Virginia is for (*Teen*) Lovers: County Level Teenage Birth Rates and Socio-Structural Spatial Processes

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I. Introduction

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Teenage pregnancy and birth rates have been associated with lower levels of parental education (Allen et. al 1997) and income (Davis 1989) in the U.S. What is decidedly less understood is how these factors influence teen birth rates across contiguous spaces, and how these spatial effects are dynamic across time. Undoubtedly these rates are tied to the effects of local health departments, school sex/health education, health care facilities, and macro level socio-political structures which are spatially relevant and operative. Logically, it is useful to inspect how specific predictors (namely education and affluence) influence teen birth rates, which vary drastically across space and time.

Spatial differences in teen birth rates can be attributed both to social factors and physical structure within places (Kane and Staiger 1996). Clinics offering induced terminations (in the case of accidental, unwanted, or forced pregnancy for pregnancies) offer antenatal teenagers a viable alternative. Hence, access to abortion clinics, along with the sociodemographic covariates could relate to teenage births rates. It is necessary and appropriate to look at both structural and social factors that relate to teen birth rates, and how these are differ and coalesce over regions.

I argue that this type of spatial process is best analyzed at the county level. However, because I am looking at Teenage birth rates, it may be argued that a study of this sort may be better for a school district level analysis. To retort, Virginia school policies are administered by county level school boards; thus policies, like reproductive education courses taught in middle and high schools, are governed by the county. Moreover, school districts and other polygons smaller than counties would provide little variation in education rates and measures of affluence. Lastly, abortion clinics are administered by county health departments, thus the presence or absence of clinics is tied to county level politics. A county level analysis is most apposite (at least in this instance).

II. Virginia as a Case Study

Virginia provides an optimal test site for investigating the spatial effects of education, income, and clinic access on teenage natal rates for several reasons. Virginia is classified by dynamic spatial variation in educational levels (ranging from 70.1% 5.5% in 2010), poverty rates (ranging from 3.9% to 27.1% in 2010), number of clinics offering induced terminations (from 4 in some counties to 0 in most other counties in 2010), and teenage births (a range of 2.3 to 63per 1,000 in in 2010). Furthermore, there is considerable ethnic clustering within the state; some counties are comprised almost exclusively of whites, whereas other counties are decidedly more ethnically diverse. Anyone with a cursory knowledge of the Commonwealth is aware of its heterogeneity.

This study is not only logistically and practically germane, but also politically salient as legislative measures have recently materialized. Following a recent approval of the Virginia State Board of Health and Governor Bob McDonnell (R) to increase state regulations of abortion clinics in Virginia, clinics must now comply with more stringent building code regulations (Bassett 2013). These stipulations include state mandated exam room sizes and hallway widths, ventilation requirements, and parking space allotment (Bassett 2013). Many pro-choice advocates fear that these restrictive measures will force the shutdown of many clinics, increasing unmet need in the Commonwealth. Indeed two clinics in Norfolk and Northern Virginia have closed rather than renovate their facility in upwards of half a million dollars (The Washington Post 2013). Additionally, a recently filed lawsuit against these regulations promises to make Virginia a battleground for pro-life pro-choice activism (Nolan, 2013). Despite the fact that teenage birth rates in Virginia have been steadily declining for the past several decades, these mandates threaten to reverse these trends and eliminate options for teen pregnancies.

Before continuing it is necessary to discuss the unique nature of "place" in Virginia. As the only state in the U.S. with cities independent of counties, careful attention must be paid to the definition of "county". At present there are 39 independent cities and 95 counties in the state. Thus, all data at the "county" level includes both counties and independent cities. These places are treated as analogous and administered politically in the same manner. Additionally, Virginia has two counties that are a spatial "islands, located on Virginia's eastern shore); thus it has no spatial "neighbors". In regard to the first issue, this analysis will maintain the independence of the cities as they are differentially located. Concerning the latter issue, the "islands" were connected to their nearest neighbors. Henceforth I will refer to the independent places in Virginia (both counties and cities) as "counties" for brevity.

