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T2 ________________		F2 ________________
T3 ________________	Problem Chosen	F3 ________________
T4 ________________	C	F4 ________________

2019
MCM/ICM
Summary Sheet

The ODE-SE Model Characterizing the Opioid Crisis

In recent years, the opioid crisis has become a worldwide problem and brought great losses to the United States. To find an effective way to solve this difficulty, our team build an opioid spreading model to find the pattern and characteristics, using PCA to process data, which makes the solution fit well with the data provided.

First, we **preprocess the data**, including the missing value of some counties. In order to keep the same amount of data every year, we add an entry with zero, which indicates the county has no drug reports in that year.

Second, in order to simplify the analysis process, we use **principle component analysis** to reduce the dimension of the original data. From the component matrix, we find the geographical significance of the factors. According to the 7 factors, we divide the 461 counties into **7 regions** with different characteristics, which can explain 100% of information.

Then, we classify all the types of drugs into **three different types**: heroin, commonly prescribed opioids and other synthetic opioids.

After that, we build an **ODE model** to describe the spread and characteristics of the opioid crisis. By adjusting the parameters in the equations, the result can fit the actual data well to some extent. Using those parameters, especially the **threshold $\mathbf{R_0}$**, we predict the outbreak of different types of drugs in different regions. For example, in the south part of the five states, there is a greater possibility to start a heroin abuse.

To make our model more accurate and effective, we divide the socio-economic data provided into five categories (**age, households, marital status, disability status, entry**) and take these five significant factors into consideration. The improved model (**ODE-SE**, ODE with socio-economic factors) fit the actual data better, especially when the curve fluctuates severely. If a county has more females, more households, more teenagers or higher proportion of unmarried, it is more likely to outbreak an opioid crisis.

Finally, for the governors of NFLIS and CDC, we prepare a memo to convey our sincere advices and recommended actions. e.g. concerning more about teenagers, which is not mature enough to resist the temptation of drugs.

Keywords: PCA, ODE Modeling, Opioid Spreading, Socio-Economic Factors

Memo
From: Team 1906771 MCM 2019

To: The Chief Administrator, DEA/NFLIS Database

Date: 28, January 2019

Subject: Ways to Counter Opioid Crisis

Purpose

Trying to model and counter the national opioid crisis USA is experiencing, we analyze the NFLIS data as well as the U.S. Census socio-economic data provided and find some patterns and characteristics of the reported opioid incidents. And we propose some options to counter the opioid crisis.

Patterns and Characteristics

Due to the huge number of total counties of the five states, we use PCA to decrease the dimension of the data. After dimensionality reduction, we divide all the counties into 7 regions, and the regions show a strong geographical significance. Region 1 and 2 are basically located near the interstate highways, which means the effect of transportation cannot be omitted. Region 3 is located in the south of the five states and region 4 is located in the west.

In addition, we classify all the drugs into three classes: heroin, commonly prescribed opioids and other synthetic opioids. After processing the data of 7 factors, we find that almost all kinds of drug reports decline with time in region 1 and 2, which might show the control of government in those places. In region 3, the south part of the 5 states, the curve shows a shape of ‘w’, which might be caused by government control and the native who take drugs.

Something more interesting appears when we take socio-economic data into account. We find that if a county has more females, more bachelors, more teenagers and more households, it will have more drug reports.

Prediction

We use our model to predict the future of the opioid crisis. And we find that different types of drug crisis might happen in different regions. For example, the counties in the south are more likely to start an opioid abuse, and counties in region 3 or region 4 are at a higher risk of other synthetic opioids outbreak.

Recommended Actions

According to our analysis, we recommend some actions for the five states to counter the opioid crisis.

Governments should consider regulating opioids to prevent people from becoming addicted to drugs.

The society needs to strengthen the propaganda on drug control which makes people realize the harm of drugs and stay away from drugs. Preventing is more import and effective than treatment.

The authorities have to focus on the treatment of drug addicts and force them to stop.

Contents

1. Introduction

1.1 Problem Background

The opioid crisis, including those involving opioids, continues to increase in the United States. Deaths from drug overdose are increasing among both men and women, all races, and adults of nearly all ages[1]. The misuse of and addiction to opioids—including synthetic and non-synthetic opioids, either for the treatment and management of pain or for recreational purposes—is a serious national crisis that affects public health as well as social and economic welfare. The situation of 2017 in five U.S. states can be seen in **Figure 1**.

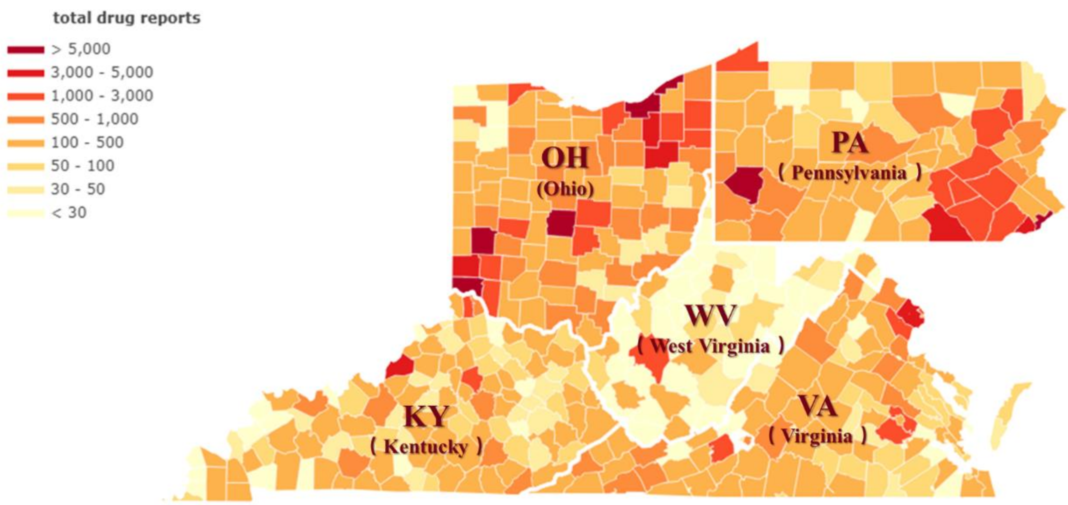

Figure 1: Total drug reports in five U.S. states on 2017.

CDC's Injury Center looks at deaths and nonfatal overdoses for four categories of opioids: Methadone, Synthetic opioids, Heroin, Other opioids.

Figure 2 on page 2 shows drug reports with three categories of opioids, as well as all opioids overall. And we are tracking how and when drug reports from the three different types of opioids have increased.

1.2 Our Work

We are asked to build a realistic, effective, and sensible model to describe the spread and characteristics of the reported opioid. Our model should consider not only the spread of the drug, the characteristics of the drug, possible start locations, onset to start, but also other socio-economic data that we consider necessary. To further present our solution, we arrange our paper as follows.

The introduction part expounds the background, significance of this thesis, problem-solving ideas and thesis structure.

In section two, we give out the reliable assumptions and notations to simplify the model.

In section three, we establish a model to solve these problems, principal component analysis model and the ODE-SE model.

In section four, through factor analysis model, we synthesize numerous indexes, eliminate overlapping information of 461 counties, and reduced the input dimension of opioid spreading model. Then we apply the opioid spreading model to predict spread and character of the different types of reported opioid based on NFLIS data. Using the opioid spreading model, meanwhile, to determine where and when they will occur in the future. Next, we analyze other critical factors. We use the U.S. Census socio-economic data provided to determine the opioid use. And we identify some possible strategy countering the opioid crisis.

Finally, the strengths and weaknesses of the model are discussed in detail.

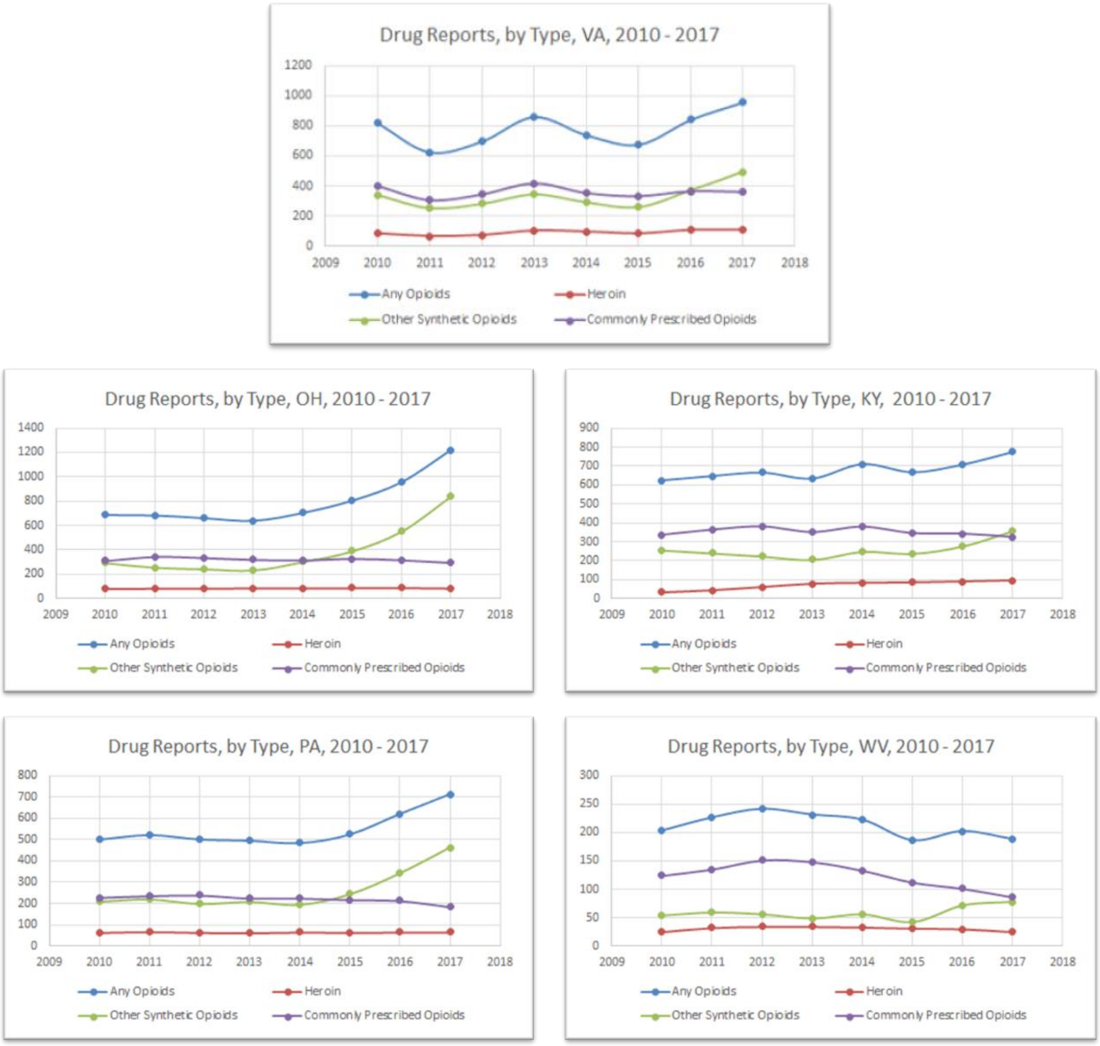

Figure 2: The drug reports with three categories of opioids in five states during 2010 to 2017.

2. Model Assumption、Terminology and Notation

2.1 Model Assumption

To simplify the problem, we made some assumptions.

- All the given data are valid and the five states have the same quantitative standards.
- The different types of drugs a person takes are independent.
- Drug users consist of those who are actively treated and those who are not.
- People who receive treatment are at risk of taking drugs again
- From 2010 to 2017, there is no change in non-human factors such as natural disasters.
- Suppose the initial state of the opioid model is N_0.

2.2 Terminology

County, (in the U.S.) an administrative or political subdivision of a state; a region having specific boundaries and some level of governmental authority.

Methadone, a synthetic opioid

Synthetic opioids, other than methadone (drugs like tramadol and fentanyl)

Heroin, an illicit (illegally made) opioid synthesized from morphine that can be a white or brown powder, or a black sticky substance.

Other opioids (including morphine and codeine) and semi-synthetic opioids (drugs like oxycodone, hydrocodone, hydromorphone, and oxymorphone)

Socio-economic factors, factors within a society that describe the relationship between social and economic status and class such as education, income, occupation, and employment.

2.3 Notation

Table 1: Notation

Symbol	Description
R_0	Basic reproduction number
N	Total population
S	The number of susceptible individuals in the population (range from age 15–64)
U_0	Number of untreated opioid users; First-time and recurrent opioid users
U_1	Number of opioid users being treated
Λ	The number of individuals entering the susceptible population
γ	Rate of natural mortality
β_0	The possibility of becoming a opioid user
β_1	The possibility that an opioid user will relapse opioid treatment
ρ	The proportion of opioid users entering the treatment
α_0	Removal rates, including mortality; Untreated rate; Spontaneous detoxification rate
α_1	Removal rates, including mortality; Success "cure" rate
Y	The number of teenagers taking opioid
C	The number of opioid users caused by gender differences
D	The number of the disabled taking opioid
Q	The number of the natives taking opioid

β_{Y_0}	The possibility of becoming an opioid user among teenagers
β_{C_0}	The possibility of becoming an opioid user caused by gender differences
β_{D_0}	The possibility of becoming an opioid user among the disabled
β_{Q_0}	The possibility of becoming an opioid user among natives
α_e	Proportion of stopping drug use due to economic conditions
α_C	Removal rates, including mortality; Untreated rate; Spontaneous detoxification rate among teenagers
α_Y	Removal rates, including mortality; Untreated rate; Spontaneous detoxification rate caused by gender differences
α_D	Removal rates, including mortality; Untreated rate; Spontaneous detoxification rate among the disabled
α_Q	Removal rates, including mortality; Untreated rate; Spontaneous detoxification rate among natives

3. The Basic Model

3.1 Factor Analysis Model

We use principal component analysis to establish the model. We recombine a number of previously correlated indicators (here, 461 county indicators) into a new set of unrelated composite indicators (here, 7 factors) to replace the original indicators.

