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Understanding Unobserved Propensities of Suicide in the United States: A Hierarchical Model with Spatially Correlated Random Effects[1]

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Abstract

This paper investigates the underlying causes of suicide. In contrast to previous literature, we use data from the United States at the county level. Our primary methodology is a two-level Bayesian hierarchical model with spatially correlated random effects. Our results show that the significant effects of observable factors on suicides found by earlier research may partially stem from excluding small area effects and time trends. Without controlling for these area and time effects, the true contribution of unobserved propensities and time trends can be hidden within observable factors. Most importantly, we find that a lot can be learned from unobserved yet persistent propensity toward suicide captured by the spatially correlated county specific random effects. We argue that resources should be allocated to counties with high suicide rates, but also counties with low raw suicide rates but high unobserved propensities of suicide.

Keywords: Suicide, Spatial dependence, Hierarchical Bayes Models

JEL Classification: C11, C21, I12, I18

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1. Introduction

Suicides in the United States have been steadily increasing in recent years, ranking as the tenth highest cause of mortality among all age groups in 2013. The U.S. suicide rate increased from 10.95 per 100,000 individuals in 2006, to 12.6 in 2013 (Centers for Disease Control and Prevention, 2009, 2015). Additionally, the lifelong medical and work-loss costs from suicides are estimated to be $50.8 billion in the United States alone (Florence et al., 2015). In an attempt to understand this major public health concern, a substantial number of studies examine the principle causes of suicide.

Some of the potential factors driving suicide mortality which prior literature has studied include: economic conditions, social and cultural factors, environmental variables, and geographic location; with most authors utilizing aggregate data from large geographic areas. For example, several studies have used national-level aggregate data to conclude that high unemployment is closely associated with increases in suicide rates (Stuckler et al., 2011, 2009; Yang and Lester, 1995). However, as Breuer (2015), Maag (2008), Andrés (2005), and Kunce and Anderson (2002) illustrate, larger geographic areas correspond to greater levels of heterogeneity across different social and economic groups within an area. Analysis across large regions is therefore unlikely to capture the sub-region-specific heterogeneity affecting suicides. Some examples of confounders leading to sub-regional heterogeneity are local labor market conditions, religion, geography, weather, race, the level of integration, and the accessibility to firearms, alcohol, and drugs. If any omitted small area propensity is correlated with the observable variables, empirical results will be biased. Consequently, several studies have applied sub-national level analysis using both U.S. states (Ruhm, 2000, 2015; Phillips and Nugent, 2014) and the Nomenclature of Units for Territorial Statistics (NUTS-2) in Europe (Breuer, 2015).[2] While these authors also find a strong causal relationship between unemployment and suicide, as Hoynes (2000) emphasizes, states in the U.S. are still too large an area to accurately capture sub-region specific labor market conditions. In this paper, we analyze county-level data for both Florida and Georgia. The use of county data allows us to capture the effects of various suicide characteristics across counties within a state.

The inclusion of regional fixed effects and time fixed effects can also have a considerable effect on empirical results. Leigh and Jencks (2007) show that without controlling for country and year fixed effects, an increase in the income share held by the top ten percent is significantly associated with reduced life expectancy and increased infant mortality. However, when using fixed effects, these associations disappear in their analyses. Time fixed effects account for both global and national trends as well as smaller area shocks which may affect suicides. Examples of such trends include across-time variation in economic conditions, weather patterns, veteran population level, and governmental regulations concerning firearms, alcohol, and drugs. With this issue in mind, it is a potential concern that most studies of suicide employing Bayesian hierarchical models exclude time trends in their analyses. Our Bayesian hierarchical model incorporates spatially correlated county random effects and time dummy variables. By including both features, we capture not only unobserved county-specific characteristics, but also the time trends that influence suicide rates.

A considerable portion of the existing literature focuses on observable determinants of suicide by including as many explanatory variables as possible. If, however, there are unobservable determinants driving suicide risk, any public health policy based solely on observable factors

[2] The NUTS-2 in the EU (European Union) correspond to states in the U.S. as similar local administrative units.

may prove misleading. The causes of suicide are complicated and influenced by a multitude of factors. Family members, friends, coworkers, and classmates who may influence an individual's suicide decision tend to live in closer proximity. In addition, suicide is a malady which not only affects individuals and entire families, but their communities. Individuals living in closer proximity to one another are more likely to share economic and social characteristics along with their living space. These characteristics could be employment status, income level, race, religion, weather, and the availability of firearms, alcohol, and drugs. Therefore, these characteristics are likely to be reflected in local area specific propensities toward suicide. Our Bayesian specification enables us to summarize the posterior distributions of unobserved suicide propensity rankings at the county level. These rank distributions provide useful information for the design and implementation of anti-suicide policy. Furthermore, our paper presents empirical evidence for the existence of spatial correlation between counties in unobserved propensity toward suicide. Allowing for spatial correlation provides additional information regarding counties which are not only at an elevated risk of suicide internally, but also more prone to transmit their risk to neighboring counties. After identifying such counties, selecting them for special treatments could be an efficient policy. Government efforts to provide proper educational facilities, public advertisement, medical treatment programs for depression, and stricter monitoring of the illegal possession of firearms and underage drinking should be concentrated in these at-risk counties.

In summary, our study provides a significant contribution to the literature for a number reasons. First, we capture the heterogeneous characteristics of suicide within a state across counties by using county-level data from Florida and Georgia. Second, by including time dummy variables, our hierarchical model captures unobserved trends and shocks which may influence suicide. Third, we produce supporting evidence for the existence of unobserved characteristics influencing suicide which vary between counties, suggesting that the true effect of unobserved propensities may be hidden within observable factors. Therefore, any public health policy implemented to prevent suicides is misguided if policymakers identify high-risk counties based solely on their observable factors. Finally, we also find that unexplained county-specific propensities toward suicide are spatially correlated. Our empirical strategy allows us to identify the counties with both high internal suicide risk and a greater likelihood of transferring their risk across county borders. To single these counties out for special treatment would be an efficient policy consideration.

The rest of the paper is structured as follows. Section 2 gives an overview of the related literature. Section 3 describes the data in our analysis. In Section 4, we present the methods utilized in the paper. Section 5 discusses our empirical results, and Section 6 concludes and discusses the policy implications of our results.

2. Literature Review

It has long been acknowledged that economic downturns lead to unfortunate increases in suicide rates. Chang et al. (2013) analyze the 2008 global financial crisis' effect on suicide trends using data from 54 countries, for which they find a resulting suicide rate increase in 2009. Furthermore, panel analyses of European countries by Stuckler et al. (2011, 2009) demonstrate significant increases in suicides associated with higher levels of unemployment in the portion of the population younger than 65. Time series regressions for twelve countries by Yang and Lester (1995) reveal a strong relationship between unemployment and suicides in four countries including the United States. Recent studies conducted by Breuer (2015) and Phillips and Nugent

(2014) examine the relationship between unemployment rates and suicide mortality at the sub-national level. Using panel data from 275 regions of 29 European countries from 1999 to 2010, Breuer (2015) finds a significant positive association between unemployment and suicides. Phillips and Nugent (2014) pool U.S. state-level data over the period of 1997 to 2010, and conduct panel analysis of the one-way fixed effects. The authors show a strong and positive causal relationship between the unemployment rate and suicide rate. Ruhm (2000, 2015) conducts a panel analysis of U.S. state-level data. Ruhm (2000) finds a significant increase in suicide mortality associated with increased unemployment rates during 1976-1995, whereas Ruhm (2015) finds no significant relationship over the 1991-2010 period.

Inequality is another important factor in the study of suicide mortality. Leigh and Jencks (2007) argue that variation in the income share held by the top ten percent of earners is unlikely to influence the suicide rates of richer countries. Using both two-way fixed effects and country-specific time trends, Andrés (2005) shows that the Gini index has little effect on suicides in fifteen European countries.

Ease of access to firearms, alcohol, and drugs has also been the subject of a considerable quantity of suicide research. Hemenway and Miller (2002), Webster et al. (2004), and Miller et al. (2013) show that higher rates of firearm ownership and the presence of less restrictive regulations over the access to firearms are likely to increase suicide rates. Rosengart et al. (2005) find no statistically significant relationship between state laws regulating firearm access and suicide rates when using state and census division-level data from the United States. Alcohol consumption and drug use are also considered to increase the risk of suicide. Andrés (2005), Kaplan et al. (2014), and Phillips and Nugent (2014) estimate a positive relationship between alcohol consumption and suicide mortality. Sullivan et al. (2013) report that death by drug overdose (poisoning) is the most common method people choose to commit suicide. The crime rate is often accepted as a natural proxy for disintegration and the accessibility to firearms, alcohol, and drugs within a region (Brainerd, 2001). Using data from the former Soviet Union in the 1990's, Brainerd (2001) finds that the crime rate is in fact not correlated with the suicide rate.

Ajdacic-Gross et al. (2010) summarize prior literature concerning the effect of seasonal changes on suicide. The authors find that the seasonal pattern of suicide in Western countries has decreased or even disappeared over time. Regarding the relationship between weather changes and suicide rates, Neumayer (2003) finds that daily sunshine hours are inversely associated with suicide rates. On the other hand, Marion et al. (1999) suggest that an increase in elderly suicides is related to warmer temperatures whereas younger suicides are related to season.[3]

Gearing and Lizardi (2009) argue that religiosity leads to a decrease in suicide risk. Becker and Woessmann (2011) show that Catholics are less likely to commit suicide than Protestants, while Neumayer (2003) finds no significant effect of religion on suicide in a panel analysis of 68 countries between 1980 and 1990.

During the Iraq and Afghanistan wars, U.S. soldiers were deployed both more often and for longer periods than in previous armed conflicts. This change has led to an increased number of studies seeking to evaluate the risk of suicide among the veteran population. Empirical findings from Kang et al. (2015), McCarten et al. (2015), and Kaplan et al. (2012) suggest that veterans are at higher risk of suicide than the general U.S. population.

There have also been several recent studies of geographical suicide patterns using Bayesian methods. Utilizing U.S. county data pooled over the five-year period from 2002 to 2006,

[3] Regarding seasonality of youth suicide, Hansen and Lang (2011) suggest that youth suicide increases when school is in session.

Congdon (2011) estimates three latent variables of deprivation, social fragmentation, and rurality based on thirteen manifest variables. Congdon (2011) also allows for spatial correlation in the latent variable estimations. Cheung et al. (2012) and Hsu et al. (2015) adopt similar Bayesian hierarchical models in the spatial analysis of suicide mortality in Australia and Hong Kong respectively. Both studies capture the spatial correlation of suicide by incorporating a conditional autoregressive (CAR) structure in the error term. Hsu et al. (2015) show weak spatial impact from neighboring areas and a strong correlation between suicide risk and observable socioeconomic variables in Hong Kong. Our paper's hierarchical specification differs from prior literature in that the variance of a county random effects stems from both county specific unobserved propensities of its own and spatial dependence among neighboring counties. Most importantly, different from prior studies, our Bayesian hierarchical random-effects model allows us to summarize the posterior distributions of county-level unobserved suicide propensity rankings.

In contrast to previous studies, we find that the significant effects of observable factors on suicides found by earlier research may partially result from the exclusion of small area effects and time trends. Without controlling for these area and time effects, the true contribution of unobserved propensities and time trends can be hidden within observable factors. We also show that unobserved county-level suicide propensity is spatially correlated.

3. Data

Our analysis uses county-level data from both Florida and Georgia. Prospective data from each of the 67 counties in Florida are available for 14 years (2000-2013), while data from each of the 159 counties in Georgia are available for 17 years (1997-2013).[4] For our specification, average suicide rate (per 1,000 residents) is used as the dependent variable. Our explanatory variables include: years of potential life loss (YPLL) excluding cause of suicide (per resident <75 years of age); mean household income; Gini index and squared Gini index; unemployment rate; veteran population rate (per resident); distance to military base; crime rate (per resident); and population rates (per resident) of county demographic characteristics such as age, race, and gender. These variables are selected based on the findings of prior literature previously discussed in Section 2.