III. Hypotheses

Based on these theoretical, political, and cultural underpinnings, I derive the following hypotheses:

H_1: *Access to a clinic offering induced terminations for pregnancies will lower county teenage birth rates*

H_2: *County education levels will predict county level teenage birth rates; specifically, counties with high levels of people with college degrees and low levels of people with high school degrees will have lower teenage birth rates.*

H_3: *Poverty and unemployment rates in counties will predict county level teenage birth rates such that those with lower levels of each will have lower teenage birth rates.*

H_4: *These relationships will be clustered and dispersed in a spatially pertinent manner.*

H_5: *These patterns will operate differently across time (2000 to 2010)*

H_6: *These trends will operate differently across the state, reflecting spatial non-stationarity*

IV. Data Set

To investigate the predictors of county level teen birth rates in Virginia, I constructed a data set from three sources. Teen birth rates by county (the dependent variable in my analysis) were collected from the Virginia Health Department Division of Health Statistics (2000 and 2010 data).[1] Point locations of clinics offering abortions were obtained using Google maps, abortion.com, and plannedparenthood.com; these locations were confirmed by visiting each location's website. The clinic sites were then aggregated up to the appropriate polygons within the state. The county percentages of African Americans, Hispanics, persons in poverty, unemployed persons, persons with less than a high school education, persons with a bachelor's degree or higher, city/county distinction, and county population size were obtained from 2000 and 2010 US Census data via American Fact Finder. Data was merged and cleaned using STATA 12, transferred into Open GeoDa to assess spatial statistics, and finally transferred to ArcGIS where I was able to create high resolution maps.

V. Sample and Methodology

To assess the city/county teen birth rates in Virginia I used teen birth rates per 1,000 live births. To investigate the structural covariates of teen births (at the county level) I used ten variables investigating four unique phenomena. Education was assessed by the percent of people with a college degree or higher and the percent of people without a high school degree (who are eligible). Affluence was operationalized using percent of people in poverty and the percent of the workforce that is unemployed. County population percent of Hispanics and African American's were used to look at ethnic differences (white was excluded to avoid virtually perfect multicollinearity). Because of the unique nature of Virginia's administrative polygons, cities were dummy coded to account for differences between "urban" and "rural" units (cites = 1, counties = 0). Further, the number of clinics offering induced terminations within the city/county boundaries was assessed via two variables to measure access to pregnancy alternatives; Locations of clinics were accounted for with both a binary coefficient for containing a center offering induced terminations, and a lagged variable (using a first order queen contiguity matrix) to account for accessibility of *neighboring* counties. Further, to control for the wide variability in population sizes per county, I included a covariate for the county population size. Teen pregnancy rates and birth to pregnancy ratios were investigated but not included due to issues with multicollinearity. These variables were collected for both the 2000 and 2010 data sets, and calculated as change over time (T_1 - T2) to unpack differences over the past ten years in the Commonwealth. The final analytic sample contains 135 cases (95 counties and 40 cities).[2]

To assess the spatial and structural effects of teenage birth rates this paper employs an exploratory spatial data analysis, ordinary least squares regression, spatial econometric techniques, and geographic visualization. I began by looking at quintile maps to look for spatial trends in the data. I then moved to assessing global spatial autocorrelation (spatial clustering) via the Moran's I statistic. Local indicators of spatial autocorrelation (LISA) were then assessed by creating LISA cluster maps showing regions of clustering; high/high, low/low, high/low, and low/high regions (e.g. high/high counties would indicate that the county has high rates of teen births and is surrounded by similar counties with high rates). Next, I ran OLS and spatial econometric regression models and compared using diagnostics. Throughout, maps were created to illustrate the findings visually (Baller et al 2001).

Based on prior research, assessing spatial relationships at the county level requires a queen matrix to allow for connectivity in all directions (in contrast to a rook matrix), and to allow for symmetric matrices (as opposed to a k-nearest neighbor conception) (Baller et al, 2001). A queen matrix allows for movement both horizontally and diagonally (like the rook matrix), but adds diagonal movement as well. Determining a proper spatial weights matrix for Virginia requires a more thoughtful conception of "neighbors" than any other U.S. state due to the nature of independent cities discussed previously. As discussed previously because some cities are embedded within one county, or between multiple counties, there is variability in the number of first order neighbors for independent cities. Additionally there is little difference in the normality of the histograms of the connectivity for first order or second order queen matrices as shown in figure 1 and 2. Lastly, as illustrated later, the substantive findings differed very little when using a first or second order queen matrix, thus facilitating the robustness of our results.