3.1.1 Standardization of Raw Indicator Data

With *n* samples （461 counties） and *p* indexes (7 factors), the data matrix X can be obtained.

$$X = \left(X_{ij}\right)_{n\times p}, i = 1,2, \dots \dots, n \tag{1}$$

n represents *n* samples (*n* = 461). *j* =1, 2..., *p* represents the p index (*p* = 7), and x_{ij} represents the $\mathrm{i^{th}}$ index value of the $\mathrm{j^{th}}$ sample.

Use z-score method to conduct standardized transformation of data:

$$Z_{ij} = \frac{x_{ij} - \overline{x_j}}{S_j} \tag{2}$$

x: The original score that needs to be standardized.

$\overline{x_j}$: The mean of the population.

$$\overline{x_j} = \sum_{i=1}^{n} \frac{x_{ij}}{n} \tag{3}$$

$\mathrm{S_j}$: The standard deviation of the population.

$$S_j^2 = \frac{\sum_{i=1}^{n}\left(x_{ij} - \overline{x_j}\right)^2}{n-1} \quad i = 1,2, \dots \dots, n \;\; j = 1,2, \dots \dots p \tag{4}$$

3.1.2 Find the Correlation Matrix of Index Data

$$R = \left(r_{jk}\right)_{p\times p} \quad j = 1, 2, \dots\dots, p \quad k = 1, 2, \dots\dots, p \tag{5}$$

r_{jk}: The correlation coefficient between index j and index k

$$r_{jk} = \frac{1}{n-1}\sum_{i=1}^{n}\frac{\left(x_{ij} - \overline{x_j}\right)^2}{S_i} \times \frac{\left(X_{ik} - \overline{X_k}\right)^2}{S_k} \tag{6}$$

Which means:

$$r_{jk} = \frac{1}{n-1}\sum_{i=1}^{n} Z_{ij}Z_{jk} \tag{7}$$

$$r_{ij} = 1, \quad r_{jk} = r_{kj} \quad i = 1, 2, \dots\dots, n \quad j = 1, 2, \dots\dots, p \quad k = 1, 2, \dots\dots, p \tag{8}$$

3.1.3 Find the Eigen Roots and Eigenvectors of the Correlation Matrix R

From the characteristic equation $\left|\lambda_{Ip} - R\right| = 0$, we get p characteristic root lambda (p = 7), sort λ_I in descending order, which is the variance of the principal component, its value describes the role of each principal component in describing the evaluated object. is the size that describes the role of each principal component in describing the evaluated object. From the characteristic equation, each characteristic root corresponds to an eigenvector.

$$\mathrm{L_g}\left(L_g = l_{g1},\ l_{g2}, \dots, l_{gp}\right) g = 1,2, \dots, p \tag{9}$$

Convert standardized indicator variables into the main components:

$$\mathrm{F_g} = l_{g1}Z_1 + l_{g2}Z_2 + \cdots + l_{gp}Zp \quad (g = 1,2, \dots, p) \tag{10}$$

F_1 is called the first principal component, F_2 is called the second principal component, …, F_p is called the p-th principal component.

3.1.4 Find the Variance Contribution Rate and Determine the Number of Principal Components

Generally, the number of principal components is equal to the number of original indicators. If there are more original indicators, it will be troublesome to carry out comprehensive evaluation

This method is to select as few as possible *k* principal components (*k* < *p*) for comprehensive evaluation, and at the same time to make the loss of information as little as possible.

k is determined by variance contribution rate:

$$\frac{\sum_{g=1}^{k}\lambda_g}{\sum_{g=1}^{p}\lambda_g} \geq P \tag{11}$$

P = 100% in this article. Therefore, we obtained 7 factor variables, which present 100 percent of the information in 461 original variables, they were:

$$F_{region1},\ F_{region2},\ F_{region3},\ F_{region4}, F_{region5},\ F_{region6},\ F_{region7}$$

3.1.5 Comprehensive Evaluation of k Principal Components

We take the linear weighting of each of the principal components:

$$F_g = l_{g1}Z_1 + l_{g2}Z_2 + \cdots + l_{gp}Z_p \quad (g = 1, 2, \dots, p) \tag{12}$$

Then the weighted sum of k principal components is obtained to get the final evaluation value. Weight is the variance contribution rate of each principal component:

$$\frac{\lambda_g}{\sum_{g=1}^{p} \lambda_g} \tag{13}$$

Final valuation:

$$F = \sum_{g=1}^{k} \frac{\lambda_g}{\sum_{g=1}^{p} \lambda_g} \mathrm{F_g} \tag{14}$$

By analyzing the composition matrix, we get the typical region represented by 7 factors, each factor can be explained by component matric (see Table 2 and Table 3), which means each region consists of several closely related counties.

Table 2: Component Matric(a)

$F_{region1}$		$F_{region2}$		$F_{region3}$		$F_{region4}$	
County	Share	County	Share	County	Share	County	Share
WV, FAYETTE	0.982	OH, FAIRFIELD	0.921	VA, CHESAPEAKE CITY	0.901	WV, GREENBRIER	0.956
WV, UPSHUR	0.972	VA, WYTHE	0.907	VA, MARTINSVILLE CITY	0.895	OH, MAHONING	0.876
PA, FRANKLIN	0.934	KY, TRIMBLE	0.888	VA, DANVILLE CITY	0.887	KY, TODD	0.816
PA, CLARION	0.918	WV, WEBSTER	0.882	VA, FAIRFAX CITY	0.886	WV, MCDOWELL	0.809
PA, NORTHAMPTON	0.913	WV, NICHOLAS	0.860	VA, SALEM	0.882	OH, PIKE	0.780
WV, PUTNAM	0.909	WV, LEWIS	0.852	VA, COLONIAL HEIGHTS CITY	0.879	OH, GREENE	0.720

Table 3: Component Matric(b)

$\mathrm{F_{region5}}$		$\mathrm{F_{region6}}$		$\mathrm{F_{region7}}$	
County	Share	County	Share	County	Share
KY, PIKE	0.834	VA, HIGHLAND	0.797	VA, FLUVANNA	0.738
WV, TUCKER	0.775	WV, GRANT	0.743	PA, LYCOMING	0.730
PA, FOREST	0.731	PA, NORTHUMBERLAND	0.733	PA, CRAWFORD	0.687
VA, HANOVER	0.697	KY, OWEN	0.714		
KY, JESSAMINE	0.678	OH, MADISON	0.686		
VA, CLARKE	0.668	KY, WOODFORD	0.681		

3.2 Opioid Spreading Model

3.2.1 Traditional Opioid Spreading Model

The spreading of opioid follows the dynamics of the opioid epidemics, treatment and ODE model, which is described by the following ordinary differential equations from [2]:

$$\begin{cases} \dfrac{dS}{dt} = \Lambda - \dfrac{\beta_0 U_0 S}{N} - \gamma S \\ \dfrac{dU_0}{dt} = \dfrac{\beta_0 U_0 S}{N} - \rho U_0 + \dfrac{\beta_1 U_0 U_1}{N} - (\gamma + \alpha_0) U_0 \\ \dfrac{dU_1}{dt} = \rho U_0 - \dfrac{\beta_1 U_0 U_1}{N} - (\gamma + \alpha_1) U_1 \\ N = S + U_0 + U_1 \\ \Lambda = \gamma \times S + (\gamma + \alpha_0) \times U_0 + (\gamma + \alpha_1) \times U_1 \end{cases} \tag{15}$$

where the symbols are as defined in **Table 1** on page 3. The approach is to match the characteristics of drug use to the susceptible exposed-infectious-recovered model[3]. Each box in **Figure 3** represents the opioid user's status.

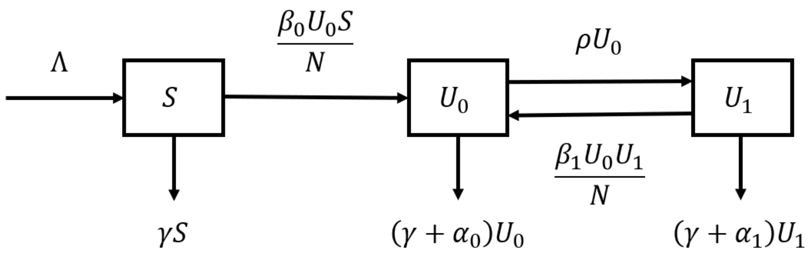

Figure 3: The model of opioid users' status

The bilinear incidence rate is used to describe the process of opioid spreading. In other words, with the increase of opioid users, the contact rate between opioid users and opioid users in treatment will also increase.

R_0 is a threshold value represent how many potential opioid users become opioid users will result from the introduction from a opioid user.

$$R_0 = \frac{\beta_0}{\rho + \gamma + \alpha_0} \tag{16}$$

The value that R_0 takes can indicate the circumstances in which opioid spreading is possible.

$R_0 = 1$ means that each opioid user will infect one potential opioid user.

$R_0 < 1$ means that opioid spreading is not caused by the introduction of an opioid user.

$R_0 > 1$ means that an outbreak will occur.

3.2.2 Improved Model (ODE-SE, ODE with socio-economic factors)

The Heroin epidemics, treatment and ODE model is a traditional opioid spreading model. However, for opioid spreading in seven regions, we need to take other critical factors into consideration:

- The difference between youth and teenagers.

- The influence of gender difference on opioid use.
- The impact of economic conditions on opioid use.
- The influence of physical state on drug taking
- The impact of migration on opioid use

Figure 4 shows a schematic of the improved model (ODE-SE, ODE with socio-economic factors), showing the opioid users' status and the flow of data between status.

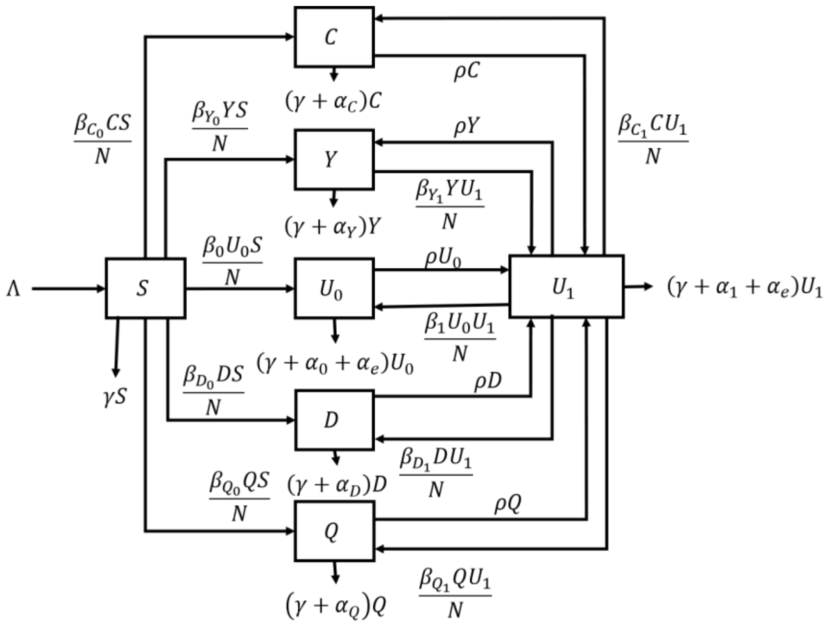

Figure 4: The ODE-SE model of opioid users' status

The ODE-SE model can be written as

$$\begin{cases} \dfrac{dS}{dt} = \Lambda - \dfrac{\beta_0 U_0 S + \beta_{Y_0} YS + \beta_{C_0} CS + \beta_{D_0} DS + \beta_{Q_0} QS}{N} - \gamma S \\ \dfrac{dU_0}{dt} = \dfrac{\beta_0 U_0 S}{N} - \rho U_0 + \dfrac{\beta_1 U_0 U_1}{N} - (\gamma + \alpha_0 + \alpha_e) U_0 \\ \dfrac{dY}{dt} = \dfrac{\beta_{Y_0} YS}{N} - \rho Y + \dfrac{\beta_{Y_1} YU_1}{N} - (\gamma + \alpha_Y) Y \\ \dfrac{dC}{dt} = \dfrac{\beta_{C_0} CS}{N} - \rho C + \dfrac{\beta_{C_1} CU_1}{N} - (\gamma + \alpha_C) C \\ \dfrac{dD}{dt} = \dfrac{\beta_{D_0} DS}{N} - \rho D + \dfrac{\beta_{D_1} DU_1}{N} - (\gamma + \alpha_D) D \\ \dfrac{dQ}{dt} = \dfrac{\beta_{Q_0} QS}{N} - \rho Q + \dfrac{\beta_{Q_!} QU_1}{N} - (\gamma + \alpha_Q) Q \\ \dfrac{dU_1}{dt} = \rho(U_0 + Y + C + Q + D) - \dfrac{(\beta_1 U_0 + \beta_{Y_1} Y + \beta_{C_1} C + \beta_{D_1} D + \beta_{Q_1} Q) U_1}{N} - (\gamma + \alpha_1 + \alpha_e) U_1 \\ N = S + U_0 + U_1 + Y + C + D + Q \\ \Lambda = \gamma * S + (\gamma + \alpha_0 + \alpha_e) * U_0 + (\gamma + \alpha_1 + \alpha_e) * U_1 + \\ \qquad (\gamma + \alpha_Y) Y + (\gamma + \alpha_C) C + (\gamma + \alpha_D) D + (\gamma + \alpha_Q) Q \end{cases} \tag{17}$$

where the symbols are as defined in Table 1 on page 3.

The value that R_0 takes can indicate the circumstances in which opioid spreading is possible.

$$R_0 = \frac{U_0\beta_0 + Y\beta_{Y_0} + C\beta_{C_0} + D\beta_{D_0} + Q\beta_{Q_0}}{\rho S + \gamma S + U_0\alpha_0 + Y\alpha_Y + C\alpha_C + D\alpha_D + Q\alpha_Q} \tag{18}$$

R_0 = 1 means that each opioid user will infect one potential opioid user.

R_0 < 1 means that opioid spreading is not caused by the introduction of an opioid user.

R_0 > 1 means that an outbreak will occur.

3.2.3 Reasons for considering these five factors

Y: The number of teenagers taking drugs. By analyzing the socio-economic data, we find a correlation between the fertility, school enrollment, educational attainment (see **Figure 5**) and total drug reports (see **Figure 6**). So, we use these three indicators to describe teenagers.

We find a positive correlation between teenagers and drug reports.