Data on suicide mortality, years of potential life loss (YPLL), and demographic characteristics are collected from the Florida Department of Health's Community Health Assessment Resource Tool Set (CHARTS), and the Georgia Department of Community Health's Online Analytical Statistical Information System (OASIS).[5] The U.S. Department of Veteran Affairs provides data on the veteran population by county in each year. Distance to military base is calculated using the crow-fly distance from a county's centroid to the nearest military base. Military base locations are collected using Google Map's Geographic Coordination System, and county coordinates are obtained from the US Census' 1990, 2000, and 2010 Gazetteer Files. Crime statistics are collected from the Florida Department of Law Enforcement and the Georgia Bureau of Investigation. Suicide rate, veteran population rate, crime rate, and county-level demographic rates of age, race, and gender are calculated for each year by dividing total counts

[4] We exclude data from the 1997-1999 period for Florida because information regarding Hispanic rate is not available over that period.

[5] Access to mortality data is usually limited. For example, beginning in 1989, the National Center for Health Statistics (NCHS) restricts all sub-national data providing less than ten deaths. As chance would have it, both the Florida CHARTS (http://www.floridacharts.com/charts/default.aspx) and the Georgia OASIS (https://oasis.state.ga.us/) databases provide county mortality data to the public.

of each variable by the county's population. Data regarding county unemployment rate are collected from the US Bureau of Labor Statistics.

Based on Brush (2007), we approximate mean household income by multiplying income per capita by average household size. Data for inflation-unadjusted income per capita and the GDP deflator (in 2009 dollars), which we use to calculate the inflation-adjusted income per capita, are collected from the US Bureau of Economic Analysis. Meanwhile, starting in 2005 the American Community Survey (ACS) provides five-year estimates for average household size.[6] To approximate average household size over the periods of 1997-1999 and 2001-2004, we employ a linear interpolation method which assumes constant growth over the periods of 1990-2000 and 2000-2005. More specifically, estimates of household size in 1997, 1998, and 1999 come from linear interpolation between the U.S. Decennial Census for the years 1990 and 2000. By the same logic, we estimate household size in 2001, 2002, 2003, and 2004 using linear interpolation between the 2000 Decennial Census and the 2005-2009 ACS five-year estimates. Table 1 summarizes the sources of data used for the average household size calculations in each year.

Table 1. Data Source of Average Household Size

<table>
<tr><th>Year</th><th>97</th><th>98</th><th>99</th><th>00</th><th>01</th><th>02</th><th>03</th><th>04</th><th>05</th><th>06</th><th>07</th><th>08</th><th>09</th><th>10</th><th>11</th><th>12</th><th>13</th></tr>
<tr><td>Household Size</td><td colspan="3">Interpolation estimates between the 1990 Decennial Census and the 2000 Decennial Census</td><td>2000 US Decennial Census</td><td colspan="4">Interpolation estimates between the 2000 Decennial Census and the 2005-2009 ACS 5 years estimates</td><td colspan="5">05-09 ACS 5 years estimates</td><td>06-10 ACS 5 years estimates</td><td>07-11 ACS 5 years estimates</td><td>08-12 ACS 5 years estimates</td><td>09-13 ACS 5 years estimates</td></tr>
</table>

To calculate the Gini index, we use median household income as well as the previously created mean household income.[7] Data on median household income is gathered from the U.S. Census Small Area Income and Poverty Estimate (SAIPE). By assuming that household income

[6] The U.S. Census explains that the 5-year estimates are typically more accurate than the 1-year or 3-year estimates.
[7] As an inequality measure, the Gini index ranges from 0 (perfect equality) to 1 (perfect inequality).

follows a log-normal distribution, mean household income is given by $e^{\mu+\frac{\sigma^2}{2}}$, and median household income is equal to e^{μ}. Solving for $\sigma = \sqrt{2\ln\frac{mean\ HH\ income}{median\ HH\ income}}$ allows us to then calculate the Gini index, such that Gini = $2\,\Phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1$, where $\Phi(.)$ is the cumulative density function of the standard normal distribution (Brush, 2007; Kelly, 2000). [8]

Descriptive statistics of our data are presented in Table 2. For the most part, Florida counties have higher crude suicide rates relative to Georgia. Figure 1 displays the time trend of average suicide rates in Florida, Georgia, and the entire United States from 1997 to 2013, making the higher propensity toward suicide in Florida relative to Georgia more clear.[9] Figure 2 maps the time-average suicide rates across counties in the two states over our research period. A larger proportion of counties in Florida have suicide rates above 0.2 per 1,000 residents relative to Georgia.

The last column of Table 2 reports the significance of differences in means. The t-tests indicate that nearly all variables in both states are significantly different from one another even though they share a common border. The Hispanic population rate in Florida is 2.5 times that of Georgia, while the black population rate in Georgia is almost double that in Florida. Florida has a higher veteran population rate, but a further distance to military base from county centroid on average. In Florida, the average crime rate is higher, and the elderly comprise a larger portion of the population. In Georgia, years of potential life loss is slightly higher, mean household income is lower, and the population contains a higher relative amount of the young and female.

[8] For more explanations about this method of inequality data construction, see Sung et al. (2017).
[9] Suicide mortality data in the United States are provided by the Centers for Disease Control and Prevention's Web-based Injury Statistics Query and Reporting System (https://www.cdc.gov/injury/wisqars/index.html).

Table 2. Descriptive Statistics

Variables	Florida (N=938)	Georgia (N=2703)	Difference
suicide rate (count per 1,000 residents)	0.1565	0.1210	***
	(0.0678)	(0.0939)	
YPLL excluding suicide cause (year per resident age<75)	0.0843	0.0895	***
	(0.0206)	(0.0241)	
mean household income ($10,000)	8.1790	7.4277	***
	(2.1433)	(1.6494)	
Gini index	0.5781	0.5677	***
	(0.0584)	(0.0609)	
unemployment rate	0.0641	0.0695	***
	(0.0278)	(0.0308)	
veteran population rate (per resident)	0.1123	0.0844	***
	(0.0293)	(0.0176)	
distance to military base (1000 miles)	0.0460	0.0342	***
	(0.2733)	(0.1655)	
crime rate (per resident)	0.0349	0.0280	***
	(0.0146)	(0.0179)	
age 15-19 population rate (per resident)	0.0638	0.0735	***
	(0.0113)	(0.0110)	
age 20-24 population rate (per resident)	0.0655	0.0680	***
	(0.0226)	(0.0247)	
age 25-34 population rate (per resident)	0.1218	0.1300	***
	(0.0249)	(0.0222)	
age 35-44 population rate (per resident)	0.1344	0.1428	***
	(0.0212)	(0.0189)	
age 45-54 population rate (per resident)	0.1381	0.1381	
	(0.0143)	(0.0147)	
age 55-64 population rate (per resident)	0.1217	0.1089	***
	(0.0212)	(0.0230)	
age over 65 population rate (per resident)	0.1789	0.1285	***
	(0.0661)	(0.0356)	
black population rate (per resident)	0.1448	0.2802	***
	(0.0956)	(0.1744)	
Hispanic population rate (per resident)	0.1114	0.0454	***
	(0.1143)	(0.0464)	
female population rate (per resident)	0.4882	0.5059	***
	(0.0363)	(0.0261)	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4. Empirical model

To analyze the relationship between suicide mortality and observable factors, we employ the following panel regression model:

$$y_{it} = x_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

The dependent variable y_{it} denotes suicide rate in county i for year t.[10] x_{it} represents the explanatory variables. α_i indicates county-specific effects that vary across counties, but are held constant over time in the fixed-effects model. Otherwise, α_i represents county-specific error components of the random-effects model. λ_t denotes year dummies that capture time trends and shocks which may affect suicides. As described in Section 3, the explanatory variables x_{it} include YPLL, mean household income, Gini index and squared Gini index, unemployment rate, veteran population rate, distance to military base, crime rate, and population rates of demographic characteristics for each county i.[11] Breuer (2015) and Brainerd (2001) find a negative relationship between life expectancy and suicide mortality as suggested by Hamermesh and Soss (1974).[12] Since data on life expectancy at the county level for Florida and Georgia are unavailable, we use YPLL in our estimation as a proxy for life expectancy which moves in the opposite direction. Crime rate is included as a proxy for disintegration (Brainerd, 2001) and the accessibility to firearms, alcohol, and drugs. The Bayesian specification and sampling algorithm employed in our analysis is given in the Appendix.

[10] The percentage of county-years without a suicide case in our sample is 2.9% in Florida and 15.6% in Georgia.
[11] We include the squared Gini index because of the assumed nonlinear effect of Gini index on suicide mortality.
[12] Hamermesh and Soss (1974) are the first to provide a theoretical foundation for suicide research from an economic perspective.

5. Results

5.1 Classical Regression Results

Tables 3 and 4 each report the results of our classical regressions for Florida and Georgia. The regression models are built based on the specification of equation (1). Column (1) provides the results of pooled ordinary least squares (OLS) estimation excluding county effects but including time dummies, column (2) shows the outcomes of random-effects estimation including time dummies, and columns (3) and (4) present the results of one-way and two-way fixed-effects estimation respectively. Column (5) provides the result of the Bayesian two-level hierarchical model with spatial correlation based on equations (2) and (3) given in the Appendix.

In general, the results of our pooled OLS and random-effects regressions seem consistent with the findings of prior literature which ignores unobserved county-specific propensity in that some observables do in fact influence suicides. The pooled OLS and random-effects estimation outcomes in columns (1) and (2) of Table 3 show that increases in YPLL, veteran population rate, crime rate, and population rate at ages 55-64, and reductions in mean household income and population rates of black and Hispanic individuals lead to statistically significant increases in suicide rates in Florida. Meanwhile, columns (1) and (2) of Table 4 demonstrate that increases in Gini index, unemployment rate, and population rates at ages 20-24, 35-44, above 65, and decreases in squared Gini index, distance to military base, and population rates of black and Hispanic individuals result in statistically significant increases in suicide rates in Georgia.

On the other hand, the two-way fixed-effects estimation results in column (4) of Tables 3 and 4 show both a loss of statistical significance and a considerable change in magnitude for most observable factor coefficients. Only coefficient estimates for the Hispanic rate in Florida (Table

3) and the Gini index in Georgia (Table 4) remain statistically significant under the two-way fixed-effects estimation.[13] Consequently, between those estimations, tests of over-identifying restrictions suggest the use of fixed-effects estimators rather than the random-effects estimators for both Florida and Georgia.[14] As Neumayer (2003) suggests, this finding provides evidence for the existence of unobserved county-specific suicide propensities.[15] Moreover, the incorporation of year dummy variables changes the fixed-effects estimation results considerably for Florida. This difference can be seen by comparing columns (3) and (4) of Table 3. The incorporation of time dummies in column (4) takes away the significance of mean household income, unemployment rate, and population rate at age 35-44 in column (3) for Florida.[16]

Our empirical findings indicate that the significant effects of observable factors on suicides in prior literature may be due to the exclusion of small area effects and time trends. Without

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[13] We assume nonlinear effect of the Gini index on suicide mortality and incorporate the quadratic term of the Gini index into our regression. Based on the estimated coefficients of the Gini index and the squared Gini index in columns (1) and (2) of Table 4 (Pooled OLS and RE), we calculate that the turning point for the Gini index is around 0.6, which is located around the 69th percentile of the Gini index distribution in Georgia counties. This suggests that 31 percent of the county-years in Georgia have Gini indices above the turning point of 0.6 and therefore experience fewer suicides as the Gini index increases. On the other hand, based on the estimated coefficients of the Gini index and the squared Gini index in column (4) of Table 4 (FE), we calculate that the turning point of the Gini index is around 0.67, which is located around the 96th percentile of the Gini index distribution in Georgia counties. This alternatively suggests that nearly all the county-years in Georgia have Gini indices lower than the turning point. Therefore, the estimated effect of the Gini index on suicide rates based on our fixed-effects estimation is generally positive, which is a more convincing result compared to the implications of the OLS and random-effects estimations.

