TIME SERIES MODELS FOR STATE LABOR FORCE ESTIMATES

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1. Introduction

The Current Population Survey (CPS), conducted by the Bureau of the Census for the Bureau of Labor Statistics (BLS), provides official labor force estimates for the nation as a whole, 11 selected states, New York City, and Los Angeles. For the less populous states and substate areas, the CPS samples are not large enough to provide reliable monthly estimates.

The time series approach to survey data has been proposed as a way to improve on the survey estimator (Bell and Hillmer 1990; Pfeffermann 1992; Scott and Smith 1974). This approach treats periodically generated sample data as a time series of stochastically-varying population values obscured by sampling error. Given a model of the population values and sampling error covariances, signal-extraction techniques are used to estimate the population values. In 1989, BLS adopted a time series approach to labor force estimation in 39 states and the District of Columbia (hereafter referred to as 40 states). In this initial implementation, not enough information was available to directly model the sampling error effects (Tiller 1989). This paper extends that work by developing signal-extraction estimates of employment-to-population ratios from joint stochastic models of the true population values and the sampling error.

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 employment models; and section 6 provides the conclusions.

2. CPS Sample

Two important features of the CPS samples that must be controlled for in the modeling process include the changing reliability of the CPS estimator and the strong autocorrelation in the sampling error.

The reliability of the state CPS estimator changes over time due to sample redesigns, sample size changes, and variations in the labor force. The strong autocorrelation in the sampling error arises from the use of a 4-8-4 rotating panel (Census 1978) which generates complex patterns of sample overlaps over time. In addition, when a cluster of housing units is permanently dropped from the sample, it is replaced by nearby units, resulting in correlations between non-identical households in the same rotation panel (Train, Cahoon, and Makens 1978).

Failure to account for the strong autocorrelation in the sampling error and the changing reliability in the CPS estimator may result in improper identification of the signal from the noise. Thus, it is important to directly control for these characteristics.

3. Time Series Component Modeling

For each state, a model for the employment-to-population ratio is developed. This section describes the basic model structure.

The observed sample estimate at time t, $y(t)$, is represented as the sum of two independent processes

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

where

$\theta(t)$ = the population value
$e(t)$ = sampling error.

The time series of population values is represented by a structural or unobserved variance component model (Harvey 1989) with explanatory variables

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

where $X(t)$ is a $1 \times k$ vector of known explanatory variables with a $k \times 1$ random coefficient vector, $\beta(t)$; $T(t)$ is a trend component; $S(t)$ is a periodic or seasonal component; $I(t)$ is an irregular component; and $O(t)$ is an outlier component. Each of these components include one or more normally distributed, mutually independent white noise disturbances. The variances of these disturbances determine the stochastic properties of the components.

It is useful to group these components 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 consists of sampling error, error that arises from sampling only a portion of the total population, plus purely random variation unaccounted for by other components plus unusually large transitory fluctuations or outliers. While sampling error is the most important component of the noise, the two other components represent variation that should be removed from the signal.

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

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

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

The trend component is represented by a locally smooth linear trend with a random level, $T(t)$, and slope, $R(t)$.

$$T(t) = T(t-1) + R(t-1) + \upsilon_T(t)$$

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

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.

$$S_j(t)=cos(\omega_j)S_j(t-1)+sin(\omega_j)S^*_j(t-1)+v_{s_j}$$

$$S^*_j(t)=-sin(\omega_j)S_j(t-1)+cos(\omega_j)S^*_j(t-1)+v_{s_j}$$

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

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 that the irregular is identically zero and can be dropped from the model.

Sampling error is the difference between the population value, $\theta(t)$, and the estimate, $y(t)$, drawn from the design distribution of the sample estimator with mean $\theta(t)$

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

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,

$$\gamma(t) = \sigma^{-1}_{e*}\sigma_{e(t)},$$

and $e^*(t)$ representing the autocorrelated part of the CPS, which is approximated by an ARMA process,

$$e^*(t) \sim ARMA(\phi,\theta),$$

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

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

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

where $w_j(t)$=1 at time $t=t_j$, zero otherwise and the coefficient, λ_j, is the change in the level of the series at time t_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 algorithm (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, consult Tiller (1989).

