Time Series Responses to the COVID-19 Pandemic at BLS for Monthly and Weekly Series December 2021

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Abstract
Statistical agencies around the world faced a number of unique challenges as the COVID-19 pandemic unfolded. The Bureau of Labor Statistics is no exception, and time series researchers developed a number of responses to these challenges. This paper will summarize work related to seasonal adjustment processing (concentrating on the Current Population Survey), changes in related software, and new research in modeling reference week calendar effects.

Key Words: Signal extraction, calendar adjustment, outlier treatments.

1. Introduction

Statistical agencies around the world faced a series of challenges as the COVID-19 pandemic permeated all aspects of our lives. The shutdown of national and world economies caused agencies to change the way they collect and analyze their economic series. The U. S. Bureau of Labor Statistics (BLS) was no exception to this, and very soon after the breadth of the crisis became apparent BLS went to work dealing with the crisis in real time.

Figure 1 shows an example of how the pandemic affected the initial unemployment claims series, The series is quite seasonal up until the pandemic effects start in the third week of March, where the series increases by an order of magnitude. The maximum before the pandemic period was about 750 thousand (a couple of times since 1988), where by the beginning of April the number of claims was over 6 million. Claims then decrease after that, but never reach the previous series level.

This paper will highlight the changes made to seasonal adjustment operations for two surveys - the Current Population Survey (Section 3.1) and the Unemployment Insurance series (Section 3.2). It details changes made in two main areas of production - seasonal adjustment mode and handling outliers in real time.

Section 4 highlights research into modeling reference week effects in CPS series that was motivated by the pandemic.

Finally, Section 5 highlights software changes that were needed to handle these challenges. Much of this work was done with software packages created by the author and implented in R (see [15]).

2. Seasonal Adjustment Mode

Multiplicative seasonal adjustment is the default at most official statistical agencies, due the ease of interpreting the results as percentages. Multiplicative seasonal effects are assumed to be proportional to the level of the series, while additive seasonal effects are assumed to be unrelated to the level of the series.

The agency needed to rethink the adjustment mode used in production considering level changes in many series encountered in the pandemic.

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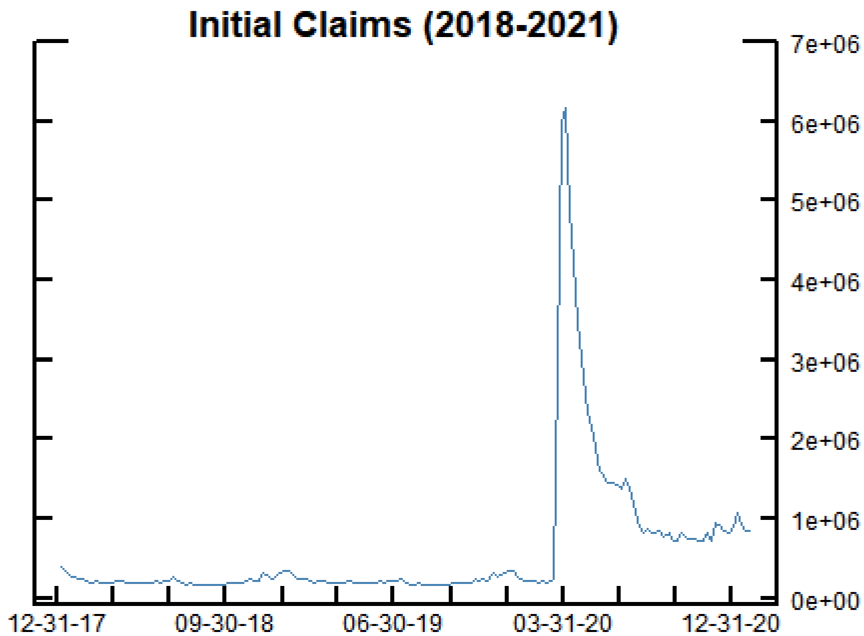

Figure 1: Initial Claims for Unemployment Insurance

Seasonality was likely to be overwhelmed by abnormally large level shifts clearly visible in the unadjusted series without the need for seasonal adjustment. Multiplicative seasonal adjustment, by magnifying seasonal variation, can obscure rather than reveal underlying movements in the series in the presence of large level shifts. This can lead to under-adjustments during periods of high seasonality and over-adjustments during periods of low seasonality. For additive seasonal adjustment, the magnitude of seasonal variation will be much smaller relative to the level of the series.

Figure 2 shows a simulation illustrating the effect of a large level shift in U.S. unemployment on the multiplicative and additive seasonal adjustments generated for the affected series. A rise of about 20 million was simulated in March 2019 that persists to the end of the series in December 2019 (the actual CPS increase was 15.9 million for April 2020 due to the pandemic). Multiplicative adjustments show deviation of 1-2 million from the unadjusted series compared to a median of 400,000 for the last 10 years. This shows the potential for significant distortion in the seasonally adjusted series.

3. BLS Series

BLS publishes thousands of seasonally adjusted time series every month or quarter, including:

- National, state, and metro employment and unemployment numbers
- Consumer and Producer Price Indexes (CPI and PPI)
- Job Openings and Labor Turnover

Another set of series that gets a lot of attention is the Unemployment Insurance series, that are published weekly. BLS does not publish the unemployment insurance data, but does compute the seasonal adjustment factors for this data.