[14] A Hausman test fails to generate valid statistics since the differences of variance matrices of FE vs. RE estimates are not positively defined. In practice, compared to the Hausman test, the test of over-identifying restrictions extends straightforwardly to heteroskedastic- and cluster-robust options, which we adopt; and is guaranteed to generate a nonnegative test statistic. With a balanced panel (under conditional homoskedasticity), the over-identification test statistic is asymptotically equivalent to the Hausman fixed-vs-random effects test. For Florida, the Sargan-Hansen test statistic is 81.01, and the χ^2 test statistic is 17. For Georgia, the Sargan-Hansen test statistic is 51.26, and the χ^2 test statistic is 28. All these test statistics provide evidence in favor of a FE estimation. One concern, however, is that the estimated magnitude of Hispanic rate in Florida seems to be inflated proportionally to its standard error in FE estimation relative to the OLS and RE estimates, and the estimated effects are statistically significant in all specifications of OLS, RE, and FE. We therefore conduct t-test for the coefficient, the results of which suggest statistically significant differences in the estimated coefficients between the RE (or OLS) and the FE model.

[15] Neumayer (2003) finds no difference between the fixed-effects estimation results and the random-effects estimation results. Based on this finding, he suggests that suicide analysis omitting unobserved area factors is still valid.

[16] As a robustness check, we additionally control for county-specific time trends in our FE model. A Hausman test suggests statistically insignificant differences in estimation results between the FE model and a specification that adds county-specific time trend to the FE model.

controlling for county and time fixed effects, the true effect of unobserved county suicide propensity may be hidden within observable factors. Therefore, suicide prevention policies focusing only on observable factors may be misguided. Instead, county-specific policies based on unobserved propensity should be used in combination with policies targeting observable factors.

Interestingly, for both states, the results of our Bayesian hierarchical model with spatially correlated random effects in column (5) are more similar to the fixed-effects estimation results in column (4) than to the random-effects estimation results in column (2).[17] Both the magnitude and statistical significance of our coefficient estimates for the fixed-effects model and the Bayesian hierarchical model are similar, supporting our hierarchical model's estimation strategy which focuses on county-specific unobserved propensity. More so, the results presented in column (5) of Tables 3 and 4 show that unobserved suicide propensity exhibits significant spatial correlation in both states. The parameter ω represents the level of spatial dependence, which we find to be both positive and within the support boundary for ω in Florida and Georgia.[18] The basic intuition behind our empirical findings is that the correlation between unobserved county-specific heterogeneity and the covariates is explained through the spatial dependence between counties, suggesting that spatial correlation should be incorporated in suicide analysis. It should also be noted that one important advantage of our hierarchical random-effects model compared to a fixed-effects model is that the Bayesian methodology allows us to summarize the posterior distributions of county-level unobserved suicide propensity rankings. We discuss this in more detail in the following section.

[17] A more detailed explanation of our Bayesian model is given by equations (2) and (3) in the Appendix.
[18] For notational convenience and comparability between models, we denote "being within the support boundary" using *.

Table 3. Regression and Bayesian Model Results for Florida

	(1)	(2)	(3)	(4)	(5)
County Effect	No	Random Effects	Fixed Effects		Spatially Correlated Random Effects
Year Effect	Yes	Yes	No	Yes	Yes
VARIABLES					
YPLL (excluding suicide cause)	0.357**	0.341*	-0.120	-0.079	-0.094
	(0.168)	(0.190)	(0.350)	(0.361)	(0.242)
mean household income	-0.004**	-0.003*	0.010*	0.008	0.007
	(0.002)	(0.002)	(0.005)	(0.006)	(0.008)
Gini index	0.131	0.104	0.095	0.208	0.229
	(0.384)	(0.410)	(0.748)	(0.745)	(0.562)
Gini index ^2	0.006	0.020	-0.187	-0.303	-0.314
	(0.374)	(0.400)	(0.671)	(0.693)	(0.544)
unemployment rate	-0.042	-0.047	0.326**	0.134	0.129
	(0.283)	(0.297)	(0.130)	(0.356)	(0.321)
veteran population rate	0.302**	0.301**	0.200	0.324	0.343*
	(0.130)	(0.134)	(0.219)	(0.252)	(0.229)
distance to military base	0.080	0.072	0.503	0.690	0.634
	(0.088)	(0.092)	(0.536)	(0.641)	(0.668)
crime rate	0.633**	0.625***	0.157	0.221	0.167
	(0.240)	(0.241)	(0.269)	(0.278)	(0.375)
age 15 to 19 population rate	0.424	0.581	1.384	1.735*	1.775**
	(0.740)	(0.759)	(0.939)	(0.957)	(1.031)
age 20 to 24 population rate	0.049	-0.014	0.593	0.500	0.412
	(0.224)	(0.242)	(0.508)	(0.778)	(0.621)
age 25 to 34 population rate	0.175	0.260	0.565	0.331	0.307
	(0.480)	(0.486)	(0.657)	(0.731)	(0.547)
age 35 to 44 population rate	0.019	-0.018	-0.981***	-0.513	-0.476
	(0.289)	(0.277)	(0.367)	(0.378)	(0.545)
age 45 to 54 population rate	0.337	0.231	-0.672*	-0.845**	-0.879*
	(0.268)	(0.267)	(0.396)	(0.383)	(0.559)
age 55 to 64 population rate	0.730**	0.807**	0.484	0.387	0.394
	(0.343)	(0.348)	(0.393)	(0.374)	(0.517)
age over 65 population rate	0.050	0.049	-0.071	-0.174	-0.237
	(0.179)	(0.177)	(0.284)	(0.278)	(0.326)
black population rate	-0.187***	-0.185***	-0.047	-0.017	0.117
	(0.036)	(0.037)	(0.326)	(0.340)	(0.232)
Hispanic population rate	-0.060**	-0.067**	-0.408***	-0.653***	-0.800***
	(0.029)	(0.028)	(0.148)	(0.199)	(0.191)
female population rate	-0.042	-0.047	0.040	0.204	0.290
	(0.133)	(0.137)	(0.396)	(0.357)	(0.346)
Constant	-0.113	-0.109	0.040	-0.017	-1.051***
	(0.218)	(0.225)	(0.303)	(0.286)	(0.352)
ω					0.1614***
					(0.0007)
Observations	938	938	938	938	938
R-squared	0.232		0.063	0.075	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Regression and Bayesian Model Results for Georgia

	(1)	(2)	(3)	(4)	(5)
County Effect	No	Random Effects	Fixed Effects		Spatially Correlated Random Effects
Year Effect	Yes	Yes	No	Yes	Yes
VARIABLES					
YPLL (excluding suicide cause)	0.047	0.027	-0.070	-0.083	-0.084
	(0.145)	(0.143)	(0.146)	(0.145)	(0.111)
mean household income	0.000	0.000	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
Gini index	0.835***	0.862***	0.996**	1.062**	1.042**
	(0.318)	(0.306)	(0.409)	(0.417)	(0.554)
Gini index ^2	-0.707**	-0.721***	-0.683*	-0.791*	-0.770*
	(0.285)	(0.274)	(0.392)	(0.404)	(0.507)
unemployment rate	0.330*	0.296*	0.189	0.079	0.078
	(0.171)	(0.174)	(0.121)	(0.229)	(0.167)
veteran population rate	0.077	0.070	0.076	0.088	0.085
	(0.123)	(0.123)	(0.210)	(0.225)	(0.213)
distance to military base	-0.241**	-0.240**	-2.230	-2.536	-0.702
	(0.119)	(0.120)	(2.436)	(2.618)	(1.643)
crime rate	0.102	0.108	0.275	0.237	0.244
	(0.112)	(0.117)	(0.301)	(0.286)	(0.227)
age 15 to 19 population rate	0.233	0.199	-0.599	-0.460	-0.489
	(0.345)	(0.349)	(0.564)	(0.647)	(0.551)
age 20 to 24 population rate	0.252*	0.224	-0.884	-0.928	-0.922**
	(0.142)	(0.141)	(0.710)	(0.738)	(0.533)
age 25 to 34 population rate	0.178	0.158	-0.252	-0.386	-0.385
	(0.242)	(0.247)	(0.583)	(0.766)	(0.493)
age 35 to 44 population rate	0.626**	0.589**	-0.271	-0.125	-0.158
	(0.244)	(0.250)	(0.846)	(1.015)	(0.608)
age 45 to 54 population rate	-0.115	-0.103	-0.416	-0.329	-0.347
	(0.276)	(0.281)	(0.644)	(0.629)	(0.465)
age 55 to 64 population rate	0.327	0.284	-0.521	-0.495	-0.537
	(0.222)	(0.225)	(0.585)	(0.503)	(0.481)
age over 65 population rate	0.451***	0.435***	-0.128	-0.343	-0.346
	(0.128)	(0.130)	(0.578)	(0.722)	(0.394)
black population rate	-0.105***	-0.104***	-0.031	-0.035	-0.023
	(0.020)	(0.019)	(0.068)	(0.070)	(0.095)
Hispanic population rate	-0.131***	-0.136***	-0.145	-0.153	-0.164
	(0.050)	(0.050)	(0.138)	(0.149)	(0.160)
female population rate	0.158	0.148	-0.118	-0.116	-0.137
	(0.108)	(0.113)	(0.569)	(0.625)	(0.357)
Constant	-0.417***	-0.399***	0.223	0.243	-0.925**
	(0.143)	(0.148)	(0.728)	(0.794)	(0.469)
ω					0.1651***
					(0.0001)
Observations	2,703	2,703	2,703	2,703	2,703
R-squared	0.056		0.011	0.017	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Unobserved propensity toward suicide

Following the Bayesian estimation algorithm provided in the Appendix, we rank a state's counties after each iteration based on their posterior unobserved propensity (δ). The posterior distribution of unobserved county propensity ranks, which are spatially correlated, can then be estimated. Figure 3 shows a scatterplot of the relationship between the ranks of estimated unobserved propensity toward suicide and the ranks of crude suicide rate. The X-axis indicates the mean and 95% highest posterior density (HPD) of county ranks of unobserved propensity toward suicide.[19] The Y-axis represents the county ranks of time-averaged crude suicide rate.[20] The higher a county's rank, the lower their ranking number and the greater their risk of suicide. For example, a county with the rank of 1 implies that it is the highest ranked county and is therefore at the greatest risk of suicide in its respective state. As evident from Figure 3(a), there is discordance between the ranks of unobserved propensity and the ranks of crude suicide rate for Florida.[21]

Miami-Dade county (43) in Florida is to the top left of Figure 3(a). This indicates that while Miami-Dade has one of lowest crude suicide rates, it is estimated to be the county with the highest risk of suicide based on unobserved propensity.[22] Alternatively, two other Florida counties, Gilchrist (20) and Holmes (29), are toward the bottom right of Figure 3(a). This implies that relative to other counties, both Gilchrist and Holmes have higher crude suicide rates compared to their lower estimated risk of suicide based on unobserved propensity. These relationships can also be seen in the maps presented in Figure 4 (a) and (c). The darker a

[19] The degree of uncertainty at the 95% confidential interval is represented by the length of solid line along a dot and the dot indicates the crude suicide rate rank and mean value of unobserved propensity ranks.
[20] The Y-axis ranks counties by average suicide rate over the study periods.
[21] The estimated correlation coefficient between the two ranks is 0.2696 in Florida and 0.8083 in Georgia.
[22] Refer to Tables A2 and A3 in the Appendix for county name and number.

county's color on the map, the higher its rank and risk of suicide. Miami-Dade, located in the southern-most tip of Florida, shows the darkest color based on unobserved propensity but the lightest color based on crude suicide rate. Gilchrist and Holmes, located in the north and north-west of Florida respectively, show the darkest color based on crude suicide rate while showing lighter colors based on unobserved propensity. Interestingly, the rank of crude suicide rates in Figure 4(a) does not show an obvious pattern of spatial clustering. In Figure 4(c) however, southern Florida presents darker coloring in unobserved suicide propensity, whereas in northern Florida, the unobserved suicide propensity is much less severe. This presents further evidence for the existence of spatial correlation when analyzing unobserved factors of suicides.