5. Results

Using the basic model structure described above, employment models are developed for each of the 40 states for the period covering January 1976 to December 1991. The Current Employment Statistics (CES) survey employment (CESEM), available by state, and intercensal population estimated by the Bureau of the Census are used in the regression component: The general form for the model is

$$CPSEP(t)=a(t)CESEP(t)+Trend(t)+Seasonal(t)+Noise(t)$$

where

CESEP=100(CESEM/Pop)
Pop=noninstitutional civilian 16+ population.

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, i.e., be uncorrelated with a zero mean and fixed variance. To be acceptable, the final model was required to show no serious departures from the white noise properties. Once satisfactory results were obtained, further decisions were based on goodness of fit (likelihood function and AIC) and on subject matter knowledge.

Often, one or more of these components could be simplified. For the signal, CESEP was able to explain a substantial amount of variation in the observed series with fixed coefficients, the trend slope could often be dropped, and the number of seasonal frequencies reduced. For the noise component, the sampling error component was held fixed, but the other components were tailored to the data. In many cases, the estimated variance of the irregular was close to zero, allowing it to be dropped from the model. Outliers were initially identified based on normalized one-step-ahead prediction errors that exceeded, in absolute value, three times their standard error.

Regression

Table 5.1 presents the specifications for each of the employment models. First consider the behavior of the regression coefficient for the CESEP variable. 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 all of the models.

Trend component

The trend consists of only the level component in 27 states; in 6 of these states, the trend reduces to a fixed level; in the remaining states, the trend is very smooth, showing little variability. The stability in the trend is not surprising since the CESEP variable accounts for most of the long-run variation in the signal (see below).

Taken together, the regression coefficients and the trend reflect long-run differences in the behavior of the CPS and CES that arise from fundamentally different ways in which the two surveys measure employment. The CPS target population is the number of persons with one or more jobs, while the CES population is the number of payroll jobs. Since multiple-job holding tends to be procyclical—increasing during economic expansions and decreasing during contractions—the CES tends to grow at a different rate from the CPS. In those states with variable trends, the trend component tends to vary procyclically with multiple job holding. Also, the coefficient of the CESEP variable is almost always less than one, a reflection of the differential in growth rates.

Seasonal component

In 18 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.

It is important to keep in mind that the seasonal component does not account for all of the seasonal variation in the signal, since the CPSEP is itself highly seasonal. Like the trend, the seasonal component reflects measurement differences between the CPS and CES that cause their seasonal patterns to diverge. In the summer months this divergence is particularly apparent in most states. Workers on vacation are counted as employed by the CPS, but are not counted by the CES unless they are paid while on vacation. CPS employment expands in July and remains high in August due to the entry of students into the labor force for summer employment, and then declines in September with the start of the new school year. In contrast, the CES tends to decline in July due to unpaid vacations and then increase in September as workers return from vacation. Therefore, the seasonal component has relatively large positive values in July and August and negative or zero values in September.

Irregular component

The variance of the irregular component is zero in 22 of the states: thus, the irregular component is identically zero and can be dropped from the model. The remaining 18 states have significant random variation present which is not accounted for by the other components.

Outliers

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 57% of the month-to-month variation in the CPSEP, which is not surprising given the standard deviation of the sampling error is large relative to the average change in the sample estimate. However, the sampling error also accounts for the same amount of relative variation over a 12-month span, 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. Over the 2- and 3-month spans, the seasonal component accounts for more of the variation in the signal than does the regression component, a reflection of major seasonal differences between the CPS and CES referred to above. Over the 12-month span the CESEP variable accounts for most of the variation in the signal, on average 89%, compared to 11% for the trend. On average, the irregular component accounts for about 3% of the month-to-month variation in the CPS; therefore, its removal results in some further smoothing.