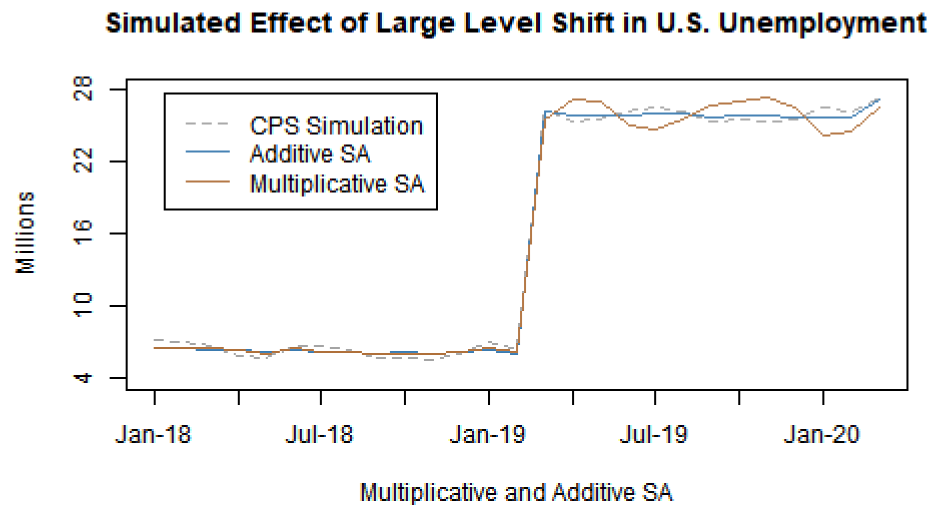

Figure 2: Simulated Effect of Large Level Shift in U.S. Unemployment

We will focus the Current Popultation Survey (CPS) and the Unemployment Insurance series (UI).[1]

3.1 Current Population Survey (CPS)

This section considers the Current Population Survey, a Labor Force survey conducted by the U.S. Census Bureau for the Bureau of Labor Statistics. BLS publishes 163 monthly and quarterly national series from this survey that are directly adjusted with X-11 (for 142 series) and SEATS (for 21 series).

CPS statisticians decided to use a technique suggested in [11], a paper that details techniques that proved useful for generating seasonal adjustments at the US Census Bureau during the Great Recession. It suggests that a sequence of AO (point) outliers be fit to advancing data. These outliers are kept in the model if they exceed a user-specified critical value in absolute value. [2]

For each CPS series, an AO outlier was added to the model for the most recent month, and the regARIMA model was estimated to generate the t-statistic for that outlier. This outlier would be added to the model when the absolute value of the t-statistic is greater than 2. In addition, if the series examined was seasonally adjusted multiplicatively at the start of the pandemic, the adjustment mode is changed to additive adjustment (and the model is fit to the original series, not the log transformed series) at the first instance of an AO outlier in the incoming series during the pandemic period.

Figure 3 shows a bar chart of the number of AO outliers identified over the first 8 months of the pandemic for monthly CPS series. Note that the number of outliers peaks in April and slowly taper off from there.

[1] Another paper [17] details the challenges of modeling and seasonally adjusting the Local Area Unemployment Statistics (LAUS) series, which consists of about a thousand labor force series, during the pandemic.

[2] Note that X-13ARIMA-SEATS has implemented sequence AO (point) and LS (level change) outlier regressors to help implement this technique, and added the `tlimit` argument to set the critical value used to remove individual outliers added by the sequence regressor.

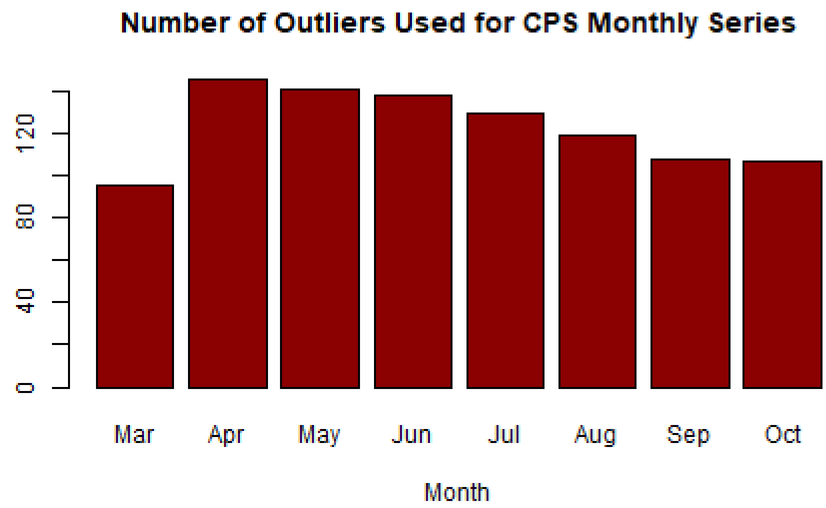

Figure 3: AO Outlier Distribution for CPS Series, March 2020 - October 2020

3.1.1 Annual Review

Every year, statisticians review the seasonal adjustment and modeling options for each of the series to determine if they need to be changed for the coming year. During the pandemic period extra care was taken to determine if a more parsimonious outlier set could be found for the pandemic period up to December of 2020.

The general procedure was to use X-13ARIMA-SEATS' automatic outlier identification procedure over the entire series to look for outliers.[3] The outlier analysis was performed over the entire series, rather than just the pandemic period, to account for the change from using the log transformation to no transformation. All outlier types were used in this examination - point (AO) outliers, which captures an outlier in a single observation; level change (LS) outliers, which captures a change in the level of the series; and temporary change (TC) outliers; which captures an effect that rises and then exponentially decreases over time. Figure 4 shows the regressor used to estimate each type of outlier.