According to Figure 3(b), Georgia is estimated to have less discordance between the ranks of unobserved suicide propensity and the ranks of crude suicide rate relative to Florida. Clarke (29) and Bulloch (16) counties in Georgia are to the top left of Figure 3(b), indicating a lower crude suicide rate, but a higher estimated unobserved suicide propensity. Alternatively, there are no noticeable counties located at the bottom-right corner of Georgia's scatterplot. Bryan (15) in Georgia is around the middle-right of Figure 3(b), implying a moderate crude suicide rate but a very low unobserved suicide propensity. These patterns are confirmed in the maps of Figure 5(a) and 5(c). Clarke and Bulloch in the north-east and east of Georgia respectively show a lighter color based on crude suicide rate, but the darkest color based on unobserved propensity. Bryan in the south-east of Georgia exhibits the lowest unobserved suicide propensity although it has a higher crude suicide rate than its neighbor, Bulloch county.[23]

[23] We also estimate unobserved propensity towards suicide by combining Florida and Georgia together in the Bayesian model. The jointly estimated map of unobserved propensity ranks produces a mostly similar pattern to the separated maps of the two states. For instance, Miami-Dade in Florida and Clarke in Georgia still show relatively higher unobserved propensity towards suicide. This jointly estimated map is available from the authors upon request.

We rank counties in each state by the time trends of crude suicide rates as well.[24] The scatter plots of time trend ranks versus unobserved propensity ranks presented in Figure 6 and comparison between the maps (b) and (c) of Figures 4 and 5 show the discordance between these two ranks.[25] In other words, incorporation of a trend of rising or falling suicide rates in each county is not likely to make differences in the discordance found above when comparing the ranks of unobserved suicide propensity and the ranks of crude suicide rate.

These findings have valuable policy implications since the unobserved propensity is empirically proved to have a statistically significant effect on a county's suicide risk as discussed in Section 5.1. Public suicide prevention policies which solely target crude suicide rate or crude suicide time trend may be either ineffective or inefficient. Unobserved propensity should be considered together with the observable factors when such policies are implemented. As an example, Florida's efforts to provide proper educational facilities, public advertisement, medical treatment programs for depression, and stricter monitoring of the illegal possession of firearms and underage drinking would be better concentrated in counties like Miami-Dade as opposed to counties like Gilchrist and Holmes.

Finally, the maps present evidence for the spatial correlation of county suicide risk. Those counties that have similar ranks of unobserved propensities for suicide are clustered geographically. For example, Figure 4 shows that Miami-Dade (43) and Hendry (25), both of which are in the southern tip of Florida, have the highest unobserved suicide risks. The counties sharing a border with Miami-Dade or Hendry also have higher ranks of unobserved propensity toward suicide regardless of their crude suicide rates. Interestingly, high unobserved propensity

[24] We simply regress crude suicide rates on time for each county. We then decide the ranking of each county by taking the largest positive estimate as the highest rank and the greatest (in magnitude) negative estimate as the lowest rank.

[25] The estimated correlation coefficient between the two ranks is -0.1664 in Florida and 0.0369 in Georgia.

toward suicide spreads outward from southern Florida, but diminishes as it moves farther northward. Therefore, these high-risk counties not only tend to have a higher suicide risk themselves, but are also more likely to diffuse their risks into neighboring counties. Again, policies should be focused on counties similar to Miami-Dade and Hendry.

5.3 Probability to be the top 20 percent most risky counties

To convey more information regarding the uncertainty of the estimated ranks, we also compute the posterior probability for each county to be in the top 20 percent most risky counties based on the posterior distribution of unobserved propensity (δ) ranks.[26] We compare these with the crude suicide rate ranks for each county in Figure 7. For Florida especially, a substantial number of counties show a discrepancy between their raw ranks and their posterior probability of being in the top 20 percent. The counties located in the bottom left of the graph have relatively higher crude suicide rates but lower probabilities of being in the top 20 percent. Counties in the top right of the graph have lower crude suicide rates but higher probabilities of being in the top 20 percent. Figure 7 supports the findings discussed in Section 5.2. In Florida, Miami-Dade (43) has a low crude suicide rate but a high posterior probability of being in the top 20 percent of most risky counties. In Georgia, Clarke also (29) has a low crude suicide rate but a high posterior probability of being in the top 20 percent.

We also map the probability of each county being in the top 20 percent of most risky counties in Figure 8. It is obvious that Miami-Dade in Florida and Clarke in Georgia show the same pattern discussed in Section 5.2. The risky counties in Florida are mostly located in the southern portion of the state, and the risky counties in Georgia are more often in the north. This enables us

[26] The top 20 percent most risky counties are those with rank≤14th for Florida and rank≤32nd for Georgia.

to identify another feature of the estimated spatial correlation. South Georgia borders North Florida directly, and the spatial correlation of unobserved propensity toward suicide in the border counties is expressed in terms of light colors clustered around the borders of both states in Figure 8. The border counties across South Georgia and North Florida show similar characteristics regarding suicide, and are less likely to be in the top 20 percent most risky counties based on unobserved propensity.

6. Conclusion

A considerable amount of literature has analyzed the causes of suicide using data aggregated at large geographic levels. For example, national or sub-national level (e.g. the states in U.S. and NUTS-2 in Europe) analysis has been used extensively in previous literature. However, analysis within a large region is unlikely to capture sub-region-specific heterogeneity affecting suicide. If any omitted area heterogeneity is correlated with observables in the model, the empirical results will be biased. Estimating county-specific propensity with spatial dependence, we show that Florida and Georgia have different geographic patterns of suicides across counties even though the states share a border. In Florida, counties at higher risk of suicide are clustered in the south; but in Georgia, risky counties are more heavily clustered in the north. This implies that a considerable amount of previous suicide research ignoring sub-region-specific heterogeneity may provide misleading or invalid outcomes. Using county-level data and a hierarchical model incorporating spatially correlated county random effects, we are able to capture the unique unobservable suicide characteristics for each county.

The presence or absence of either sub-regional heterogeneity or time fixed effects can bring about different results in an empirical analysis of suicide. We find that the statistically significant effects of observable factors on suicide found in prior literature may be due to the exclusion of small area effects and time fixed effects. Without controlling for them, the true effect of unexplained county propensity and time trends may be hidden in observable factors. Therefore, policies focusing only on observable factors may rarely prove effective. Our empirical approach captures both county-specific effects and time trends which influence suicide mortality.

We also show that the unobserved county-specific propensity toward suicide is spatially correlated. The spatial dependence of county unobservable propensity has important policy implications. Our hierarchical model incorporating spatially correlated county random effects enables us to identify the counties which are not only likely at a greater risk of suicide themselves, but are also more likely to transmit their inclination to neighboring counties. Miami-Dade county in Florida and Clarke county in Georgia are particularly telling examples. Miami-Dade is one of the United States' most highly populated counties, and a common tourist destination for many Americans each year. It contains several cities and is also adjacent to the Atlantic Ocean. Those local area specific characteristics which tend to be spatially correlated should be considered in the analysis of suicide risk given their potential influence. Clarke county is home to the University of Georgia, implying that the mental health of friends and classmates living near one another may influence suicide decisions. Therefore, the mental state of college students should be adequately considered when structuring suicide prevention policy. To single out these and other similar counties for special treatment would perhaps be the most efficient policy. Government efforts targeting educational facilities, public advertisement, medical treatment for depression, and stricter monitoring of the illegal possession of firearms and underage drinking should be concentrated in such counties. Suicide prevention policies based solely on observables are likely to overlook counties similar to Miami-Dade and Clarke whose observable factors obscure their true risk.

While our study provides a substantial contribution to the literature, there are still limitations. Due to inaccessibility of similar mortality data for more states, our analysis is confined to Florida and Georgia. In addition, some potentially important variables are omitted in our analysis due to lack of data. For example, variables of home foreclosures, marital records, religion, and weather are not included in our estimation. With this said, it is likely that many of the omitted variable's characteristics are subsumed by the unobserved county-specific propensity which we are able to capture in our model.

