Variance Estimation for Weekly Seasonally Adjusted National UI Claims Series[1] November 2016

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Abstract
Two of the timeliest U.S. economic indicators are initial claims and continuing claims from the Unemployment Insurance (UI) program. These series are collected and processed weekly by the States, and are seasonally and calendar adjusted by the Bureau of Labor Statistics for release by the Department of Labor. Weekly data are difficult to seasonally adjust as the series do not have constant periodicity. Seasonal adjustment is carried out utilizing a locally-weighted regression approach originally described in Cleveland (1993). Week-to-week changes can be both relatively large and variable, so the changes can be difficult to interpret. To account for this problem, we utilize the parametric bootstrap. Standard errors for week-to-week changes from this method are analyzed for both initial claims and continued claims series.

Key Words: Bootstrap, high-frequency time series

1. Background

The Employment and Training Administration (ETA) of the U.S. Department of Labor publishes a press release each Thursday with seasonally adjusted data from the Unemployment Insurance (UI) program. Initial claims are reported for the previous week ending on Saturday. With only a week's time lag, the initial claims series is one of the timeliest indicators for the U.S. economy. Continued (insured) claims are reported a week later.

The claims series are seasonally adjusted by the Bureau of Labor Statistics. Seasonal effects for initial claims are often strong as seen in Figure 1. Seasonality is strong at the beginning of the year and slowly declines until a rise around the July 4th holiday. Seasonality then dampens until November when claims begin to rise again. Continued claims have a similar, but less intense pattern (see Figure 2). During a recession, the number of claims tends to rise quickly.

Unfortunately, week-to-week changes for both series can be highly variable and can confound data users. ETA publishes a four-week moving average for both seasonally adjusted series, but that does little to solve our problem. This paper directly addresses that problem by estimating confidence intervals for the week-to-week changes.

The method used to seasonally adjust the weekly series is explained in Section 2. There is a brief discussion in Section 3 on ways to estimate variances for UI data. Results are given in Section 4 and Section 5 offers a brief summary. Figures are in the appendix.

[1] Any opinions expressed in this paper are those of the authors and do not constitute policy of the Bureau of Labor Statistics.

2. Seasonal Adjustment of Weekly Data

The program utilized by BLS for seasonally adjusting weekly UI data is based on work by Pierce, Grupe, and Cleveland (1984). The first weekly seasonal adjustment program used at BLS is described by Cleveland (1986) and is based on the Pierce, et al., paper. A regression model with trigonometric, holiday and outlier variables produces fixed seasonal factors. In 2002, BLS moved to a new program by Cleveland (1993) that uses the same regression approach as before, but adds locally-weighted regressions to allow for stochastic seasonality. This was especially important during the recent Great Recession since the sudden changes in economic activity appeared to affect seasonality. The new approach is demonstrated for UI data in Cleveland and Scott (2007). BLS has modified the latest program by Cleveland to make the program easier to execute, account for possible level shifts, and to add more plots and diagnostics (Evans and Byun 2010). We refer to the revised program as MoveReg for “moving regressions.”

Our basic model is here:

$$Y_t = T_t S_t I_t H_t O_t$$

where Y_t is the observed series (at time t), T is the trend component, S is the seasonal component, I is the irregular component, H is the holiday component, and O is the outlier component. In practice, the log transformed series is first differenced, and the trend component is not explicitly modeled.

There are other approaches to seasonally adjust weekly data. Harvey, Koopman, and Riani (1997) use a structural time series model with splines. Recently, BLS has explored using a state-space model for the UI series. The Census Bureau has also performed similar research (Monsell and McElroy 2016) with promising results. An advantage to using structural time series models is that the trend and irregular components are explicitly modeled in addition to the seasonal, holiday, and outlier components.

