STATE UNEMPLOYMENT RATE TIME SERIES MODELS

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Abstract: Time series modeling is applied to Current Population Survey (CPS) unemployment rate data for 39 states and the District of Columbia to reduce the effects of large fluctuations in sampling error. A signal-plus-noise model of the CPS estimates is formulated. Models are estimated for each state. Results are presented on the characteristics of the estimated signal components, potential efficiency gains over the survey estimator, and the importance of accounting for the sample design.

Key Words: Small area estimation, signal extraction, Current Population Survey, structural time series model, Kalman filter

1. Introduction

To reduce variability arising from small sample sizes, the Bureau of Labor Statistics (BLS) has adopted a time series approach to survey estimation (Bell and Hillmer 1990, Pfeffermann 1992, Scott and Smith 1974). This approach is used to produce labor force estimates from the Current Population Survey (CPS) in 39 states and the District of Columbia (hereafter referred to as 40 states). In a previous paper, (Evans, Tiller, and Zimmerman 1993), models were developed for the employment-to-population ratio. This paper presents results from modeling the unemployment rate.

The remainder of this paper is organized as follows: Section 2 discusses the state CPS sample design relevant to time series modeling; Section 3 describes the time series component models; Section 4 explains the estimation process; Section 5 presents the results for the 40 unemployment models; and Section 6 provides the conclusions.

2. CPS Sample

The Current Population Survey (CPS) is a monthly household survey that is designed to provide monthly unemployment rate estimates for the nation, 11 states, New York City, and Los Angeles with a prespecified level of reliability. For the remaining 40 states, the reliability requirements are eight percent coefficient of variation on an annual average unemployment rate of 6 percent. However, the coefficient of variation for the monthly unemployment rate in the 40 states averages 14 percent, an unacceptably high level of variability. Time series models have been developed to reduce this variability.

In modeling the CPS data, it is important to account for two characteristics in the sample design. First, the reliability of the CPS estimator changes over time due to sample redesigns, sample size changes, and variations in the labor force. Secondly, strong autocorrelations in the sampling error arise from the use of a 4-8-4 rotation scheme (Census 1978) and the periodic replacement of households. Failure to account for the strong autocorrelation in the sampling error and the changing reliability in the CPS estimator is likely to result in confounding the noise with the signal.

3. Time Series Component Modeling

In this paper, a model for the unemployment rate is developed for each of the 40 states. The CPS sample estimate at time t, $y(t)$, is represented as the sum of two independent processes

$$y(t) = \theta(t) + e(t)$$

$\theta(t) =$ the population value of unemployment rate

$e(t) =$ sampling error.

The population values are represented by a structural time series model with explanatory variables (Harvey 1989)

$$\theta(t) = X(t)\beta(t) + T(t) + S(t) + I(t) + O(t).$$

The $1 \times k$ vector $X(t)$ contains known explanatory variables while the $k \times 1$ vector $\beta(t)$ contains the random coefficients associated with them. $T(t)$ represents a trend component, $S(t)$ a seasonal component, $I(t)$ an irregular component, and $O(t)$ an outlier component. Each of these components include one or more normally distributed, mutually independent white noise disturbances,

$$\upsilon_j(t) \sim \mathrm{N}\left(0, \sigma_j^2\right)$$

where j indexes the individual components. The stochastic properties of these components are determined by the variances of these disturbances.

These components are grouped into either a signal, $\Gamma(t)$ or noise, $\eta(t)$, component

$$\Gamma(t) = X(t)\beta(t) + T(t) + S(t)$$

$$\eta(t) = e(t) + I(t) + O(t)$$

The signal component represents all of the variation in the sample values related to systematic movements in the true values. The noise component is the sum of sampling error, purely random variation unaccounted for by other components, and unusually large transitory fluctuations or outliers. While sampling error is the most important component of the noise, the other two components represent highly transitory variation that obscure the normal behavior of the series and, thus, removed from the signal.