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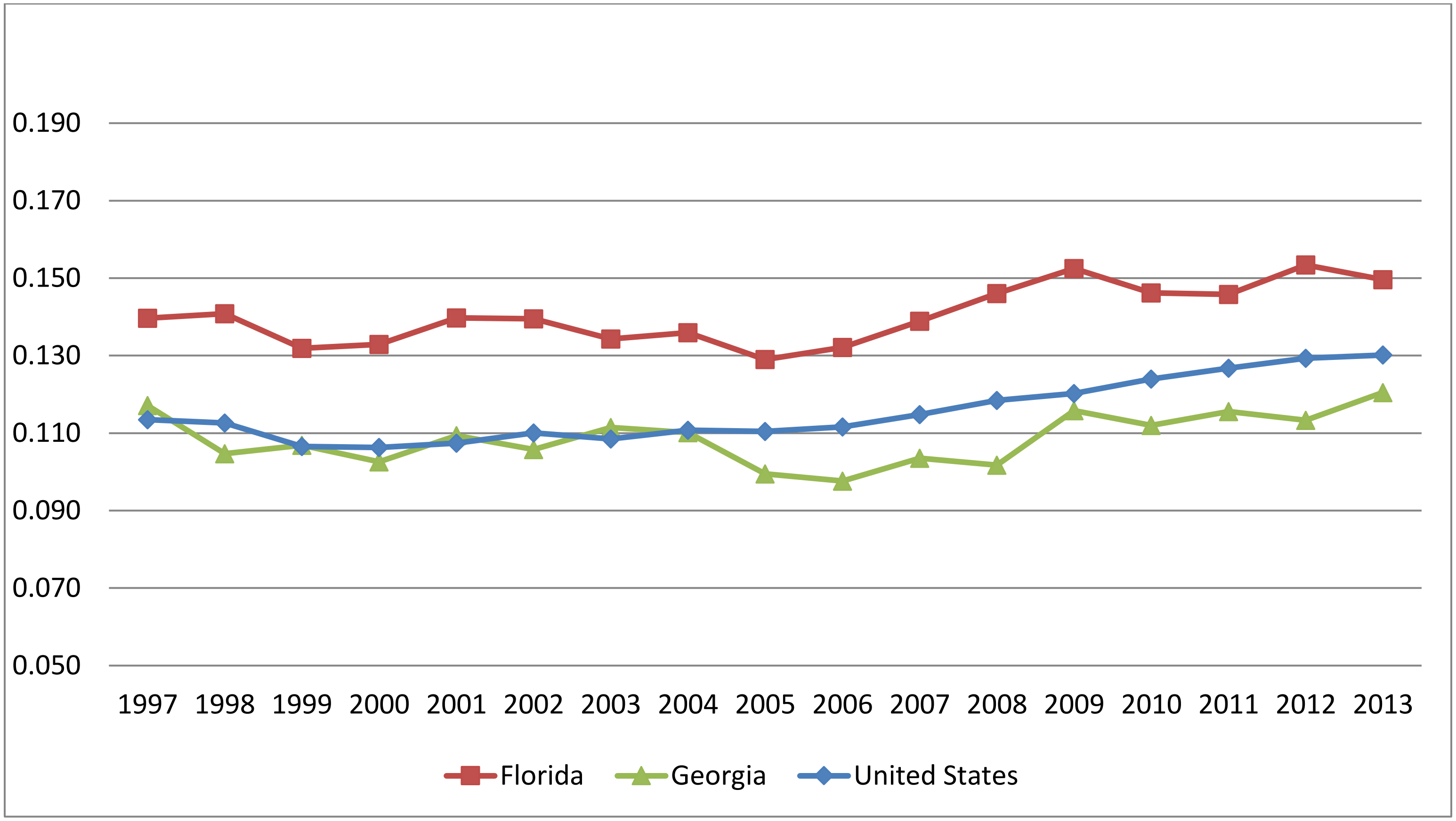
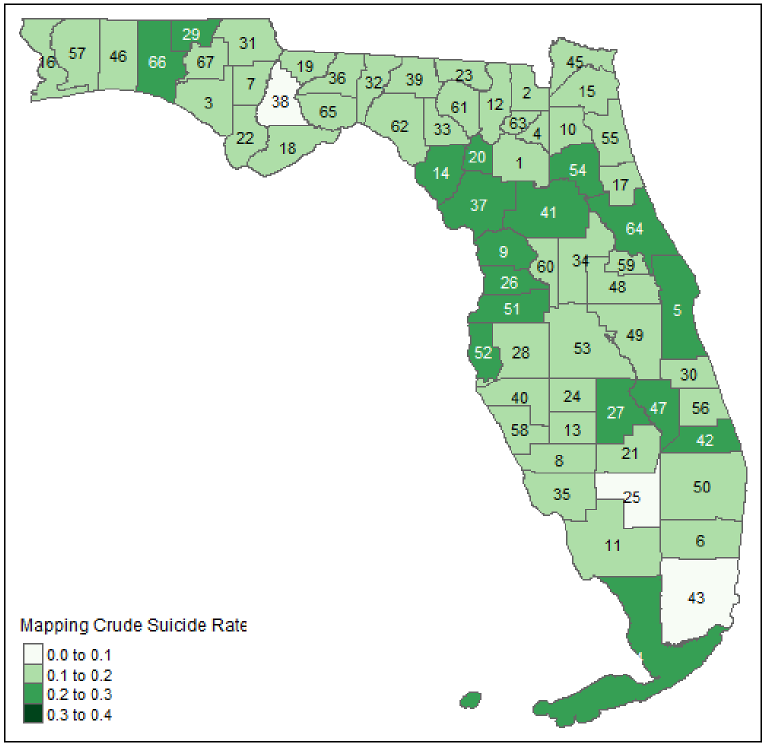
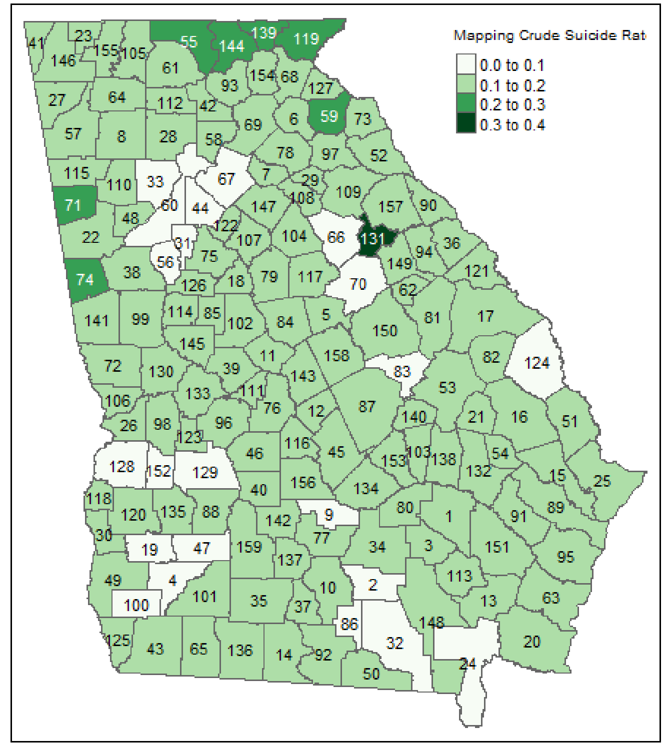


Figure 1. Time Trends of Suicide Rate (per 1,000 population) in Florida, Georgia and U.S.



(a) Florida



(b) Georgia

Figure 2. County Maps of Suicide Rate (per 1,000 population)