VI. Preliminary Results

Inspecting the connectivity histograms of for first and second order queen matrix (Q1 and Q2) used in the analysis, I found little difference in normality and opted for a Q2 for my analysis. A Q2 conceptualization is more

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[1] Teen birth rate data for Falls Church city, Manassas park city, and Highland county was not reported in 2010, and data for Highland county was not reported in 2000. For the 2010 data, the two former locations (the cities) reported data points for 2011, which were imputed to create values for teen birth rates, while the later county has never reported these statistics and was imputed using the averages of the two contiguous neighbors (Augusta and Bath County) to create a value for this case. The same process was done for Highland county in 2000.

[2] Clifton Forge was an independent city in the 2000 Census, but not in 2010. To preserve data (rather than eliminate it), I let Clifton Forge exist as a polygon in the 2010 data as well. Thus, allowing for contiguity and effective comparisons.

substantively consistent with Virginia's Health Planning districts in terms of grouping, and allows for cities embedded in counties to have more than one neighbor. Next, I observed noticeable visual clustering of teen birth rates at 2010, and more minor clustering in 2000, initially supporting my hypotheses that spatial variation exists, and has changed over time in Virginia. Moreover, higher levels of affluence and education seem to be clustered in the Northern Virginia area and parts of the central piedmont region, while lower levels are clustered around the southwest/south-central regions. Here there is almost a complete reversal of patterning with higher rates clustered in the north and lower rates in the south. Again, as hypothesized, teen birth rates seem to be negatively related to higher levels of education and affluence. Further, it appears (at least visually) that there may be spatial processes at work. Lastly, racial clustering in Virginia demonstrated a great deal of variation in county ethnic composition.

I assessed global spatial autocorrelation using the Moran's I statistic which assesses spatial clustering or "hotspots" (Getis and Ord, 2010). Shown in Table I are the Moran's I statistics for each of the continuous covariates (significance was assessed using 999 permutations). The highly significant Moran's I statistics for most of the variables indicate spatial processes may be operating. Further summary information on the outcome variable and each of the continuous covariates is available in table I (the binary variables for presence/absence of a clinic and city/county distinction as well as the lagged clinic variable are not included). Teen birth rates and high school graduation rates have declined overall, while poverty and unemployment rates have slightly increased reflecting U.S. trends from 2000 to 2010. Also of note is that while the African American population has remained rather stable, the Hispanic population has increased, most notably in the Northern Virginia (D.C. metro) region.

For the final step of my exploratory spatial data analysis, I investigated local spatial autocorrelation of the dependent variable at T_1, T_2, and the change score. I created LISA maps showing significant clusters of teen birth rates characterized by high/high, high/low, low/high, and low/low county relationship. Shown in figure I is an example of one LISA map showing the local spatial clustering and the corresponding significance map illustrating the polygons with significant relationships. As evidenced, there seems to be initial evidence that the phenomenon of teen birth rates by county in Virginia is spatially clustered and occurs in hypothesized directions within hypothesized regions in both 2010 and 2000, and that these relationships have not been stable over time.[3] This and other LISA maps demonstrate some initial evidence supporting my hypotheses, as there is a significant cluster of counties and cities in the Northern Virginia area (metro D.C) that have low teenage birth rates ($p<.05$), where there is also a high concentration of abortion clinics and the highest education levels in the state. Additionally, there was an equally significant ($p<.05$) cluster of high/high teen birth rate clusters in southwestern Virginia where the nearest abortion clinic is approximately 3 hours by car (in Roanoke, Va.), and the rates of people with a bachelor's degree are very low. This clustering is of little surprise to those familiar with the regional variation of the Commonwealth as Northern Virginia is characterized by more white-collar professional jobs, higher housing prices, high population density, and a more ethnically diverse population; whereas southwestern Virginia has been dominated by blue collar manufacturing and coal mining, low education and income levels, and a predominantly white population. Politically distinct as well, the clustering of teen birth rates of high/high (red) and low/low (blue) are ironically archetypal of the differences in political ideologies of the regions.

