Modeling CPS Labor Force Estimates with Missing Observations Due to the Federal Government Shutdown in 2025 October 2026

Lizhi Liu, Jennifer Oh
U.S. Bureau of Labor Statistics
Office of Employment and Unemployment Statistics
Statistical Methods Staff
Suitland, MD
liu.lizhi@bls.gov, oh.jennifer@bls.gov

Abstract

BLS produces monthly local area unemployment estimates for states based on data from the Current Population Survey (CPS). Due to small sample sizes, structural time series models expressed in state-space form, requiring a continuous time series, are fit to CPS estimates to produce more stable estimates. A federal government shutdown interrupted data collection resulting in missing data for October 2025. Fortunately, the Kalman filter (KF) algorithm used to generate the model estimates readily accommodates missing observations. A well-known solution to missing data is to skip the update step in the KF algorithm. As new data accumulates, a smoothing process is used to revise the predictions.

This paper shows the advantage of using the KF algorithm prediction step to impute missing values. The initial predicted values along with their standard errors for October are compared with previous values with complete data to quantify the effects of uncertainty due to the missing data. Also shown are the effects of revisions to the initial predictions for October as additional data become available. The October estimates used in the paper are unofficial and unpublished.

Key Words: Smoothing, State-space Models, Kalman Filter, Missing Observations

Disclaimer: The information in this article is being released for research purposes only and to inform interested parties. All views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

1. Introduction

The Local Area Unemployment Statistics (LAUS) program, administered by the U.S. Bureau of Labor Statistics (BLS), delivers monthly and annual labor force statistics for divisions, states and metropolitan areas. These statistics are derived from labor force estimates produced via the Current Population Survey (CPS), a monthly survey encompassing approximately 60,000 eligible households.

In October 2025, the CPS was not conducted due to a lapse in federal appropriations that coincided with both the reference and interview weeks. Consequently, October 2025 became the first missing month in CPS, resulting in the absence of published estimates for that period. Data absence reduces estimate precision and increases uncertainty. Failure to appropriately address missing observations can introduce bias and limit the scope of analyses. Proper mitigation strategies and applying suitable methods to manage them is critical for generating robust estimates.

1.1 Background of LAUS Model of CPS Series

Every month, the LAUS models produce unemployment and employment estimates for 9 divisions, all states, and 10 metropolitan areas using over 50 years of historical data. These models use a signal plus noise approach, blending survey sampling with time series modeling to identify patterns over time and adjust for seasonal changes. The direct survey estimator (CPS) for a given state, y_t, is represented as the sum of two independent processes, the true population values, signal (Y_t), and the survey errors, noise (e_t),

$$y_t = Y_t + e_t. \quad (1)$$

Time series modeling facilitates the handling of issues such as gaps arising from missing observation months. Covariate models are incorporated into states and metropolitan areas.

1.2 Model of Noise

The noise component serves to integrate key aspects of the CPS sample design and its estimates directly into the model. This noise is viewed as resulting solely from errors associated with sampling just part of the whole population. Secondly, the CPS utilizes an overlapping sample design known as the 4-8-4 rotation. In this structure, households are interviewed for four consecutive months, removed from the sample for eight months, and then reintroduced for another four-month interview period.

This sampling approach introduces two primary challenges for time series modeling: heteroscedasticity and autocorrelation in the sampling error. Its variability systematically shifts over time due to changes in population values, sample size, and sample design. Secondly, the overlapping nature of the CPS sample results in pronounced autocorrelation within survey errors. Addressing these characteristics is essential for accurately modeling the underlying signal. For detailed methodology on how to handle heteroscedasticity and autocorrelation in the survey error model, see Tiller (2006).

Estimates for the noise model, e_t, are derived from CPS variances and lag-covariances calculated using sample data. The noise model is expressed in a multiplicity form:

$$e_t = \sigma_t e_t^*$$

$$e^*_t = \phi_1\, e^*_{t-1} + \phi_2\, e^*_{t-2} + \phi_3\, e^*_{t-3} + \ldots + \phi_{14}\, e^*_{t-14} + \phi_{15}\, e^*_{t-15} + V_t \qquad (2)$$

where σ_t is the CPS standard error, representing the measurement deviation, V_t is the error in current sample uncorrelated with the past, and e_t^* is the autocorrelated component of the CPS error with autoregressive coefficients, ϕ_i. It's calculated using the Yule-Walker equations applied to the CPS covariances, and the variance of e^*_t is normalized to one.

This noise model reflects the basic CPS error structure with zero mean, a standard error equivalent to the CPS survey error, and lag correlations that match the CPS correlations. The autoregressive form of the model allows it to be incorporated with the signal model into a more general state-space model discussed below.