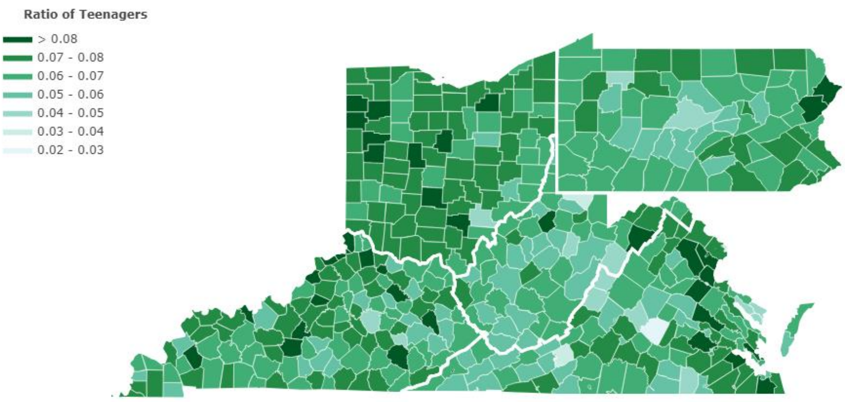

Figure 5: the ratio of teenagers and total drug reports

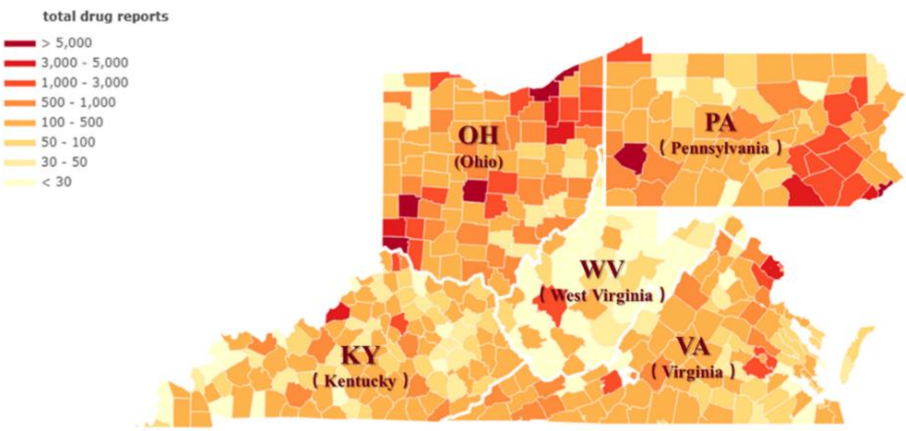

Figure 6: total drug reports

C: The number of opioid users caused by gender differences. By analyzing the socio-economic data, we find a correlation between the marital status(see **Figure 7**), ratio of males and females (see **Figure 8**) and total drug reports (see **Figure 6** on page 9). So, we use these two indicators to describe gender differences.

We find that the higher the proportion of females, the more drug reports, the higher the singleton ratio, the more drug reports.

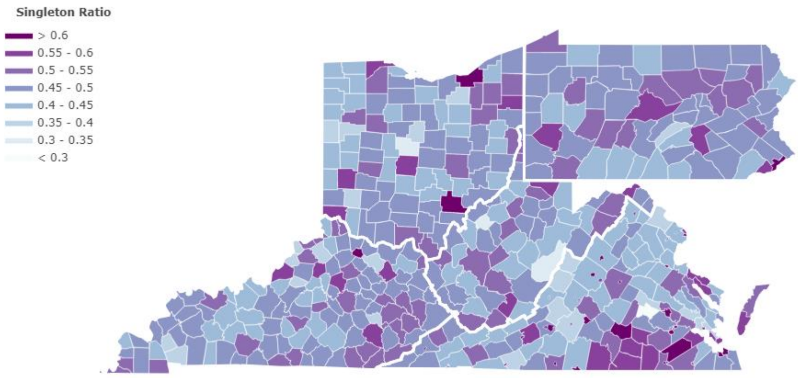

Figure 7: The singleton ratio

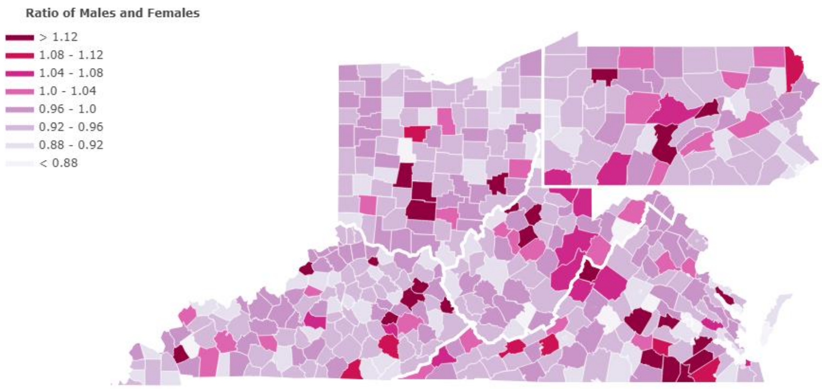

Figure 8: The ratio of males and females

α_e: Proportion of stopping drug use due to economic conditions. From the data provided by the U.S. Census, we find a correlation between the households (see **Figure 9**) and total drug reports (see **Figure 6** on page 9). The more houses, the larger the corresponding population, the better the economic situation. Therefore, we use the number of total houses to describe economic conditions.

We find a positive correlation between total houses and drug reports.

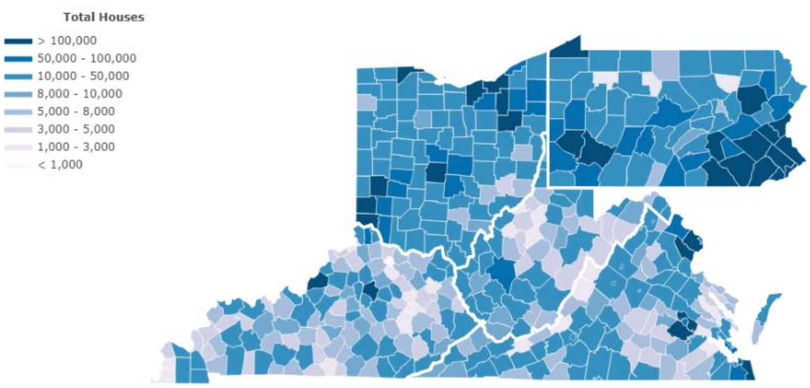

Figure 9: The number of total houses

D: The number of the disabled taking opioid. From the Census socio-economic data, we find a correlation between veteran status, disability status of the civilian noninstitutionalized population(see Figure 10) and total drug reports (see Figure 6 on page 9). Therefore, we use these two indicators to describe disability status.

We find that disability status was not associated with opioid reports.

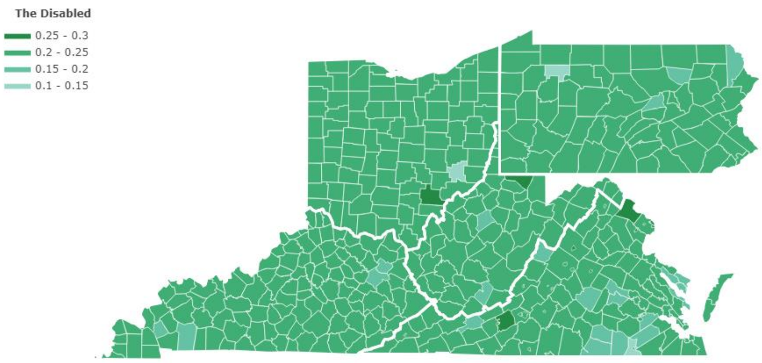

Figure 10: The ratio of the disabled

Q : The number of the natives taking opioid. By analyzing the socio-economic data, we find a correlation between place of birth, U.S. citizenship status, year of entry of the civilian noninstitutionalized population and total drug reports (see Figure 6 on page 9). Therefore, we use these three indicators to describe disability status.

We find a positive correlation between the natives and drug reports.

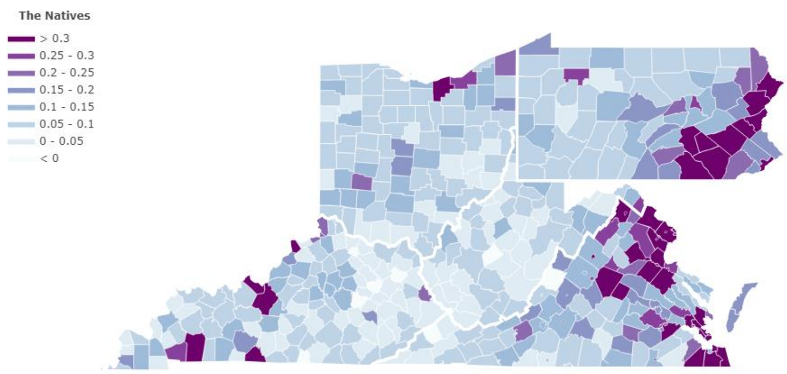

Figure 11: The ratio of natives

4. Applications and Analysis

After all the factors and formulations have been determined, our model is completed. Next, we focus on solving relative problems and giving out analysis as well.

4.1 Task 1: Build a Traditional Spread and Characteristics Model

4.1.1 Build a Model

In the preprocessing step, we added zeros to the data that did not exist, and obtain the corresponding FIPS (Federal Information Processing Standards) and drug reports of each county.

We conducted the dimensionality reduction processing based on the crime data of 461 counties from 2010 to 2017, using the principal component analysis. The top seven factors from the scree plot (see **Figure 12**) can represent 100% of the information. Each factor can be explained by component Matric (see **Table 2** and **Table 3** on page 6), which means each region consists of several closely related counties (see **Figure 13**).

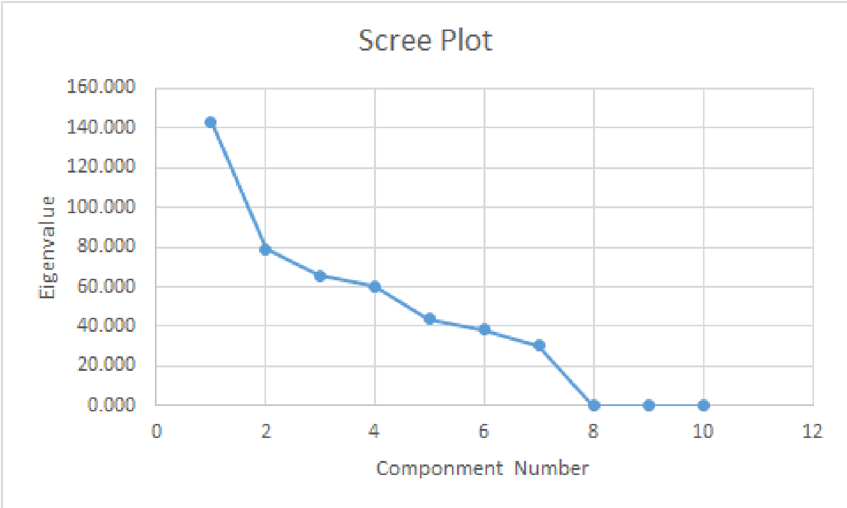

Figure 12: scree plot

Because the seven regions can represent 100% of the information. In the following, we will replace 461 counties with 7 regions for analysis.

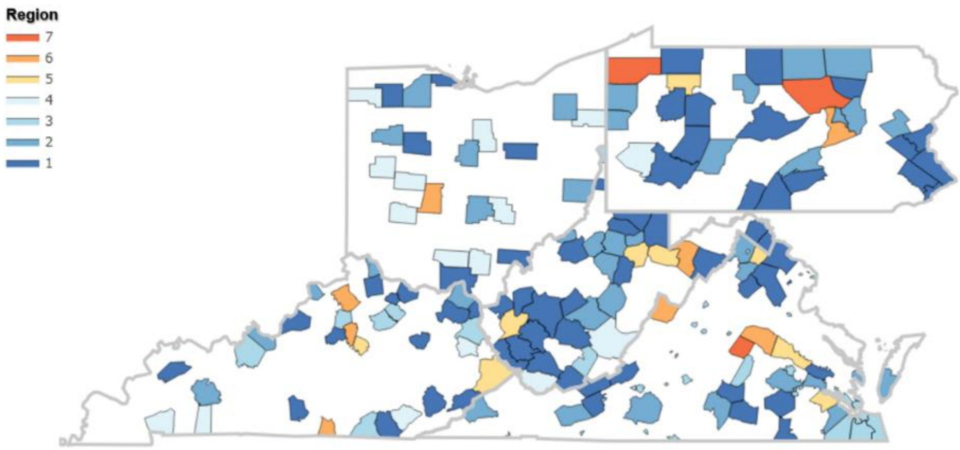

Figure 13: The typical region represented by 7 factors

Then we apply the traditional spreading model (the Heroin epidemics, treatment and ODE model) to describe the spread and characteristics of three types opioids in and between seven regions.

CDC's Injury Center looks at deaths and nonfatal overdoses for four categories of opioids: Methadone, Synthetic opioids, Heroin, Other opioids. We use ρ and $\mathbf{R_0}$ to describe the characters of seven regions.