To begin looking at specific regression results of the data, I ran an OLS model using the Q2 weights matrix for each of the three sets of data (2000, 2010 and the change scores). Results and summary statistics of the 2000 model are shown in Table II, under model I. Initial results show that county unemployment rates, percentages of those without high school degrees, percentages of African Americans, and cities (as opposed to counties) are all related to higher teen birth rates, while county rates of college graduates is inversely related to the rate of teenage births within the county as hypothesized. These findings again lend themselves to affirming H_2 and H_3. However, while both affluence measures (poverty and unemployment) are statistically significant, only one of the education variables is significant (the county rate of non-high school graduates is not significant).

I then ran diagnostic tests for multicollinearity and heteroskedasticity and found a multicollinearity condition number of 25.33, illustrating the multicollinearity was not an issue as only values over 30 are suggestive of issues (Anselin 2004-2005). Further the Jarque-Bera test looks at the normality of the distribution of the standard errors using a chi-squared distribution with two degrees of freedom and our statistic (.62) is suggestive of relatively stable normality in the errors (Anselin 2004-2005). However, the final three diagnostics (the Koenker-Bassett test, Breusch-Pagan test, and White test) show that heteroskedasticity may be an issue in the model, however it is often difficult to separate heteroskedasticity from spatial autocorrelation; in other words, if there is spatial autocorrelation present, then this may inflate the white test statistic (Anselin 2004-2005). Thus it is permissible to allow for these minor assumption violations as long as the multicollinearity condition number is suitable (Anselin 2004-2005). Finally, I ran diagnostics for spatial autocorrelation. The Lagrange multiplier test statistic for the spatial lag and

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[3] Note that the LISA map for 2000 teen birth rates shows some clustering, albeit less than 2010

spatial error models shows no significance ($p<.05$); the statistics for both the lag variable and lambda (the spatial error term) as neither is significant and model fit is not improved. This casts doubt that these processes are spatially meaningful in the 2000 data as the spatial econometric models do not improve our understanding of the covariates predicting teen birth rates over ordinary least squares regression.

In the same manner I looked at the 2010 data using the same steps described in the 2000 data analysis: OLS, diagnostics, spatial error, and spatial lag. Results for the 2010 data are shown in Table III, under model I. These results show many consistencies with the 2010 data. Specifically, county unemployment rates and cities (as opposed to counties) increased teen birth rates, while county rates of college graduates decreases the rate of teenage births within the county. I again tested for multicollinearity and heteroskedasticity using model diagniostics. Like the 2000 data, multicollinearity was not problematic (assed via the multicollinearity number), and the Jarque-Bera test suggests stable normality in the errors (Anselin 2004-2005). However, unlike the 2000 data, the Lagrange multiplier for the error model and for the lag model were both significant (.01 and .03 respectively). Thus, spatial processes seem to be operating in this model (using 2010 data), thus necessitating the investigation of the spatial econometric models. Table III (under model II) shows the results for the spatial error model (for 2010 data). Note that all independent variables from the OLS model are included with the addition of a new variable, lambda. Spatial error models, as opposed to spatial lag models which estimate the strength of the neighboring counties' direct influence the county across some variable (in this case teen birth rates), assumes that the errors in the model are correlated spatially (Ward and Gleditsch 2007). In simple terms, the error model is one of "spatial nuisance" while the lag model is one of "spatial spillover effects" (Ward and Gleditsch 2007). In the spatial error model there are two error terms, one that is not spatially associated (like a normal error term in OLS), and another spatial error component (Ward and Gleditsch 2007). Lambda is a parameter which estimates the degree to which the errors are correlated in one area with its neighbors (in this case how errors in the predicted values of the county rates of teenage births are related to errors in the neighboring counties). Thus, in spatial error models the observed clustering is based on unknown or unmeasured constructs.