Seasonal adjustment of monthly and quarterly data can be challenging depending on the characteristics of the series. However, seasonally adjusting weekly data can be even more difficult. As weekly data do not have constant periodicity, standard seasonal adjustment programs such as X-13ARIMA-SEATS cannot be used. The number of weeks vary in a year with either 52 or 53. Regardless of the ending day that is used to define a week, the position of each day changes from year to year. This means that even if seasonality is deterministic, the seasonal factors will show variability from year to year. The solution to this problem with weekly data is to represent seasonality with sine and cosine functions that represent the seasonality of each day of the year. Leap years are handled by changing the denominator of the sine and cosine terms from 365 to 366.

Another problem with seasonally adjusting weekly data is that all holidays can affect the data and will be “moving.” For example, Thanksgiving can fall in either week 47 or 48 and Easter can range from week 12 to week 18. The day of the week that a holiday falls can have additional effects. For example, for the initial claims data, when July 4th falls on a Wednesday or when Christmas is on Friday, the number of claims filed for those weeks can vary in addition to the normal effects. A “late” Thanksgiving affects the continued claims data. The effect of the New Year holiday in initial claims data can spread over the first two weeks of the year depending on the day of the week where the New Year falls. It is always important to have a reasonably long time series for weekly data in order to capture the numerous holiday effects since they do not occur every year.

The MoveReg program starts with a global regression to estimate holiday and outlier effects. The original series is logged to help stabilize the seasonal factors and differenced to remove any trend effects. The seasonal component is estimated with sine and cosine terms keyed to the day of the year. Holiday effects are considered to be special seasonal effects and are removed from the final seasonally adjusted series. The holidays can have varying weights though some are simple dummy variables. Outliers are modeled as dummy variables, and temporary level shifts are treated with strings of additive outliers. Testing determines the number of sine and cosine frequencies since all are not needed in the model. Locally weighted regressions by year allow for stochastic seasonal coefficients as detailed by Cleveland and Scott (2007).

Currently, seasonal adjustment in the current year is done by the projected factor method. The seasonal factors for each series are forecasted out a year and these factors are applied to new data as they become available. Because the weekly production schedule is tight, ETA is hesitant to move to concurrent seasonal adjustment which requires running MoveReg each week to use current data. There has also been some concern that the numerous holiday effects could lead to issues with concurrent adjustment. However, Evans (2012) showed that concurrent adjustment would actually produce smoother seasonally adjusted UI series with lower revisions even around holidays.

3. Variance Method

The locally-weighted regression model described above is somewhat complicated. Thus, it may not be obvious as to how to calculate variances. One possible method is described in Burck and Sverchkov (2001). This approach starts by utilizing the impulse response method to calculate observation weights. Once the weights are available, variances are calculated in a similar manner as shown in Pfeffermann and Sverchkov (2014). This is still work in progress.

A straightforward way to calculate variances for the UI series is to use the bootstrap. One could use either a nonparametric or parametric bootstrap, and they should give similar results using the same underlying model assumptions. Since we already have a simple model, we decided to use the parametric approach which is fairly easy to implement.

Our model is:

$$\widehat{S}_t = \widehat{CY}_t / \widehat{SA}_t$$

where S_t is the seasonal component (at time t), CY is the "cleaned" observed series (cleaned of outliers and holidays), and SA the "clean" seasonally adjusted series. Our assumptions for the model are that $ln(T_t)$ is locally linear and that $ln(I_t)$ is white noise. Note that under these assumptions

$\mathrm{var}[\ln(\widehat{SA}_t) - \ln(\widehat{SA}_{t-1})] \cong \mathrm{var}[\ln(\hat{I}_t) - \ln(\hat{I}_{t-1})] = 2\,\mathrm{var}[\ln(\hat{I}_t)]$ and therefore

$\mathrm{var}[\ln(\hat{I}_t)]$ can be estimated by $\frac{1}{2}\mathrm{var}[\ln(\widehat{SA}_t) - \ln(\widehat{SA}_{t-1})]$.

There are several steps in order to get the variances we need.

1) We use data for the official seasonal adjustments from the last week in January in 1988 through the last week of January of the current year. In this case, we will use data from January 1988 through January 2015 (N=1410).
2) The logarithm of the observed series is differenced.