1.3 Model of Signal

The signal (Y_t), or true population value, is represented by a classical time series model that includes stochastic components for trend ($T_{Y,t}$), seasonal ($S_{Y,t}$) and irregular ($I_{Y,t}$),

$$Y_t = T_{Y,t} + S_{Y,t} + I_{Y,t}. \qquad (3)$$

Each component includes mutually independent normal disturbance (η) terms assumed to have zero means and fixed variances that allow each of the three components to vary over time. An extension of the structural model involves relating one or more unobserved signal components to corresponding components in another series that is independent of the CPS sample error. The CPS signal can be enhanced with a covariate model,

$$C_t = T_{C,t} + S_{C,t} + I_{C,t}\,, \qquad (4)$$

with the same basic form as for the CPS to form "Seemingly Unrelated Time Series Equations (SUTSE)" (Harvey, 1989) where the trend level disturbances of the two series are correlated. For the unemployment model, the monthly covariate used is continued claims without earnings from the regular Unemployment Insurance (UI) program and for the employment model, total non-farm payroll employment estimated by the Current Employment Statistics (CES) program is used.

In this bivariate time series model, the two series, Y_t and C_t are treated as related by correlations between their respective trend disturbances. As a result, the covariate trend assists in estimating the CPS trend disturbance via a regression coefficient.

2. State-Space Modeling of LAUS Series

To support efficient estimation of the model components, the signal plus noise model is formulated within a state-space framework. This approach also offers an effective method for addressing issues related to missing data in time series analysis.

2.1 Estimation of Time Series Components

The standard state-space model consists of an observation and a transition equation. The observation equation expresses the observed series as a linear combination of unobserved state variables,

$$\underset{n\times 1}{y_t} = \underset{n\times m}{z_t}\ \underset{m\times 1}{\alpha_t} \tag{5}$$

where,

y_t : Observed variables
n : Number of observed series
m : Number of state variables
α_t : Vector of state variables representing unobserved trend, seasonal and irregular components and correlated survey error
z_t : Observation matrix (rows define linear combinations of state variables producing the observed series)

There is no separate measurement error term in the observation equation. The KF assumes measurement error is unrelated to past values and has constant variance. If measurement error is correlated, such as with CPS survey error, it is commonly removed from the observation equation and included in the state vector, which works because CPS sampling error follows an autoregressive pattern which naturally has a state-space form (Tiller, 2006).

The transition equation describes the dynamics of the state space variables as a 1st order vector autoregressive process,

$$\underset{m\times 1}{\alpha_t} = \underset{m\times m}{F_t}\ \alpha_{t-1} + \underset{m\times 1}{\eta_t}\ ;\ \eta_t \sim NIID(0, Q), Q = Diag\left(\sigma_{\eta j}^2\right) \tag{6}$$

where,

F_t : State transition matrix shows how the state variables change over time prior to the occurrence of external disturbances.
$F_t = block\ diagonal\left(F_{1,t}, \dots, F_{n,t}\right)$
η_t : Vector containing white noise disturbances of the component models with a $m \times m$ diagonal covariance matrix, Q.

2.2 Kalman Filter

The Kalman Filter is formulated using two sets of equations derived from the state-space model: the prediction and update equations. The prediction equation generates a one-step ahead prediction, $\hat{\alpha}_{t|t-1}$, along with its covariance matrix, $\hat{P}_{t|t-1}$,

$$\begin{aligned} \hat{\alpha}_{t|t-1} &= F_t \hat{\alpha}_{t-1|t-1} \\ \hat{P}_{t|t-1} &= F_t \hat{P}_{t-1|t-1} F_t' + Q \end{aligned} \tag{7}$$

where,

$\hat{\alpha}_{t|t-1}$: Estimated state vector at time *t* using data up to *t*-1

$\hat{P}$: The state prediction error covariance matrix

Q: State disturbance covariance matrix

The filter is initialized with $\hat{\alpha}_0 = 0$ and diagonal covariance matrix, $\hat{P}_0$, with large values on the diagonal. When a new observation becomes available, the predictions are updated with $\hat{\alpha}_{t|t}$ and its covariance matrix, $\hat{P}_{t|t}$, to incorporate the latest information.

$$\begin{aligned} \hat{\alpha}_{t|t} &= \hat{\alpha}_{t|t-1} + K_t v_t \\ \hat{P}_{t|t} &= (I - K_t Z_t)\hat{P}_{t|t-1} \end{aligned} \tag{8}$$

where,

$v_t = y_t - Z_t \hat{\alpha}_{t|t-1}$, one step ahead error vector in predicting observed series
$f_{t|t-1} = Var(v_t) = Z_t \hat{P}_{t|t-1} Z_t'$