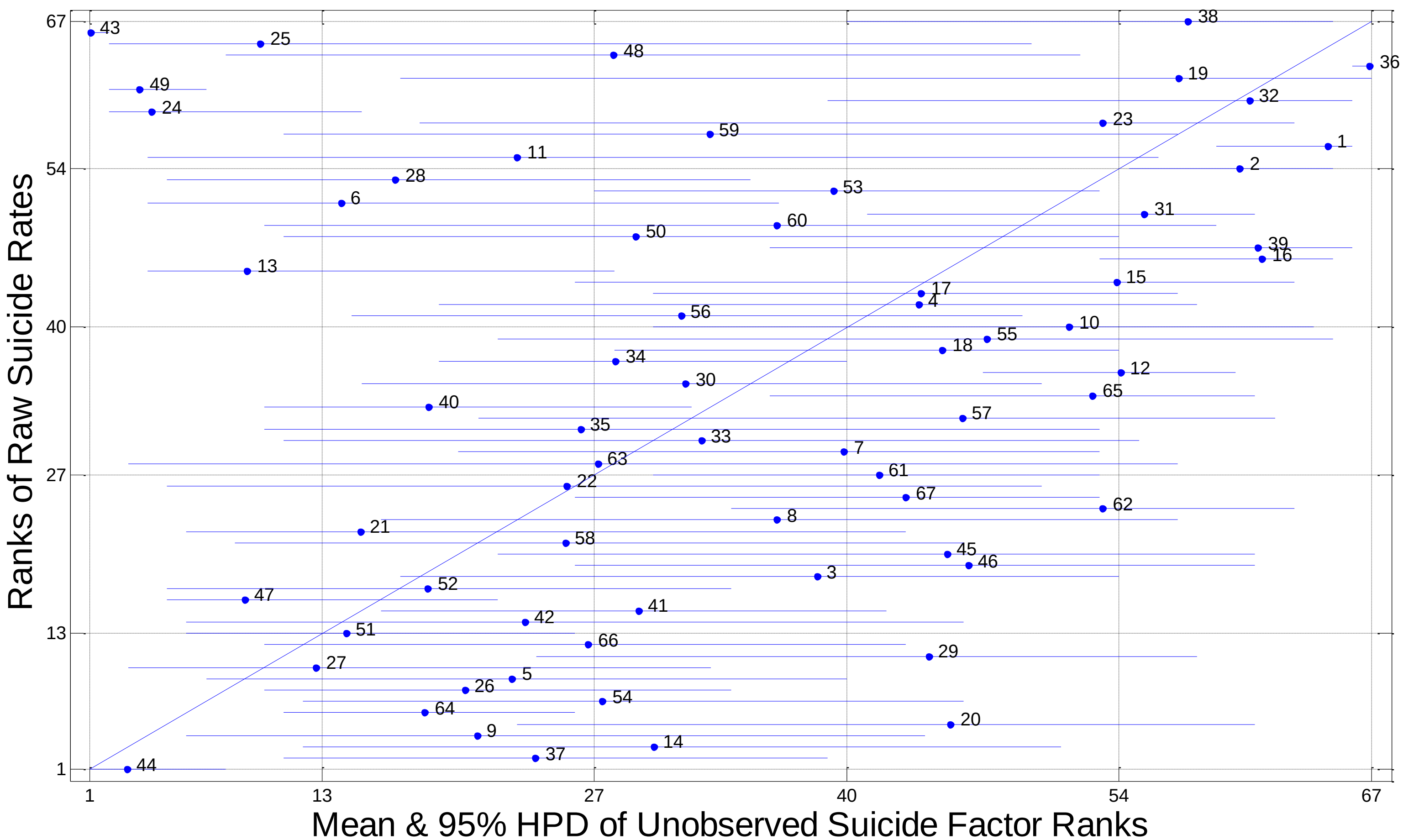


Figure 3 (a). Florida - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Rate

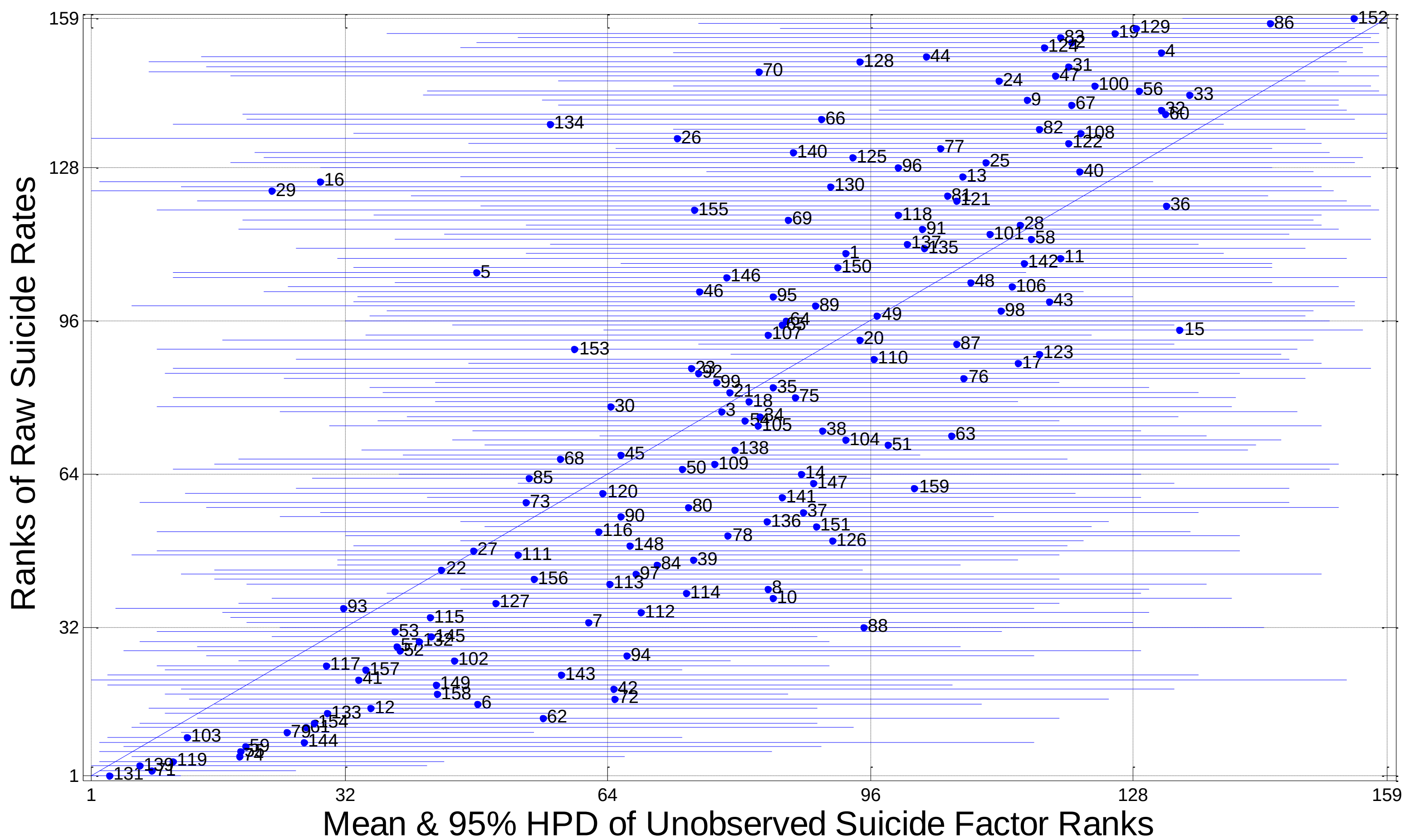
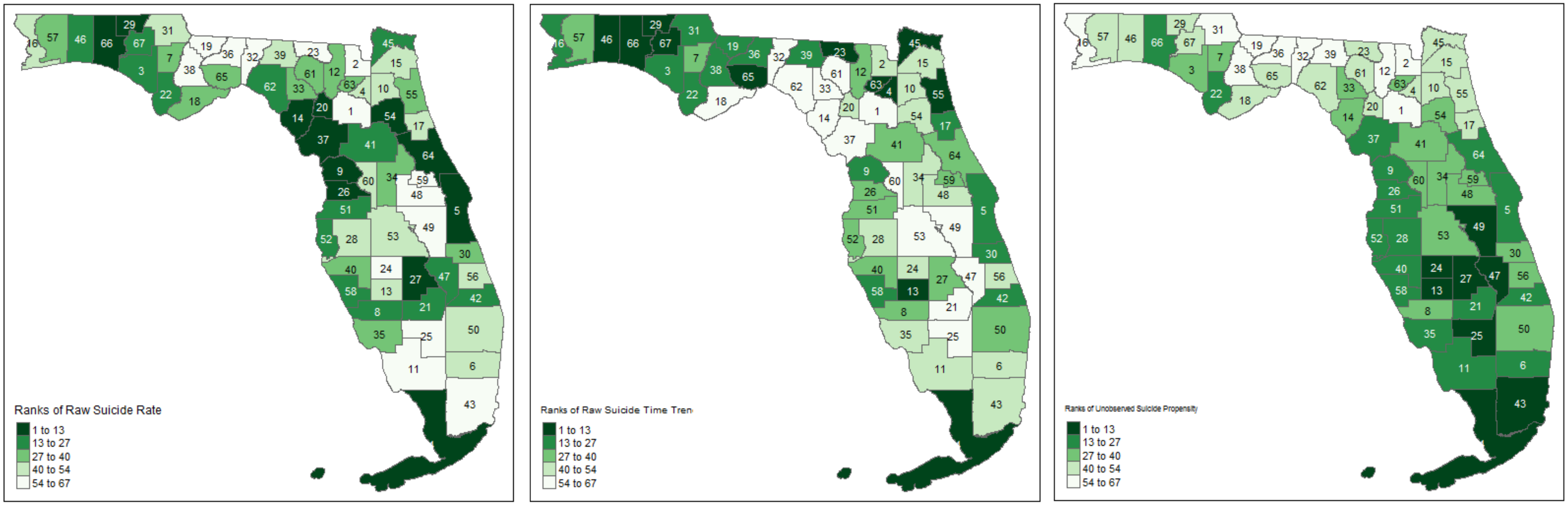
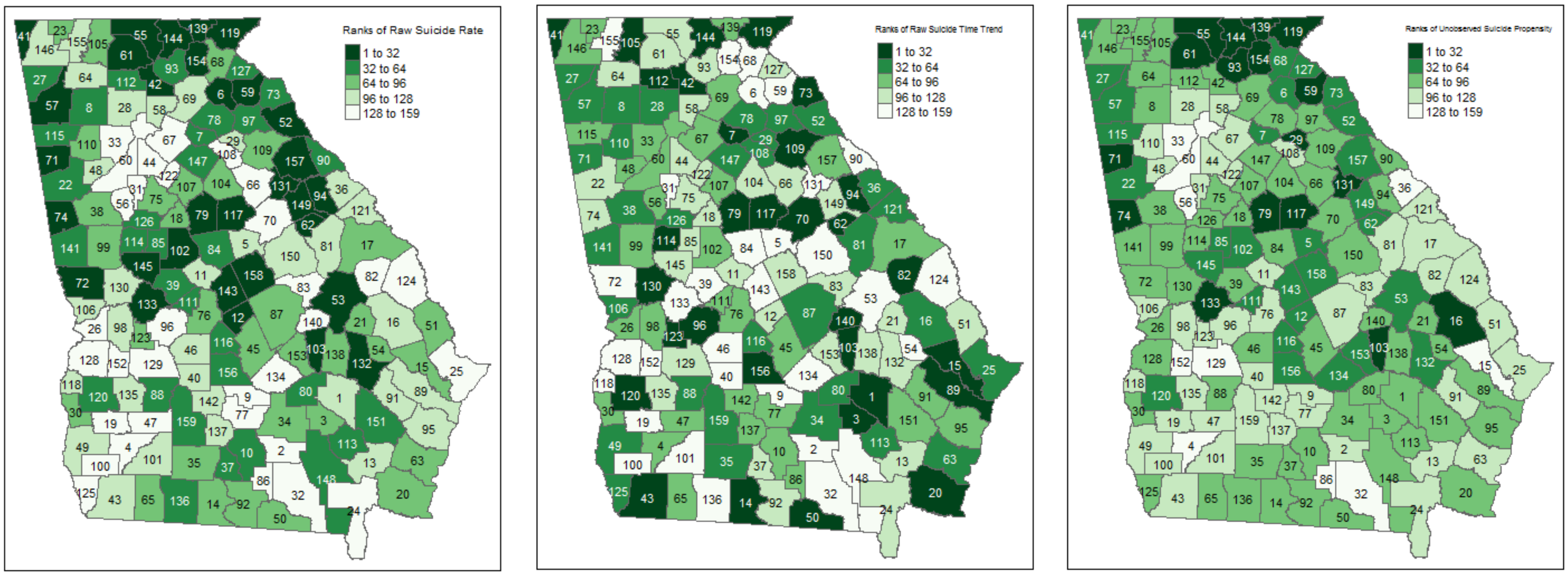


Figure 3 (b). Georgia - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Rate



(a) Rank of Time-Average Crude Suicide Rate **(b) Rank of Crude Suicide Rate Time Trend** **(c) Average Rank of Unobserved Propensity**

Figure 4. Maps of County Ranks in Florida



(a) Rank of Time-Average Crude Suicide Rate **(b) Rank of Crude Suicide Rate Time Trend** **(c) Average Rank of Unobserved Propensity**

Figure 5. Maps of County Ranks in Georgia

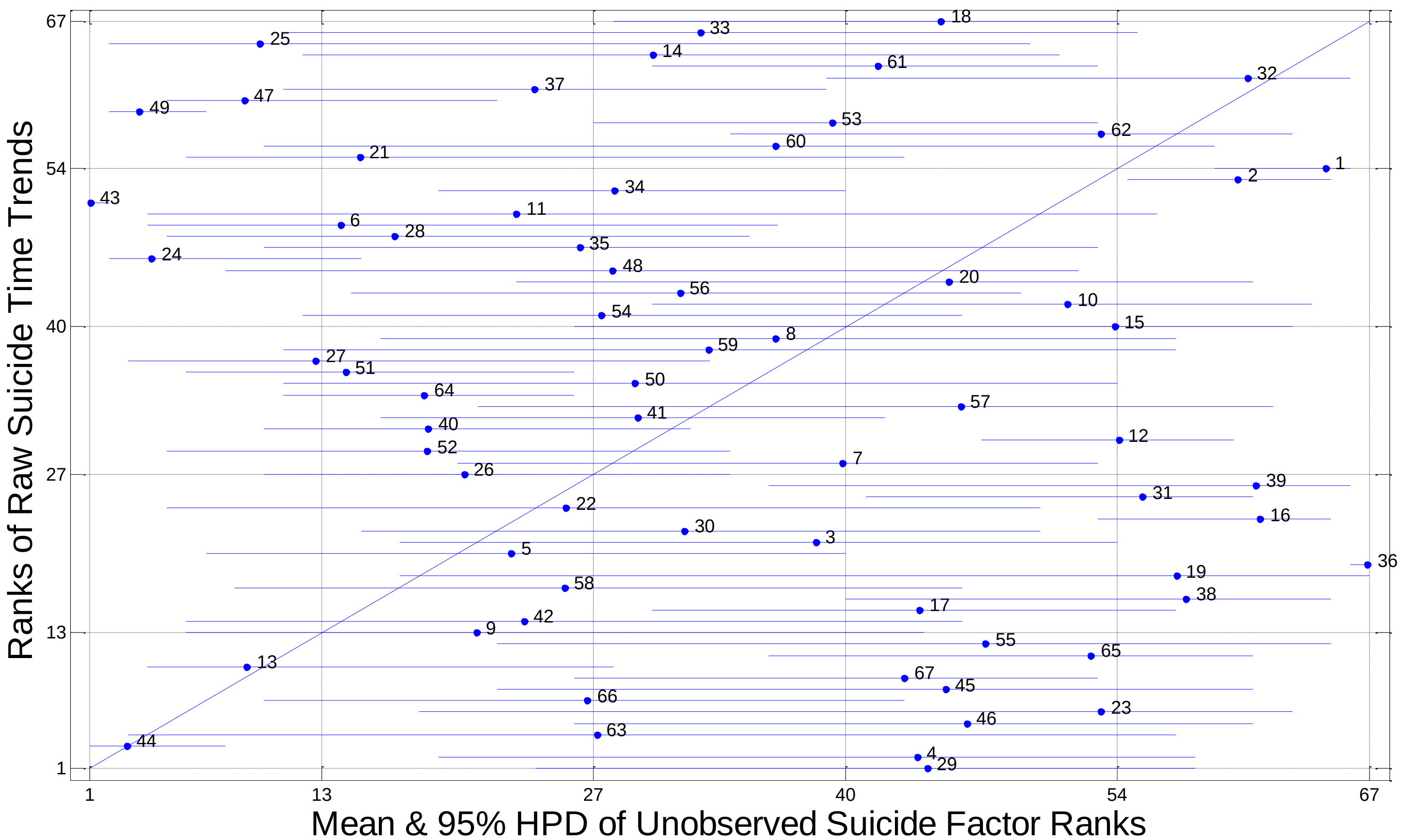


Figure 6 (a). Florida - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Time Trend

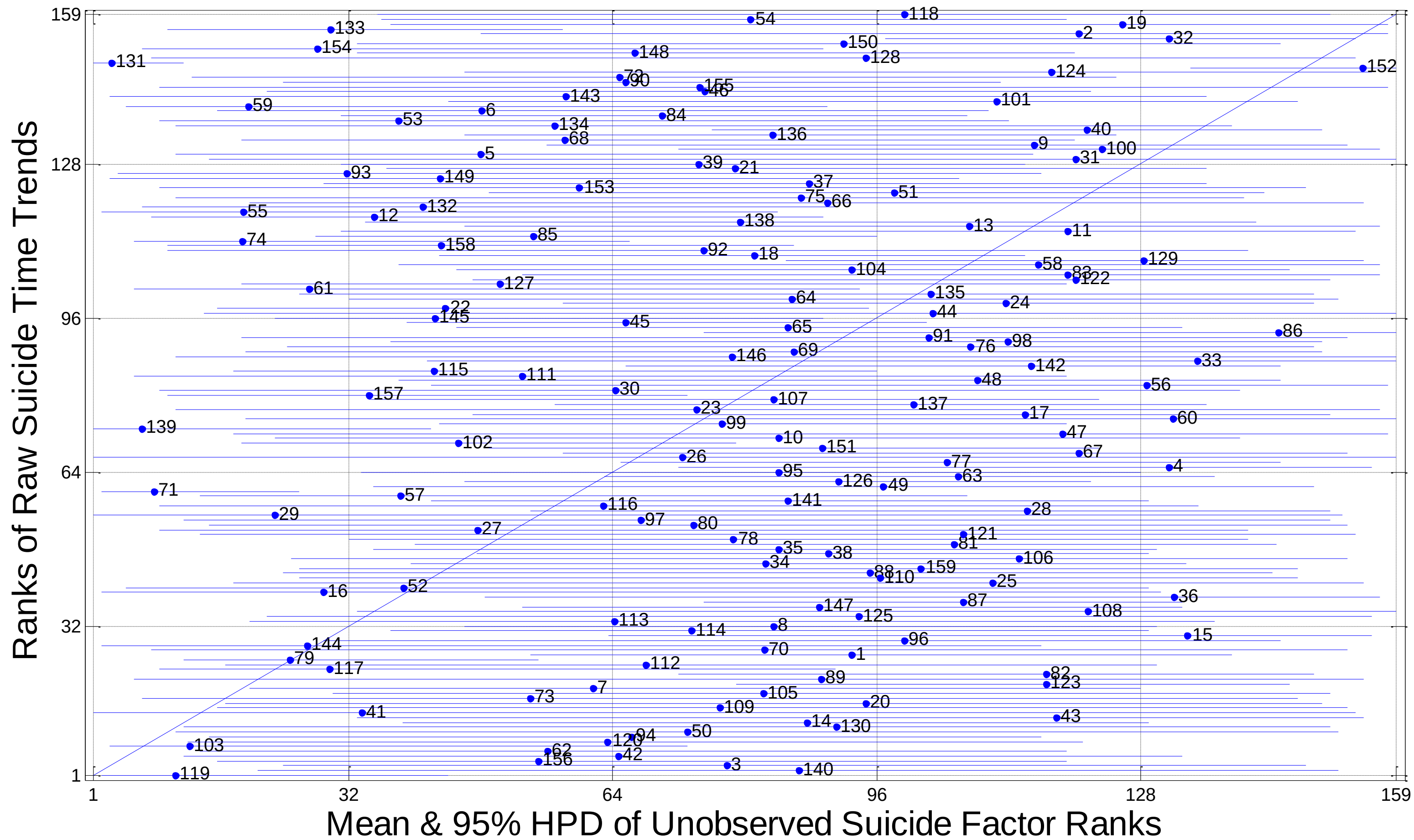


Figure 6 (b). Georgia - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Time Trend