The resulting outlier sets were visually examined and updated as necessary - a few series needed their outlier sets adjusted early in the pandmemic to maintain the level of the pre-pandemic series.

Figure 5 shows the number of each type of outlier identified for monthly CPS series over the months examined. Note that the identification of LS and TCs are most prevalent early in the pandemic to handle the change in level.

After annual review, the CPS production system continued to check for AO outliers for each incoming observation. As the economy opens with COVID-19 restrictions being removed, BLS statisticians to be cautious about flagging too many observations as AO outliers. So early in 2021, the outlier critical value used to check the incoming AO outliers was changed from 2 to 3.32. This was derived using an algorithm developed in [10] to determine the critical value based on the length of the series being tested.

[3] For more information on the automatic outlier identification procedure used in X-13ARIMA-SEATS see [7] and [18].

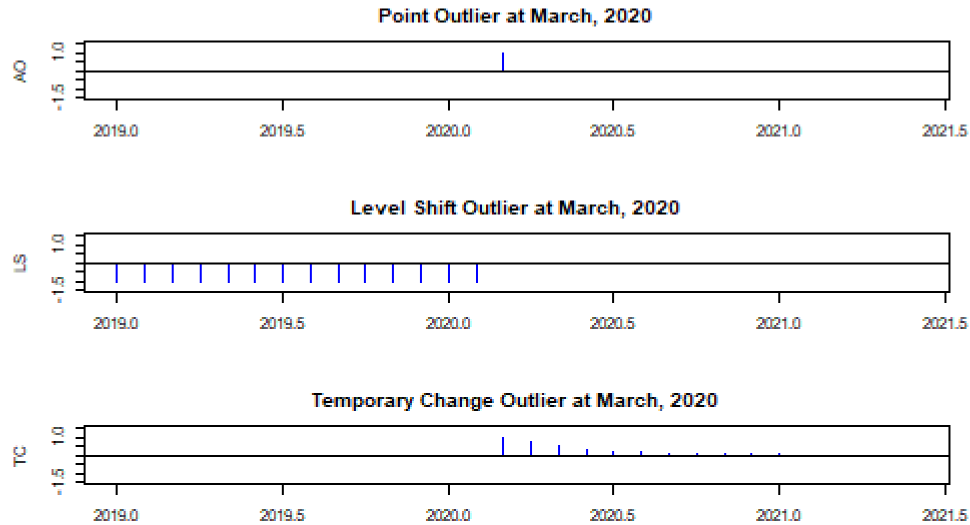

Figure 4: All Outlier Types

3.2 Unemployment Insurance (UI)

This section describes the work done with the US Unemployment Insurance (UI) series. One of the series, Initial Claims (IC), is one of the timeliest macroeconomic data published for the labor market.

BLS seasonally adjusts these data as a service to the Employment and Training Administration of the U.S. Department of Labor, which collects the data from the State Unemployment Insurance systems. For more information on how this data is collected, consult Section 3.1 of [6]; general information about how the series is seasonally adjusted is given in [1].

BLS normally uses multiplicative projected seasonal factors estimated using the Cleveland method ([5]), which estimates weighted regressions of trigonometric seasonal terms for each year of the series, and uses a Fortran implementation developed by William Cleveland with modifications made by BLS called MoveReg (see [3] and [4]).

As we saw before, both UI series were hugely affected by the Covid-19 pandemic. The reaction to the official adjustments was swift. The best example of this was [9], a blog post titled ”Beware of Seasonal Adjustment”, where the authors warn ”The multiplicative approach does not work well with [recent initial jobless claims] . . . economists should just look at the raw data before any seasonal adjustment”.

Given this, a priority was given to replace the multiplicative projected factors with additive factors. The MoveReg program needed to be revised to allow additive seasonal adjustment, among a number of other changes that are documented in Section 5. As with the CPS series, additive outliers were added for each week of the pandemic period as described in [11] and with these addional outlier terms additive factors could be generated. The AO outliers in the pandemic period were extremely significant.

After discussions with the Department of Labor, a new set of additive seasonal adjustments were provided in August of 2020, changing the official adjustments.

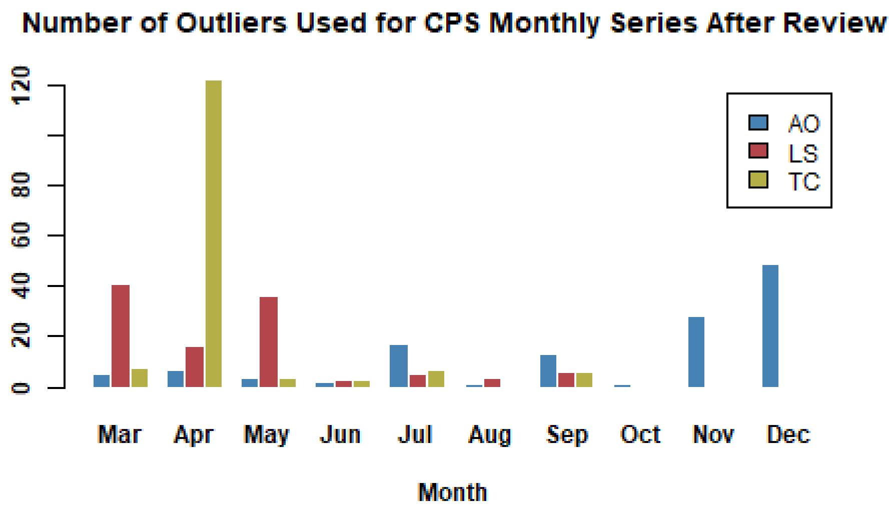

Figure 5: Final Outlier Distribution for CPS Series, March 2020 - December 2020

3.2.1 Annual Review

In the annual review of the UI series, we fit various models to the two claims series looking for a more parsimonious outlier set to use to generate projected factors for 2021. The default set of AO outllers these alternative outlier sets were compared to is given in Table 1.