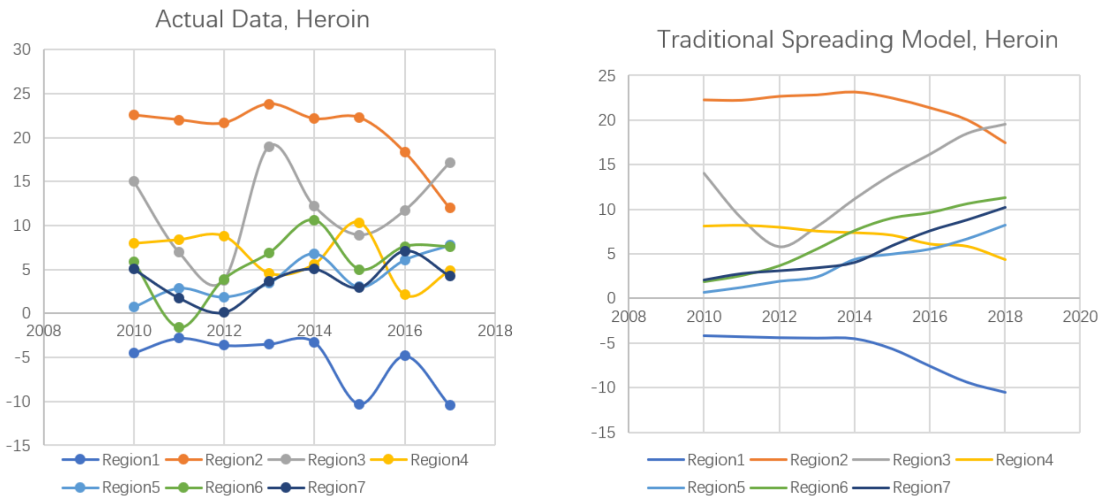

Figure 14: the results of the traditional Heroin spreading model and the actual data

Table 4: Parameter values for the traditional spreading model, Heroin

Parameter	$F_{region1}$	$F_{region2}$	$F_{region3}$	$F_{region4}$	$F_{region5}$	$F_{region6}$	$F_{region7}$
β_0	0.346	0.287	0.301	0.235	0.356	0.203	0.312
β_1	0.015	0.019	0.013	0.014	0.017	0.014	0.016
γ	0.08	0.075	0.084	0.082	0.088	0.083	0.076
ρ	0.31	0.27	0.014	0.21	0.063	0.054	0.092
α_0	0.023	0.015	0.012	0.019	0.013	0.009	0.015
α_1	0.027	0.019	0.011	0.017	0.014	0.007	0.02
R_0	0.8378	0.7972	2.8396	0.7807	2.2112	1.4397	1.7238

Figure 15 compares for the seven regions the results of the traditional Commonly Prescribed spreading model with the actual data. The values of the parameters are shown in **Table 5**.

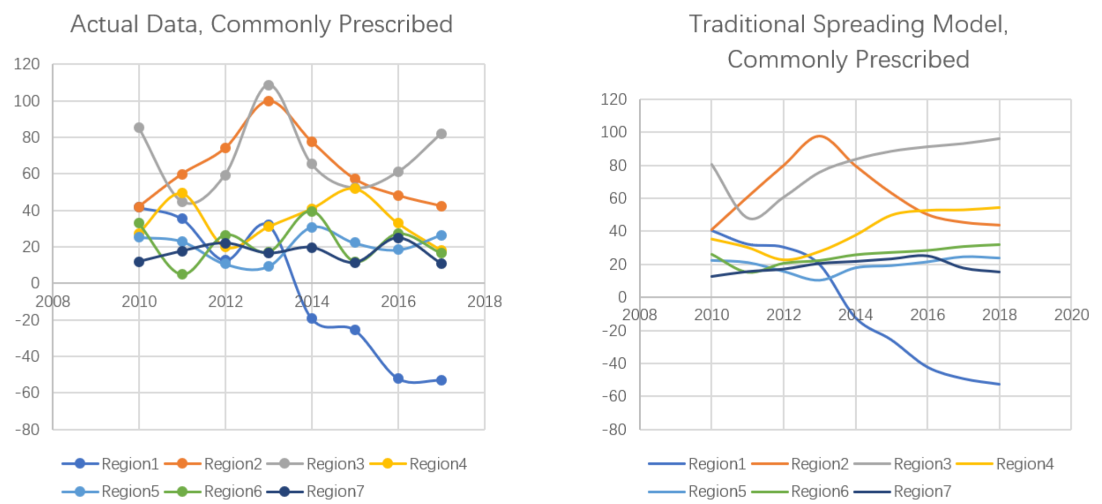

Figure 15: the results of the traditional Commonly Prescribed spreading model and the actual data

Table 5:
Parameter values for the traditional spreading model, Commonly Prescribed Opioids

Parameter	$F_{region1}$	$F_{region2}$	$F_{region3}$	$F_{region4}$	$F_{region5}$	$F_{region6}$	$F_{region7}$
β_0	0.214	0.363	0.331	0.314	0.363	0.326	0.324
β_1	0.028	0.025	0.014	0.027	0.025	0.021	0.019
γ	0.087	0.081	0.089	0.082	0.085	0.079	0.076
ρ	0.42	0.197	0.092	0.073	0.097	0.088	0.37
α_0	0.033	0.023	0.031	0.027	0.023	0.024	0.026
α_1	0.036	0.617	0.027	0.031	0.017	0.035	0.025
R_0	0.3963	1.206	1.5613	1.7253	1.7707	1.7068	0.6864

Figure 16 compares for the seven regions the results of the traditional Other Synthetic spreading model with the actual data. The values of the parameters are shown in **Table 6**.

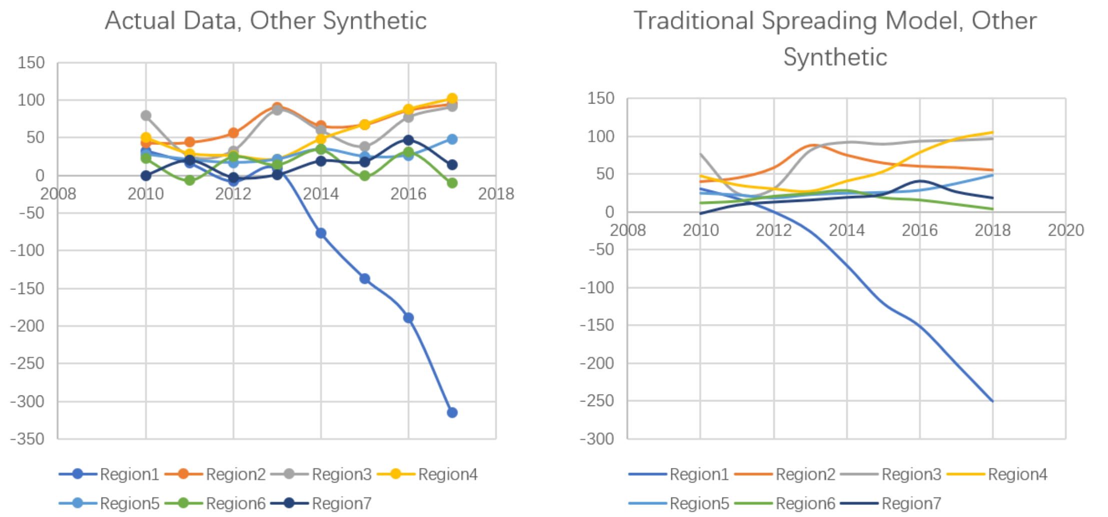

Figure 16: the results of the traditional Other Synthetic spreading model and the actual data

Table 6: Parameter values for the traditional spreading model, Other Synthetic Opioids

Parameter	$F_{region1}$	$F_{region2}$	$F_{region3}$	$F_{region4}$	$F_{region5}$	$F_{region6}$	$F_{region7}$
β_0	0.114	0.426	0.226	0.259	0.264	0.251	0.071
β_1	0.018	0.037	0.067	0.053	0.073	0.067	0.077
γ	0.067	0.099	0.079	0.069	0.097	0.094	0.053
ρ	0.62	0.162	0.022	0.047	0.031	0.47	0.029
α_0	0.043	0.013	0.021	0.032	0.028	0.031	0.017
α_1	0.046	0.016	0.023	0.036	0.019	0.007	0.011
R_0	0.1562	1.5547	1.8525	1.7501	1.6923	0.4218	0.7172

4.1.2 Analyze the Characters and Identify Any Possible Locations

The larger the value of ρ is, the more likely the opioid users are to receive treatment, and the model shows a downward trend, so the number of opioid users in this region will be less and less. The larger the value of R_0 is, the more opioid users one person drives, and the model shows an upward trend, so the number of drug users in this region will increase. When $R_0 > 1$, an outbreak will occur.

Heroin: $F_{region3}$ has the smallest ρ (only 0.1) and the biggest R_0 (as high as 2.8396), so the counties in $F_{region3}$ are more likely to start opioid abuse. $F_{region5}$ also has small ρ and big R_0.These counties are shown in **Figure 17**.

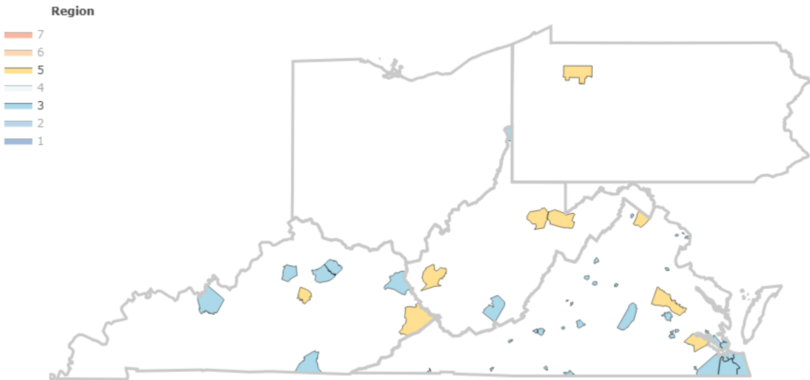

Figure 17: Counties at high risk of Heroin outbreak

Commonly Prescribed Opioids: $F_{region6}$ has the small ρ (only 0.088) and the big R_0 (as high as 1.7707), so the counties in $F_{region6}$ are more likely to start opioid abuse. $F_{region5}$ also has small ρ and big R_0.These counties are shown in **Figure 18**.

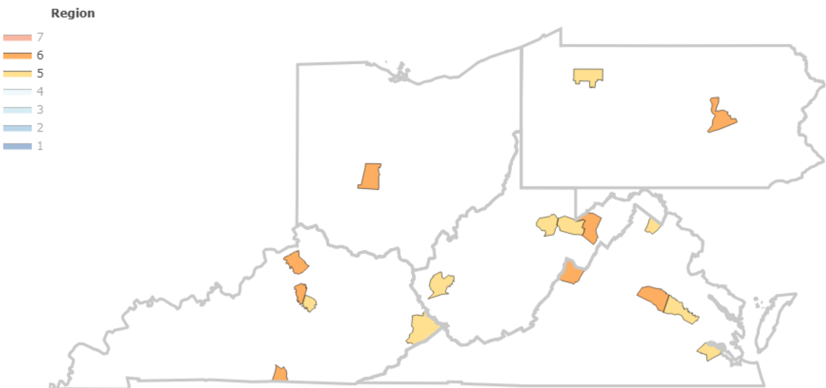

Figure 18: Counties at high risk of Commonly Prescribed Opioids outbreak

Other Synthetic Opioids: $F_{region3}$ has the smallest ρ (only 0.022) and the biggest R_0 (as high as 1.8525), so the counties in $F_{region3}$ are more likely to start opioid abuse. $F_{region4}$ also has small ρ and big R_0.These counties are shown in **Figure 19** .

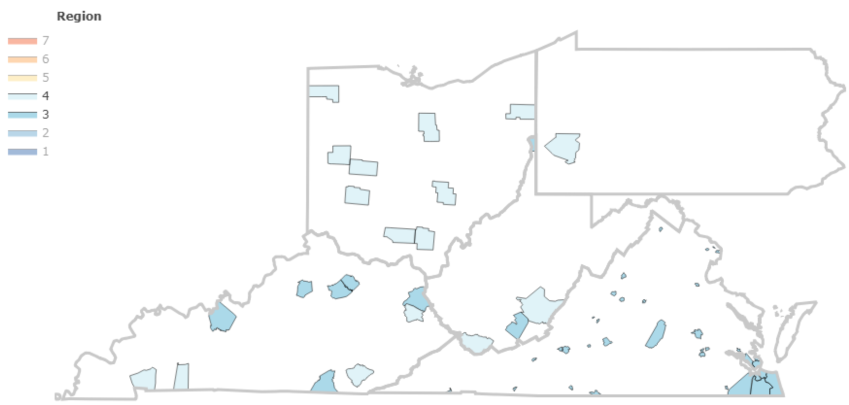

Figure 19: Counties at high risk of Other Synthetic Opioids outbreak

4.1.3 Specific Concerns the U.S. Government Should Have

- Governments should consider regulating opioids to prevent more people from becoming addicted to drugs.
- Society needs to strengthen the propaganda on drug control which makes people realize the harm of drugs and stay away from drugs
- The authorities have to focus on the treatment of drug addicts and forced them to quit.

4.1.4 Threshold Levels

Table 7: The difficulty of outbreak

$\mathbf{R_0}$	< 0.5	< 1	= 1	> 1.5	> 2
	Very difficult	**Difficult**	**Unable to determine**	**Easy**	**Very easy**

4.1.5 Where the Disaster May Have Breakout

By analyzing $\mathbf{R_0}$ in **Table 4**, **Table 5**, **Table 6**, we believe that when r is greater than the threshold, $F_{region3}$, $F_{region4}$, $F_{region5}$, $F_{region6}$ are more likely to start opioid abuse.

4.2 Task 2: ODE-SE Model

According to the ODE-SE model, we divided 16 categories into five categories (see **Figure 20**). By adding five important factors, we can better explain the actual data and analyze its characteristics. Due to space constraints, we present only the results of three factors.

Figure 21 compares for the $F_{region4}$ results of the ODE-SE Model, C (The number of opioid users caused by gender differences) with the actual data. The values of the parameters are shown in **Table 8**.

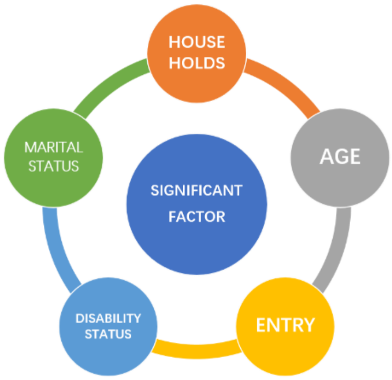

Figure 20: Other critical factors

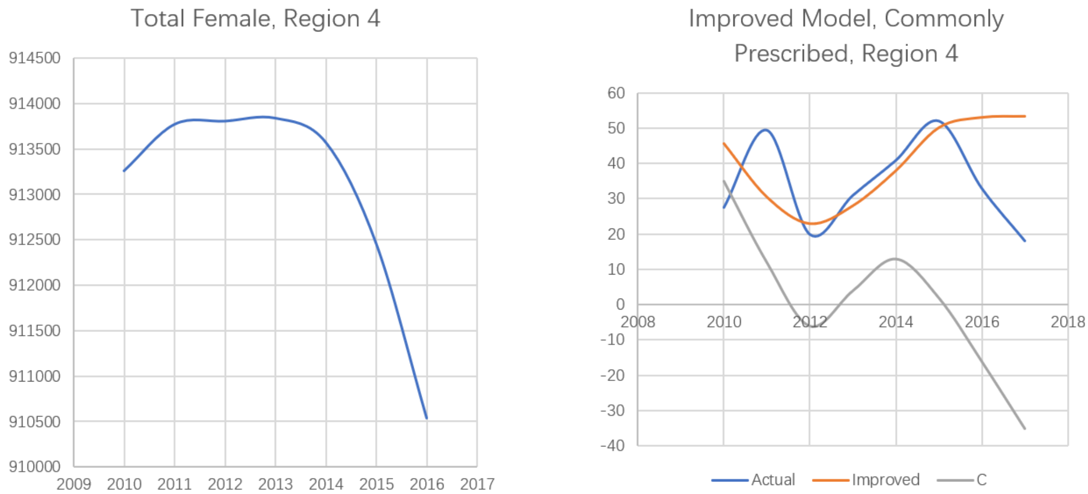

Figure 21: the results of the ODE-SE model and the actual data considering gender differences

Figure 22 compares for the $F_{region2}$ results of the ODE-SE Model, Y (The number of teenagers taking opioid) with the actual data. The values of the parameters are shown in **Table 8**.