The regression coefficients are specified to follow a random walk process,

$$\beta(t) = \beta(t-1) + \upsilon_{\beta(t)}$$

$$E[\upsilon_\beta(t)\upsilon_\beta(t)'] = Diag(\sigma^2_{\beta_1}, \ldots, \sigma^2_{\beta_k}).$$

The trend component is represented by a locally smooth linear trend with a random level, $T(t)$, slope, $R(t)$, and allows for the possibility of shocks to the trend level white noise disturbance term, $\upsilon_T(t)$. These shocks are innovation outliers that cause permanent shifts in the level of the trend.

$$T(t) = T(t-1) + R(t-1) + \upsilon_T(t)'$$

$$R(t) = R(t-1) + \upsilon_R$$

$$\upsilon_T(t)' = \sum_{k=1}^{m} \delta_k \xi_k + \upsilon_T(t)$$

$$\xi_k(t) = \begin{cases} 1 \text{ if } t = t_k \\ 0 \text{ if } t \neq t_k \end{cases}$$

The seasonal component is the sum of up to six stochastic trigonometric terms associated with the 12-month frequency and its five harmonics

$$S(t) = \sum_{j=1}^{6} S_j(t)$$

where each frequency component is represented by a pair of variables, each containing white noise disturbances.

$$S_j(t) = \cos(\omega_j)S_j(t-1) + \sin(\omega_j)S_j^*(t-1) + \upsilon_{s,j}$$

$$S_j^*(t) = -\sin(\omega_j)S_j(t-1) + \cos(\omega_j)S_j^*(t-1) + \upsilon_{s,j}$$

$$\omega_j = 2\pi p_j^{-1}, \quad p = \{12, 6, 4, 3, 2.4, 2\}.$$

The white noise disturbances are assumed to have a common variance, so that the change in the seasonal pattern depends upon a single parameter.

The irregular component is specified as consisting of a single white noise disturbance,

$$I(t) = \upsilon_I(t).$$

A zero variance for this component means it can be dropped from the model.

Sampling error is the difference between the population value, $\theta(t)$, and the estimate, $y(t)$,

$$e(t) = \theta(t) - y(t)$$

where $e(t)$ has the following properties:

$$E[e(t)] = 0, \; Var[e(t)] = \sigma^2_{e(t)}$$

$$\rho_e(l) = E(e(t)e(t-l))/\sigma^2_{e(t)}.$$

To capture the autocorrelated and heteroscedastic structure of $e(t)$, we express it in multiplicative form as

$$e(t) = \gamma(t)e^*(t)$$

with $\gamma(t)$ representing the heteroscedastic part of the CPS,

$$\gamma(t) = \sigma_{e*}^{-1}\sigma_{e(t)}.$$

The autocorrelated part of the CPS, $e^*(t)$, can be approximated by an ARMA process,

$$e^*(t) \sim \text{ARMA}(\phi, \theta'),$$

where the θ' and ϕ parameters are derived from the sampling error lag correlations.

An outlier represents a transitory shift in the level of the observed series,

$$O(t) = \sum_j \lambda_j \zeta_j(t)$$

$$\text{where } \zeta_j(t) = \begin{cases} 1 \text{ if } t = j \\ 0 \; otherwise. \end{cases}$$

The coefficient, λ_j, is the change in the level of the series at time j.

4. Estimation

The parameters of the noise component are derived directly from design-based variance-covariance information. The state CPS variance estimates are obtained through the method of generalized variance functions (Census 1978). State level autocorrelations of the sampling error are based on research conducted by Dempster and Hwang (1990) that used a variance component model to compute autocorrelations for the sampling error. After the unobserved signal and noise components are put into the state-space form, the unknown parameters of the variance components of the signal are estimated by maximum likelihood using the Kalman filter (Harvey 1989). Given these parameter values, the filter calculates the expected value of the signal and the noise components at each point of time conditional on the observed data up to the given time point. As more data become available, previous estimates are updated by a process called smoothing (Maybeck 1979). For more details, see Tiller (1989).