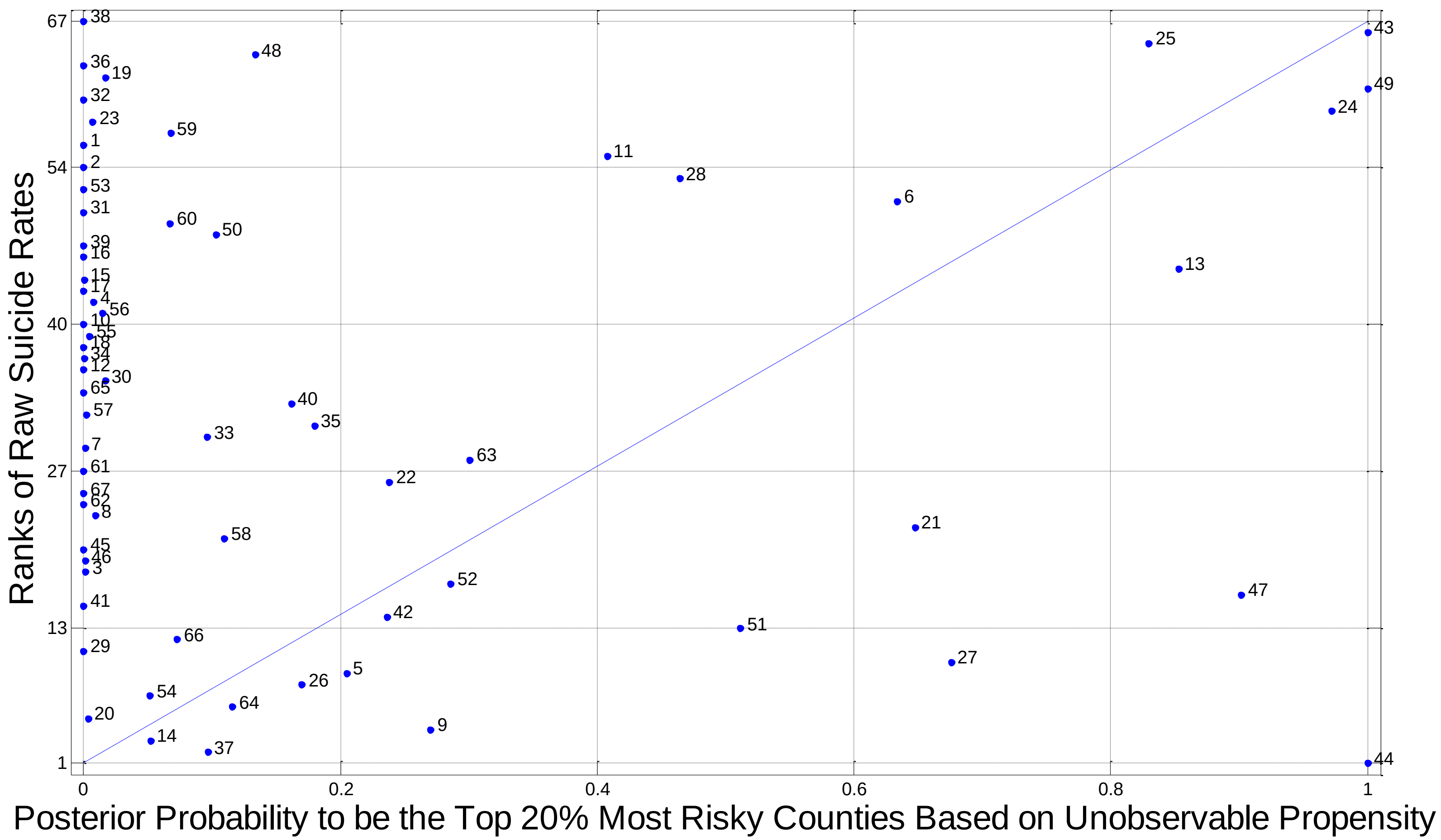


Figure 7 (a). Florida - Posterior Probability to be the Top 20% Most Risky Counties V.S. Ranks of Crude Suicide Rate

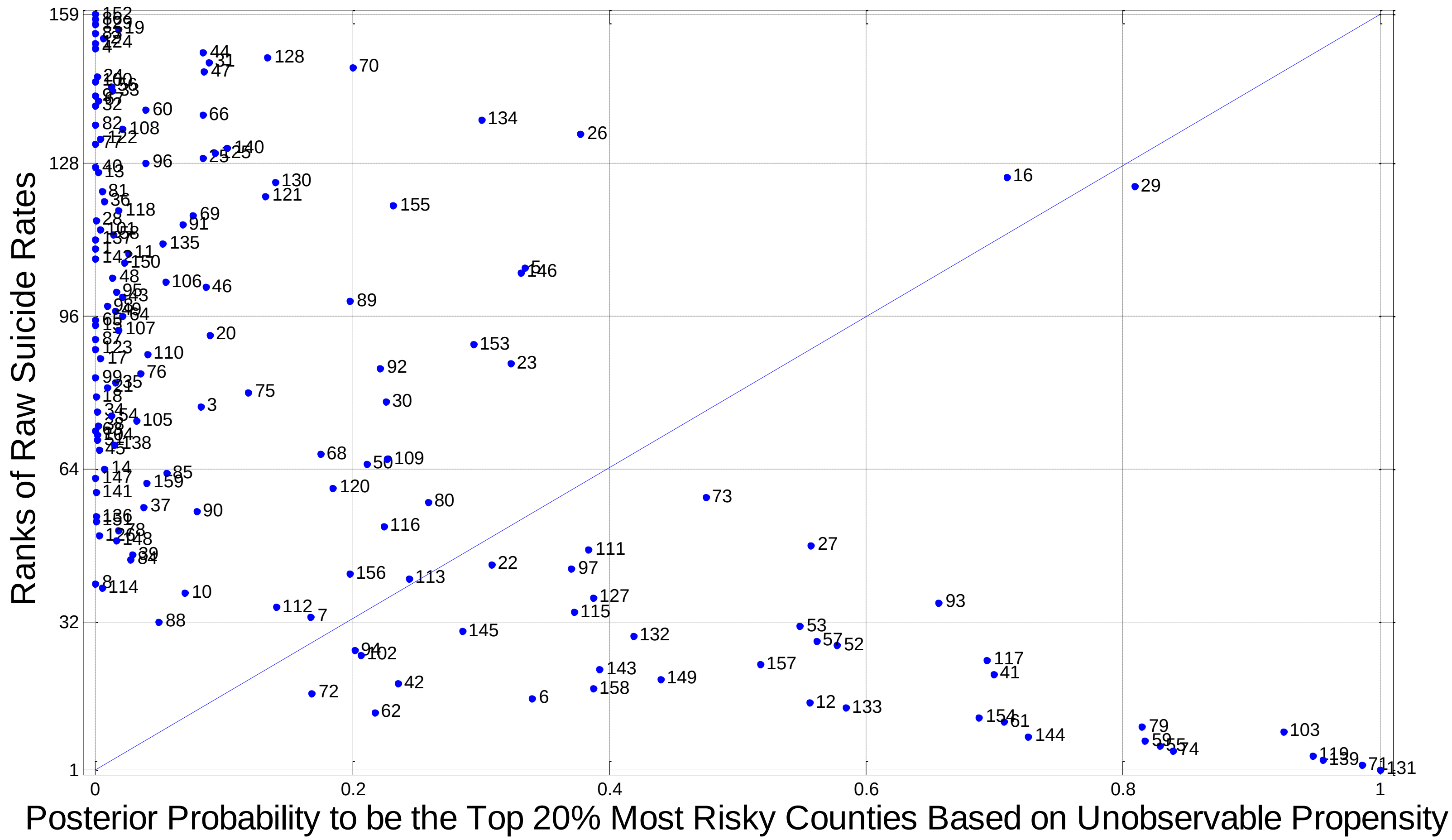
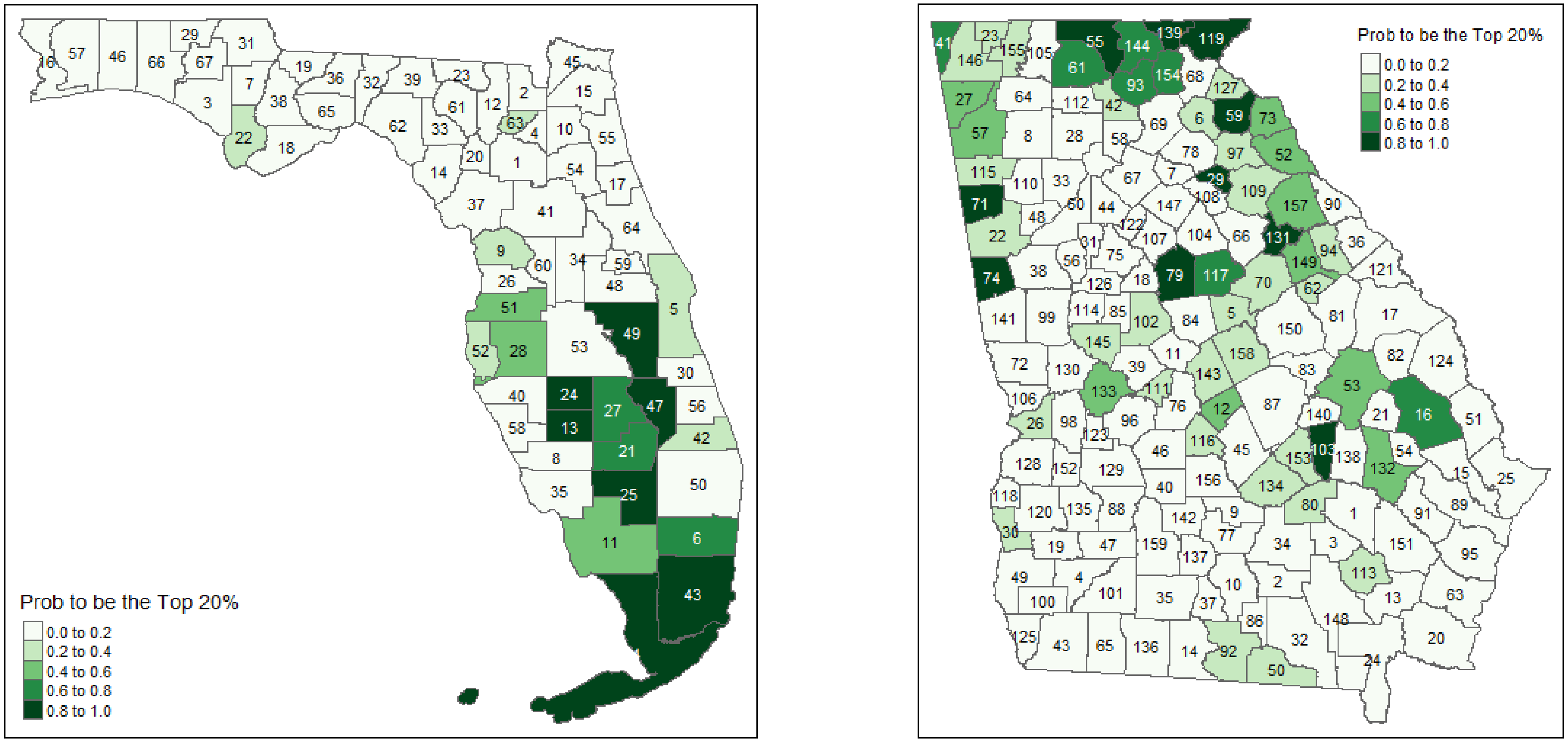