3) Using the coefficients of the official seasonal adjustment runs, the observed series is cleaned of holidays and outliers.
4) Seasonally adjust the logged transformed and differenced $\widehat{CY}$.
5) Estimate the parameter σ^2 as follows:

$$\sigma^2 = \frac{1}{N-1}\sum_{t=1}^{N-1}\{[\ln(\widehat{SA}_{t+1}) - \ln(\widehat{SA}_t)] - \frac{1}{N-1}\sum_{k=1}^{N-1}[\ln(\widehat{SA}_{k+1}) - \ln(\widehat{SA}_k)]\}^2$$

Plots for the logged and differenced seasonally adjusted series are in Figures 3 and 4. Note that they are essentially normally distributed. Since the seasonally adjusted series is basically *T* + *I*, differencing the seasonally adjusted series will effectively leave the logged irregular component as our bootstrap.

6) Generate *B* independent bootstrap series of length N-1. Multiply $\frac{1}{\sqrt{2}}\sigma$ by a random variate from a standard normal distribution and multiply by logged *CY*. We find *B*=1000 is sufficient for both series, so our bootstrap matrix is 1409x1000.
7) Variances are calculated by observation (row of the bootstrap matrix):

$$Var(\widehat{SA}_t) = \frac{1}{B}\sum_{b=1}^{B}(\widehat{SA}_{bt} - \overline{\widehat{SA}}_t)^2$$

8) Calculate variances for week-to-week changes as above (but with $\widehat{SA}_t - \widehat{SA}_{t-1}$) by row using the usual $\pm 1.96\sqrt{Var}$ formula.
9) Calculate symmetric 95% confidence intervals (CIs) for historical week-to-week change series by row.
10) Forecast CIs for the current year by regressing time on last year's bounds.

Note that we originally estimated CIs using projected seasonal factors for each bootstrap series. However, it was clear that the resulting CIs were too noisy and that forecasts should be better.

4. Results

Logged week-to-week changes for initial claims starting in 2006 are in Figure 5. A summary of the number of significant changes is in Table 1. About 13% of the week-to-week changes are significant for the historical period, compared to almost 30% during the forecast period. It is likely that concurrent seasonal adjustment will help reduce the number of significant changes in the current year, and we plan to test this shortly.

Table 1: Number of Significant Week-to-Week Changes
Seasonally Adjusted Initial Claims

Time Period	Total Observations	Significant Changes	Percent Significant
All	1461	200	13.7
Historical	1409	185	13.1
Forecast	52	15	29.9

An interesting change in the initial claims series occurred in November of 2012 and is marked by “Sandy” for Superstorm Sandy which hit the east coast of the U.S. Other significant events that strongly affected initial claims were 9-11 in 2001 and Hurricane Katrina in 2005. These events accounted for about 14 of the 185 significant changes in the historical period.

Logged week-to-week changes for continued claims starting in 2006 are in Figure 6. A summary of the number of significant changes is in Table 2. About 9% of the week-to-week changes are significant for the historical period. In this case, only about 12% are significant during the forecast period. This is not surprising since continued claims tend to show less volatility than initial claims. Continued claims have much fewer outliers than initial claims and most of those are due to Hurricane Katrina, so we can only attribute 2 of the 139 significant changes during the historical period to known events.

Table 2: Number of Significant Week-to-Week Changes
Seasonally Adjusted Continued Claims

Time Period	Total Observations	Significant Changes	Percent Significant
All	1461	139	9.5
Historical	1409	133	9.4
Forecast	52	6	11.5

Since the data are log transformed in the model, it is natural and statistically preferable to use those data to estimate the bounds. However, since the week-to-week changes are reported in levels, it is possible that data users will prefer to see the bounds shown in levels as well. These results are shown in Figures 7 and 8. The number and timing of significant changes are almost the same. One difference is that the significance bounds follow the level of the series.

5. Summary

Overall, the CIs appear to be reasonable and useful. However, the bounds for the projected period could be improved. It is also important to make more runs for the last few years with preliminary data created by projected factors and compare those bounds with those from historical runs.