$\underset{m\times n}{K_t} = \hat{P}_{t|t-1}\, Z_t'\, \underset{n\times n}{f_{t|t-1}^{-1}}$, is the Kalman gain, with more weight given to estimate with greater certainty

Additionally, incorporating data at time *t* further decreases uncertainty as more information is added ($\hat{P}_{t|t} \leq \hat{P}_{t|t-1}$, see (8)). The KF predicted value reflects all past data up to time *t*-1, while the updated estimate incorporates both historical and current information. This predictor is only a linear projection and therefore is a best linear unbiased predictor (Tiller 2006). After each update step, $\hat{\alpha}_{t|t}$ and $\hat{P}_{t|t}$ become the starting points for the following period, and the process repeats. As a result, the KF only requires previous period's estimates and observed data at time *t* to make updates of the predictions for y_t, enabling the algorithm to generate real-time estimates as data arrives and provide immediate insights about unobserved components.

2.3 Smoothing

To update estimates with future data, "smoothing" is used, which recursively adjusts KF estimates from the latest observation backward. This batch process considers all data before and after a given time, applying the fixed interval smoother by Dejong (1989).

$$\begin{aligned} \hat{\alpha}_{t|n} &= \hat{\alpha}_{t|t-1} + \hat{P}_{t|t-1} r_{t-1} \\ \hat{P}_{t|n} &= \hat{P}_{t|t-1}\left(I - N_{t-1}\hat{P}_{t|t-1}\right) \end{aligned} \tag{9}$$

where,

$$\begin{aligned} \underset{m\times 1}{r_{t-1}} &= Z_t' f_{t|t-1}^{-1} v_t + L_t' r_t \\ \underset{m\times m}{N_{t-1}} &= Z_t' f_{t|t-1}^{-1} Z_t + L_t' N_t L_t \\ \underset{m\times m}{L_t} &= F_t - F_t K_t Z_t \end{aligned} \tag{10}$$

for *t* = n,…, 2, 1 initialized with $r_n = 0$ and $N_n = 0$.

The smoothing error vector, r_{t-1}, is responsible for bringing information from the future to the past. The first part, $Z_t' f_{t|t-1}^{-1} v_t$, contains correction from the prediction based on new information at time *t* and the latter part, $L_t' r$, adds all available future information. When the prediction at time *t* is less certain, the first part becomes smaller. If the observed series provide little new information at time *t*, the first part becomes very small as $f_{t|t-1}$ becomes very large.

The term, N_{t-1}, (10), refers to the additional precision gained from new information at time *t* and in subsequent periods. When N_{t-1} value is high, $\hat{P}_{t|n}$, (9), becomes much smaller than the $\hat{P}_{t|t-1}$. The first part, $Z_t' f_{t|t-1}^{-1} Z_t$, evaluates how much uncertainty is reduced by information received at time *t*, while the second part, $L_t' N_t L_t$,

considers the cumulative impact of all future observations. The $\hat{P}_{t|n}$ is always less than or equal to the $\hat{P}_{t|t-1}$, since having more information lowers uncertainty and the estimates appear "smoother" than those produced by the KF. Smoothed estimates use data from the entire sample and are not available in real time. In practice, smoothing is performed annually to minimize revisions and prevent confusion for users.

3. Approaches to Addressing Missing Observations

Due to the government shutdown in October 2025, the CPS was not conducted for that month. As a result, the dependent variable for the signal is absent from the dataset for this period. Our standard software, which was designed under the assumption of a continuous time series, did not produce valid estimates and required modifications to address this gap.

When all observations are absent at time *t*, the usual update and smoothing equations still function by assigning zero to both the Kalman gain and prediction error, and by setting the prediction error variances very large. However, if only a portion of the observations are missing at time *t*, the Kalman gain will have some non-zero elements.

3.1 Missing All Series at time *t*

Suppose the CPS and covariate variables are missing at time *t*. The KF prediction step remains unchanged to generate $\hat{\alpha}_{t|t-1}$ and $\hat{P}_{t|t-1}$. The update step can be executed by setting Kalman gain (K_t) see (8) and prediction error vector (v_t) to zeros, effectively skipping the update process by assigning

$$\begin{aligned} \hat{\alpha}_{t|t} &= \hat{\alpha}_{t|t-1} \\ \hat{P}_{t|t} &= \hat{P}_{t|t-1}. \end{aligned} \tag{11}$$

Since the update step is skipped, the covariance $\hat{P}$ grows with each missing observation, reflecting the filter's increasing uncertainty about the state in the absence of actual measurements at time *t*. Once data becomes available again, the state estimate generally realigns quickly with the true trajectory. When all the values for the observation vector at time *t* are missing, both K_t and v_t have zero values. Consequently, the smoothing equations are simplified. The r_{t-1} and N_{t-1} in (10) become

$$\begin{aligned} r_{t-1} &= F_t' r_t \\ N_{t-1} &= F_t' N_t F_t \end{aligned} \tag{12}$$

in the absence of a new measurement at time *t* (Durbin and Koopman, 2012). The formula for smoothed state variances remains unchanged, but the value of N_{t-1} decreases while $\hat{P}_{t|n}$ increases. Therefore, even without new information at time *t*, the smoother continues to revise predictions using future data. Unlike the filter, the smoother does not require an observation at time *t* to refine its estimate for that time point.

