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Seasonal Adjustment of State and Metro CES Jobs Data

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Abstract

Hybrid time series data often require special care in estimating seasonal factors. Series such as the state and metro area Current Employment Statistics produced by the Bureau of Labor Statistics (BLS) are composed of two different source series that often have two different seasonal patterns. In this paper we address the process to test for differing seasonal patterns within the hybrid series. We also discuss how to apply differing seasonal factors to the separate parts of the hybrid series. Currently the BLS simply juxtaposes the two different sets of seasonal factors at the transition point between the benchmark part of the data and the survey part. We argue that the seasonal factors should be extrapolated at the transition point or that an adjustment should be made to the level of the unadjusted data to correct for a bias in the survey part of the data caused by differing seasonal factors at the transition month.

Keywords: Current Employment Statistics; Seasonal Adjustment; Hybrid Time Series

JEL Codes: C13, C8

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1. Introduction

The monthly change in employment is one of the most important and timely indicators available to measure how the economy is doing at the state and metro level. This series not only gives timely information about the strength of economic activity but also the sources. Texas nonfarm employment from the Current Employment Statistics (CES) program, produced by the Bureau of Labor Statistics (BLS) in cooperation with the Texas Workforce Commission (TWC), is generally available the third Friday of the month following the reporting month[2]. Not only is this data timely but also available for a wide range of industries and metro areas. In order to enhance its usefulness, many analysts adjust the data for normal seasonal patterns so that they can more easily analyze the cyclical movements in the data.

In this article we discuss how the CES data is produced and what it means for the optimal method of seasonal adjustment. One salient feature of CES data is that it is a hybrid series calculated from two different series with two potentially different seasonal patterns. For instance, a typical seasonally unadjusted CES series $H_t\,(1 \le t \le T\,)$ at time t can be described as $H_t = \begin{cases} B_t, & if \quad t \le T_0 \\ S_t, & if \quad t \ge T_0 \end{cases}$

where B_t is the benchmarked employment data and S_t is the sample survey data and H_t represents the hybrid series. In the next section we will discuss both B_t and S_t in more details. The last benchmark date T_0 is also where B_t and S_t joins, thus $H_{T_0} = B_{T_0} = S_{T_0}$.

Because CES data is a hybrid time series, standard seasonal procedures such as the Census X-13 do not perform well for this data. We first show a simple method for testing if the seasonal patterns differ in the two components of the CES series. We then discuss the appropriate way to apply differing

[2] The job estimates for January and February are delayed due to the annual benchmark processes – the remaining months follow the third Friday schedule.

seasonal factors. Currently the Federal Reserve Bank of Dallas applies a two-step seasonal adjustment process to the CES data for Texas and its metro areas. The BLS, however, applies a different two-step seasonal adjustment method for all 50 states. As a result, the reported seasonally adjusted Texas employment numbers from the two agencies are different.

2. Testing for Different Seasonal Patterns

The question of statistically testing whether different series, or separate parts of a hybrid series, have different seasonal patterns is intrinsically complicated as seasonality itself can take a variety of forms[3]. However, in practice, it is still possible to find an applied solution without seeking formal mathematical treatment. In this paper we focus on such an applied method.

Consider two seasonally unadjusted time series X_t and Y_t, which span the same time interval but with two possibly different seasonal patterns. Our simple method consists of the following three steps: First, we seasonally adjust one of the series, say, X_t to make sure all seasonal movements are removed. In this step we estimate the seasonal factors m_X from series X_t; second, we seasonally adjust series Y_t by applying the seasonal factors estimated from the first step m_X. Denoting this seasonally adjusted series as Y_t^{sa}, the last step requires testing for residual seasonality in the adjusted series Y_t^{sa}. The intuition behind this method is straightforward; if X_t and Y_t have the same seasonal patterns, we should not expect any seasonality in Y_t^{sa}. However, if residual seasonality is found in Y_t^{sa}, we conclude that X_t and Y_t have statistically detectable different seasonal patterns. Otherwise, we conclude that the seasonal patterns from the two series are statistically indistinguishable. The key advantage of the proposed method is its simplicity. With tools for seasonal adjustment and seasonality testing widely available in various software packages, users can implement the above test very easily.