The results of model II in table II illustrate that like in the OLS model, rates of teenage live births is positively associated with county unemployment, and negatively related to rates of college educated citizens; this relationship persists after controlling for spatial effects. Lambda is highly significant indicating spatial clustering of the error terms, implying that some unmeasured or unknown factor is clustering teenage birth rates spatially in the Commonwealth. This model also shows that the percentage of blacks per county is positively associated with the number of teen births (ceterus paribus). This model is a better fitting model based on the AIC (909.1) and Log-Likelihood test (-443.5)[4]. The LR test further confirmed that the spatial error model was preferable.[5]

I concluded this portion of the analysis by looking at the change scores of each of the covariates (however the binary and aged variables remained as they were in the 2000 and 2010 data analyses). Shown in table IV, the change in the unemployment rate and changes in the percent of county residents without a high school degree are the sole significant correlates to changes in the county teen birth rate (ceterus paribus). Specifically, the changes in these variables between 2000 and 2010 are related to higher teen birth rates, and these processes are spatially relevant (as illustrated by a significant Lagrange multiplier and lambda coefficient). Thus, the change scores illustrate that certain vicissitudes in Virginia's counties have driven the heightened clustering of teen birth rates between 2000 and 2010, namely declines in high school graduation rates and increased unemployment.

Finally, I checked the residuals of the models to check for spatial autocorrelation therein. The residuals showed no spatial structure in any of the three analyses (2000, 2010, or the change scores), thus further evidencing that the model selected, OLS for 2000 and the spatial error model for 2010 and the change scores, is the best specified model. Indeed this amplifies the robustness of the findings. Additionally, I ran a spatial error model with a *first* order queen contiguity matrix as well for each of the three data sets. Results showed the same significant covariates for each model in the same direction, and all the covariates that were not significant in the Q2 spatial error model were again non-significant. The Log likelihood test statistic was also showed that the Q1 weights matrix was not a significant improvement over the Q-2 matrix (if anything it was slightly worse). This further strengthens the conclusions and lends support to the robustness of this model.

VII. Discussion

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[4] note that smaller values of AIC are preferred, while statistics closer to zero are preferred for the Log-Likelihood test

[5] For comparative purposes I ran a spatial lag model as well. Shown in table III, model III, the AIC and Log-likelihood statistics show no major improvements over the OLS model. Thus, the spatial error model is the superior model to both the OLS and spatial lag models.

Virginia has seen a marked decline in teen birth rates between 2000 and 2010; however these processes have not occurred congruently across the state. The significant clustering of both the dependent variable (teenage birth rates) and all covariates (in both 2000 and 2010) supports that these phenomenon are not randomly assorted spatially. The improvement of the spatial error model over the OLS model in predicting the change scores in both the teen birth rates confirms that there are spatial processes at work, and that the clustering of county level teenage birth rates is based on clustering of the error terms. However, while the supremacy of the spatial error model is seen at T_2 and in the change from T_1 to T_2, there is no spatial patterning in 2000 which reflects a disturbing trend in Virginia. While some areas are certainly lowering teen births, other areas seem to be losing the battle at the same time. Furthermore, these changes seem to be tied to changes in unemployment and high school graduation rates.

Thus, there is strong support for H_2 and H_3 that affluence and education are inversely related to teen births. Surprisingly, no support was found for H_1, as being close to a clinic offering induced pregnancy terminations did not significantly predict county teen birth rates. H_4 was confirmed for 2010 and the change from 2000 to 2010 as this process is decidedly spatial for these models and the spatial error model was a significant improvement over the OLS model. However, spatial structure did not exist in 2000 raising some important social and political queries. Lastly, H_5 was somewhat supported as these spatial processes were variable over time.

What about Virginia specifically changed from 2000 to 2010 to yield a more clustered variation in teen birth rates despite an overall decline? As illustrated by the superiority of the spatial error model, there is some underlying unmeasured process that is driving the clustering of teen birth rates *aside* from the affluence, education, demographic and urban/rural covariates included in the model. Indeed the Northern Virginia region has clearly benefitted while Southwestern Virginia has been left behind. This could reflect state congressional spending on infrastructure, education and social welfare which is exponentially higher in the densely populated northern region than the rural southwest. It could also reflect some sort of economic transition as the southwestern region is characterized by the dominance of the coal industry and declining manufacturing, while the Northern Virginia has witnessed a boom in the biotech, higher education, and government sectors. Indeed economic investments and an emphasis on education would be sensible, as these are the significant changes tied to changes in teen birth rates. Lastly, religiosity and political identification too could play a key role as the southwest region is decidedly protestant and conservative, while the northern region is more liberal and religiously diverse. Moving forward, these processes must be taken into account to understand this patterning in a more refined and nuanced fashion.