An obvious way to improve the projected bounds is to move toward concurrent seasonal adjustment. Implementing concurrent adjustment will also reduce revisions and week-to-week changes. Work will continue in this area.

Acknowledgements

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Appendix

Figure 1: Initial Claims

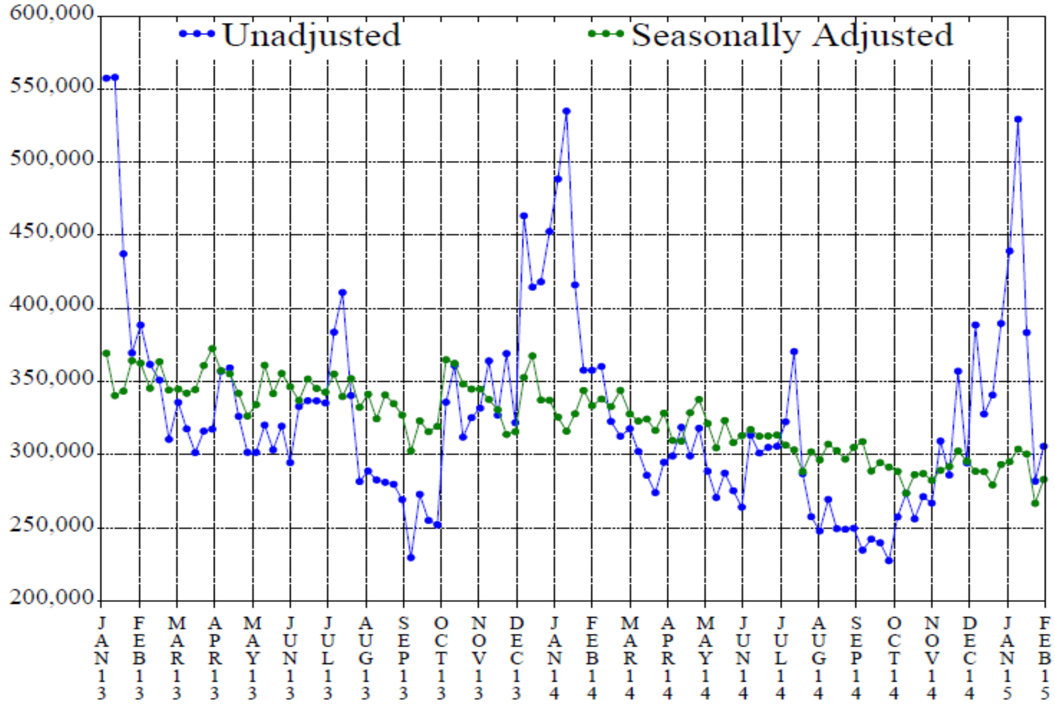


Figure 2: Continued Claims

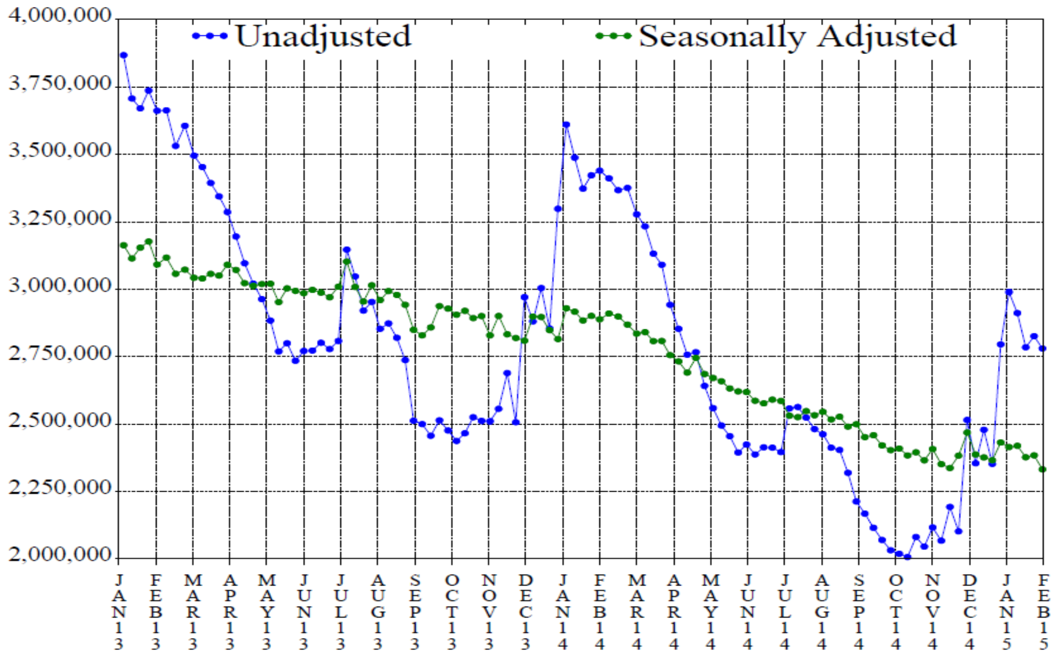


Figure 3: Initial Claims

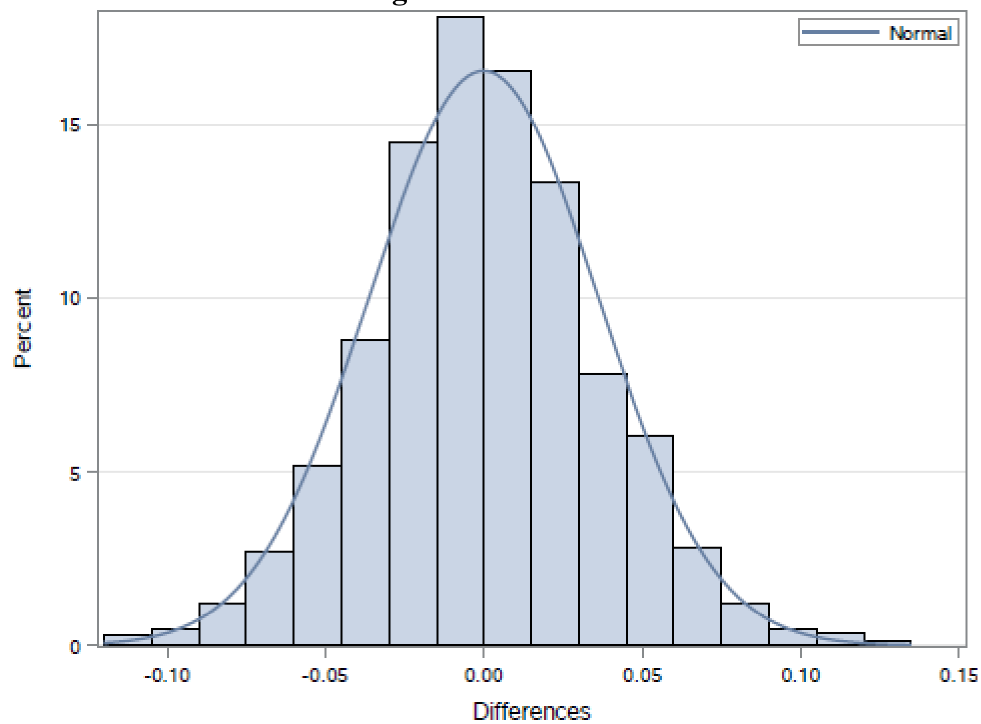


Figure 4: Continued Claims

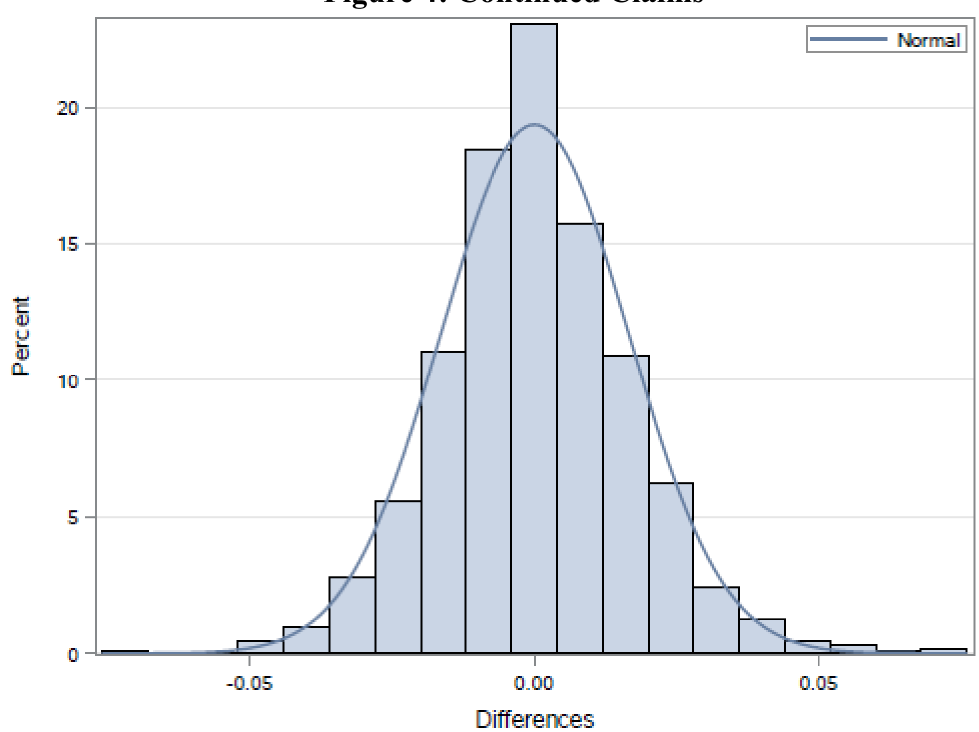