To identify an outlier set for weekly series, an R package for high-frequency time series developed by Jean Palate of the Bank of Belgium (see [14]) was utilized. This module will be included in a future version of Jdemetra+ (see [8]). An automatic outlier identification option within the fractional airline modeling routines of the package was utilitzed with a critical value derived from the algorithm in [10]. Additional outlier sets were generated by including a temporary change (TC) outlier in the 13th week of 2020 before automatic outlier identification. The decay rate for the TC was derived to be $0.7^{(12/52.17857)} = 0.92125$, similar to what is done in X-13ARMA-SEATS.

Figure 6 is a plot of seasonal adjustments of Initial Claims, using additive and multiplicative modes, including two different outlier sets identified by the automatic outlier routine in [14] - one using level shifts for selected observations in the pandemic period (see Table 2 for this set of outliers fit to the original series), and another with a TC included in the 13th week of 2020 along with many level shifts (see Table 3 for this set of outliers fit to the original series). Note how the multiplicative adjustments underestimate the peak of the pandemic in late March of 2020 and overestimate the level of the adjusted series after that. The additive seasonal adjustments follow the level of the original series, and it is difficult to differentiate between the two outlier adjustments.

4. Reference Week Holiday Regressors

Several BLS series measure hours at work or average duration at work for a given industry. Often the presence of a holiday in the reference week of a survey depresses the number of hours worked for a given month. So it is useful to try and capture that effect.

A survey's reference week for a given month is the week that contains the 12th of the month. The week is assumed to start on Sunday. This is true for many surveys EXCEPT

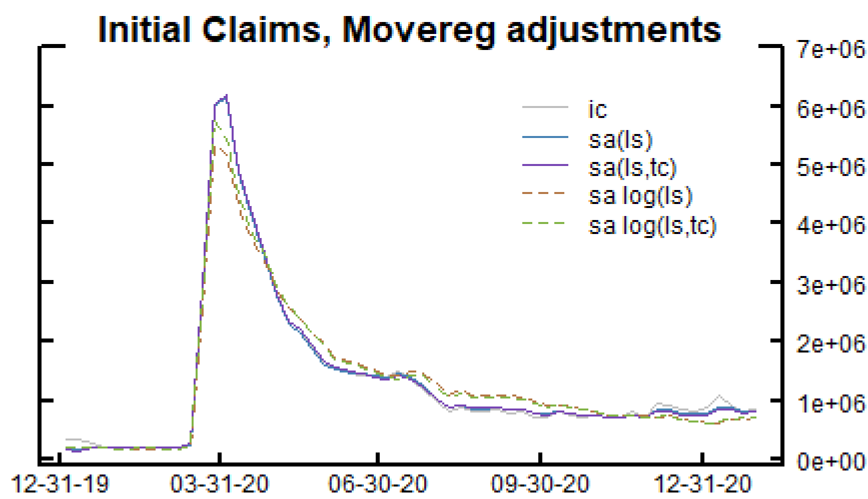

Figure 6: Initial Claims, MoveReg Seasonal Adjustments

for November and December. For December, the reference week is moved back one week if the week that contains December 5th is entirely within December. For November (since 2006), the reference week is moved back one week if Thanksgiving falls on the week that contains November 19th. The reference week can also be moved back if the Census Bureau determines there is not enough processing time before the interview week in December.

There are five major US holidays that have dates that fall within the reference week:

- Good Friday,
- Easter,
- Labor Day,
- Columbus Day, and
- Veteran's Day.

Traditionally, these effects were handled with separate point outliers at each occurance of a holiday in a reference week. It was felt that this would allow the individual instances of the holiday to be estimated separately and therefore be more flexible. I will refer to this as the individual effect method. Table 4 shows the regARIMA model for the CPS series Total Actual Hours at Work starting in January 2003 through December of 2019. The series is not transformed, and the ARIMA part of the model is the airline model - $(011)(011)_{12}$. There are 35 regressors representing the 5 holidays given above. Table 5 shows chi-squared tests for each of the sets of regressors and the regressors as a whole - all the holidays are significant at the 5 percent level except for Columbus Day, and the set of user-defined regressors are significant as a whole.

During the pandemic, it is impossible to separate the pandemic effect from the reference week effect; you cannot have a point outlier for the pandemic and a point outlier for the reference week effect for the same month. A different approach was needed.

It was decided to try an approach we are calling **grouped reference week regressors**. Each holiday is grouped into its own regressor, rather than expressed as separate point outliers.

For Good Friday, one can define a grouped reference week regressor GF_t for month t where

$$GF_t = \begin{cases} 1 & \text{if the reference week for month } t \text{ contains the Good Friday holiday,} \\ 0 & \text{otherwise.} \end{cases}$$

Grouped reference week regressors can be defined for Easter and Labor Day in the same way.

For Columbus Day and Veteran's Day, the holiday is almost always in the usual reference week, so for these holidays the grouped reference week effect is keyed off whether the references week does not contain the holiday. So one can define a Columbus Day grouped reference week regressor CD_t for month t where

$$CD_t = \begin{cases} 1 & \text{if the reference week for month } t \text{ does not contain the Columbus Day holiday,} \\ 0 & \text{otherwise} \end{cases}$$

A similar construction can be used for Veteran's Day.

