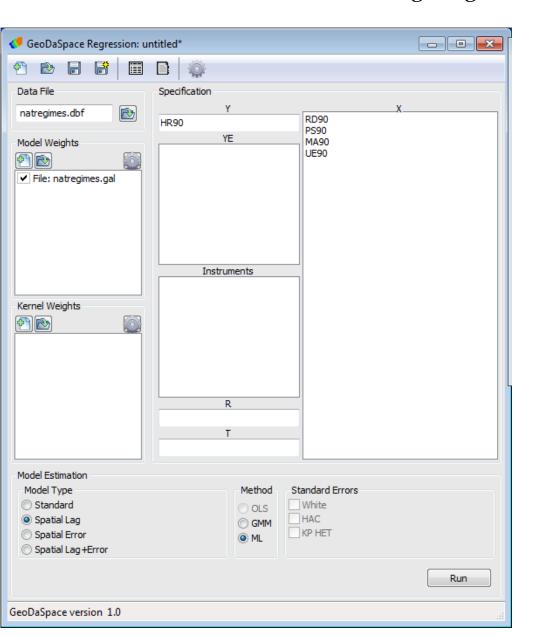
UE90=Unemployment Rate



Review the output on the right from GeoDaSpace



### Now I will build a Spatial Lag Model – MA90 is no longer significant



SUMMARY OF OUTPUT: M							
Data set							
Weights matrix	:File: na	tregimes.	gal				
Dependent Variable	:	HR90		Number	of Observation	ns:	3085
Mean dependent var	: 6.	1829		Number	of Variables	:	(
S.D. dependent var	: 6.	6414		Degree	s of Freedom	:	3079
Pseudo R-squared	: 0.	4349					
Spatial Pseudo R-squ	ared: 0.	3982					
Sigma-square ML	: 24	.927		Log li	kelihood	:	-9360.23
S.E of regression	: 4	.993		Akaike	info criterio	n :	18732.473
				Schwar	z criterion	:	18768.679
					z-Statistic		
					6.3811034		
MA90	-0.	0203630	0.027	1588	-0.7497753		0.4533901
PS90	1.	4365892	0.099	4735	14.4419316		0.0000000
RD90	3.	6242501	0.138	9813	26.0772478		0.0000000
UE90	-0.	1986542	0.038	5328	-5.1554564		0.0000003
W HR90	0.	2788219	0.022	0929	12.6204172		0.0000000

#### Now I will build a spatial regime model