Figure 5: Logged Transformed Week-to-Week Changes with 95% Bounds Initial Claims, (NBER Recession in Gray)

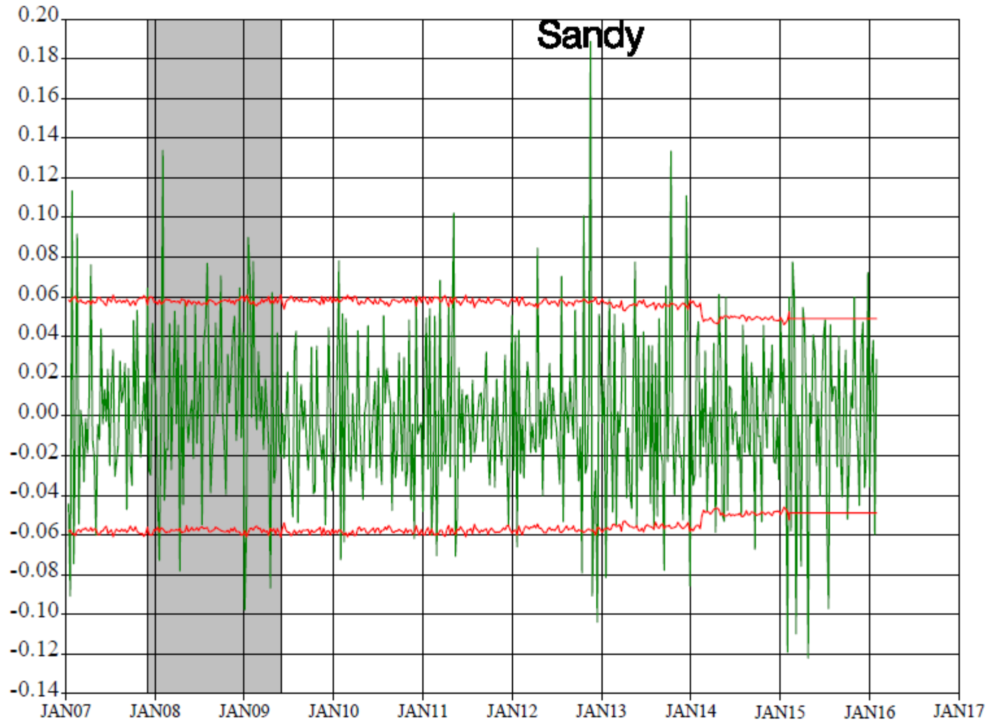


Figure 6: Logged Transformed Week-to-Week Changes with 95% Bounds Continued Claims, (NBER Recession in Gray)