This analysis is not without limitations. First the cross sectional nature of the variables may hide dynamic processes of poverty and education as well as changes in teen birth rates. Also, though clustering was seen in Virginia, it is not an island and perhaps the significant clustering seen in both the southwestern and northern parts of the state are more reflective of their “outside state” neighbors than those within the state. An investigation using some conception of these neighbors as well may aid the analysis. Finally, any spatial analysis must consider the modifiable areal unit problem (MAUP) when interpreting results.

VIII. Next Steps: Spatial Non-Stationarity

To investigate H_6 I have begun to examine spatial non-stationarity by examining the R^2 maps in ArcGIS to look at model fit across space. Figure II shows the R^2 map for teen birth rates in 2010, providing initial support for some non-stationary patterning (R^2 values ranged from 0.53 to 0.59 in 2010) (Charlton et al.). For future analyses, I propose converting the data into the software package GWR to assess statistics measuring spatial non-stationary (after assessing the fit of the model) (Brunsdon et. al 1998). I will consider using dummy variables indicating regions to respecify a global model allowing for spatial non-stationarity, or creating of several “localized models.” Lastly, some of the explanations offered in the discussion for the spatial variation in teen birth rates will be explored.

Table 1: Descriptive Statistics for All Continuous Covariates and the Dependent Variable

A. 2000 Data

Variable (County Level)	Mean	S.D.	25th	75th	Range	Moran's I
Teen Birth rate (per 1,000 live births)	18.51	9.99	11.5	16.9	62.2	0.203***
Percent Black	18.58	16.55	5.1	29.31	79.1	0.556***
Percent Hispanic	4.4	5.09	1.63	2.65	32.52	0.496***
Percent Unemployed	6.56	2.75	4.7	8.35	14	0.208***
Percent in Poverty	13.49	6.7	7.85	17.85	29.5	0.237***
Percent Less than High School	18.95	7.08	13.75	23.95	32	0.384***
Percent Bachelors or Above	22.95	12.78	13.5	28.4	65.5	0.445***
County Population	59,300	116,300	13,930	54,500	1,079,679	0.119**

B. 2010 Data

Variable (County Level)	Mean	S.D.	25th	75th	Range	Moran's I
Teen Birth rate (per 1,000 live births)	23.02	10.36	14.95	27.85	49.4	0.066*
Percent Black	19.43	16.98	5.78	31.61	77.5	0.582***
Percent Hispanic	2.45	3.27	0.75	2.7	18.6	0.53***
Percent Unemployed	4.81	2.23	3.2	6.25	12.6	0.132**
Percent in Poverty	12.16	5.92	7.1	15.95	28.4	0.203***
Percent Less than High School	25.4	8.77	19.3	31.6	43	0.457***
Percent Bachelors or Above	19.7	11.47	11.1	23.65	57.3	0.45***
County Population	52,430	102,000	12,790	48,260	967,164	0.104**

C. Change Scores

Variable (County Level)	Mean	S.D.	25th	75th	Range	Moran's I
Teen Birth rate (per 1,000 live births)	-4.16	8.24	-7.95	-0.65	72.6	0.067**
Percent Black	-0.85	3.19	-1.8	0.47	23.32	0.02
Percent Hispanic	1.95	2.61	0.71	2.33	22.04	0.347***
Percent Unemployed	1.76	2.65	0.7	3.2	17.8	0.139***
Percent in Poverty	1.34	3.26	-0.55	2.8	21.3	0.135***
Percent Less than High School	-6.45	3.76	-8.7	-4.25	25.94	0.167***
Percent Bachelors or Above	3.25	4.1	1.3	4.35	43.8	0.034
County Population	6,862	19,990	107	6,208	151,701	0.167***

*Two Tailed Significance Test: *p<.05 **p<.01 ***p<.001

Figure I. Spatial Clustering Illustrated by LISA Cluster Map (Left) and LISA Significance Map (Right) of Teenage Birth Rates (per 1000 Live Births) by County in Virginia 2010 Data