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 turn to the potential gains from using the model-based employment 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 CPS, expressed as a percentage. 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. 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. 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. 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 67% over the period 1980 to 1991, an efficiency gain of 33%. For the latest year, the gains for the KF estimator are smaller, but still substantial, with a signal-to-noise ratio of 74%.

Potential Efficiency Gains from Employment Models

	Median ratio of standard error of signal to CPS over 40 states (in %)	
	1980-91	1991
Kalman Filter	77.9	74.1
Kalman Smoother	67.1	71.5

6. Conclusions

Time series models of the CPS employment-to-population ratio 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.

References

Bell, W.R. and Hillmer, S.C. (1990), "The Time Series Approach to Estimation for Repeated Surveys," *Survey Methodology*, 16, 195-215.

Bureau of the Census (1978), *The Current Population Survey: Design and Methodology*, Technical Paper 40, Washington, D.C.: Author.

Dempster, A.P., and Hwang, J.S. (1990), "A Sampling Error Model of Statewide Labor Force Estimates from the CPS," Paper prepared for the U.S. Bureau of Labor Statistics.

Harvey, A.C. (1989), *Forecasting, Structural Time Series Models and the Kalman Filter*, Cambridge: Cambridge University Press.

Maybeck, P.S. (1979), *Stochastic Models, Estimation, and Control* (Vol. 2, Orlando: Academic Press.

Pfeffermann, D. (1992) "Estimation and Seasonal Adjustment of Population Means Using Data from Repeated Surveys," *Journal of Business and Economic Statistics*, 9, 163-175.

Scott, A.J., and Smith, T.M.F. (1974), "Analysis of Repeated Surveys Using Time Series Methods," *Journal of the American Statistical Association*, 69, 674-678.

Scott, A.J., Smith, T.M.F., and Jones, R.G. (1977), "The Application of Time Series Methods to the Analysis of Repeated Surveys," *International Statistical Review*, 45, 13-28.

Tiller, R. (1989), "A Kalman Filter Approach to Labor Force Estimation Using Survey Data," in *Proceedings of the Survey Research Methods Section, American Statistical Association*, pp. 16-25.

Tiller, R. (1992), "An Application of Time Series Methods to Labor Force Estimation Using CPS Data," *Journal of Official Statistics*, 8, 149-166.

Train, G., Cahoon, L., and Makens, P., (1978), "The Current Population Survey Variances, Inter-Relationships, and Design Effects," in *Proceedings of the Survey Research Methods Section, American Statistical Association*, pp. 443-448.