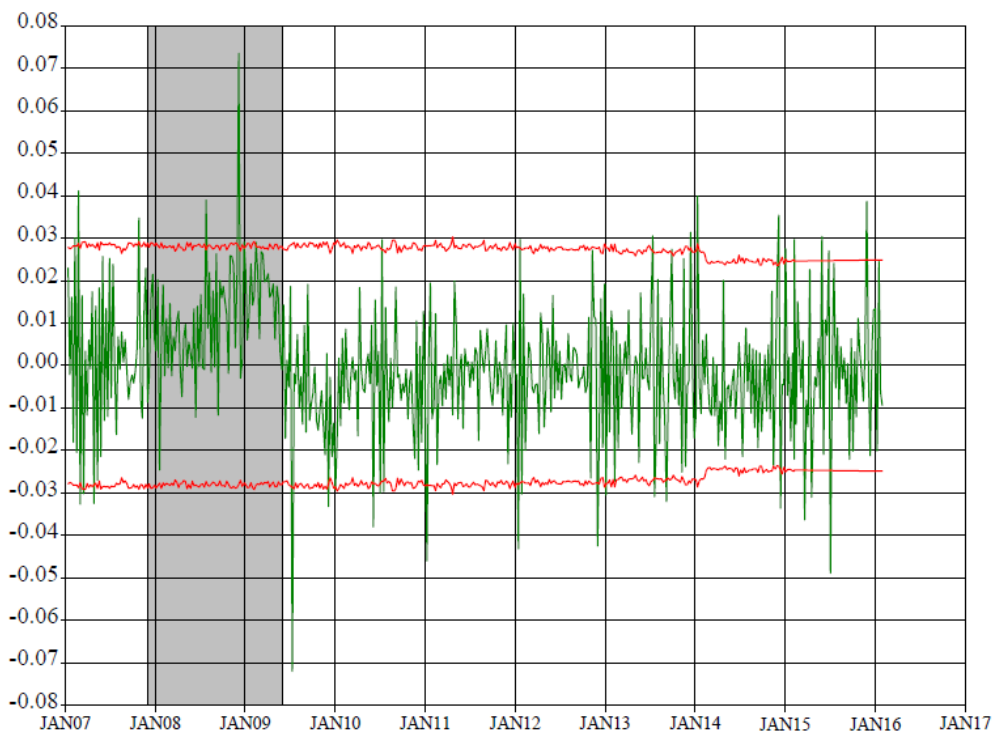


Figure 7: Week-to-Week Changes with 95% Bounds
Initial Claims, (NBER Recession in Gray)