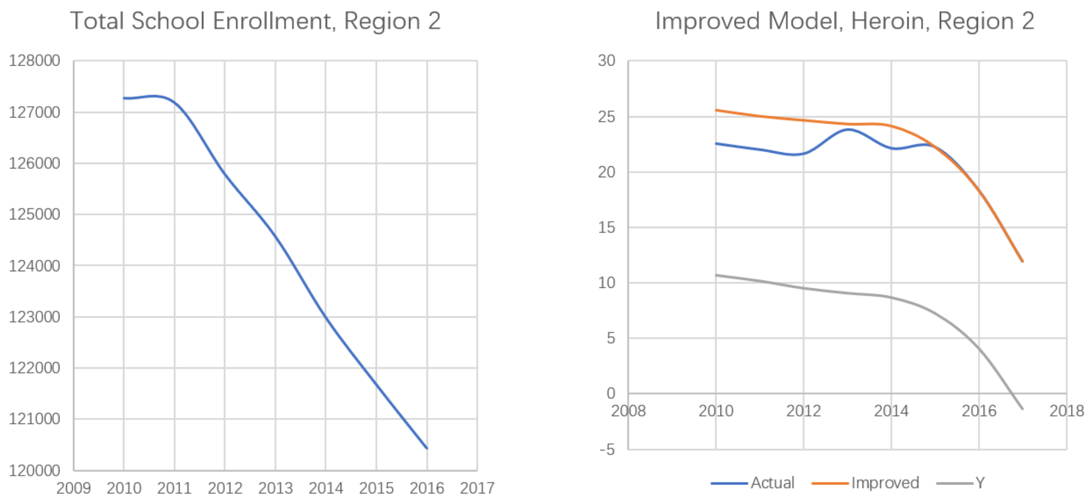

Figure 22: the results of the ODE-SE model and the actual data considering age

Figure 23 compares for the $F_{region6}$ results of the ODE-SE Model, D (The number of the disabled taking opioid) with the actual data. The values of the parameters are shown in **Table 8.**

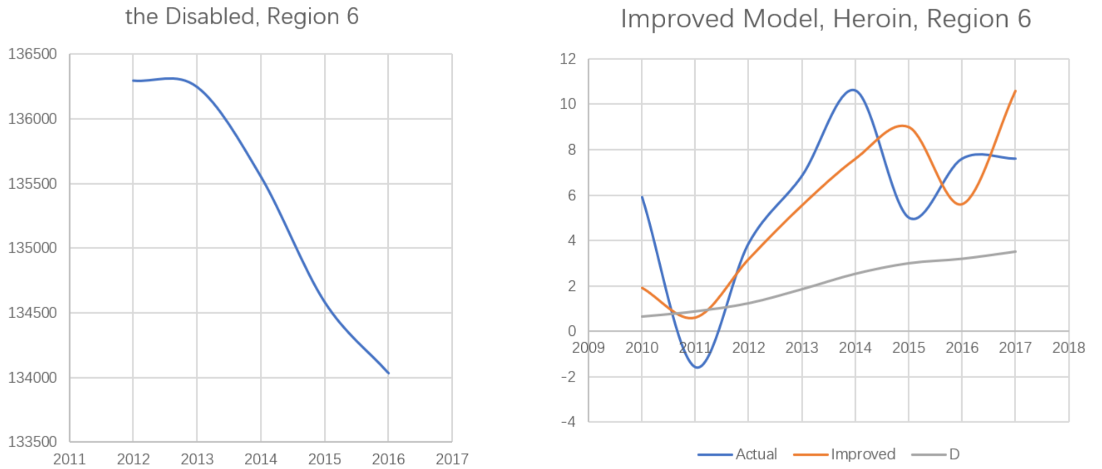

Figure 23: the results of the ODE-SE model and the actual data considering disability status

Figure 24 compares for the $F_{region3}$ results of the ODE-SE Model, Q (The number of the natives taking opioid) with the actual data. The values of the parameters are shown in **Table 8.**

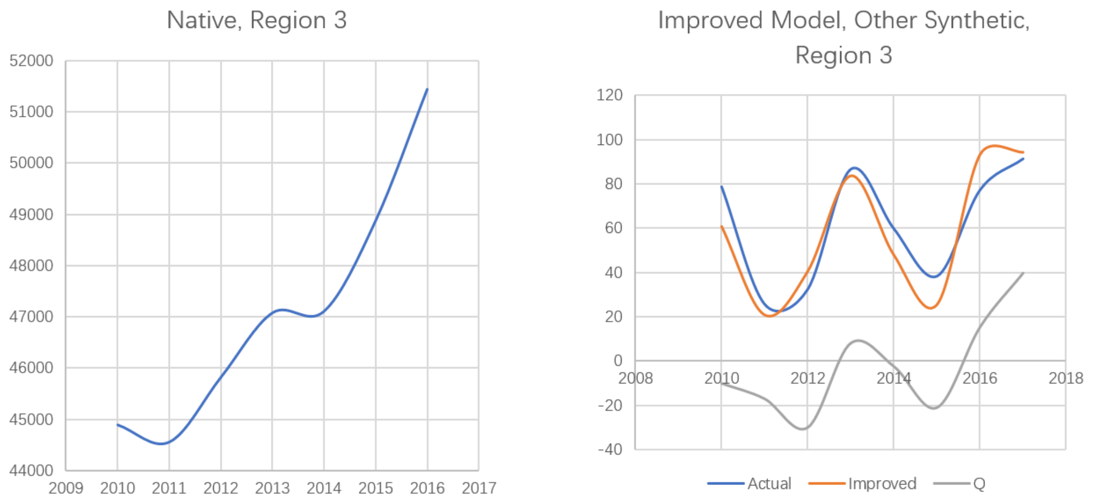

Figure 24: the results of the ODE-SE model and the actual data considering entry

Table 8:

Parameter values for the ODE-SE model, gender differences, age, disability status, entry

Parameter	$F_{region4}$	$F_{region2}$	$F_{region6}$	$F_{region3}$
β_{D_0}	0.579	0.437	0.213	0.248
β_{D_1}	0.020	0.006	0.015	0.167
α_D	0.016	0.038	0.216	0.037

Figure 25 compares for the $F_{region4}$ results of the ODE-SE Model, α_e (Proportion of stopping drug use due to economic conditions) with the actual data. The values of the parameters are shown in **Table 9.**

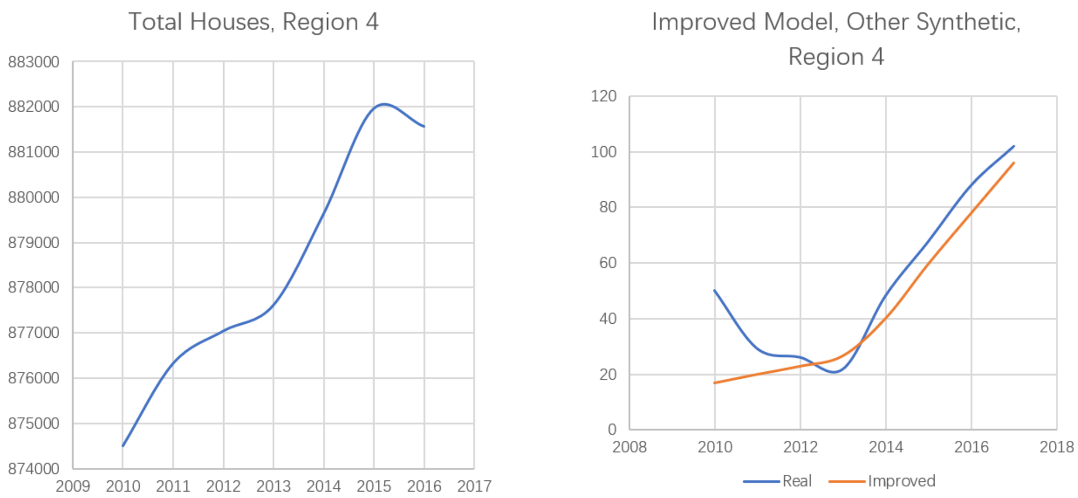

Figure 25: the results of the ODE-SE model and the actual data considering entry

Table 9: Parameter values for the ODE-SE model, households

Parameter	$F_{region4}$
α_e	0.412

4.3 Task 3: Possible Strategies

Government should pay more attention to regulating opioids to prevent more people from becoming addicted to drugs. Decline β_0 is beneficial to hold back the overuse of opioid.

The society needs to strengthen the propaganda on drug control, making people realize the dangers of drugs and stay away from them. These measures will reduce α to decrease the number of deaths caused by opioid.

The authorities have to focus on the treatment of drug addicts and forced them to stop. Enlarging the group of people who are treated can do good to ρ and control the spread of opioid.

5. Strengths and Weaknesses

5.1 Strengths

- PCA (Principal Component Analysis) effectively reduces the dimensions of the data which makes the data more convenient in processing without losing its comprehensiveness.
- There are a lot of mature theories about linear ordinary differential equations, and this makes our model completer and more reliable.
- Careful analysis of the model ensures the accuracy of the results, which is in good agreement with the data provided, so that we can be flexible when dealing with large amounts of data.

5.2 Weaknesses

- There are still some factors which we have failed to consider. In some places where we can be sure that there are some factors that cause such a change, however, we cannot give out detailed calculation without more valid information.
- In order to simplify the model, we must give up some factors with some necessary assumptions.

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Appendix

Component Matrix [a]							
	Component						
	1	1	3	4	5	6	7
KY, ADAIR	-0.481	-0.192	-0.646	-0.310	-0.290	0.172	-0.324
KY, ALLEN	0.434	-0.396	0.104	-0.634	-0.140	0.470	-0.035
KY, ANDERSON	0.704	-0.347	-0.388	-0.054	0.136	-0.189	0.420
KY, BALLARD	-0.125	-0.694	0.192	0.063	-0.342	-0.426	-0.404
KY, BARREN	0.519	-0.627	0.037	-0.287	0.297	-0.405	0.040
KY, BATH	0.192	0.088	-0.182	0.338	-0.206	-0.438	-0.757
KY, BELL	-0.888	-0.172	0.002	0.346	0.090	0.219	0.077
KY, BOONE	-0.738	0.240	0.254	-0.118	-0.342	-0.039	-0.448
KY, BOURBON	0.008	-0.292	0.730	0.210	-0.341	0.233	0.409
KY, BOYD	0.738	0.258	-0.001	-0.101	0.444	-0.324	-0.277
KY, BOYLE	-0.626	-0.493	0.439	-0.240	0.220	0.246	0.071
KY, BRACKEN	0.401	0.222	-0.473	-0.065	-0.488	0.293	0.487
KY, BREATHITT	0.565	-0.083	0.493	0.312	-0.479	0.302	-0.113
KY, BRECKINRIDGE	0.534	-0.214	0.699	-0.327	0.087	-0.154	0.207
KY, BULLITT	0.210	-0.197	-0.006	-0.725	0.474	-0.161	-0.376
KY, BUTLER	0.455	-0.522	0.033	0.198	-0.409	0.278	0.485
KY, CALDWELL	-0.219	-0.193	-0.450	0.004	-0.682	0.420	-0.267
KY, CALLOWAY	-0.713	-0.185	0.148	-0.215	-0.001	0.120	0.612
KY, CAMPBELL	-0.284	0.725	-0.169	0.262	-0.191	-0.334	0.385
KY, CARLISLE	0.440	-0.284	-0.010	0.493	-0.178	0.585	-0.330
KY, CARROLL	-0.604	0.194	0.015	-0.685	0.179	0.305	-0.053
KY, CARTER	0.821	-0.385	-0.321	0.185	-0.102	0.176	-0.001
KY, CASEY	0.052	-0.061	-0.184	0.589	-0.557	-0.087	-0.543
KY, CHRISTIAN	0.251	-0.213	0.353	0.505	0.400	-0.030	0.592
KY, CLARK	0.189	-0.040	-0.768	-0.109	0.413	0.253	0.355
KY, CLAY	0.455	0.328	-0.291	0.341	-0.312	-0.193	0.592
KY, CLINTON	-0.429	-0.444	-0.034	0.379	-0.164	0.668	0.030
KY, CRITTENDEN	0.538	0.370	0.056	0.545	-0.136	-0.269	0.427
KY, CUMBERLAND	-0.809	-0.272	-0.238	0.086	-0.012	-0.019	0.454
KY, DAVIESS	-0.620	0.023	0.081	0.409	0.599	0.154	0.243
KY, EDMONSON	0.497	-0.726	-0.213	-0.039	-0.047	-0.414	-0.070
KY, ELLIOTT	0.644	-0.605	0.007	0.273	0.251	0.285	-0.025
KY, ESTILL	-0.411	-0.562	0.037	-0.186	0.288	0.613	0.145
KY, FAYETTE	0.430	-0.240	0.403	-0.309	0.321	-0.168	-0.607
KY, FLEMING	0.341	-0.519	-0.353	-0.212	-0.517	0.170	-0.385
KY, FLOYD	-0.596	-0.690	0.105	0.306	0.222	-0.020	-0.121
KY, FRANKLIN	0.222	-0.347	0.741	-0.349	-0.342	-0.085	0.189
KY, FULTON	-0.042	-0.680	-0.305	-0.647	-0.033	0.155	0.001
KY, GALLATIN	0.301	0.611	-0.413	0.001	0.066	0.355	-0.484
KY, GARRARD	0.211	-0.806	0.070	-0.366	-0.070	0.296	0.272
KY, GRANT	-0.750	0.032	-0.236	0.187	0.239	0.505	0.183
KY, GRAVES	-0.685	-0.203	-0.217	0.223	0.444	-0.382	0.225
KY, GRAYSON	0.447	-0.667	0.049	0.273	0.351	0.392	-0.028