Table 6 shows the regARIMA model for the CPS series Total Actual Hours at Work with the grouped reference week regressors. Again, the series is not transformed, and the ARIMA part of the model is the airline model - $(011)(011)_{12}$. The added holiday effects are very significant - all the t-statistics are significant, and the overall chi-squared test is significant (1070.32 with 5 degrees of freedom, p-value = 0.00).

One could redefine the individual regressors for Columbus Day and Veteran's Day in the same way as above, essentially reversing those two holidays. Table 7 shows the regARIMA model for the CPS series Total Actual Hours at Work for this configuration, and Table 8 shows the results of chi-square tests for the user-defined regressors - all of the groups are significant.

Another method that incorporates reference weeks into a modeling framework is to model the number of days between reference weeks. This technique is documented in [2], and is used to model this effect for several employment series. As this type of regression is already in use at BLS, it was included in this analysis.

4.1 Example: CPS At Work Series

The four reference week models listed above were fit to the pre-pandemic period (before 2020) for a set of CPS at work series, shown in Table 9. Each set of regressors (4-5 week regressors, individual (point outlier) reference week regressors, individual reference week regressors with Columbus Day and Veteran's Day reversed, and grouped reference week regressors) to the base regARIMA model for the individual series, and generates the AICC for the model fit with each set of reference week regressors

Table 10 shows that grouped reference week regressors were preferred to both the 4/5 and individual reference week regressors by AICC. In addition, the grouped and individual reference week coefficients were consistently significant, based on individual t-tests and grouped chi-square tests.

5. Software Changes

Along the way, the software used for seasonal adjustment needed to be revised on the fly to deal with the challenges of the pandemic. I made all the changes listed below for the software used for seasonal adjustment.

For the weekly seasonal adjustment program MoveReg, the software was updated to generate additive seasonal adjustment, and incorporated built-in temporary change (TC) regressors, and allows user to specify the decay rate for the TC regressors. An option was added so that users could specify X-13ARIMA-SEATS style level change regressors. Additionally, the output of the program was changed to allow printing larger numbers in the program output and to facilitate the transfer of signal extraction components to R.

I also created a X-13ARIMA-SEATS research build for BLS, mostly used for the LAUS survey ([17]). There is a change in specifying sequence outlier regressors that provides a flexible end date, so that users would not have to change the end date of the sequence outlier from month to month. For example, to add a sequence of level shift outliers to the regARIMA model from March, 2020 to the end of the series, an analyst can specify `LSS2020.Mar-0.0` as one of the regressors specified in the `variables` argument of the regression spec.

To enable this for sequence LS regressors, the software was changed to allow an LS outlier to be specified for the final observation. Both of these are among the changes in the most recent Census Bureau release of X-13ARIMA-SEATS ([18]).

Recently, I incorporated a new argument into the `regression` spec that allows users to include temporary change (TC) outliers into the trend component. The default for X-13ARIMA-SEATS is to treat these effects the same as AO (point) outliers, but as LAUS statisticians produce estimates of the trend, it was decided that these effects should be included in the trend component.

In addition, the author has continued developing R packages to support this work and my own research. All routines used to generate reference week regressors can be accessed from the `refweekreg` package, which generates these regressors for use in the `seasonal` package (see [16]).

Many useful routines for using Palate's implementation of the fractional airline model ([14]) were collected into the `airutilites` package. The appendix of [6] shows an example of how functions from the `airutilities` and `sautilities` package to produce a fractional airline model decomposition of the initial claims series with holiday and outlier regressors.

Other packages for producing plots useful to seasonal adjustment analysts and useful utilities, including functions for collecting seasonal adjustment diagnostics and selecting optimal seasonal filters, are briefly described in [12]. Both utilize output from the `seasonal` package mentioned earlier. These packages can be made available by the author upon request.

6. Future Work

For future work, statisticians for many BLS surveys will be looking to see if they can return to normal operations. One of the main issues is the impact of changing the adjustment from additive adjustment back to multiplicative adjustment for those series where this change would be appropriate. It is not clear how fast we'll be able to do this, or how much revision there will be to the historical series. It may be necessary to do a hybrid adjustment - additive adjustment for the early pandemic, multiplicative adjustment going forward. We will assess this during our annual review period.

We will also continue to monitor and test for changes in the outlier specs with a goal of judiciously unwinding the pandemic effects.

For CPS series, we will consider seasonally adjusting more series with SEATS, and will examine using grouped reference week regressors for more series.

For the UI series, we are looking to replace the MoveReg program with one of two potentual methods: a structural time series model in Proc SSM currently under development by Tom Evans of BLS, and the Fractional Airline implementation in R developed by Jean Palate ([13]). A comparison of these methods can be found in [6].

7. Acknowledgements

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- William Bell of the U. S. Census Bureau, for helpful conversations on modeling reference week effects, and
- Jean Palate of the Bank of Belgium, for providing me with the preliminary version of their high frequency modeling package implemented in R.

References

[1] Bureau of Labor Statistics. Seasonal Adjustment for Weekly Unemployment Insurance Claims, March 2021. https://www.bls.gov/lau/seasonal-adjustment-for-weekly-unemployment-insurance-claims.htm [Online; posted 24-March-2021].