Table 5.1. Employment Model Specifications

State	Regression	Trend: Level	Trend: Slope	Seasonal	Irregular	Seasonal frequencies	Outliers
	Standard Deviations of Disturbances						
AL	1.7E-04*	1.6E-02	1.1E-02	1.9E-03*	3.5E-01	6 4	JUN90
AK		4.0E-01	5.0E-04	3.3E-02	5.8E-01	12 6 4 2.4	DEC80 SEP81 JUL85
AZ	3.4E-03	2.5E-01		1.4E-03*	5.1E-01	12 6 4	FEB79 JUN85 JUL85 NOV90
AR	7.4E-03	1.8E-01	1.5E-04	8.3E-03		12 6 4 2	MAR78 SEP79 SEP82 OCT82
CO	4.7E-03	2.7E-01		1.5E-02	4.9E-01	12 4	JAN83
CT	1.8E-03*	8.9E-02	2.1E-04	1.2E-05*		12 6 4 3 2.4	AUG87 DEC88
DE	6.0E-03	1.8E-01*		2.6E-03*		6 4 3	
DC	5.0E-03	2.7E-01	2.8E-03	5.6E-04*		12 6 4 3	SEP87 JUN90
GA	7.8E-05*	1.4E-03	2.3E-04	9.4E-03		6 4 2.4	JUN85 DEC90
HI	3.0E-03	2.3E-01	6.0E-04	6.0E-04*	4.1E-01	6 4 3	JAN80 NOV87
ID	5.0E-03	4.4E-02	3.4E-04	5.4E-04*	4.5E-01	12 6 4	SEP78
IN	5.9E-03	9.7E-02	1.3E-04	9.7E-05*	2.3E-01	12 6 4 3	AUG90
IA	6.3E-03	3.7E-03*		2.5E-02		12 6 4 3	
KS	6.9E-05*	1.9E-01		2.1E-04*		12 6 4 3	JAN82 OCT82
KY	5.8E-03	2.0E-01		1.6E-02	3.4E-01	12 6 4	JUL84 MAY86
LA	2.1E-03	1.7E-01		1.8E-02		12 4 3	
ME	3.2E-03	1.7E-01	6.1E-04	6.8E-04*	4.3E-01	12 6 4 3 2.4	APR85 JAN87 FEB87 MAY87
MD	6.6E-04*	1.8E-01		1.4E-02		12 6 4 3 2	NOV90 DEC90
MN	2.5E-03	1.9E-01		1.7E-02		12 4 3 2.4	JAN83 MAY87 APR89 FEB91
MS	6.2E-03	9.0E-02		1.2E-03*		6 4 2.4	JUL83 DEC91
MO	1.4E-04*	1.0E-01		1.6E-02		12 6 4 3	
MT	1.6E-04*	2.4E-01		1.2E-02		12 6 4 3	
NE	3.5E-03	1.2E-02*		7.9E-03	4.1E-01	12 6 4 3	AUG90
NV	4.3E-03	3.8E-02*		1.1E-02	4.6E-01	12 6 4 3 2.4 2	
NH	1.3E-04*	2.4E-01		1.6E-02		12 6 4 3 2.4	DEC90 NOV84 JAN91
NM	6.7E-04*	1.5E-01		1.3E-02		4 3	
ND	9.6E-05*	3.6E-03	1.3E-02	1.2E-02		12 6 4 2	AUG81
OK	1.4E-03*	2.7E-01		4.7E-04*		12 4 3	
OR	5.2E-04*	3.7E-01		1.8E-04*	2.9E-01	12 6 4 2	DEC79 JAN80
RI	3.1E-03*	1.9E-01		3.5E-04*	4.2E-01	12 6 4 3	SEP85 DEC91
SC	6.3E-04*	1.9E-01		2.3E-02	2.5E-01	12 4	FEB80 MAR80
SD	2.4E-05*	1.5E-02*		1.5E-02	2.4E-01	12 6 4 3	DEC85
TN	1.1E-06*	2.6E-03*		7.9E-03		12 4	JUN88
UT	3.0E-05*	1.6E-01	7.5E-04	1.1E-04*		12 6 4 3	JAN83
VT	3.3E-04*	1.4E-01		5.9E-02	3.6E-01	12 6 4	SEP88
VA	7.7E-04*	1.2E-01		1.3E-02		12 6 4 3	
WA	3.7E-03	1.1E-01		1.4E-02		12 6 4 3 2.4	
WV	1.3E-03*	5.0E-02		3.9E-05*	3.1E-01	12 6	OCT82
WI	3.4E-03	2.5E-02	8.1E-05	3.1E-04*		12 6 4 3	
WY	8.3E-05*	3.0E-01		1.2E-03*	4.4E-01	12 4 3 2	NOV83