[3] For a complete econometrical analysis for seasonal time series, see for example, Ghysels and Osborn (2001).

We apply the above method to study the Texas CES data. To ensure the reliability of historical numbers and to provide timely job estimates for the most recent months, the state CES payroll employment consists of two data sources. The most recent months' estimates, or the non-benchmarked data, are taken from the CES establishment survey, which samples about one-third of all US business. Data other than the most recent months' estimates are benchmarked by BLS annually. The benchmarked numbers are more comprehensive as the benchmark covers more firms than the payroll survey does. For instance, the major source data of BLS's benchmark, the Quarterly Census of Employment and Wages (QCEW), covers about 97 percent of nonfarm payroll employees in the US. The drawback of benchmark data such as QCEW is the delay of its production. For the same reference month, QCEW data is released up to seven months after the initial release of its CES counterpart. Because of this and other issues, BLS only benchmarks the CES employment once a year, with the most recent months' numbers being based on the payroll employment survey. As a result, the CES is a hybrid time series, or in other words, two series spliced together[4]. As first documented in Berger and Philips (1993), a spurious January blip that used to be found in the seasonally adjusted payroll employment data was likely caused by applying a standard seasonal adjustment procedure without taking into account different seasonal patterns in the two source components of the data. Following Berger and Phillips (1993) and their follow-up study for all states in 1994, the BLS began instituting a two-step seasonal adjustment process for the state employment series.

The findings in Berger and Phillips (1993) necessitates a formal test to see whether the benchmark and survey component of the CES series have different seasonal patterns. There is one issue that needs to be addressed before we can apply the test proposed above. Namely, the benchmark

[4] The benchmarking is done differently at the national level than it is at the regional level. At the national level a wedge back is used to adjust the March to March differences and thus the seasonal pattern of the survey is maintained throughout the series. But at the regional level, which is the focus of this paper, each month is benchmarked to the QCEW. As a result, the seasonal pattern in most of the data series is not that of the survey except for the end portion.

and survey components, which together form the BLS payroll employment series, do not overlap in their sample except at the transition point. The payroll survey part of the data typically consists of the past 4 to 16 months data, depending on the reference month and the month where the official benchmark ends. Usually for state level payroll employment, the January data release includes the annual benchmark which ends in the third quarter of the previous year. For example, with the January data released on March 20, 2015, BLS benchmarked the data up through the third quarter 2014. While we have sufficiently long time series that go through September 2014 for the benchmark component, for the survey component, we only have four observations starting from October 2014 to January 2015. As the year progresses the survey part of the data extends, reaching a maximum of 16 months at the end of the year. But even after reaching its maximum length, the survey component of the CES series is still too short to conduct any meaningful seasonal adjustment.

Fortunately, each year we have archived the vintage survey data before they are benchmarked by BLS. After the initial release of state level payroll employment data, the data will usually be revised at least twice afterwards. We refer to the first time released number as the first estimate. The first estimate will be revised in the immediate following month. We define this revised number as the second estimate. The second estimate will be revised again once a year during the annual benchmark. We call this the third or final estimate. Because at any point in time the non-benchmarked part of the series contains all second estimates, (with the exception of the last month which is first estimate) and because the final estimate has already been benchmarked, the second estimate is the preferred vintage survey data. From all years' archived second estimates, we are able to construct a reasonably long enough series that consists of only second estimate survey data. More specifically, we first calculate the growth rates for each year's archived real time sample data. To construct a whole series, we then extrapolate the starting year's level using all the following years' growth rates. The extrapolation method preserves the seasonal pattern in the survey sample data while avoiding level shifts in the so-constructed real time sample series that could have possibly resulted from BLS' annual benchmark.