KY, GREEN	0.323	-0.499	0.265	0.070	0.185	0.288	-0.674
KY, GREENUP	0.209	0.754	-0.245	0.082	-0.540	-0.074	-0.155
KY, HANCOCK	-0.511	0.101	-0.103	0.110	0.568	0.494	0.374
KY, HARDIN	0.188	-0.341	-0.788	-0.325	0.332	0.077	0.073
KY, HARLAN	0.296	0.043	-0.552	-0.420	-0.411	0.405	-0.311
KY, HARRISON	-0.481	0.478	0.240	0.592	-0.328	0.153	-0.031
KY, HART	0.544	0.220	-0.698	-0.338	-0.004	0.229	0.048
KY, HENDERSON	-0.711	-0.301	0.223	0.211	-0.441	0.066	0.334
KY, HENRY	-0.878	0.192	-0.029	-0.179	-0.256	0.306	-0.025
KY, HICKMAN	0.239	0.393	-0.291	0.004	0.440	-0.431	0.570
KY, HOPKINS	-0.664	0.206	0.172	-0.313	0.416	-0.460	0.058
KY, JACKSON	0.647	-0.480	-0.450	-0.251	0.116	-0.145	0.224
KY, JEFFERSON	0.872	-0.070	-0.074	-0.424	0.192	-0.087	-0.071
KY, JESSAMINE	0.497	-0.191	-0.385	0.213	0.678	0.238	0.086
KY, JOHNSON	0.232	-0.277	0.417	0.670	0.283	-0.132	-0.387
KY, KENTON	-0.468	0.093	0.390	-0.631	0.372	0.089	-0.274
KY, KNOTT	0.387	-0.517	0.426	-0.027	-0.303	0.393	0.394
KY, KNOX	0.155	-0.444	0.214	0.705	-0.352	0.155	-0.297
KY, LARUE	0.071	-0.586	-0.087	0.299	0.523	0.527	-0.058
KY, LAUREL	0.461	-0.591	-0.001	-0.170	0.601	-0.142	0.169
KY, LAWRENCE	-0.226	-0.286	0.687	0.533	-0.221	-0.103	-0.226
KY, LEE	0.564	0.021	-0.372	-0.240	-0.017	-0.679	0.153
KY, LESLIE	0.853	-0.073	-0.009	-0.256	-0.324	0.305	0.054
KY, LETCHER	0.756	-0.565	-0.011	0.269	0.130	-0.123	0.062
KY, LEWIS	-0.317	-0.075	0.072	-0.098	0.608	0.137	-0.701
KY, LINCOLN	0.492	-0.140	-0.568	-0.004	0.362	-0.521	0.115
KY, LIVINGSTON	-0.475	0.594	0.504	0.085	-0.072	0.187	0.347
KY, LOGAN	-0.631	0.571	0.141	-0.098	0.465	-0.151	0.079
KY, LYON	-0.864	-0.132	0.206	0.215	-0.103	0.077	0.363
KY, MCCRACKEN	-0.002	-0.037	0.031	-0.537	0.257	-0.786	0.161
KY, MCCREARY	0.062	-0.234	0.672	0.375	0.394	0.212	-0.385
KY, MCLEAN	0.076	0.116	0.565	0.603	0.482	-0.061	0.249
KY, MADISON	-0.677	0.487	0.428	-0.099	-0.182	0.263	0.095
KY, MAGOFFIN	0.250	0.368	0.345	0.125	0.036	-0.745	-0.332
KY, MARION	-0.788	-0.542	0.056	-0.227	-0.090	0.106	-0.111
KY, MARSHALL	-0.196	-0.132	0.156	-0.661	0.040	0.351	-0.598
KY, MARTIN	-0.510	-0.252	-0.058	0.388	-0.195	-0.316	-0.620
KY, MASON	0.829	-0.112	0.063	0.255	0.180	0.441	0.060
KY, MEADE	0.131	0.818	-0.065	-0.406	-0.126	0.314	-0.173
KY, MENIFEE	0.896	-0.271	-0.080	-0.109	0.194	-0.242	-0.099
KY, MERCER	-0.323	-0.442	-0.371	-0.145	0.620	-0.100	0.383
KY, METCALFE	0.812	-0.336	-0.248	0.354	-0.085	0.085	0.161
KY, MONROE	0.062	-0.841	0.266	-0.404	-0.079	0.108	-0.195
KY, MONTGOMERY	0.445	0.644	-0.253	-0.178	0.529	-0.061	-0.090
KY, MORGAN	0.380	-0.649	-0.106	-0.069	0.143	-0.602	0.190
KY, MUHLENBERG	-0.075	0.851	0.368	0.150	0.030	-0.258	0.210
KY, NELSON	-0.904	-0.260	0.099	-0.319	0.064	0.005	-0.005
KY, NICHOLAS	0.392	0.004	0.774	0.370	-0.144	-0.290	0.072

KY, OHIO	-0.289	-0.647	0.361	-0.293	-0.344	0.304	0.266
KY, OLDHAM	-0.609	-0.480	-0.003	0.273	-0.168	-0.404	-0.365
KY, OWEN	-0.003	0.475	-0.022	-0.493	-0.041	0.714	-0.140
KY, OWSLEY	0.510	-0.165	-0.599	-0.004	0.350	-0.470	0.109
KY, PENDLETON	0.771	0.527	0.073	-0.031	0.223	-0.144	-0.228
KY, PERRY	0.303	-0.475	-0.334	-0.186	-0.412	-0.209	0.568
KY, PIKE	-0.118	0.380	-0.128	0.280	0.834	0.022	0.226
KY, POWELL	-0.027	0.471	0.382	0.138	0.511	0.348	0.480
KY, PULASKI	-0.204	-0.650	0.175	0.509	-0.359	-0.004	-0.343
KY, ROBERTSON	0.690	-0.052	-0.545	0.379	-0.195	0.063	-0.198
KY, ROCKCASTLE	-0.368	-0.309	-0.625	0.578	-0.063	-0.111	-0.164
KY, ROWAN	0.604	-0.172	-0.356	0.581	0.169	0.237	-0.237
KY, RUSSELL	-0.182	-0.841	0.437	-0.246	-0.069	-0.049	-0.035
KY, SCOTT	0.298	0.594	0.453	-0.292	-0.127	0.440	0.242
KY, SHELBY	-0.842	-0.258	-0.047	0.412	-0.056	-0.217	0.042
KY, SIMPSON	0.095	0.256	0.167	-0.872	-0.266	0.127	0.226
KY, SPENCER	0.588	-0.276	-0.409	-0.485	0.113	-0.395	-0.078
KY, TAYLOR	-0.227	-0.676	0.528	0.206	-0.284	-0.039	-0.296
KY, TODD	0.406	0.222	0.052	0.816	-0.335	-0.059	0.049
KY, TRIGG	-0.370	0.332	0.284	0.682	-0.061	0.413	-0.181
KY, TRIMBLE	-0.154	0.888	0.329	0.061	-0.030	0.274	0.001
KY, UNION	0.260	0.589	-0.496	-0.057	-0.219	-0.514	0.152
KY, WARREN	0.299	-0.923	0.016	0.049	0.041	0.234	-0.007
KY, WASHINGTON	-0.224	-0.684	-0.329	0.402	0.333	-0.134	-0.288
KY, WAYNE	-0.340	-0.903	0.082	-0.234	0.068	-0.037	0.035
KY, WEBSTER	0.771	0.055	0.043	-0.232	-0.165	0.233	0.514
KY, WHITLEY	0.803	0.028	0.335	-0.047	-0.205	0.438	-0.085
KY, WOLFE	-0.153	0.202	-0.372	0.455	-0.396	-0.446	-0.484
KY, WOODFORD	-0.088	0.012	-0.151	-0.473	-0.459	0.681	-0.264
OH, ADAMS	0.555	-0.149	0.066	0.419	-0.265	0.645	0.056
OH, ALLEN	-0.091	0.732	-0.240	0.564	-0.012	0.263	0.105
OH, ASHLAND	-0.815	0.047	-0.021	0.257	-0.498	-0.141	-0.001
OH, ASHTABULA	-0.670	0.613	-0.183	0.275	-0.204	0.142	-0.067
OH, ATHENS	0.307	0.576	0.342	-0.471	0.235	-0.329	0.268
OH, AUGLAIZE	-0.756	0.230	-0.015	-0.272	-0.416	0.349	-0.075
OH, BELMONT	-0.496	0.731	0.065	0.121	0.409	-0.155	-0.094
OH, BROWN	-0.683	0.177	-0.196	0.410	-0.391	-0.124	-0.356
OH, BUTLER	-0.813	0.288	0.431	-0.176	0.176	-0.047	-0.081
OH, CARROLL	0.390	0.269	-0.292	-0.455	0.641	-0.200	0.179
OH, CHAMPAIGN	-0.546	0.024	0.124	0.685	-0.267	-0.238	-0.298
OH, CLARK	-0.888	-0.286	0.280	-0.178	-0.059	-0.129	0.011
OH, CLERMONT	-0.908	-0.299	-0.004	-0.191	0.208	-0.076	0.034
OH, CLINTON	-0.849	-0.360	-0.031	0.200	-0.105	0.183	-0.252
OH, COLUMBIANA	-0.849	0.267	0.028	0.330	0.056	0.113	0.287
OH, COSHOCTON	-0.929	-0.157	0.216	-0.017	-0.207	-0.068	-0.133
OH, CRAWFORD	-0.621	0.577	-0.096	0.328	-0.062	0.389	0.095
OH, CUYAHOGA	-0.772	0.383	0.107	-0.376	-0.096	0.279	-0.132
OH, DARKE	-0.469	0.272	-0.156	0.393	0.616	-0.150	-0.355

OH, DEFIANCE	-0.487	0.403	0.290	0.690	-0.014	0.015	-0.199
OH, DELAWARE	0.552	-0.541	0.036	0.600	0.200	0.029	-0.024
OH, ERIE	-0.762	0.511	-0.022	0.183	0.119	0.169	0.285
OH, FAIRFIELD	-0.104	0.921	-0.088	-0.014	-0.307	-0.167	-0.103
OH, FAYETTE	-0.886	0.026	0.036	0.177	0.350	0.089	0.225
OH, FRANKLIN	-0.854	0.455	0.104	-0.013	0.160	-0.125	0.108
OH, FULTON	-0.637	0.280	-0.388	-0.157	-0.325	-0.085	-0.476
OH, GALLIA	-0.717	-0.503	0.175	0.421	-0.003	-0.155	0.020
OH, GEAUGA	-0.696	0.429	-0.041	0.453	0.187	0.300	-0.023
OH, GREENE	-0.593	0.067	-0.080	0.720	-0.303	-0.021	0.165
OH, GUERNSEY	-0.985	-0.016	0.046	0.072	0.009	-0.021	-0.150
OH, HAMILTON	-0.748	-0.567	0.283	-0.182	0.044	-0.014	-0.058
OH, HANCOCK	-0.891	0.056	-0.019	0.431	-0.082	0.094	0.031
OH, HARDIN	0.731	0.234	-0.335	-0.330	-0.361	-0.103	-0.219
OH, HARRISON	-0.507	0.373	-0.013	-0.160	-0.384	-0.641	-0.138
OH, HENRY	0.728	0.250	-0.526	-0.217	-0.209	-0.201	-0.021
OH, HIGHLAND	0.428	0.526	0.087	0.410	-0.211	0.555	-0.108
OH, HOCKING	-0.839	-0.170	0.310	-0.277	-0.004	-0.059	0.301
OH, HOLMES	0.687	0.100	0.191	-0.426	-0.519	0.138	-0.109
OH, HURON	-0.596	0.593	0.002	0.501	-0.150	-0.088	-0.108
OH, JACKSON	-0.500	-0.299	0.195	0.652	-0.370	-0.190	0.157
OH, JEFFERSON	0.143	0.529	-0.129	0.495	-0.087	-0.616	-0.225
OH, KNOX	-0.662	0.195	0.427	-0.492	-0.237	-0.186	0.089
OH, LAKE	-0.928	-0.191	0.105	-0.153	-0.197	-0.167	0.039
OH, LAWRENCE	-0.915	0.070	-0.077	-0.284	0.027	0.165	-0.206
OH, LICKING	0.617	-0.025	-0.537	0.466	-0.180	-0.282	-0.025
OH, LOGAN	-0.241	-0.874	0.050	-0.102	0.216	-0.344	0.024
OH, LORAIN	-0.916	-0.242	0.039	0.083	-0.250	-0.165	0.061
OH, LUCAS	0.304	-0.058	0.004	-0.189	-0.865	-0.332	-0.105
OH, MADISON	-0.030	0.356	-0.401	0.333	0.290	0.686	0.214
OH, MAHONING	0.309	0.157	-0.210	0.876	-0.043	0.093	0.241
OH, MARION	-0.782	0.385	0.197	0.397	0.046	-0.102	0.177
OH, MEDINA	-0.607	0.325	-0.279	0.620	-0.004	0.096	-0.236
OH, MEIGS	0.666	0.487	-0.082	-0.283	-0.479	-0.051	-0.034
OH, MERCER	0.276	0.414	-0.512	-0.112	0.319	-0.607	0.088
OH, MIAMI	-0.980	-0.131	0.023	-0.018	0.142	-0.025	0.009
OH, MONROE	-0.810	0.194	0.042	-0.003	0.476	0.183	-0.209
OH, MONTGOMERY	-0.389	0.517	0.617	-0.202	-0.061	-0.365	0.151
OH, MORGAN	0.511	-0.580	0.465	0.263	0.044	0.029	-0.339
OH, MORROW	-0.338	0.700	-0.306	0.123	0.171	0.503	-0.060
OH, MUSKINGUM	-0.916	-0.126	-0.047	0.012	0.294	-0.081	0.221
OH, NOBLE	-0.616	0.027	-0.320	0.276	0.122	-0.651	0.055
OH, OTTAWA	0.668	0.445	-0.054	-0.370	-0.450	0.115	0.003
OH, PAULDING	-0.555	0.267	-0.081	0.614	-0.310	-0.268	-0.263
OH, PERRY	0.128	0.157	-0.510	0.707	-0.289	-0.341	0.018
OH, PICKAWAY	0.618	0.582	-0.229	0.190	0.223	0.289	-0.239
OH, PIKE	0.287	-0.459	0.279	0.780	-0.087	-0.102	-0.060
OH, PORTAGE	-0.234	0.816	0.060	0.517	0.074	0.053	-0.023