3.2 Missing Partial Series at time *t*

When only a subset of series is missing—in this case, CPS is missing but covariates are not—the prediction step remains unchanged, but it's necessary to adjust the observation equation by removing rows corresponding to the absent data as follows (Durbin and Koopman, 2012 & Shumway, R. H., & Stoffer, D. S., 2010),

$$y_t^* = Z_t^* \alpha_t^* \tag{13}$$

where,

$y_t^* = w_t\, y_t,\ \ Z_t^* = w_t\, Z_t,\ \ v_t^* = w_t v_t$

Let s denote the number of missing series at time *t*, and w_t represent an information adjustment matrix,

$$w_t = \begin{Bmatrix} n \times n \text{ identity matrix} & \text{if } s = 0 \\ (n - s) \times n \text{ matrix} & \text{if } 0 < s < n \end{Bmatrix}$$

Consider the following examples:

- If there are no series missing at time *t*,
  then $y_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}$, $w_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, and $y_t^* = \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix}, v_t^* = \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix}$, $Z_t^* = m \times m$ matrix
- If y_t includes two series and $y_{2,t}$ is missing,
  then $y_t = \begin{bmatrix} y_{1,t} \\ \cdot \end{bmatrix}$, $w_t = [1 \quad 0]$, and $y_t^* = [y_{1,t}]$, $v_t^* = [v_{1,t}]$, $Z_t^* = (n\text{-}1) \times m$ matrix
- If y_t includes three series and $y_{2,t}$ is missing,
  then $y_t = \begin{bmatrix} y_{1,t} \\ \cdot \\ y_{3,t} \end{bmatrix}$, $w_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, and $y_t^* = \begin{bmatrix} y_{1,t} \\ y_{3,t} \end{bmatrix}$, $v_t^* = \begin{bmatrix} v_{1,t} \\ v_{3,t} \end{bmatrix}$, $Z_t^* = (n\text{-}1) \times m$ matrix

When dealing with partial information, one or more series are absent, but not all. As a result, at least one component of the prediction error vector must differ from zero. The gain retains the same number of rows, *m*, as there are state variables in the system. This means update weights are produced for each state variable, regardless of whether observations are missing. However, some weights may be nearly zero implying no updates.

The KF update step equations for missing partial series closely resemble those used when all series are present. However, the Kalman gain, observation matrix, and prediction error are appropriately reduced by excluding rows corresponding to the missing data.

$$\underset{m\times 1}{\hat{\alpha}_{t|t}^*} = \hat{\alpha}_{t|t-1} + \underset{m\times(n-s)}{K_t^*} \underset{(n-s)\times 1}{v_t^*} \qquad (14)$$
$$\hat{P}_{t|t}^* = (I - K_t^* Z_t^*)\hat{P}_{t|t-1},$$

where,

$$\underset{m\times(n-s)}{K_t^*} = \hat{P}_{t|t-1} \underset{m\times(n-s)}{(Z_t^*)'} \underset{(n-s)\times(n-s)}{\left(f_{t|t-1}^*\right)^{-1}}$$
$$\underset{(n-s)\times(n-s)}{f_{t|t-1}^*} = \underset{(n-s)\times m}{Z_t^*} \hat{P}_{t|t-1} \underset{m\times(n-s)}{(Z_t^*)'}.$$

Even if some series are missing at time *t*, the Kalman gain will have some non-zero elements corresponding to the non-missing covariates at time *t* if there are cross correlations between the relevant series. For example, consider two series, *i* and *j*. If measurements for the i^{th} series are absent but one of its state variable estimates is correlated with another state variable, *j*, whose series data is available (i.e. the appropriate off-diagonal element of $\hat{P}_{t|t-1}$ is not zero), the state variable for *i* will still be updated alongside those linked to non-missing information. This occurs because the observable series, *j*, provides information about the missing series at time *t*. Of course, the updated covariance matrix for partial information, $\hat{P}_{t|t}^*$, will be smaller or no larger than the prediction variance, $\hat{P}_{t|t-1}$, used at time *t* when all information is missing.