* zero standard deviation

Table 5.2. Sum of Squares Decomposition of Change in CPSEP

	1-Month Span						3-Month Span						12-Month Span					
State	SIG	REG	TRD	SEA	IRR	CPS	SIG	REG	TRD	SEA	IRR	CPS	SIG	REG	TRD	SEA	IRR	CPS
AL	22.5	9.7	0.3	12.6	9.4	68.1	28.2	14.8	0.7	12.6	2.5	69.3	52.0	43.4	8.6	0.0	2.0	46.0
AK	74.7	0.0	0.7	74.0	6.4	18.9	89.0	0.0	0.9	88.1	1.4	9.6	36.9	0.0	36.7	0.2	9.7	53.4
AZ	31.7	9.0	0.4	22.3	14.2	54.1	41.6	14.5	0.9	26.2	6.3	52.1	33.4	25.1	8.3	0.0	6.0	60.6
AR	36.2	4.8	0.1	31.3	0.0	63.8	46.2	4.8	0.1	41.3	0.0	53.8	27.5	26.4	1.1	0.0	0.0	72.5
CO	44.5	6.3	0.5	37.7	16.6	38.9	71.8	4.7	0.8	66.3	3.2	25.0	57.5	45.5	12.0	0.0	6.2	36.3
CT	46.0	9.0	0.1	36.9	0.0	54.0	61.5	8.0	0.2	53.3	0.0	38.5	32.5	26.9	5.6	0.0	0.0	67.5
DE	28.2	9.9	0.1	18.2	0.0	71.8	25.1	14.9	0.2	10.0	0.0	74.9	42.1	41.3	0.8	0.0	0.0	57.9
DC	39.3	10.0	0.2	29.1	0.0	60.7	50.6	13.1	0.4	37.0	0.0	49.4	72.2	69.4	2.9	0.0	0.0	27.8
GA	33.8	6.3	0.0	27.4	0.0	66.2	30.7	12.7	0.0	18.0	0.0	69.3	33.1	32.8	0.3	0.0	0.0	66.9
HI	20.1	1.9	0.3	17.9	7.0	72.9	11.7	1.4	0.7	9.6	2.6	85.7	10.7	4.4	6.2	0.0	3.3	86.0
ID	40.4	7.3	0.0	33.1	7.5	52.0	61.6	9.3	0.1	52.2	1.8	36.6	4.2	30.9	3.3	0.0	3.7	62.1
IN	49.4	16.5	0.0	32.9	1.4	49.2	65.9	21.6	0.0	44.2	0.3	33.8	76.8	76.3	0.5	0.0	0.3	22.9
IA	60.7	18.1	0.0	42.6	0.0	39.3	54.4	34.7	0.0	19.7	0.0	45.6	55.9	55.8	0.0	0.1	0.0	44.1
KS	36.2	9.7	0.2	26.4	0.0	63.8	42.3	14.3	0.3	27.8	0.0	57.7	22.8	20.0	2.8	0.0	0.0	77.2
KY	49.8	14.2	0.2	35.5	4.3	45.9	61.1	14.2	0.3	46.7	1.0	38.0	40.8	37.9	2.9	0.0	1.5	57.8
LA	43.4	7.0	0.2	36.3	0.0	56.6	50.7	12.3	0.3	38.2	0.0	49.3	44.2	41.7	2.4	0.0	0.0	55.8
ME	60.0	14.9	0.1	44.9	6.4	33.7	70.1	22.6	0.2	47.3	1.4	28.5	38.8	32.2	6.6	0.0	4.3	56.9
MD	41.8	13.7	0.1	28.0	0.0	58.2	55.8	19.8	0.3	35.6	0.0	44.2	41.8	39.2	2.6	0.0	0.0	58.2
MN	51.4	14.2	0.2	37.1	0.0	48.6	60.6	20.8	0.2	39.5	0.0	39.4	49.6	46.8	2.7	0.0	0.0	50.4
MS	25.9	4.6	0.0	21.3	0.0	74.1	19.4	7.9	0.0	11.5	0.0	80.6	36.4	36.2	0.2	0.0	0.0	63.6