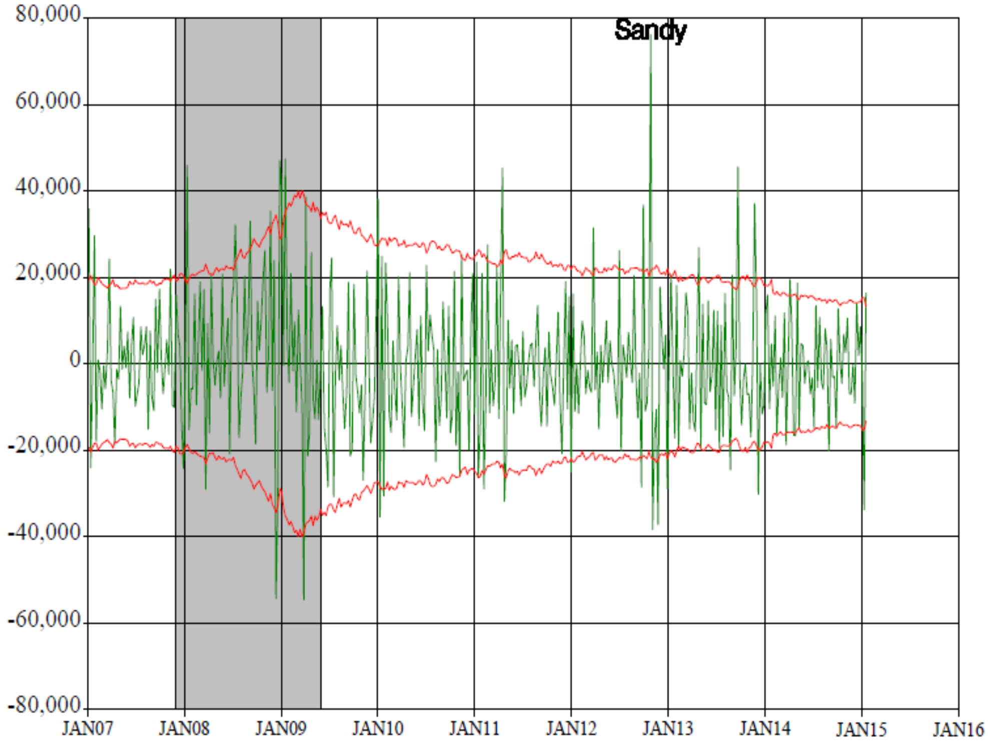
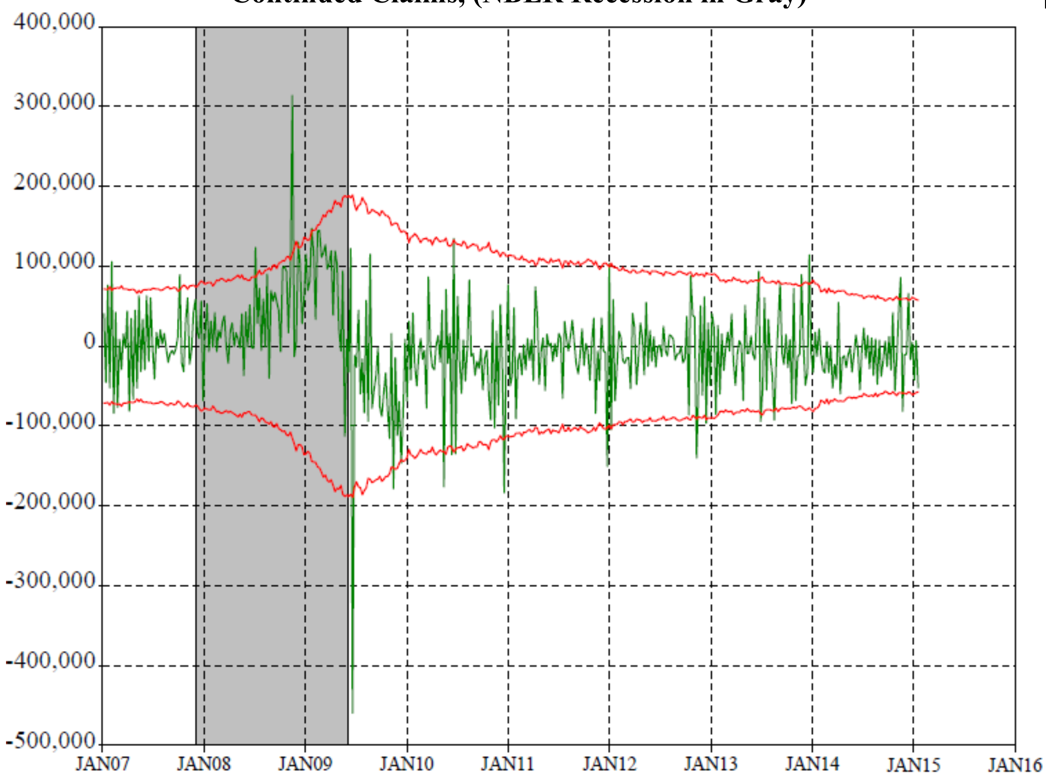


Figure 8: Week-to-Week Changes with 95% Bounds
Continued Claims, (NBER Recession in Gray)



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