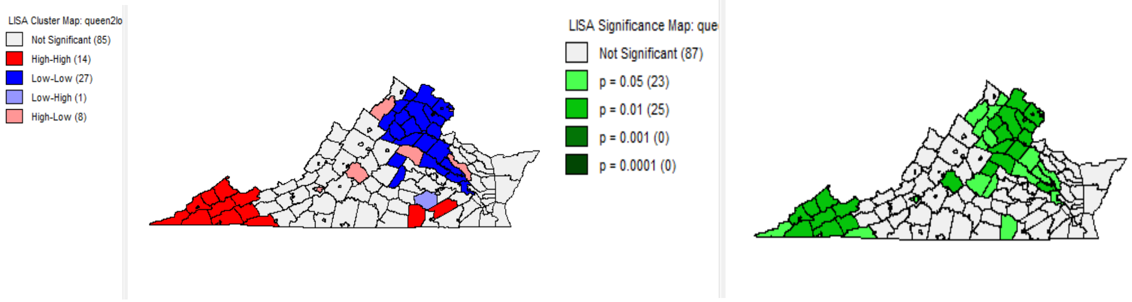

Figure II: Local R^2 Map of Teen Birth Rates in Virginia by County (2010 Data)

Table II. Three Models Regressing Virginia County Level Teen Birth Rates (Per 1,000 Live births) on Predictive Covariates Using Data from 2000

Variable	Ordinary Least Squares	Spatial Error	Spatial Lag
	Model I	Model II	Model III
Percent Black	0.14 (.04)***	0.15 (.05)***	0.14 (.04)***
Percent Hispanic	0.49 (.29)	0.47 (.28)	0.46 (.29)
Percent Unemployed	1.32 (.45)**	1.36 (.43)**	1.31 (.43)**
Percent Poverty	-0.42 (.21)*	-0.46 (.20)*	-0.41 (.20)*
Percent B.A and Higher	-0.26 (.21)*	-0.25 (.12)*	-0.26 (.11)*
Percent Less Than High School	0.44 (.18)**	0.46 (.18)**	0.45 (.17)**
Abortion Clinic	1.21 (2.19)	1.24 (2.09)	1.33 (2.1)
Lagged Abortion	-2.44 (3.75)	2.52 (3.67)	-2.35 (3.59)
County Population	0.01 (.00)	0.01 (.00)	0.01 (.00)
City	7.66 (1.93)***	7.82 (1.85)***	7.62 (1.85)***
Lambda		0.19 (.20)	
Lag Variable (W_TeenBirth)			-0.09 (.16)
Model Fit Statistics			
Log likelihood	-453.51	-453.2	-453.4
AIC	929.10	928.4	930.8
R-Squared	0.54	0.55	0.55

*Two Tailed Significance Test: *p<.05 **p<.01 ***p<.001

Table III. Three Models Regressing Virginia County Level Teen Birth Rates (Per 1,000 Live births) on Predictive Covariates Using Data from 2010

Variable	Ordinary Least Squares	Spatial Error	Spatial Lag
	Model I	**Model II**	**Model III**
Percent Black	0.06 (.04)	0.31 (.07)***	0.07 (.04)
Percent Hispanic	0.02 (.17)	0.15 (.18)	0.13 (.16)
Percent Unemployed	0.67 (.3)**	0.53 (.28)*	0.62 (.29)*
Percent Poverty	0.12 (.15)	0.07 (.15)	0.07 (.14)
Percent B.A and Higher	-0.23 (.09)**	-0.3 (.09)***	-0.22 (.08)**
Percent Less Than High School	0.36 (.17)*	-0.02 (.17)	0.31 (.16)*
Abortion Clinic	-0.15 (2.15)	-2.11 (1.85)	-0.12 (2.03)
Lag Abortion	-2.38 (3.72)	-2.89 (3.64)	-2.82 (3.50)
County Population	0.00 (.00)	0.00 (.00)	0.00 (.00)
City	5.64 (1.96)**	4.14 (1.75)**	5.75 (1.84)**
Lambda		0.81 (.08)***	
Lag Variable (W_TeenBirth)			0.32 (.13)**
Model Fit Statistics			
Log likelihood	-451.5	-443.5	-449.3
AIC	925.10	909.10	922.60
R-Squared	0.53	0.61	0.55