Smoothing utilizes the same reduced matrices generated during the update step, y_t^*, Z_t^*, v_t^*, $f_{t|t-1}^*$, and K_t^*. Since partial information is available at time *t*, the corresponding term $Z_t^{*\prime} f_{t|t-1}^{*-1} v_t^*$ is retained for r_{t-1}^* and $Z_t^{*\prime} f_{t|t-1}^{*-1} Z_t^*$ for N_{t-1}^* in (15) below. These components incorporate new data directly and indirectly from time *t* to retrospectively refine state estimates in (9). As before in the case when all series are missing at time *t*, future information propagates backward through the terms $L_t' r_t^*$ and $L_t' N_t^* L_t$.

$$\underset{m\times 1}{r_{t-1}^*} = Z_t^{*\prime} f_{t|t-1}^{*-1} v_t^* + L_t' r_t \qquad (15)$$
$$\underset{m\times m}{N_{t-1}^*} = Z_t^{*\prime} f_{t|t-1}^{-1} Z_t^* + L_t' N_t L_t$$

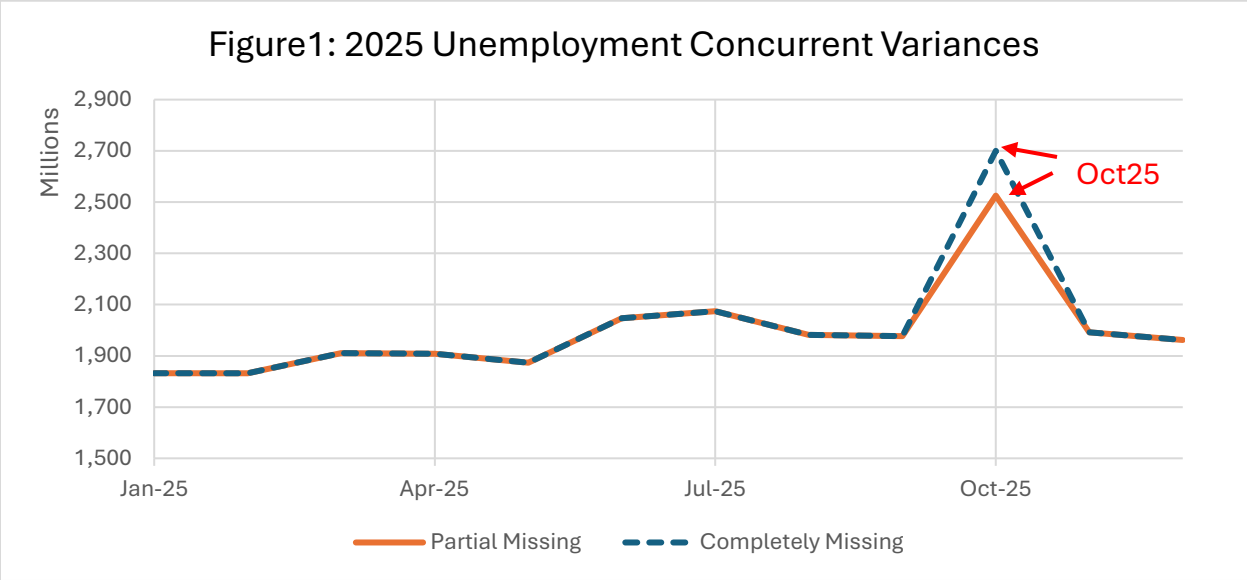
To sum up, the smoothed covariance matrix, $\hat{P}_{t|n}$, reaches its maximum when no information is present at *t*. When partial information is available, uncertainty is reduced but is still larger than at observed time points.

4. Results

This section shows how missing October 25 affects states' concurrent variances, explores the impact of adding partial information, examines how smoothing restores precision, and outlines resulting changes in model estimates. In multivariate cases there is also the possibility there might be partial information on the signal of covariate data is available while data for signal is missing.

In the example state shown in the figures below, the CPS and covariate are highly correlated with each other. This configuration is leveraged to quantitatively assess the effects of two distinct missing series scenario: 1. missing partial series in October 2025 (partially missing), where only CPS is absent, and 2. missing all series in October 2025 (completely missing), where both CPS and the covariate series are missing. The figures illustrate how the strength of the association between CPS and the covariate modulates variances introduced under each scenario, thereby providing insight into the robustness of statistical inference in the presence of missing data.

Figure 1 illustrates a comparison example of a state's unemployment variances when analyzing partial (solid line) versus completely missing (dotted line) series for the signal observed in 2025. In October 2025, variances increased due to limited data availability in both scenarios, compared to months without missing information. It is notable that the variance associated with missing partial series data is lower than that with completely missing series, as supplemental information was accessible. For the remainder of the year, as new data becomes available in subsequent months, the concurrent variances return to typical levels as anticipated.