Our study primarily focuses on the super-sectors which include Logging and Mining, Construction, Manufacturing, Trade Transportation and Utilities, Information, Financial Activities, Professional and Business Services, Education and Health Services, Leisure and Hospitality, Other Services, and Government. Some real time sample series of these super-sectors such as Construction and Government are constructed using an aggregation method. That is, they are derived as the sum of their individual real time component series. For example, the real time sample of the government employment series is the sum of the real time sample series of federal government, state government and local government[5]. In addition, we also construct a real time sample series for total nonfarm employment by adding up all these super sectors' real time sample series. In our study, the common sample for the benchmark and survey sample series starts in October 2002 and ends in September 2014.

Once we have the real time survey series constructed, we then test for different seasonal patterns between the constructed real time sample survey series and BLS benchmark series for the same sector. We use the Census-X12 procedure in statistical software package SAS to conduct the seasonal adjustment and seasonality test[6]. In the first step of our procedure, as a byproduct of seasonal adjustment, the SAS X-12 procedure also produces a residual seasonality check to ensure the seasonal movements in the benchmark series are adequately removed. The extra test from the first step helps validate the third step of our test. We can examine the residual seasonality from the sample series that has been adjusted using factors estimated from the benchmark series. In the X12 procedure there are

[5] One reason for us to choose aggregate super-sectors is that, in some cases, the sub-sectors within a super-sector may show very different seasonal patterns. We did study every possible detail sectors, whose results are available upon request.

[6] We use Cenus-X12 procedure because the newer Cenus-X13 procedure was not available in SAS yet at the time when this paper was written. However, the newly added features in Census-X13 procedure do not affect any of the results in the paper.

three seasonality tests that are readily available for this purpose. The stable seasonality test assumes the seasonal factors are stable. The moving seasonality test assumes the seasonal factors change over time. The last one combines the first two tests, along with a non-parametric Kruskal-Wallis test for stable seasonality, to test the presence of identifiable seasonality. Accounting for the stable seasonality test, the third combo test contains the same information as the moving seasonality test. Thus here we only report the results from the stability seasonality test and the combo test.

Table 1 summarizes the test results for total nonfarm employment and its super-sectors. Based on the results from the joint seasonality test, we find that for 6 out of the 11 super-sectors in Texas, the seasonal pattern of their benchmark series significantly differs from the seasonal pattern of their survey sample series. Moreover, the employment from these 6 super-sectors has a very large share in the total nonfarm employment. For instance, in 2014, they accounted for more than 78 percent of all total nonfarm jobs in Texas. Not surprisingly, when we apply our method to the total nonfarm employment series, we find the seasonal pattern of the benchmark series significantly differs from the seasonal pattern of the constructed survey series. Our findings echo the results in Groen (2011). Using US national level data, Groen (2011) finds important qualitative differences in the seasonal patterns between QCEW and CES survey series in most industries. Our study differs from the study in Groen (2001) in that our main focus is on US regional level data, namely, the state of Texas.

Table 1. Different Seasonality in Sample VS Benchmark Data

Various Texas Sectors

Super-sector	F Stat for Stable Seasonality Tests (*)	Different Seasonality - Present or not
Logging and Mining	1.5	Not Present
Construction	75.8	Present
Manufacturing	2.0	Not Present
Trade, Transportation, and Utilities	14.3	Present
Information	5.7	Probably Not Present
Financial Activities	3.9	Not Present
Professional and Business Services	23.2	Present
Education and Health Services	30.9	Present
Leisure and Hospitality	13.3	Present
Other Services	1.4	Not Present
Government	526.6	Present
Total Nonfarm	8.7	Present

(*) 0.1 percent Critical Value = 3.1. For seasonality test, we follow the convention and use the 0.1 percent critical value.

3. Standard Seasonal Adjustment for Hybrid Series

In this section, we study the relatively simple case of deterministic seasonality. Within a regression model framework, we show analytically that simple seasonal adjustment for hybrid series can cause bias in the estimation of seasonal factors and thus produce incorrect seasonal adjustment. The presence of bias will also determine the way in which seasonal adjustment should be handled in the survey part of the hybrid CES series for Texas. Although multiplicative seasonal decomposition is much more common in macroeconomic time series, to better illustrate the potential bias caused by standard seasonal adjustment procedures, in this section, we assume an additive seasonal decomposition of the series so that the sum of 12 months seasonality factors within one year is restricted to zero.[7] We follow the notation in Ghysels and Obsorn (2001) closely.