5. Results

Using the basic model structure described above, models were fit to the CPS unemployment rate series (CPSRT) for each of the 40 states, covering the period January 1976 to December 1991. With the exception of Oklahoma, each state model has only one explanatory variable in the regression component—the state claims rate (CLR). The claims rate is defined as the ratio of the state unemployment insurance claims to payroll employment from the state Current Employment Statistics survey. In addition to CLR in the regression component, Oklahoma's unemployment rate model uses an unemployment insurance exhaustee rate (EXHRT), defined as the ratio of the unemployed exhaustees to the CES employment. The general form of the model is given by,

$$CPSRT(t) = \beta_1(t)CLR(t) + \beta_2(t)EXHRT(t) + Trend(t) + Seasonal(t) + Noise(t).$$

Once estimated, these models were subjected to diagnostic testing. In a well-specified model, the standardized one-step-ahead prediction errors should behave approximately as white noise. An acceptable model exhibits no serious departures from the white noise properties. Once satisfactory results were obtained, further decisions were based on goodness of fit and on subject matter knowledge.

Regression

Table 5.1 presents the specifications for each of the unemployment rate models. The standard deviations of the white noise disturbances to the coefficients (column two of Table 5.1) are small, resulting in either fixed or nearly fixed values for 18 of the models. For the remaining models, the substantial variation in the model's coefficient indicates an unstable relationship between the CPS rate and CLR.

Trend component

Taken together, the regression coefficients and the trend reflect long-run differences in the behavior of the CPSRT and CLR. Nationally, there have been large changes in the long-term relationship between the CPSRT and CLR. From the 1970's through 1980's, the proportion of unemployed job losers collecting unemployment insurance benefits dropped from 75% to 50%. This has reduced the sensitivity of the claims rate to recessions. In most states, the trend component corrects for this bias in the claims rate by increasing during the recessions and decreasing during expansions.

There have also been some major level shifts in the CPS rate in selected states that are not explained by either the CLR variable or the normal evolution of the trend component. These level shifts are modeled as innovation outliers in the trend level.

We identified level shifts using the following procedure. First, we fit an ARIMA model directly to the CPS data, using SCA time series analysis software, and used an automatic outlier detection procedure to detect potential level shifts. If a level shift in the CPS is identified, we examine the prediction errors from the model for lack-of-fit at the point at which the level shift occurred. Then, we add an intervention variable to the model to estimate the statistical significance and magnitude of the shift. If the shift is found to be highly significant, we add it to the model. We identified level shifts in 5 states.

Seasonal component

Since the CLR is itself highly seasonal, the seasonal component does not account for all of the seasonal variation in the signal. Like the trend, the seasonal component reflects seasonality in CPS not reflected in CLR. In most states, the divergence in the seasonal pattern of the two series is particularly reflected in the large positive value of the seasonal component in June. This is primarily due to the entry of summer vacationing students into the labor force. Since this group is not usually eligible for UI benefits, the seasonal component adjusts CLR by increasing the total rate in June.

In 23 states, the variance of the seasonal component is effectively zero, resulting in a fixed seasonal pattern. The remaining states have some variation in their seasonal patterns over time. Table 5.1 shows the frequency composition of the seasonal component under the column labeled seasonal frequencies. Rarely was it necessary to include all of the 6 frequencies.

Irregular component

The variance of the irregular component is zero in 35 of the states: thus, the irregular component is identically zero and can be dropped from these models. The remaining 5 states have significant random variation present which is not accounted for by the other components.

Outliers

Outliers were identified based on normalized one-step-ahead prediction errors that exceeded, in absolute value, three times their standard error. The outliers identified in each model are shown in the last column. They correspond to unusually large one-time deviations of the CPS from its usual range of fluctuation. We have not been able to associate any of these outliers with unusual economic events. Therefore, they have been treated as part of the noise. The maximum number of outliers identified per state never exceeds four. Out of 192 observations, this does not appear to be an excessive number.

Relative importance of components

To measure the empirical importance of each of the components, we decompose the sum of squares of the change in the sample estimates into its component parts, where change is computed by taking 1-, 3-, and 12-month differences. These differences play an important role in data analysis. Month-to-month change in a reported labor force statistic receives considerable public attention as an indicator of current labor market conditions, as does over-the-year change as an indicator of long-run developments. Also, it is common to report over-the-quarter change.