It is well established that the presence of missing data leads to an increase in the variances. However, to what degree is the signal variances inflation mitigated by correlation with the covariate included in the model? Table 1 summarizes variances reduction in October 2025 for all states when covariate information is included. Incorporating extra information reduces unemployment model variances by an average of 3.4% (maximum 14%) and employment model variances by an average of 0.4% (maximum 2%).

Table 1. Concurrent Variances Reduction (%) in October 2025 with Partial Information (All States)

Model	Average	Maximum
Unemployment	3.4	14.0
Employment	0.4	2.0

The CPS variances (green lines in Figures 2 and 3) indicate data variability, which decreased after filtering in the concurrent year (blue lines in Figures 2 and 3). The concurrent variances only used information up to current month, no future information. Then incorporating future information through smoothing techniques on the example in Figure 1 subsequently led to a substantial reduction in these variances in both partially (Figure 2) and completely (Figure 3) missing series cases. The smooth variances (dotted lines in Figure 2 and 3) show a continuous rise with a slight acceleration in October. Except for the final observation, smoother assigns considerably less weight to individual CPS observations compared to the concurrent estimator.

Figure 2: 2025 Unemployment Variances
(Partially Missing)

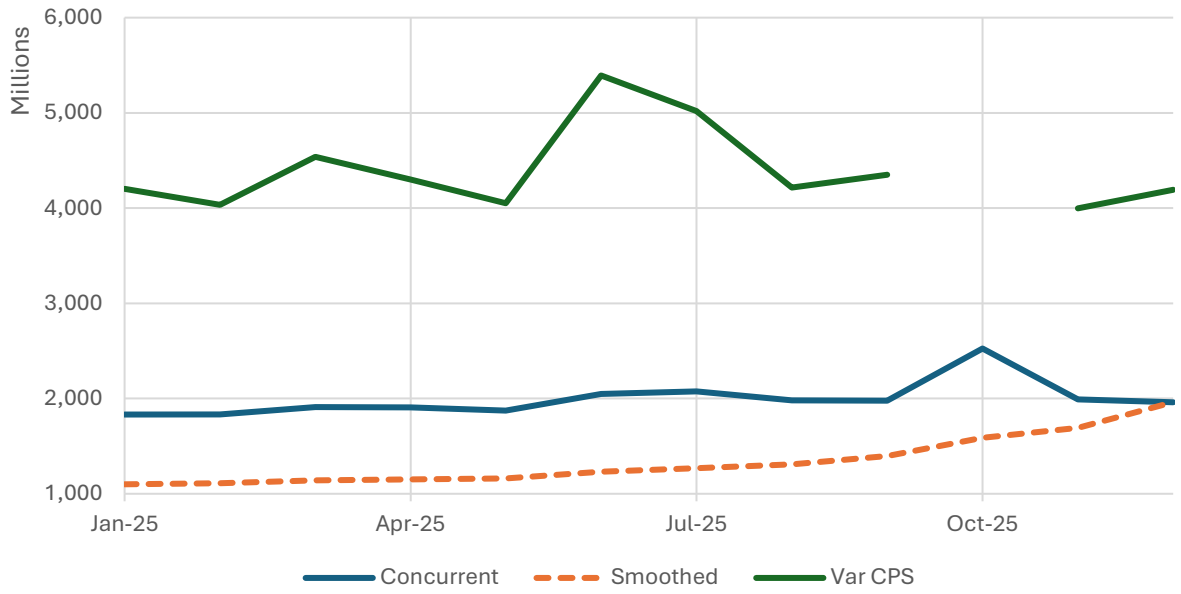
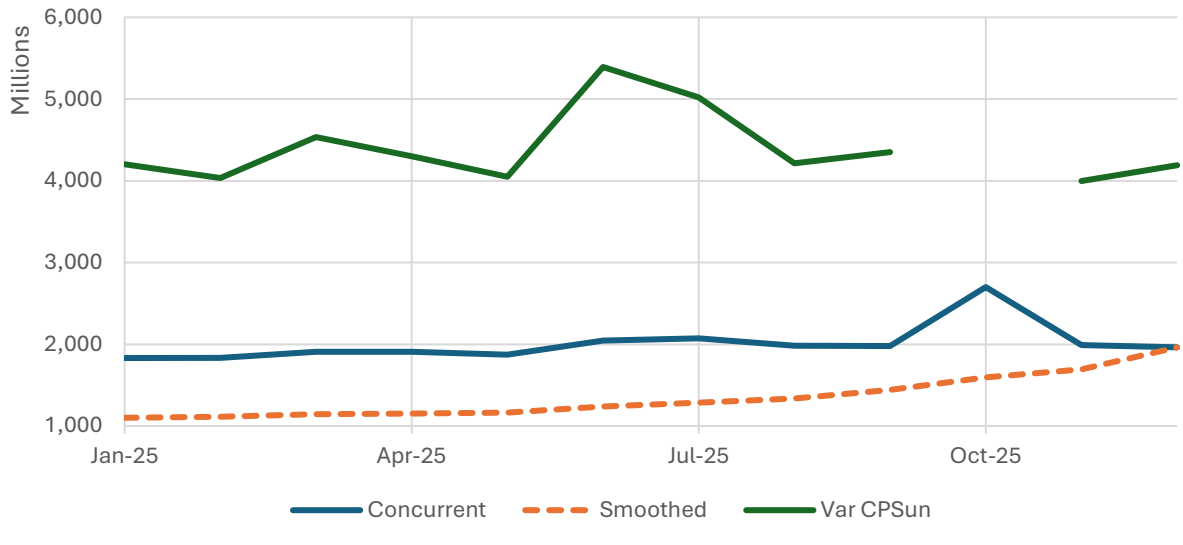