[2] S. Cano, P. Getz, J. Kropf, S. Scott, and G. Stamas. Adjusting for a Calendar Effect in Employment Time Series. 1996. BLS Research Paper, U.S. Bureau of Labor Statistics https://www.bls.gov/osmr/research-papers/1996/pdf/st960190.pdf.

[3] W. P. Cleveland, T. D. Evans, and S. Scott. *Eurostat Handbook of Seasonal Adjustment*, chapter Weekly Seasonal Adjustment: A Locally-weighted Regression Approach. Eurostat, Luxembourg, 2018.

[4] W. P. Cleveland, J. Fields, S. Scott, T. Evans, and D. Byun. *MoveReg Guide Version 5.0 (DRAFT)*. U.S. Bureau of Labor Statistics, U.S. Department of Labor, 2020.

[5] W. P. Cleveland and S. Scott. Seasonal Adjustment of Weekly Time Series with Application to Unemployment Claims and Steel Production. *Journal of Official Statistics*, 23(2):209–221, 2007.

[6] T. D. Evans, B. C. Monsell, and M. Sverchkov. Review of Available Programs for Seasonal Adjustment of Weekly Data. 2021. In JSM Proceedings, Business and Economic Statistics Section. Alexandria, VA: American Statistical Association.

[7] D. F. Findley, B. C. Monsell, W. R. Bell, M. C. Otto, and B. C. Chen. New capabilities of the X-12-ARIMA seasonal adjustment program (with discussion). *Journal of Business and Economic Statistics*, 16:127–77, 1998. http://www.census.gov/ts/papers/jbes98.pdf.

[8] S. Grudkowska. *JDemetra+ Reference Manual, Version 2.1*. Narodowy Bank Polski, Department of Statistics, Warsaw, Poland, 2016. https://ec.europa.eu/eurostat/cros/system/files/jdemetra_reference_manual_version_2.1_0.pdf.

[9] K. Heerdt and J. H. Wright. Beware of Seasonal Adjustment, April 2020. https://cfe.econ.jhu.edu/beware-seasonal-adjustment/ [Online; posted 24-April-2020].

[10] G. Ljung. On Outlier Detection in Time Series. *Journal of Royal Statistical Society B*, 55:559–567, 1993.

[11] D. Lytras and W. R. Bell. Modeling Recession Effects and the Consequences on Seasonal Adjustment. *Proceeding of the American Statistical Association, Business and Economic Statistics Section*, 2013. Available online at `https://www.census.gov/ts/papers/jsm2013lytrasfinal.pdf`.

[12] B. C. Monsell. Using R in Seasonal Adjustment Production of Official Statistics. 2020. In JSM Proceedings, Business and Economic Statistics Section. Alexandria, VA: American Statistical Association.

[13] J. Palate. Fractional airline decomposition, 2019. `https://github.com/nbbrd/jd3-rtests/wiki/Fractional-airline-decomposition`, Last changed on 2019-11-26.

[14] J. Palate. *rjdhighfreq: Routines for modelling and seasonal adjustment of high frequency series, Version 0.0.4*. Bank of Belgium, Brussels, Belgium, August 2020. `https://github.com/palatej/rjdhighfreq`.

[15] R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2019. `https://www.R-project.org/`.

[16] C. Sax and D. Eddelbuettel. Seasonal adjustment by X-13ARIMA-SEATS in R. *Journal of Statistical Software*, 87(11):1–17, 2018.

[17] R. Tiller, J. Oh, and L. Liu. Adapting the Seasonal Adjustment of Local Area Unemployment Statistics to the Covid-19 Pandemic. 2021. In JSM Proceedings, Government Statistics Section. Alexandria, VA: American Statistical Association.

[18] Time Series Software Group. *X-13ARIMA-SEATS Reference Manual, Version 1.1*. U.S. Census Bureau, U.S. Department of Commerce, 2021. `https://www2.census.gov/software/x-13arima-seats/x13as/windows/documentation/docx13ashtml.pdf`.

Table 1: Initial Claims Outliers, AO Only

Name	Coefficients	Standard Error	T-Value
AO2005.37	0.7342	0.2029	3.6440
AO2005.38	0.7547	0.2557	2.9832
AO2005.39	0.2369	0.2717	0.8824
AO2005.40	0.3995	0.2554	1.5810
AO2005.41	0.5225	0.2021	2.6027
AO2006.1	0.1205	0.1623	0.7457
AO2007.2	-0.1955	0.1634	-1.2019
AO2008.4	0.3276	0.1632	2.0163
AO2012.45	0.8280	0.1681	4.9495
AO2017.35	0.3331	0.1572	2.1273
AO2020.12	26.7226	0.2215	121.6317
AO2020.13	57.3677	0.3147	185.1992
AO2020.14	58.9345	0.3897	154.9129
AO2020.15	46.1199	0.4549	104.6920
AO2020.16	39.6004	0.5126	80.4176
AO2020.17	32.0952	0.5669	59.4129
AO2020.18	25.5300	0.6182	43.6870
AO2020.19	20.7881	0.6675	33.2147
AO2020.20	19.2409	0.7150	28.9391
AO2020.21	16.5952	0.7612	23.6360
AO2020.22	13.8914	0.8065	18.8292
AO2020.23	12.7822	0.8513	16.5524
AO2020.24	11.9525	0.8941	14.8570
AO2020.25	11.8420	0.9371	14.1613
AO2020.26	11.5776	0.9799	13.3520
AO2020.27	10.9097	1.0226	12.1588
AO2020.28	11.4979	1.0651	12.4080
AO2020.29	10.8693	1.1062	11.3872
AO2020.30	9.6816	1.1480	9.8564
AO2020.31	7.5886	1.1899	7.5174
AO2020.32	5.9655	1.2316	5.7579
AO2020.33	6.6462	1.2735	6.2570
AO2020.34	5.9767	1.3154	5.4942
AO2020.35	6.1134	1.3576	5.4924
AO2020.36	6.2874	1.4012	5.5217
AO2020.37	5.9125	1.4430	5.0850
AO2020.38	5.9941	1.4850	5.0523
AO2020.39	5.2284	1.5278	4.3207
AO2020.40	4.9549	1.5709	4.0171
AO2020.41	5.5025	1.6143	4.3791
AO2020.42	5.3221	1.6579	4.1603
AO2020.43	4.7830	1.7020	3.6740
AO2020.44	4.9098	1.7463	3.7081
AO2020.45	4.2585	1.7911	3.1635
AO2020.46	4.5594	1.8362	3.3332
AO2020.47	5.0407	1.8818	3.6277
AO2020.48	4.4745	1.9278	3.1715