In Table 5.2, each component sum of squares is expressed in relative form by dividing by the total sum of squares. The table entries show the proportion of the sum of squares of the sample estimates over various time spans which can be attributed to changes in its signal and noise components. The proportional contributions in the table sum to 100, except for rounding error. The column headed SIG refers to the sum of the regression (REG), trend (TRD), and seasonal (SEA) components. The CPS column label refers to sampling error, and the IRR column refers to the irregular component.

First, consider the importance of sampling error. On average, it accounts for 71% of the monthly variation in CPSRT, which is not surprising given the standard deviation of the sampling error is large relative to the average change in the sample estimate. It also accounts for 55% of the yearly variation, illustrating the importance of the strong autocorrelation induced by the sample design.

Next, we examine the relative importance of the regression, trend, and seasonal components in explaining the total variation in the signal. Although most of the monthly, seasonal, and long-run variation in the estimate of the signal is accounted for by the claims rate (CLR roughly accounts for an average 53% of the monthly variation in the signal, 72% of the variation over a 3-month span, and for 68% over a 12-month span), the trend and seasonal components of the model do show significant contributions. The trend component plays an important role in adjusting the claims rate for long-run drift away from the total rate.

Efficiency gains

To obtain a reliability measure for the models, we use the error covariance matrices obtained from the Kalman Filter (KF) and Kalman Smoother (KS). These error measures represent uncertainty resulting from stochastic variation in the population and the inability to observe the state variables directly. These measures do not account for uncertainty in estimating the variance parameters of the signal and the parameters of the sampling error model. Therefore, the model reliability measures must be considered experimental.

With the above caveats in mind, we estimated the potential gains from using the model-based unemployment estimator over the survey-based estimator. The efficiency gain is measured as the ratio of the standard deviation of the estimated signal to the standard deviation of the sample estimate. The median of this ratio for all states was calculated for the KF and KS estimates for monthly values over two time periods, 1980-91 and 1991. We use the period 1980-91, dropping early years because the large transient induced by the initialization of the KF results in poor estimates of the covariance matrices in the early part of the sample. We select 1991, the last year in our sample as an indicator of model reliability in real time. The results are presented in the table below. The smoother is more efficient than the forward filter, particularly in the middle of the series. However, the forward filter represents the most efficient estimator available at the time the estimates are first made and reported. Clearly, the gains from modeling are largest in historical time when the smoother can be used. The ratio of the standard deviation of the signal to the noise is 52% over the period 1980 to 1991, an efficiency gain of 48%. For the latest year, the gains for the KF estimator are smaller, but still substantial, with a signal-to-noise ratio of 64%.

Potential Efficiency Gains from Unemployment Rate Models

	Median ratio of standard error of signal to CPS over 40 states (in %)	
	1980-91	1991
Kalman Filter	64.9	63.5
Kalman Smoother	51.6	56.9

6. Conclusions

Time series models of the CPS unemployment rate were fit to 40 state series. These models account for both the dynamics of the true population values and the sampling error structure. The models, in general, adequately fit the data and produce much smoother series than the sample estimates.

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Table 5.1. Unemployment Rate Model Specifications