Figure 3: 2025 Unemployment Variances
(Completely Missing)



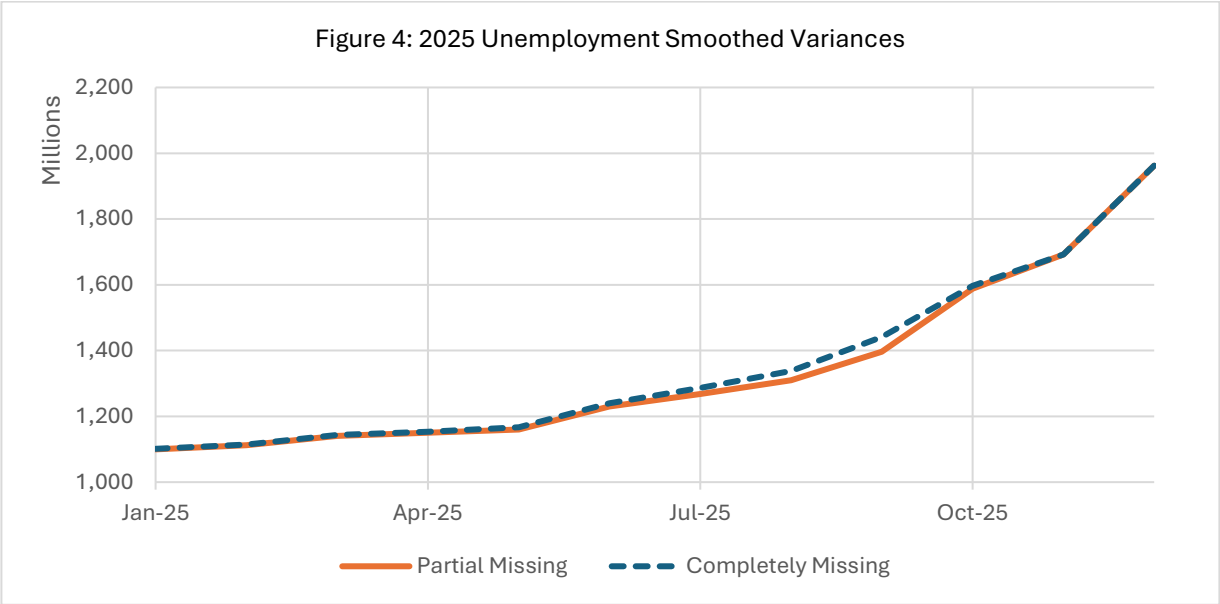
Tables 2 and 3 report the percentage reduction in variances for October 2025 across all states, achieved through the application of smoothing techniques. Table 2 pertains to the partially missing data scenario, whereas Table 3 addresses the completely missing data scenario. In both cases, the incorporation of future information resulted in a substantial decrease in variances. The reduction was notably greater in the completely missing case (Table 3), as concurrent variances in the completely missing scenario tended to be higher. Upon applying smoothing, the resulting variances converged closely between the two scenarios, as illustrated by the example presented in Figure 4.

Table 2. Variances Reduction (%) in Smoothed Levels, All States October 2025 (Partially Missing)

Model	Average	Median	Maximum
Unemployment	24.4	25.0	37.2
Employment	13.7	12.8	24.5

Table 3. Variances Reduction (%) in Smoothed Levels, All States October 2025 (Completely Missing)

Model	Average	Median	Maximum
Unemployment	30.7	30.3	42.0
Employment	13.6	12.9	25.1



Tables 4 (partially missing) and Tables 5 (completely missing) present the absolute percent revision statistics for the October 2025 state model estimates, incorporating additional information from November and December 2025. It is noteworthy that the completely missing case exhibited smaller revisions in the estimates compared to the partially missing case. This outcome arises because the smoothing technique revises the one-step-ahead predictions, $\hat{\alpha}_{t|t-1}(7)$, and their covariance, $\hat{P}_{t|t-1}(7)$, in a backward manner without recomputing all updates. When smoothing is applied in the partially missing scenario in October 2025, the Kalman Filter estimates are revised including the term $Z_t^{*\prime} f_{t|t-1}^{*-1} v_t^*$ (15), which adds supplementary information to the smoothed estimate $\hat{\alpha}_{t|n}$ (9), consequently, larger revisions. In contrast, this additional information does not occur in the completely missing case, which leads to smaller revisions in the estimates.