*Two Tailed Significance Test: *p<.05 **p<.01 ***p<.001

Table IV. Three Models Regressing Virginia County Level Teen Birth Rates (Per 1,000 Live births) on Predictive Covariates Using Change Scores

Variable	Ordinary Least Squares	Spatial Error	Spatial Lag
	Model I	**Model II**	**Model III**
Percent Black	0.4 (.23)	0.33 (.22)	0.38 (.22)
Percent Hispanic	-0.57 (.31)	-0.38 (.32)	-0.46 (.30)
Percent Unemployed	0.59 (.27)*	0.75 (.26)**	0.66 (.25)**
Percent Poverty	-0.07 (.23)	-0.13 (.23)	-0.12 (.22)
Percent B.A. and Higher	-0.07 (.19)	-0.04 (.18)	-0.05 (.18)
Percent Less Than High School	0.55 (.22)**	0.6 (.21)**	0.59 (.21)**
Abortion Clinic	-1.33 (2.24)	-1.67 (2.09)	-1.4 (2.11)
Lag Abortion	-3.22 (3.58)	-3.46 (3.61)	-2.69 (3.40)
County Population	0.0 (.00)	0.0 (.00)	0.0 (.00)
City	-1.56 (1.93)	.1.41 (1.77)	-1.62 (1.82)
Lambda		0.4 (.16)**	
Lag Variable (W_TeenBirth)			0.36 (.16)*
Model Fit Statistics			
Log likelihood	-464.9	-462.5	-462.9
AIC	951.40	947.02	949.7
R-Squared	0.15	0.19	0.18

*Two Tailed Significance Test: *p<.05 **p<.01 ***p<.001

IX. Works cited:

Allen, Joseph P, Philliber, Susan, Herrling, Scott, Kuperminc, Gabriel P. 1997. “Preventing Teen Pregnancy and Academic Failure: Experimental Evaluation of a Developmentally Based Approach.” *Child Development* 68(4): 729-742.

Anselin, Luc. 2004-2005. *Exploring Spatial Data with GeoDa: A Workbook*. Department of Geography. University of Illinois Champagne.

Baller, Robert D, Anselin, Luc, Messner, Steven F, Deane, Glenn, Hawkins, Darnell F. 2001. “Structural Covariates of U.S. County Homicide

Bassett, Laura. 2013. “Virginia Abortion Clinic Restrictions Passed By Board Of Health.” *The Huffington Post.* September, 2013. http://www.huffingtonpost.com/2013/04/12/virginia-abortion-clinic_n_3070320.html

Rates: Incorporating Spatial Effects.” *Criminology* 39(3): 561-590.

Brundson, Chris, Fotheringham, Stewart, Charlton, Martin. 1998. “Geographically Weighted Regression – Modeling Spatial Non-Stationarity.” *The Journal of the Royal Statistical Society: Series D (The Statistician).* 47(3): 431-443.

Charlton, Martin, Fotheringham, Stewart, Brundson, Chris. *Geographically Weight Regression Workbook.*

Davis, S. 1989. “Pregnancy in Adolescents.” *Pediatric Clinics of North America* 36(3): 665-680.

Kane, Thomas J. and Douglas Staiger. 1996. “Teen Motherhood and Abortion Access.” *The Quarterly Journal of Economics* 111 (2): 467-506.

Nolan, Jim. 2013. “Virginia Abortion Clinic Regulations Challenged In Lawsuit By Falls Church Healthcare Center.” *The Richmond Times Dispatch*. September, 2013. http://www.huffingtonpost.com/2013/06/14/virginia-abortion-clinic-regulations-lawsuit_n_3439641.html.

Ord, J. K. and Getis, Arthur. 2010 “Local Spatial Autocorrelation Statistics: Distributional Issues and an Application.” *Geographical Analysis* 27(4): 286-306.

Ward, Michael D., Gleditsch, Kristain. 2007 *An Introduction to Spatial Regression Models in the Social Science.*

The Washington Post (Editorial Board). 2013. “Virginia’s next governor will determine whether most abortion clinics close.” September, 2013. http://articles.washingtonpost.com/2013-09-16/opinions/42115753_1_walk-in-clinics-existing-clinics-abortion