State	Standard Deviations of Disturbances: Regression	Trend: Level	Trend: Slope	Seasonal	Irregular	Seasonal Freq	Additive Outliers	Level Shifts
AL	6.0E-03 *	2.8E-01	7.3E-03	2.6E-03		12 4 2.4 2	JUL77	
AK	4.0E-02	1.5E-01	1.5E-04	1.6E-02	3.7E-01	6 4		
AZ	5.1E-02	2.9E-01		1.8E-03		12 4 3	JUL84 JAN88 OCT89	
AR	3.2E-02	1.6E-01		3.1E-02		12 6	MAY80 OCT80 SEP83	
CO	6.1E-02	1.4E-02	7.4E-05	1.7E-02		12 6 4 3 2.4	OCT78 MAR81 OCT84	
CT	4.7E-03	9.8E-02		1.7E-03 *		12 6 4		
DE	1.4E-04 *	3.1E-01		7.9E-03		6 4 2.4	MAR79 NOV81	SEP90
DC	4.3E-03	4.7E-01	5.6E-04	2.2E-02		12 6 4 2.4	SEP84	
GA	6.7E-02	8.9E-02		3.9E-03		12 4 3 2	JUL78 AUG82 MAY91	MAR91 JAN92
HI	6.2E-02	1.7E-01		1.3E-03 *		12 4 2.4	JUN82	
ID	5.1E-04 *	2.2E-01	4.0E-04				DEC77 MAY83 FEB90	
IN	2.3E-03 *	2.5E-01	3.5E-03				AUG90	
IA	8.1E-04 *	6.1E-02	8.7E-03	4.6E-05 *		3 2.4	JAN79 AUG80	
KS	7.3E-04 *	5.5E-02		1.0E-02		4 3 2.4	APR79	JUL82 AUG92
KY	7.9E-02	7.3E-02	4.0E-03	2.5E-04 *		4 2.4	AUG77 AUG79 JUL84 MAY86	
LA	7.5E-04 *	3.8E-01		3.2E-04 *		6 4 3 2.4		
ME	1.1E-03 *	1.8E-01	2.3E-04	1.6E-04 *		12 6 4 3 2.4	JUN80	
MD	1.1E-03 *	1.3E-01		3.6E-04 *		12 6 4 3 2.4 2		
MN	2.7E-04 *	1.5E-01	1.5E-03	1.7E-04 *		12 4 3 2.4	MAR83 APR84 MAR90	
MS	7.6E-02	2.9E-01		1.7E-03 *		12 4 3 2.4	FEB79	
MO	3.4E-02	2.9E-01		2.3E-04 *		6 2.4	JUL81 JAN79	
MT	4.1E-04 *	2.1E-01		3.6E-04 *		12 6 4 3		
NE	4.8E-02	8.9E-02	2.9E-03	1.1E-02		12 6 4 3 2.4 2		
NV	3.3E-03 *	2.1E-01	2.7E-03	6.1E-04 *		12 6 4 3 2.4		
NH	2.4E-03 *	2.9E-01		4.4E-04 *		12 3 2.4	SEP86 APR87	
NM	1.4E-03 *	8.8E-02	1.1E-03	1.3E-03 *	3.8E-01	12 6 4 3 2.4		
ND	5.4E-02	2.6E-02	2.0E-03	2.2E-04 *		12 6 3 2.4		
OK	3.6E-03 *	6.3E-02	3.3E-04	1.8E-03 *	2.1E-01	12 4		JUN80 DEC80
OR	6.0E-02	5.6E-02		3.9E-04 *		6 4 3 2.4	SEP88	
RI	1.8E-03 *	3.4E-01		9.8E-04 *		12 6 4	MAR90	DEC89
SC	2.9E-02	2.6E-01		5.5E-04 *	2.2E-01	12 6 4 3	JUN87 APR83	
SD	1.0E-01	4.0E-03	2.7E-03	1.4E-02		12 6 4 3 2.4	JAN88	
TN	2.8E-02	1.4E-02	2.3E-02	2.1E-04 *		12 4 2.4	DEC82	
UT	8.3E-02	9.3E-02	3.2E-03	8.0E-03		12 4 3 2.4 2		
VT	4.2E-04 *	1.3E-01		1.7E-03 *		12 4 2.4		
VA	7.2E-02	7.2E-02		5.2E-03		12 6 4 3 2.4	JUN87 APR81	
WA	2.0E-03 *	2.1E-01		1.1E-03 *		12 4		
WV	5.2E-02	3.6E-01				12 6 4		
WI	3.1E-02	2.2E-01		2.8E-05 *		12 4 2.4		
WY	3.9E-02	7.5E-04	7.0E-03	2.3E-02	3.1E-01	12 6 4	JUL91	