Table 1: Initial Claims Outliers (continued)

Name	Coefficients	Standard Error	T-Value
AO2020.49	5.4575	1.9741	3.8111
AO2020.50	6.0542	2.0210	4.1668
AO2020.51	5.0933	2.0682	3.4560
AO2020.52	4.6677	2.1239	3.1165
AO2021.1	4.6531	2.1648	3.0713
AO2021.2	5.4306	2.2133	3.5375
AO2021.3	5.6508	2.2627	3.6332
AO2021.4	5.3196	2.3122	3.3772
AO2021.5	5.4397	2.3626	3.4105

Table 2: Outliers Fit to Initial Claims Series, Automatic Outlier Idenfication

Name	Coefficients	Standard Error	T-Value
LS2008.48	0.4830	0.0654	7.3900
LS2020.12	1.4603	0.0650	22.4747
LS2020.13	4.8065	0.0650	73.9901
LS2020.14	4.4318	0.0650	68.2278
LS2020.15	3.8375	0.0650	59.0781
LS2020.16	1.6331	0.0650	25.1406
LS2020.17	4.0583	0.0650	62.4738
LS2020.18	-0.7975	0.0650	-12.2767
AO2020.19	3.9589	0.0650	60.9422
LS2020.19	-1.7154	0.0917	-18.7265
LS2020.23	-0.4136	0.0650	-6.3674
LS2020.24	-0.8662	0.0650	-13.3317
LS2020.26	-0.8601	0.0651	-13.2255
AO2020.27	0.8212	0.0478	17.1931
AO2020.29	0.7326	0.0461	15.8978
LS2020.31	-0.6164	0.0650	-9.4837
LS2020.32	-1.0489	0.0650	-16.1398
LS2020.34	-0.6560	0.0651	-10.0886
AO2020.35	0.5308	0.0496	10.7125
LS2020.38	-1.2888	0.0651	-19.8062
LS2020.39	-0.8540	0.0650	-13.1388
LS2020.40	-1.1916	0.0650	-18.3342
LS2020.41	-0.8206	0.0651	-12.6148
LS2020.42	-0.6809	0.0652	-10.4430
LS2020.43	-0.5558	0.0651	-8.5413
LS2020.44	-0.4417	0.0653	-6.7703
AO2020.47	-0.3200	0.0464	-6.8929

Table 3: Outliers Fit to Initial Claims Series, Automatic Outlier Idenfication with TC2020.13 added

Name	Coefficients	Standard Error	T-Value
AO2008.49	0.8975	0.1687	5.3444
AO2019.47	-0.3439	0.1812	-1.9081
LS2020.12	26.7079	0.2386	112.9863
TC2020.13	30.5628	0.2370	130.1514
AO2020.14	10.6130	0.2428	44.1299
LS2020.14	-6.6523	0.3439	-19.7156
LS2020.16	-4.4900	0.2429	-18.6605
LS2020.17	-5.6387	0.2392	-23.7955
LS2020.18	-4.8455	0.2388	-20.4775
LS2020.19	-3.1594	0.2388	-13.3546
LS2020.21	-1.3061	0.2391	-5.5130
LS2020.22	-1.4691	0.2389	-6.2072
LS2020.28	1.3535	0.2449	5.5821
LS2020.31	-1.5160	0.2386	-6.4144
AO2020.32	-1.1254	0.1685	-6.7105
LS2021.2	0.8623	0.2402	3.6240

Table 4: regARIMA Model for Total Actual Hours at Work, Usually Fulltime, Using Individual Reference Week Regressors.