OH, PREBLE	-0.642	-0.020	0.326	-0.627	-0.261	0.138	0.041
OH, PUTNAM	-0.073	-0.614	0.083	0.194	-0.723	-0.140	0.175
OH, RICHLAND	-0.723	0.030	0.084	0.673	-0.036	0.028	0.117
OH, ROSS	0.623	-0.583	0.198	0.399	0.193	-0.146	-0.122
OH, SANDUSKY	-0.852	0.175	-0.032	0.087	-0.339	0.167	0.302
OH, SCIOTO	0.737	0.173	-0.310	-0.012	-0.522	0.028	0.238
OH, SENECA	-0.343	0.623	0.074	0.611	0.150	-0.256	0.164
OH, SHELBY	0.083	0.040	0.235	0.715	-0.281	-0.408	0.424
OH, STARK	-0.669	-0.564	-0.117	0.302	0.298	-0.002	0.203
OH, SUMMIT	-0.767	-0.373	0.262	-0.370	0.109	-0.133	-0.196
OH, TRUMBULL	-0.786	0.281	-0.059	0.430	-0.043	0.191	-0.278
OH, TUSCARAWAS	-0.654	-0.229	0.161	0.561	0.395	0.038	-0.149
OH, UNION	-0.015	-0.031	-0.756	-0.530	-0.372	0.075	0.057
OH, VAN WERT	0.146	0.102	-0.739	0.069	0.437	0.467	-0.088
OH, VINTON	-0.427	0.416	-0.115	0.437	-0.536	-0.153	0.361
OH, WARREN	-0.705	0.582	0.088	0.045	-0.196	-0.192	0.282
OH, WASHINGTON	-0.881	-0.307	0.277	-0.043	-0.107	-0.027	0.196
OH, WAYNE	-0.887	0.086	-0.083	-0.258	-0.200	-0.243	0.180
OH, WILLIAMS	-0.371	0.583	0.358	-0.467	-0.284	-0.055	0.304
OH, WOOD	0.369	0.669	-0.278	0.580	0.019	0.024	0.037
OH, WYANDOT	-0.964	-0.197	0.089	0.053	0.144	0.007	-0.018
PA, ADAMS	-0.718	-0.373	0.203	0.222	-0.384	-0.279	0.171
PA, ALLEGHENY	-0.484	0.321	0.104	0.677	0.073	0.345	0.264
PA, ARMSTRONG	0.586	-0.376	-0.588	0.269	-0.038	-0.070	0.300
PA, BEAVER	-0.492	-0.479	-0.255	0.127	-0.453	0.266	0.414
PA, BEDFORD	-0.082	0.315	0.041	-0.301	-0.467	-0.245	-0.724
PA, BERKS	-0.614	0.610	0.015	-0.064	-0.006	0.029	0.495
PA, BLAIR	0.199	-0.140	-0.533	0.581	0.350	0.438	-0.068
PA, BRADFORD	0.173	0.804	-0.168	-0.145	-0.452	0.259	0.051
PA, BUCKS	0.710	-0.163	-0.518	0.200	0.310	0.256	0.018
PA, BUTLER	-0.596	-0.109	-0.497	-0.027	0.584	0.151	0.147
PA, CAMBRIA	0.031	0.786	-0.085	0.489	0.068	-0.090	0.350
PA, CAMERON	0.309	0.689	0.560	-0.202	-0.191	-0.142	-0.135
PA, CARBON	-0.017	0.760	-0.181	0.119	0.577	-0.021	-0.205
PA, CENTRE	0.662	-0.678	0.110	0.212	0.090	-0.176	0.075
PA, CHESTER	0.641	-0.497	-0.298	0.245	0.210	-0.365	0.125
PA, CLARION	0.918	-0.148	-0.051	0.016	-0.068	-0.353	0.054
PA, CLEARFIELD	-0.329	-0.007	0.094	0.630	0.611	-0.026	-0.335
PA, CLINTON	-0.323	-0.011	-0.605	0.548	-0.340	0.311	0.128
PA, COLUMBIA	-0.325	0.692	-0.464	-0.310	-0.081	-0.147	0.275
PA, CRAWFORD	-0.406	0.284	0.392	0.337	-0.119	0.031	0.687
PA, CUMBERLAND	0.791	-0.144	-0.269	0.208	-0.292	0.288	-0.264
PA, DAUPHIN	-0.344	-0.333	-0.199	0.448	0.610	0.054	-0.393
PA, DELAWARE	-0.777	0.314	-0.016	0.503	-0.054	-0.203	0.005
PA, ELK	0.212	-0.396	-0.569	0.324	0.241	0.555	-0.061
PA, ERIE	0.463	-0.407	-0.630	0.437	0.161	-0.032	-0.071
PA, FAYETTE	0.604	0.421	-0.430	0.175	0.362	0.009	0.334
PA, FOREST	-0.058	-0.632	-0.183	0.049	0.731	-0.063	0.155

PA, FRANKLIN	0.934	0.012	-0.056	0.337	0.086	-0.047	0.022
PA, FULTON	0.861	-0.251	0.124	0.166	0.255	-0.211	0.209
PA, GREENE	-0.516	-0.080	0.612	0.506	-0.178	-0.158	0.202
PA, HUNTINGDON	0.172	-0.664	-0.303	-0.241	0.396	-0.418	-0.219
PA, INDIANA	0.745	-0.474	-0.235	0.066	0.032	-0.325	0.234
PA, JEFFERSON	0.707	0.402	-0.240	0.058	0.489	0.179	-0.077
PA, JUNIATA	-0.177	0.260	0.055	-0.609	-0.079	0.426	-0.582
PA, LACKAWANNA	-0.382	-0.822	-0.008	0.289	-0.228	-0.178	0.108
PA, LANCASTER	-0.493	-0.561	-0.021	-0.495	0.286	-0.123	-0.315
PA, LAWRENCE	0.296	0.740	0.142	0.215	0.540	0.029	0.069
PA, LEBANON	-0.886	0.289	-0.048	0.115	0.324	0.107	-0.018
PA, LEHIGH	0.881	-0.304	-0.080	0.118	0.204	-0.235	0.120
PA, LUZERNE	-0.907	0.080	0.145	-0.153	0.341	-0.021	-0.096
PA, LYCOMING	0.197	-0.377	0.202	0.049	0.269	0.413	0.730
PA, MCKEAN	0.291	0.212	0.643	0.023	-0.506	0.033	0.446
PA, MERCER	0.008	0.732	-0.440	0.251	0.245	0.176	-0.341
PA, MIFFLIN	-0.650	-0.423	-0.398	-0.185	-0.040	0.204	0.404
PA, MONROE	0.471	0.505	-0.652	0.095	0.012	-0.103	-0.279
PA, MONTGOMERY	0.780	-0.098	-0.305	-0.235	-0.037	-0.385	0.290
PA, MONTOUR	-0.161	0.739	-0.099	-0.172	0.537	0.108	0.297
PA, NORTHAMPTON	0.913	-0.320	0.000	0.109	0.019	-0.159	0.161
PA, NORTHUMBERLAND	-0.385	0.286	-0.371	-0.228	0.161	0.733	0.131
PA, PERRY	0.100	0.681	-0.201	-0.299	0.241	0.163	0.558
PA, PHILADELPHIA	0.797	-0.517	0.076	0.104	-0.283	-0.028	-0.033
PA, PIKE	0.496	-0.058	-0.345	0.095	-0.436	-0.563	0.340
PA, POTTER	0.705	0.379	-0.301	0.068	0.295	0.089	-0.412
PA, SCHUYLKILL	-0.906	0.089	-0.067	0.332	-0.171	-0.117	0.120
PA, SNYDER	-0.248	-0.447	0.443	-0.647	-0.110	-0.149	0.299
PA, SOMERSET	0.225	0.408	0.409	-0.216	0.580	-0.482	0.013
PA, SULLIVAN	0.737	0.006	-0.387	-0.305	0.401	-0.153	0.172
PA, SUSQUEHANNA	-0.734	0.487	-0.317	0.108	0.153	0.227	-0.194
PA, TIOGA	-0.158	0.674	-0.238	0.064	-0.066	-0.401	-0.543
PA, UNION	-0.652	-0.454	0.383	-0.451	-0.070	0.106	0.048
PA, VENANGO	0.026	-0.296	-0.142	-0.770	-0.045	0.075	-0.540
PA, WARREN	0.665	-0.340	-0.375	0.370	0.048	0.383	-0.120
PA, WASHINGTON	-0.041	0.551	-0.368	0.509	-0.117	-0.117	0.522
PA, WAYNE	0.526	-0.250	-0.462	0.358	-0.178	0.534	-0.035
PA, WESTMORELAND	0.738	0.544	-0.198	0.251	-0.073	0.022	0.229
PA, WYOMING	-0.602	0.170	-0.296	0.647	-0.242	0.079	0.195
PA, YORK	-0.746	0.508	0.055	-0.200	0.213	-0.107	-0.293
VA, ACCOMACK	0.304	0.525	-0.625	-0.154	0.311	0.077	0.339
VA, ALBEMARLE	-0.160	-0.589	-0.003	0.519	0.253	0.161	0.519
VA, ALLEGHANY	-0.767	-0.289	-0.139	0.345	0.195	0.270	-0.282
VA, AMELIA	0.618	0.465	0.496	-0.216	0.310	0.113	-0.007
VA, AMHERST	0.406	-0.484	0.469	-0.308	-0.150	0.502	-0.109
VA, APPOMATTOX	-0.781	-0.226	0.070	-0.476	0.178	0.227	0.153
VA, ARLINGTON	-0.924	0.056	0.132	-0.183	-0.159	-0.020	0.258
VA, AUGUSTA	-0.505	-0.468	0.000	-0.258	0.317	0.349	0.487

VA, BATH	0.582	-0.382	-0.173	-0.230	0.344	-0.523	-0.203
VA, BEDFORD	-0.498	0.252	0.094	-0.685	0.357	0.027	-0.286
VA, BLAND	0.128	0.046	-0.237	-0.304	-0.905	0.043	0.106
VA, BOTETOURT	-0.526	-0.289	0.245	-0.570	0.494	-0.064	0.081
VA, BRUNSWICK	0.155	-0.185	0.080	-0.290	-0.596	0.649	0.272
VA, BUCHANAN	-0.761	-0.137	0.241	-0.230	-0.109	-0.117	-0.516
VA, BUCKINGHAM	0.348	0.253	0.574	-0.294	0.593	-0.215	-0.003
VA, CAMPBELL	0.081	-0.151	0.013	-0.873	-0.218	0.394	0.073
VA, CAROLINE	0.017	0.128	-0.338	-0.718	0.441	-0.399	-0.025
VA, CARROLL	-0.735	0.085	-0.331	-0.158	-0.413	0.035	0.384
VA, CHARLES CITY	0.121	0.740	0.497	-0.362	-0.052	-0.043	-0.233
VA, CHARLOTTE	0.188	0.666	0.605	-0.005	-0.094	0.255	-0.285
VA, CHESTERFIELD	-0.546	0.664	-0.159	-0.194	0.177	0.373	0.166
VA, CLARKE	-0.384	0.358	-0.161	0.483	0.668	0.105	0.094
VA, CRAIG	0.811	-0.317	0.136	0.294	0.211	0.268	-0.142
VA, CULPEPER	0.621	-0.066	-0.104	-0.699	0.079	0.260	0.191
VA, CUMBERLAND	0.429	0.465	0.652	-0.203	0.263	0.250	-0.038
VA, DICKENSON	-0.685	-0.272	0.263	-0.264	0.534	0.013	-0.181
VA, DINWIDDIE	0.895	0.080	0.261	0.170	0.298	0.079	0.006
VA, ESSEX	0.564	0.192	-0.014	-0.497	-0.495	-0.064	0.386
VA, FAIRFAX	-0.230	-0.318	-0.048	-0.848	-0.177	-0.161	0.260
VA, FAUQUIER	0.717	0.576	-0.075	-0.317	-0.170	0.010	-0.136
VA, FLOYD	-0.012	0.576	0.324	-0.280	0.571	-0.110	0.383
VA, FLUVANNA	-0.540	-0.290	0.143	-0.032	-0.104	-0.218	0.738
VA, FRANKLIN	-0.385	0.780	0.421	0.142	0.077	0.184	0.080
VA, FREDERICK	0.049	0.710	-0.037	-0.200	0.514	-0.423	-0.097
VA, GILES	0.809	-0.168	0.196	-0.263	-0.164	0.260	0.341
VA, GLOUCESTER	0.351	0.265	-0.112	-0.634	-0.592	0.132	-0.152
VA, GOOCHLAND	-0.412	-0.652	0.319	-0.296	0.171	-0.341	0.265
VA, GRAYSON	-0.549	-0.391	0.512	-0.510	0.151	0.015	-0.009
VA, GREENE	0.378	-0.267	-0.392	-0.100	-0.672	-0.410	-0.053
VA, GREENSVILLE	0.778	-0.379	-0.401	0.035	-0.267	0.007	-0.136
VA, HALIFAX	0.602	0.319	0.213	-0.613	0.092	0.255	-0.203
VA, HANOVER	0.148	0.158	0.270	-0.626	0.697	-0.048	-0.009
VA, HENRICO	-0.932	-0.200	0.170	-0.229	-0.065	-0.025	0.075
VA, HENRY	-0.730	-0.062	-0.118	-0.348	0.195	0.339	-0.418
VA, HIGHLAND	0.212	0.097	-0.153	0.297	0.442	0.797	0.063
VA, ISLE OF WIGHT	0.156	0.796	0.407	-0.153	-0.176	0.343	-0.075
VA, JAMES CITY	-0.108	-0.418	0.071	-0.690	0.243	0.176	-0.492
VA, KING AND QUEEN	-0.508	0.287	-0.137	-0.512	-0.300	0.348	-0.410
VA, KING GEORGE	-0.486	-0.366	0.269	-0.221	0.568	-0.243	-0.357
VA, KING WILLIAM	-0.265	-0.348	0.080	-0.237	0.649	0.568	-0.044
VA, LANCASTER	-0.706	-0.065	0.112	-0.578	-0.250	-0.086	0.286
VA, LEE	-0.854	-0.067	0.156	-0.375	0.073	0.286	-0.119
VA, LOUDOUN	0.749	0.014	-0.039	-0.175	0.414	-0.433	-0.219
VA, LOUISA	0.476	-0.033	-0.451	0.217	0.085	0.671	-0.254
VA, LUNENBURG	0.790	-0.015	-0.083	0.158	0.346	0.465	-0.093
VA, MADISON	0.413	-0.374	0.058	0.570	0.101	0.571	0.159