* zero standard deviation

Table 5.2. Sum-of-Squares Decomposition of Change in CPSRT

	1-Month Span						3-Month Span						12-Month Span					
State	SIG	REG	TRD	SEA	CPS	IRR	SIG	REG	TRD	SEA	CPS	IRR	SIG	REG	TRD	SEA	CPS	IRR
AL	32.7	12.4	0.7	19.5	67.3	0.0	45.8	27.5	3.0	15.3	54.2	0.0	58.5	32.0	26.5	0.0	41.5	0.0
AK	37.0	24.7	0.1	12.1	60.0	3.0	66.2	60.6	0.1	5.4	32.7	1.1	44.0	41.9	2.1	0.0	54.0	2.0
AZ	23.3	9.6	0.7	13.1	76.7	0.0	47.0	30.0	2.7	14.3	53.0	0.0	70.8	59.4	11.4	0.0	29.2	0.0
AR	18.9	5.0	0.1	13.8	81.1	0.0	45.0	12.6	0.4	32.0	55.0	0.0	17.7	10.7	6.8	0.1	82.3	0.0
CO	39.6	21.4	0.0	18.2	60.4	0.0	58.2	50.1	0.0	8.1	41.8	0.0	51.6	51.5	0.1	0.0	48.4	0.0
CT	29.0	21.1	0.1	7.9	71.0	0.0	54.1	42.2	0.2	11.6	45.9	0.0	45.9	43.5	2.4	0.0	54.1	0.0
DE	23.1	5.8	1.4	15.9	76.9	0.0	36.5	6.7	4.8	25.1	63.5	0.0	40.2	4.4	35.8	0.0	59.8	0.0
DC	18.3	0.5	2.4	15.4	81.7	0.0	27.6	1.2	9.2	17.1	72.4	0.0	46.3	1.7	44.6	0.0	53.7	0.0
GA	28.0	9.8	0.2	18.0	72.0	0.0	37.0	19.0	1.0	16.9	63.0	0.0	48.7	37.7	10.9	0.0	51.3	0.0
HI	15.9	2.6	0.2	13.0	84.1	0.0	13.4	5.3	1.2	6.9	86.6	0.0	25.9	18.4	7.5	0.0	74.1	0.0
ID	36.4	36.1	0.2	0.0	63.6	0.0	64.9	64.4	0.5	0.0	35.1	0.0	37.8	30.1	7.7	0.0	62.2	0.0
IN	16.0	15.0	1.1	0.0	84.0	0.0	39.2	36.0	3.2	0.0	60.8	0.0	53.3	32.2	21.0	0.0	46.7	0.0
IA	28.2	20.3	0.1	7.7	71.8	0.0	54.3	52.4	0.6	1.3	45.7	0.0	34.1	23.2	10.9	0.0	65.9	0.0
KS	21.9	8.2	0.0	13.7	78.1	0.0	27.3	22.2	0.3	4.8	72.7	0.0	29.6	25.8	3.7	0.0	70.4	0.0
KY	26.7	18.8	0.0	7.9	73.3	0.0	48.0	44.1	0.1	3.8	52.0	0.0	49.3	47.3	2.0	0.0	50.7	0.0
LA	35.3	1.9	1.8	31.6	64.7	0.0	51.8	4.6	6.3	40.9	48.2	0.0	55.5	14.8	40.6	0.0	44.5	0.0
ME	45.5	45.3	0.1	0.0	54.5	0.0	70.0	69.5	0.5	0.0	30.0	0.0	40.5	32.5	7.9	0.0	59.5	0.0
MD	27.6	13.4	0.1	14.1	72.4	0.0	40.2	26.5	0.4	13.2	59.8	0.0	39.0	32.9	6.1	0.0	61.0	0.0
MN	49.7	27.5	0.1	22.1	50.3	0.0	74.7	62.7	0.3	11:7	25.3	0.0	43.1	35.7	7.4	0.0	56.9	0.0
MS	33.3	10.8	0.5	21.9	66.7	0.0	46.5	28.2-	1.5	16.8	53.5	0.0	51.2	38.9	12.4	0.0	48.8	0.0