Figure 7 (b). Georgia - Posterior Probability to be the Top 20% Most Risky Counties V.S. Ranks of Crude Suicide Rate



(a) Florida **(b) Georgia**

Figure 8. Maps of "Probability to be the Top 20% Most Risky Counties" based on Unobserved Propensity

Appendix

Bayesian Algorithm with Spatially Correlated Random Effects

To examine the determinants of suicide, we employ the following two-level hierarchical model with spatially correlated random effects. The conditionally autoregressive (CAR) specification is applied to allow for any spatial correlation (Besag 1974; Hogan and Tchernis 2004; Chamarbagwala and Tchernis 2010; Eibich and Ziebarth 2014).

$$\text{Level I:} \quad Y = X\beta + C\delta + \varepsilon \tag{2}$$

$$\text{Level II:} \quad \delta \sim N(0_N, \psi T) \tag{3}$$

For Level I: Y is an $NT\times 1$ vector of y_{it}, with $i = 1, \dots, N$ and $t = 1, \dots, T$.[27] X is an $NT\times K$ matrix of x_{it} and λ_t. β is a $K\times 1$ vector of regression coefficients. C is an $NT\times N$ indicator matrix with $C_{it} = 1$ for county i at any time t. δ is an $N\times 1$ vector of county random effects. δ represents unobserved county propensity toward suicide. ε is the $NT\times 1$ vector of idiosyncratic error, such that $\varepsilon_{it} \sim iid\ N(0, \sigma^2)$.

For Level II: $\psi = (I - \omega R)^{-1}$, where R is an $N\times N$ spatial correlation matrix, with $R_{ij} = 1$ if county i and $j \neq i$ share a border. Otherwise $R_{ij} = 0$, and $R_{ii} = 0$. ω is the degree of spatial dependence. $T = I_N \tau^2$ measures the county variation in δ independent of the spatial correlation level.[28]

[27] Suicide death is considered a Poisson random variable in prior Bayesian literature because of its rarity. Alternatively, we use average suicide rate as our dependent variable. This facilitates direct comparison with the results of our panel regressions, which is one of our paper's most important contributions. Additionally, the percentage of county-years without a suicide in our sample is only 2.9% in Florida and 15.6% in Georgia, implying that it is rather common.

[28] Our method is different from how prior literature incorporates spatial correlation. For example, a Bayesian hierarchical model constructed by Cheung et al. (2012) and Hsu et al. (2015) is that Standardized Mortality Ratio

Using the Markov Chain Monte Carlo (MCMC) technique, we estimate the posterior distributions of the parameters: $\beta, \delta, \sigma^2, \omega$, and τ^2. Our estimation uses 3500 total iterations, and the first 500 iterations are removed for burn-in. For each iteration, the steps of the estimation algorithm are summarized in Table A1. We use both a Gibbs sampling algorithm and a Metropolis-Hasting algorithm for ω. Diffuse conjugate prior densities for each parameter are used in the estimation.[29] β and δ are normally distributed while σ and τ follow inverse gamma distribution. Specifically, as is described in Table A1, in step 1, we sample β from $Y - C\delta = X\beta + \varepsilon$. In step 2, we sample δ from $Y - X\beta = C\delta + \varepsilon$. In step 3, we sample σ^2 from $Y = (X\beta + C\delta) + \varepsilon$. In step 4, we sample ω using a Metropolis-Hasting algorithm, where $\xi_1, \dots, \xi_N$ are the ordered eigenvalues of the spatial correlation matrix R, ξ_1 is the minimum eigenvalue, and ξ_N is the maximum eigenvalue. In step 5, we sample τ^2 from $\psi^{-\frac{1}{2}}\delta = U$, where $U \sim N(0, T)$.

SMR $= \alpha + h_i + b_i$, or SMR $= X\beta + h_i + b_i$, where α is the overall level of relative risk, h_i represents regional variation independent of spatial correlation, and b_i indicates variation due to spatial dependence. $h_i + b_i$ is referred to as the error term. Our specification, however, separates the unobserved county propensity toward suicide (δ) from the error term (ε).

[29] For example, a diffuse prior with mean of 0 and variance of 1,000 is used in step 1 for β.

Table A1. Gibbs Sampling Algorithm for β, δ, σ^2, ω, and τ^2

Step 1	**Prior Distributions**	**Posterior Distributions**
β	$N(b,B)$	$N(a,A)$
	$b=0$	$A=(B^{-1}+X^{'}X/\sigma^2)^{-1}$
	$B=1000$	$a=A(bB^{-1}+X^{'}(Y-C\delta)/\sigma^2)$
Step 2	**Prior Distributions**	**Posterior Distributions**
δ	$N(0_N,V_\delta)$	$N(d,D)$
	$V_\delta=\psi T$	$D=(V_\delta{}^{-1}+C^{'}C/\sigma^2)^{-1}$
	$\psi=(I-\omega R)^{-1}$, $T=I_N\tau^2$	$d=D(C^{'}(Y-X\beta)/\sigma^2)$
Step 3	**Prior Distributions**	**Posterior Distributions**
σ^2	$IG(\alpha_0,\gamma_0)$	$IG(\alpha_1,\gamma_1)$
	$\alpha_0=0.001$	$\alpha_1=NT/2+\alpha_0$
	$\gamma_0=0.001$	$\gamma_1=(Y-X\beta-C\delta)'(Y-X\beta-C\delta)/2+\gamma_0$
Step 4	**Prior Distribution**	**Proposal Density**
ω	$\pi(\omega)$	$q(\omega^t\|\omega^c)=\omega^c+u$, random walk
	$N(0,V_\omega)I(\xi_1^{-1}<\omega<\xi_N^{-1})$	$u\sim N(0,\rho^2)$, where $\rho^2$is a tuning parameter
	The candidate ω^t is accepted with probability: $min\{1,\frac{f(\delta\|\psi^t,T)\pi(\omega^t)q(\omega^c\|\omega^t)}{f(\delta\|\psi^c,T)\pi(\omega^c)q(\omega^t\|\omega^c)}\}$ where $f(\delta\|\psi,T)\pi(\omega)$ is the target density of ω	
Step 5	**Prior Distributions**	**Posterior Distributions**
τ^2	$IG(\alpha_{00},\gamma_{00})$	$IG(\alpha_{11},\gamma_{11})$
	$\alpha_{00}=0.001$	$\alpha_{11}=N/2+\alpha_0$
	$\gamma_{00}=0.001$	$\gamma_{11}=\ (\psi^{-\frac{1}{2}}\delta)'(\psi^{-\frac{1}{2}}\delta)/2+\gamma_{00}$

Table A2. County Names and Number in Florida

#	Name	#	Name	#	Name	#	Name	#	Name	#	Name
1	Alachua	13	Desoto	25	Hendry	37	Levy	49	Osceola	61	Suwannee
2	Baker	14	Dixie	26	Hernando	38	Liberty	50	Palm Beach	62	Taylor
3	Bay	15	Duval	27	Highlands	39	Madison	51	Pasco	63	Union
4	Bradford	16	Escambia	28	Hillsborough	40	Manatee	52	Pinellas	64	Volusia
5	Brevard	17	Flagler	29	Holmes	41	Marion	53	Polk	65	Wakulla
6	Broward	18	Franklin	30	Indian River	42	Martin	54	Putnam	66	Walton
7	Calhoun	19	Gadsden	31	Jackson	43	Miami-Dade	55	Saint Johns	67	Washington
8	Charlotte	20	Gilchrist	32	Jefferson	44	Monroe	56	Saint Lucie		
9	Citrus	21	Glades	33	Lafayette	45	Nassau	57	Santa Rosa		
10	Clay	22	Gulf	34	Lake	46	Okaloosa	58	Sarasota		
11	Collier	23	Hamilton	35	Lee	47	Okeechobee	59	Seminole		
12	Columbia	24	Hardee	36	Leon	48	Orange	60	Sumter		

Table A3. County Names and Number in Georgia

#	Name	#	Name	#	Name	#	Name	#	Name	#	Name
1	Appling	31	Clayton	61	Gilmer	91	Long	121	Richmond	151	Wayne
2	Atkinson	32	Clinch	62	Glascock	92	Lowndes	122	Rockdale	152	Webster
3	Bacon	33	Cobb	63	Glynn	93	Lumpkin	123	Schley	153	Wheeler
4	Baker	34	Coffee	64	Gordon	94	McDuffie	124	Screven	154	White
5	Baldwin	35	Colquitt	65	Grady	95	McIntosh	125	Seminole	155	Whitfield
6	Banks	36	Columbia	66	Greene	96	Macon	126	Spalding	156	Wilcox
7	Barrow	37	Cook	67	Gwinnett	97	Madison	127	Stephens	157	Wilkes
8	Bartow	38	Coweta	68	Habersham	98	Marion	128	Stewart	158	Wilkinson
9	Ben Hill	39	Crawford	69	Hall	99	Meriwether	129	Sumter	159	Worth
10	Berrien	40	Crisp	70	Hancock	100	Miller	130	Talbot		
11	Bibb	41	Dade	71	Haralson	101	Mitchell	131	Taliaferro		
12	Bleckley	42	Dawson	72	Harris	102	Monroe	132	Tattnall		
13	Brantley	43	Decatur	73	Hart	103	Montgomery	133	Taylor		
14	Brooks	44	DeKalb	74	Heard	104	Morgan	134	Telfair		
15	Bryan	45	Dodge	75	Henry	105	Murray	135	Terrell		
16	Bulloch	46	Dooly	76	Houston	106	Muscogee	136	Thomas		
17	Burke	47	Dougherty	77	Irwin	107	Newton	137	Tift		
18	Butts	48	Douglas	78	Jackson	108	Oconee	138	Toombs		
19	Calhoun	49	Early	79	Jasper	109	Oglethorpe	139	Towns		
20	Camden	50	Echols	80	Jeff Davis	110	Paulding	140	Treutlen		
21	Candler	51	Effingham	81	Jefferson	111	Peach	141	Troup		
22	Carroll	52	Elbert	82	Jenkins	112	Pickens	142	Turner		
23	Catoosa	53	Emanuel	83	Johnson	113	Pierce	143	Twiggs		
24	Charlton	54	Evans	84	Jones	114	Pike	144	Union		
25	Chatham	55	Fannin	85	Lamar	115	Polk	145	Upson		
26	Chattahoochee	56	Fayette	86	Lanier	116	Pulaski	146	Walker		
27	Chattooga	57	Floyd	87	Laurens	117	Putnam	147	Walton		
28	Cherokee	58	Forsyth	88	Lee	118	Quitman	148	Ware		
29	Clarke	59	Franklin	89	Liberty	119	Rabun	149	Warren		
30	Clay	60	Fulton	90	Lincoln	120	Randolph	150	Washington		