MO	43.9	18.9	0.0	24.9	0.0	56.1	53.1	26.4	0.1	26.7	0.0	46.9	50.1	49.3	0.8	0.0	0.0	49.9
MT	45.4	19.1	0.2	26.1	0.0	54.6	61.1	31.8	0.5	28.8	0.0	38.9	34.2	24.5	9.7	0.0	0.0	65.8
NE	45.5	8.8	0.0	36.7	7.3	47.3	50.7	10.7	0.0	40.0	1.9	47.4	28.9	28.9	0.0	0.0	3.6	67.5
NV	20.3	10.2	0.0	10.0	11.1	68.7	28.3	23.8	0.0	4.5	4.3	67.5	41.8	41.8	0.0	0.0	3.5	54.7
NH	50.1	11.0	0.3	38.8	0.0	49.9	53.0	18.6	0.7	33.7	0.0	47.0	48.9	40.9	8.0	0.0	0.0	51.1
NM	22.2	7.9	0.0	14.2	0.0	77.8	21.4	13.8	0.2	7.5	0.0	78.6	26.2	24.9	1.3	0.0	0.0	73.8
ND	62.2	8.4	0.1	53.7	0.0	37.8	84.7	8.7	0.2	75.8	0.0	15.3	42.0	27.4	14.6	0.0	0.0	58.0
OK	43.0	5.0	0.5	37.4	0.0	57.0	45.2	6.7	1.4	37.1	0.0	54.8	42.5	27.8	14.8	0.0	0.0	57.5
OR	35.2	5.0	2.0	28.3	2.1	62.7	59.2	4.6	2.6	52.0	0.4	40.4	41.6	15.7	25.9	0.0	0.7	57.7
RI	39.0	21.4	0.1	17.5	6.7	54.3	49.2	29.0	0.2	20.0	2.2	48.6	50.9	48.5	2.5	0.0	2.3	46.8
SC	24.1	3.0	0.2	21.0	1.7	74.2	35.1	2.8	0.3	32.0	0.4	64.6	18.5	13.4	5.1	0.0	0.6	80.8
SD	49.7	6.3	0.0	43.4	0.6	49.7	70.2	7.7	0.0	62.5	0.1	29.7	18.0	18.0	0.0	0.0	0.4	81.6
TN	24.6	6.7	0.0	17.9	0.0	75.4	36.4	8.0	0.0	28.4	0.0	63.6	25.3	25.3	0.0	0.0	0.0	74.7
UT	22.6	4.7	0.1	17.7	0.0	77.4	38.5	4.8	0.2	33.5	0.0	61.5	25.2	19.6	5.6	0.0	0.0	74.8
VT	47.3	16.0	0.0	31.3	2.5	50.2	53.5	11.4	0.1	42.1	0.6	45.9	48.3	46.8	1.0	0.5	0.9	50.8
VA	30.7	2.6	0.0	28.0	0.0	69.3	48.9	3.4	0.1	45.4	0.0	51.1	15.0	12.2	2.9	0.0	0.0	85.0
WA	39.6	18.6	0.0	21.0	0.0	60.4	41.9	24.3	0.0	17.5	0.0	58.1	57.4	57.2	0.2	0.0	0.0	42.6
WV	32.0	25.3	0.0	6.7	3.3	64.7	47.0	36.0	0.0	11.0	1.0	52.0	42.0	41.9	0.0	0.0	1.0	57.0
WI	51.3	30.3	0.0	21.0	0.0	48.7	68.4	40.9	0.1	27.4	0.0	31.6	60.8	59.0	1.8	0.0	0.0	39.2
WY	48.3	10.2	0.4	37.8	3.7	47.9	56.8	18.3	0.8	37.7	1.2	42.1	36.8	24.9	1.9	0.0	2.4	60.9
Ave.	40.0	10.8	0.2	29.0	2.8	57.3	49.9	14.9	0.3	34.7	1.1	49.0	40.1	35.8	4.3	0.0	1.6	58.2
Med.	40.4	9.0	0.1	28.0	0.0	56.6	50.7	13.1	0.2	33.7	0.0	48.6	41.6	32.8	2.6	0.0	0.0	57.9