MO	23.7	10.5	1.6	11.6	76.3	0.0	45.7	22.4	4.8	18.4	54.3	0.0	48.8	13.4	35.4	0.0	51.2	0.0
MT	26.0	14.3	0.3	11.4	74.0	0.0	52.0	44.5	0.9	6.6	48.0	0.0	26.4	9.4	17.0	0.0	73.6	0.0
NE	22.0	13.3	0.1	8.6	78.0	0.0	53.2	44.0	0.2	9.0	46.8	0.0	28.5	24.8	3.7	0.0	71.5	0.0
NV	26.1	13.7	0.3	12.1	73.9	0.0	56.6	42.0	1.1	13.5	43.4	0.0	57.4	47.0	10.5	0.0	42.6	0.0
NH	19.5	7.2	1.6	10.8	80.5	0.0	30.6	15.7	7.8	7.1	69.4	0.0	62.7	15.7	47.0	0.0	37.3	0.0
NM	31.2	10.0	0.0	21.2	65.5	3.3	48.3	27.5	0.0	20.7	50.0	1.7	42.9	42.4	0.5	0.0	55.4	1.7
ND	54.5	37.1	0.0	17.4	45.5	0.0	79.4	68.7	0.0	10.6	20.6	0.0	28.9	27.6	1.2	0.0	71.1	0.0
OK	15.0	6.1	0.2	8.8	84.3	0.6	27.9	17.3	1.1	9.4	71.8	0.4	61.1	56.7	4.4	0.0	38.7	0.2
OR	30.1	17.3	0.0	12.8	69.9	0.0	51.1	45.3	0.0	5.8	48.9	0.0	46.3	46.2	0.1	0.0	53.7	0.0
RI	30.9	12.5	1.4	17.1	69.1	0.0	50.5	22.6	4.4	23.5	49.5	0.0	51.9	9.2	42.7	0.0	48.1	0.0
SC	21.1	4.9	0.7	15.5	78.3	0.6	29.5	12.0	3.4	14.1	70.1	0.4	50.6	24.8	25.8	0.0	49.1	0.3
SD	33.8	15.6	0.0	18.2	66.2	0.0	54.1	47.0	0.1	7.0	45.9	0.0	29.0	25.6	3.4	0.1	71.0	0.0
TN	25.2	9.9	0.3	15.0	74.8	0.0	39.9	26.5	1.9	11.4	60.1	0.0	46.5	21.0	25.5	0.0	53.5	0.0
UT	35.2	16.0	0.1	19.1	64.8	0.0	58.4	44.2	0.2	14.0	41.6	0.0	48.6	45.4	3.2	0.0	51.4	0.0
VT	40.5	24.5	0.1	16.0	59.5	0.0	61.9	54.0	0.2	7.7	38.1	0.0	38.4	35.4	3.0	0.0	61.6	0.0
VA	28.5	12.6	0.0	15.9	71.5	0.0	44.8	30.9	0.1	13.8	55.2	0.0	35.4	34.3	1.1	0.0	64.6	0.0
WA	25.7	19.1	0.4	6.2	74.3	0.0	47.8	40.2	1.3	6.2	52.2	0.0	45.3	31.5	13.8	0.0	54.7	0.0
WV	15.5	14.5	1.0	0.0	84.5	0.0	43.4	39.7	3.7	0.0	56.6	0.0	60.9	33.9	27.0	0.0	39.1	0.0
WI	28.8	19.7	0.7	8.4	71.2	0.0	62.5	51.4	2.0	9.1	37.5	0.0	53.0	28.4	24.6	0.0	47.0	0.0
WY	32.6	28.9	0.0	3.7	64.7	2.7	65.7	61.1	0.1	4.4	33.5	0.9	59.4	56.9	2.4	0.0	39.7	0.9
Ave.	28.7	15.1	0.5	13.1	71.1	0.2	48.3	34.7	1.8	11.7	51.7	0.1	45.5	30.9	14.6	0.0	54.5	0.1
Med.	28.1	13.4	0.2	13.7	71.9	0.0	47.9	33.4	1.0	11.0	52.1	0.0	46.4	32.0	9.2	0.0	53.6	0.0