Name	Coefficients	Standard Error	T-Value
AO2010.Feb	-0.7821	0.1046	-7.48
AO2011.Jan	-0.6211	0.1049	-5.92
AO2014.Feb	-0.6332	0.1042	-6.07
good friday 2006	-0.8064	0.1060	-7.61
good friday 2017	-0.5381	0.1055	-5.10
easter 2004	-0.1833	0.1065	-1.72
easter 2007	-0.2835	0.1058	-2.68
easter 2009	-0.2844	0.1054	-2.70
easter 2012	-0.1492	0.1051	-1.42
labor day 2009	-2.6103	0.1072	-24.36
labor day 2015	-2.5501	0.1072	-23.78
columbus day 2003	-0.2554	0.1286	-1.99
columbus day 2004	-0.1008	0.1282	-0.79
columbus day 2005	-0.1807	0.1279	-1.41
columbus day 2006	-0.2792	0.1276	-2.19
columbus day 2007	-0.1930	0.1254	-1.54
columbus day 2008	-0.2002	0.1268	-1.58
columbus day 2009	-0.5433	0.1287	-4.22
columbus day 2010	-0.2095	0.1265	-1.66
columbus day 2011	-0.3037	0.1258	-2.41
columbus day 2012	-0.2044	0.1236	-1.65
columbus day 2014	-0.2055	0.1250	-1.64
columbus day 2015	-0.2955	0.1272	-2.32
columbus day 2016	-0.3632	0.1252	-2.90
columbus day 2017	-0.2244	0.1252	-1.79
columbus day 2018	-0.2524	0.1233	-2.05
veteran’s day 2007	-0.3671	0.1149	-3.20
veteran’s day 2004	-0.4018	0.1144	-3.51
veteran’s day 2005	-0.3566	0.1141	-3.13
veteran’s day 2006	-0.3246	0.1136	-2.86
veteran’s day 2008	-0.5283	0.1130	-4.67
veteran’s day 2009	-0.6134	0.1144	-5.36
veteran’s day 2010	-0.5038	0.1134	-4.44
veteran’s day 2011	-0.4229	0.1124	-3.76
veteran’s day 2014	-0.3793	0.1121	-3.38
veteran’s day 2015	-0.5416	0.1135	-4.77
veteran’s day 2016	-0.3967	0.1124	-3.53
veteran’s day 2017	-0.1985	0.1124	-1.77
θ_1	0.6359	0.0531	11.98
θ_{12}	0.9114	0.0449	20.32

Table 5: regARIMA Model for Total Actual Hours at Work, Usually Fulltime, Using Individual Reference Week Regressors

Regression	Degrees of Freedom	Chi-Square	P-Value
Good Friday	2	79.02	0.00
Easter	4	15.72	0.00
Labor Day	2	1097.82	0.00
Columbus Day	15	24.05	0.06
Veteran's Day	12	69.51	0.00
All Holiday Regressors	35	1265.16	0.00

Table 6: regARIMA Model for Total Actual Hours at Work, Usually Fulltime, Using Grouped Reference Week Regressors

Name	Coefficients	Standard Error	T-Value
AO2010.Feb	-0.7507	0.1117	-6.72
AO2011.Jan	-0.6145	0.1115	-5.51
AO2014.Feb	-0.6319	0.1119	-5.65
good friday	-0.6748	0.0829	-8.14
easter	-0.2209	0.0636	-3.47
labor day	-2.5235	0.0813	-31.03
columbus	0.2543	0.0833	3.05
veteran's day	0.4106	0.0588	6.98
θ_1	0.6339	0.0531	11.95
θ_{12}	0.9172	0.0439	20.91

Table 7: regARIMA Model for Total Actual Hours at Work, Usually Fulltime, Using Individual Reference Week Regressors with Columbus Day and Veteran's Day Reversed

Name	Coefficients	Standard Error	T-Value
AO2010.Feb	-0.7525	0.1094	-6.88
AO2011.Jan	-0.6145	0.1091	-5.63
AO2014.Feb	-0.6242	0.1099	-5.68
good friday 2006	-0.8097	0.1112	-7.28
good friday 2017	-0.5408	0.1108	-4.88
easter 2004	-0.1903	0.1117	-1.70
easter 2007	-0.2881	0.1110	-2.59
easter 2009	-0.2709	0.1107	-2.45
easter 2012	-0.1507	0.1104	-1.36
labor day 2009	-2.5218	0.1094	-23.05
labor day 2015	-2.5227	0.1096	-23.02
columbus day 2013	0.3216	0.1116	2.88
columbus day 2019	0.2011	0.1159	1.74
veteran's day 2007	0.4448	0.1102	4.04
veteran's day 2012	0.2706	0.1102	2.46
veteran's day 2013	0.4635	0.1127	4.11
veteran's day 2018	0.4429	0.1114	3.98
veteran's day 2019	0.4368	0.1197	3.65
θ_1	0.6235	0.0536	11.62
θ_{12}	0.9177	0.0437	21.02

Table 8: regARIMA Model for Total Actual Hours at Work, Usually Fulltime, Using Individual Reference Week Regressors with Columbus Day and Veteran's Day Reversed

Regression	Degrees of Freedom	Chi-Square	P-Value
Good Friday	2	72.19	0.00
Easter	4	14.12	0.01
Labor Day	2	1003.36	0.00
Columbus Day	2	10.72	0.00
Veteran's Day	5	53.02	0.00
All Holiday Regressors	15	1121.70	0.00

Table 9: CPS At Work Series

Series Name	Description
n2005054	Total Actual Hours at Work
n2505054	Total Actual Hours at Work Usually Fulltime
n2033120	NonAgricultural Actual Avg Hours at Work
n2533120	NonAgricultural Actual Hours at Work Usually Fulltime
n2033251	Wage and Salary Avg Actual Hours at Work
n2533251	Wage and Salary Actual Hours at Work Usually Fulltime

Table 10: AICC for Different Reference Week Models

Series	None	4-5 weeks	Individual	Individual Reversed	Grouped
n2005054	72.05	75.78	-205.45	-244.77	-260.32
n2505054	132.94	132.23	-155.13	-192.42	-209.47
n2533120	136.20	136.55	-154.63	-192.72	-209.58
n2533251	132.17	139.17	-166.03	-202.50	-220.06
n2033120	74.61	78.08	-205.64	-246.03	-261.36
n2033251	82.00	88.91	-200.54	-239.53	-256.25