VA, MATHEWS	0.013	0.741	-0.092	0.377	-0.460	0.165	-0.249
VA, MECKLENBURG	0.195	0.217	-0.179	-0.683	-0.470	0.441	-0.037
VA, MIDDLESEX	0.065	-0.275	-0.261	-0.789	0.227	-0.422	0.007
VA, MONTGOMERY	-0.864	0.009	0.295	-0.313	0.045	-0.204	-0.158
VA, NELSON	-0.552	-0.433	0.327	-0.555	0.281	0.000	-0.118
VA, NEW KENT	0.780	0.187	-0.095	-0.282	0.104	0.419	-0.285
VA, NORTHAMPTON	-0.232	0.692	-0.559	-0.132	-0.142	0.003	0.343
VA, NORTHUMBERLAND	-0.789	-0.005	-0.043	0.260	-0.435	-0.339	0.064
VA, NOTTOWAY	0.115	0.191	-0.160	0.024	0.478	-0.471	-0.689
VA, ORANGE	-0.728	-0.143	-0.085	-0.093	-0.212	0.180	-0.597
VA, PAGE	0.094	0.127	-0.017	-0.845	0.108	-0.376	0.328
VA, PATRICK	-0.593	-0.195	-0.111	-0.338	-0.401	0.021	0.568
VA, PITTSYLVANIA	-0.748	0.139	0.159	0.502	-0.042	-0.376	-0.002
VA, POWHATAN	0.187	-0.658	0.573	0.192	0.364	0.178	-0.046
VA, PRINCE EDWARD	0.684	0.421	-0.081	-0.209	0.352	0.120	0.408
VA, PRINCE GEORGE	0.622	0.562	0.287	-0.293	0.306	0.179	-0.059
VA, PRINCE WILLIAM	-0.631	0.448	0.140	-0.581	-0.087	0.019	-0.192
VA, PULASKI	0.757	0.125	0.096	-0.383	0.327	-0.162	0.351
VA, RAPPAHANNOCK	0.877	0.033	-0.232	-0.386	0.072	-0.060	-0.137
VA, ROCKBRIDGE	-0.783	0.149	0.418	-0.357	-0.037	0.227	-0.097
VA, ROCKINGHAM	-0.532	0.504	0.273	-0.397	0.402	0.237	0.112
VA, RUSSELL	0.541	0.438	-0.188	-0.427	0.301	0.432	-0.146
VA, SCOTT	-0.119	-0.275	-0.648	0.269	0.525	0.372	0.053
VA, SHENANDOAH	-0.327	0.189	-0.144	0.514	0.141	-0.678	0.303
VA, SMYTH	-0.666	-0.397	0.261	-0.411	-0.190	0.153	0.320
VA, SOUTHAMPTON	0.447	0.579	-0.036	0.146	-0.279	-0.195	-0.572
VA, SPOTSYLVANIA	-0.120	-0.002	-0.227	-0.697	-0.575	0.136	0.314
VA, STAFFORD	-0.581	-0.119	0.013	-0.745	-0.258	-0.096	0.134
VA, SURRY	0.374	0.031	-0.044	-0.475	0.655	0.415	-0.175
VA, SUSSEX	0.432	0.341	-0.626	-0.089	-0.216	0.233	-0.443
VA, TAZEWELL	-0.918	0.186	0.103	0.284	0.081	0.124	0.093
VA, WARREN	0.286	0.662	-0.332	-0.234	0.487	0.206	0.188
VA, WASHINGTON	-0.414	-0.031	-0.280	-0.786	0.179	-0.171	0.265
VA, WESTMORELAND	-0.781	-0.278	-0.336	-0.328	-0.028	0.285	0.099
VA, WISE	0.331	0.788	0.039	-0.122	0.215	0.113	-0.441
VA, WYTHE	-0.162	0.907	-0.243	0.264	0.031	0.015	-0.147
VA, YORK	0.321	-0.074	-0.060	-0.802	-0.192	0.238	0.389
VA, ALEXANDRIA CITY	0.597	-0.288	0.739	0.059	-0.085	-0.058	0.022
VA, BEDFORD CITY	0.354	-0.443	0.775	0.012	0.081	0.131	-0.230
VA, BRISTOL	0.563	0.078	0.799	0.028	-0.044	0.130	-0.135
VA, BUENA VISTA CITY	0.395	0.415	0.811	0.061	0.039	-0.086	0.028
VA, CHARLOTTESVILLE CITY	0.492	0.092	0.840	0.153	0.087	0.107	-0.036
VA, CHESAPEAKE CITY	0.422	0.074	0.901	0.068	0.019	-0.009	-0.015
VA, COLONIAL HEIGHTS CITY	0.439	0.160	0.879	0.042	0.015	-0.054	-0.067
VA, COVINGTON CITY	-0.512	-0.420	0.216	-0.549	0.301	-0.023	-0.350
VA, DANVILLE CITY	0.451	-0.013	0.887	0.079	-0.033	-0.008	-0.041
VA, EMPORIA CITY	0.594	-0.242	0.644	0.334	0.036	0.243	-0.045
VA, FAIRFAX CITY	0.044	-0.344	0.886	-0.236	-0.117	0.139	-0.075

VA, FALLS CHURCH CITY	0.572	-0.138	0.774	0.200	-0.037	0.082	-0.084
VA, FRANKLIN CITY	0.434	0.167	0.860	0.172	0.090	0.074	0.021
VA, FREDERICKSBURG CITY	0.508	0.005	0.825	0.207	0.028	0.133	0.025
VA, GALAX CITY	0.479	-0.283	0.722	0.293	-0.189	0.132	0.176
VA, HAMPTON CITY	0.514	0.041	0.840	0.160	-0.026	0.034	-0.037
VA, HARRISONBURG CITY	0.215	0.458	0.737	-0.292	-0.186	0.093	0.269
VA, HOPEWELL CITY	0.496	0.146	0.840	0.150	0.060	0.027	0.003
VA, LEXINGTON CITY	0.417	0.386	0.808	0.015	-0.015	-0.151	-0.036
VA, LYNCHBURG CITY	0.470	0.144	0.864	0.109	-0.020	-0.024	-0.002
VA, MANASSAS CITY	0.846	-0.456	0.160	0.170	-0.005	-0.143	0.026
VA, MARTINSVILLE CITY	0.386	0.148	0.895	-0.009	-0.008	-0.166	-0.012
VA, NEWPORT NEWS CITY	0.568	-0.167	0.760	0.237	-0.041	0.119	-0.011
VA, NORFOLK CITY	0.460	-0.006	0.866	0.157	0.053	0.098	-0.026
VA, NORTON CITY	0.533	-0.587	0.388	0.356	-0.072	0.291	-0.066
VA, PETERSBURG CITY	0.495	0.218	0.828	0.139	0.048	0.009	-0.025
VA, POQUOSON CITY	0.441	0.346	0.816	0.035	-0.019	-0.131	-0.040
VA, PORTSMOUTH CITY	0.528	-0.017	0.813	0.218	0.019	0.107	-0.014
VA, RADFORD	0.467	0.209	0.853	0.079	-0.011	-0.060	-0.032
VA, RICHMOND	0.469	0.090	0.866	0.142	0.004	0.031	0.002
VA, ROANOKE	0.417	0.151	0.859	-0.206	-0.011	-0.140	0.063
VA, SALEM	0.457	-0.009	0.882	0.099	-0.002	0.015	-0.061
VA, STAUNTON CITY	0.521	0.074	0.836	0.152	-0.018	0.015	-0.030
VA, SUFFOLK CITY	0.412	0.297	0.855	0.055	-0.005	-0.088	0.020
VA, VIRGINIA BEACH CITY	0.516	0.093	0.841	0.133	-0.023	0.012	-0.009
VA, WAYNESBORO CITY	0.318	0.394	0.831	-0.125	0.020	-0.168	-0.097
VA, WILLIAMSBURG CITY	0.339	0.455	0.802	0.025	0.181	-0.034	-0.032
VA, WINCHESTER CITY	0.468	0.152	0.861	0.102	0.047	0.047	-0.036
WV, BARBOUR	0.365	-0.023	0.576	-0.271	0.654	-0.178	0.033
WV, BERKELEY	0.891	-0.209	-0.295	-0.161	-0.174	-0.129	0.061
WV, BOONE	0.679	-0.419	-0.284	0.153	0.153	-0.485	0.016
WV, BRAXTON	0.585	-0.400	0.156	-0.125	-0.532	0.416	0.055
WV, BROOKE	0.613	0.538	0.424	-0.248	-0.214	-0.177	-0.125
WV, CABELL	0.896	0.082	-0.177	-0.179	0.164	-0.249	0.196
WV, CALHOUN	0.135	0.160	-0.399	-0.415	-0.458	0.641	0.058
WV, CLAY	0.894	0.051	-0.391	-0.116	0.175	0.000	0.044
WV, DODDRIDGE	0.325	0.720	0.267	-0.327	0.024	-0.350	0.272
WV, FAYETTE	0.982	0.040	0.063	0.061	-0.071	-0.145	-0.018
WV, GILMER	0.001	0.336	-0.082	0.049	-0.181	-0.919	0.019
WV, GRANT	0.496	0.377	-0.034	0.217	0.084	0.743	-0.071
WV, GREENBRIER	0.163	-0.023	0.085	0.956	0.021	0.219	-0.057
WV, HAMPSHIRE	0.264	0.530	-0.382	-0.245	-0.191	-0.571	-0.284
WV, HANCOCK	0.399	-0.005	0.833	-0.060	0.293	-0.082	0.223
WV, HARDY	0.659	0.413	-0.574	-0.097	-0.128	0.169	-0.105
WV, HARRISON	0.033	0.725	0.183	-0.295	-0.524	0.238	0.145
WV, JACKSON	0.570	-0.333	-0.600	0.094	0.267	-0.239	0.260
WV, JEFFERSON	0.655	-0.450	-0.250	0.037	-0.247	0.259	0.421
WV, KANAWHA	0.815	-0.273	-0.270	-0.352	0.241	-0.080	0.009
WV, LEWIS	0.014	0.852	0.390	0.105	0.333	-0.005	0.003

WV, LINCOLN	-0.134	0.322	-0.216	0.293	0.661	0.533	0.157
WV, LOGAN	0.691	0.478	-0.082	0.051	-0.106	0.050	0.521
WV, MCDOWELL	0.431	0.140	0.094	0.809	-0.188	-0.271	0.153
WV, MARION	0.788	0.366	-0.070	-0.185	-0.449	-0.069	-0.007
WV, MARSHALL	0.493	0.510	0.087	0.158	0.089	0.499	0.455
WV, MASON	0.627	0.316	0.012	0.277	-0.521	0.137	-0.375
WV, MERCER	0.833	0.119	0.029	0.305	-0.293	-0.233	0.239
WV, MINERAL	0.642	-0.382	-0.390	-0.447	-0.083	0.260	-0.124
WV, MINGO	0.786	0.121	0.500	0.004	-0.253	0.177	-0.151
WV, MONONGALIA	0.809	-0.202	0.287	0.261	0.109	0.377	0.032
WV, MONROE	0.585	-0.514	0.429	0.251	0.085	0.280	0.246
WV, MORGAN	0.372	0.386	-0.568	-0.346	-0.198	0.478	-0.046
WV, NICHOLAS	-0.196	0.860	0.323	-0.010	-0.068	0.333	0.042
WV, OHIO	0.860	0.458	0.050	0.008	0.184	-0.095	0.070
WV, PENDLETON	0.414	-0.158	-0.485	-0.129	0.312	-0.642	0.206
WV, PLEASANTS	0.223	0.739	-0.114	0.172	-0.015	-0.504	-0.327
WV, POCAHONTAS	0.529	0.482	-0.176	-0.160	-0.438	-0.406	-0.274
WV, PRESTON	0.669	0.241	-0.405	-0.319	-0.131	-0.453	-0.077
WV, PUTNAM	0.909	0.270	0.147	-0.037	-0.079	0.250	-0.090
WV, RALEIGH	0.515	0.627	-0.242	0.313	0.068	0.356	0.231
WV, RANDOLPH	0.134	0.540	0.079	-0.598	-0.058	0.217	0.525
WV, RITCHIE	0.889	0.102	-0.200	-0.171	-0.009	0.351	0.087
WV, ROANE	0.364	0.183	-0.844	-0.060	-0.156	0.261	-0.159
WV, SUMMERS	0.573	0.371	0.669	-0.011	-0.012	-0.293	-0.015
WV, TAYLOR	0.158	0.766	0.435	0.029	0.432	-0.024	0.106
WV, TUCKER	-0.352	-0.051	-0.007	-0.012	0.775	0.516	-0.079
WV, TYLER	0.532	-0.550	-0.126	0.476	0.234	-0.081	0.331
WV, UPSHUR	0.972	-0.133	0.004	-0.010	-0.188	-0.037	0.018
WV, WAYNE	-0.407	0.452	0.286	-0.126	0.519	-0.508	0.062
WV, WEBSTER	0.017	0.882	-0.062	-0.256	0.328	0.007	0.213
WV, WETZEL	-0.096	0.326	-0.416	0.634	0.472	0.176	-0.236
WV, WIRT	0.386	-0.625	0.405	0.373	-0.207	0.278	0.194
WV, WOOD	-0.502	0.147	-0.087	-0.449	-0.622	-0.355	0.070
WV, WYOMING	0.732	0.466	0.082	-0.479	-0.078	-0.065	-0.023