Table 4. Absolute % Historical Revisions Model Estimates All States, October 2025 (Partially Missing)				
Model	Minimum	Average	Median	Maximum
Unemployment	0.33	5.7	4.6	17.6
Employment	0.01	0.6	0.5	1.5

Table 5. Absolute % Historical Revisions Model Estimates All States, October 2025 (Completely Missing)				
Model	Minimum	Average	Median	Maximum
Unemployment	0.01	3.4	2.9	11.5
Employment	0.02	0.4	0.4	0.8

5. Conclusion

The October 2025 federal government shutdown created an unprecedented gap in CPS input data for LAUS modeling. Although CPS data were missing, the model continued to function by modifying the observation and update steps to handle incomplete data. This study provides a comprehensive assessment of the effects of missing data in October 2025 on state-level unemployment and employment model variances. The results demonstrate that both missing partial and missing all series led to increased variances during the affected month, with missing partial series case showing lower variances due to the availability of covariate information. As additional data becomes available in subsequent months, concurrent variances return to typical levels, confirming the anticipated recovery.

The smoothing techniques, incorporation of future information, substantially reduce variances in both scenarios. The reduction is more pronounced in the completely missing series case, reflecting the higher initial concurrent variances. Notably, smooth variances converge closely between two cases, underscoring the effectiveness of smoothing in restoring precision.

Revision statistics further reveal that the completely missing series scenario results in smaller revisions compared to the missing partial series scenario when covariate information for the missing month is integrated. This distinction is attributed to the smoothing process, which revises one-step-ahead predictions and their covariances in a backward manner without recomputing all updates. In the partially missing scenario, supplementary information is incorporated into the smoothed estimates, leading to larger revisions.

Overall, these findings highlight the critical role of partial information and advanced smoothing techniques in maintaining the reliability and stability of statistical model estimates under conditions of incomplete data. These results highlight the robustness of the LAUS modeling framework, illustrating that structural time-series techniques can preserve continuity and extract valuable insights even when real-world disruptions impact the data stream.

6. Future Work

Soon, we intend to perform simulations in which several consecutive months of CPS data are deliberately excluded. This approach will enable a systematic assessment of the effects that extended input data gaps have on variances

within the LAUS modeling framework. Through analysis of these scenarios, our objective is to obtain a more comprehensive understanding of model robustness and evaluate the efficacy of smoothing algorithms when faced with prolonged data disruptions.

Acknowledgment

The authors gratefully acknowledge Richard Tiller (retired BLS employee) for his constructive feedback and thoughtful insights. All errors in the paper remain the responsibility of the authors.

References

- De Jong, P. (1989). Smoothing and interpolation with the state-space model. *Journal of the American Statistical Association*, *84*(408), 1085–1088.
- De Jong, P. (1991). The Diffuse Kalman Filter. *The Annals of Statistics*, 19(2), 1073–1083.
- Durbin, J., & Koopman, S. J. (2012). *Time series analysis by state space methods* (2nd ed.). Oxford University Press.
- Evans, T. D., Tiller, R. B., & Zimmerman, T. S. (1993). Time series models for state labor force estimates. *In Proceedings of the Section on Survey Research Methods, American Statistical Association*, 358–363.
- Harvey, A. C. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge University Press.
- Shumway, R. H., & Stoffer, D. S. (2010). *Time series analysis and its applications: With R examples* (3rd ed.). Springer.
- Tiller, R. (1989). A Kalman filter approach to labor force estimation using survey data. *In Proceedings of the Section on Survey Research Methods, American Statistical Association*, 16–25.
- Tiller, R. (2006). *Model-based labor force estimates for sub-national areas with large survey errors* (Research Paper st060010). U.S. Bureau of Labor Statistics.
- U.S. Bureau of Labor Statistics. (2026, March 11). *2025 federal government shutdown impact on the Current Population Survey*. https://www.bls.gov/cps/methods/2025-federal-government-shutdown-impact-cps.htm.
- U.S. Bureau of Labor Statistics, & U.S. Census Bureau. (2019). *Current Population Survey: Design and methodology* (Technical Paper 77). U.S. Census Bureau.