Consider series Y_t which has only one set of deterministic seasonality in mean with a total of S seasons. A conventional dummy variable representation for the series can be written as

$$Y_t = \mu + \sum_{s=1}^{S} m_s \, \delta_{s_t} + \varepsilon_t \qquad (1)$$

Where μ is the unconditional mean of Y_t. $m_s, s = 1, \dots, S$ is the deterministic seasonal effect for season s. δ_{s_t} are the seasonal dummy variables; so $\delta_{s_t} = 1$ if $s_t = s$ and equals zero otherwise for $s = 1, \dots, S$. Note that by definition, the sum of seasonal effects is restricted to zero. That is, $\sum_{s=1}^{S} m_s = 0$. As usual, the error term ε_t is assumed to be a weakly stationary zero mean process.

For a hybrid series H_t with two sets of deterministic seasonality that has a known joint time, say, T_0 , straightforward generalization of (1) allows us to write its dummy variable representation for the series as

[7] A multiplicative seasonal decomposition in the original series is equivalent to an additive seasonal decomposition in the logarithmic transformation of the original series. For more detailed discussion on these two ways of decomposition, see for example, Chapter 4 in Ghysels and Obsorn (2001).

$$H_t = \mu + \sum_{s=1}^{S} \mathrm{m}_{1,s}\, \delta_{S_t} + \sum_{s=1}^{S} (1 - D_{T_0})(\mathrm{m}_{2,s} - \mathrm{m}_{1,s})\delta_{S_t} + \varepsilon_t \qquad (2)$$

Unlike (1), here we assume $m_{1,s}, s = 1, \ldots, S$ is the deterministic seasonal effect of H_t for season s before time T_0. Similarly, for any time after T_0, $m_{2,s}, s = 1, \ldots, S$ is the deterministic seasonal effect for season s. D_{T_0} is a dummy variable which equals 1 for any $t > T_0$ and equals 0 for any $t \leq T_0$. As in (1), δ_{s_t} are seasonal dummy variables. Again, the sum of seasonal effects is restricted to zero. So $\sum_{s=1}^{S} m_{1,s} = 0$ and $\sum_{s=1}^{S} m_{2,s} = 0$.

We can further simplify the notation in (2) by denoting $M_{1,S} = (\mathrm{m}_{1,1}, \ldots, \mathrm{m}_{1,S})$, $X_1 = (\delta_{1t}, \ldots, \delta_{St})'$, $M_{2,S} = (\mathrm{m}_{2,1} - \mathrm{m}_{1,1}, \ldots, \mathrm{m}_{2,S} - \mathrm{m}_{1,S})$, $X_2 = ((1 - D_{T_0})\delta_{1t}, \ldots, (1 - D_{T_0})\delta_{St})'$. Thus (2) can be written as

$$H_t = \mu + M_1 X_1 + M_2 X_2 + \varepsilon_t \qquad (3)$$

Clearly, if equation (3) is the correct model but we specify the model as in (1), as long as T_0 is not the starting or ending date for hybrid series H_t, the estimate of seasonal effect before T_0 M_1 will biased due to omitted variables X_2 . Ignoring for the restrictions imposed on M_1 and M_2 for the moment, standard textbooks tell us that the bias for M_1 from the wrongly specified model (1) for a hybrid series can be written as $Est(M_1) = M_1 + M_2 \frac{Cov(\mathrm{X}_1, \mathrm{X}_2)}{\mathrm{Var}(\mathrm{X}_1)}$. Since $m_{\mathbf{1},s}$ and $m_{\mathbf{2},s}$ are completely exchangeable in the above discussion, by symmetry**,** we know that the estimate for $m_{\mathbf{2},s}$ will also be biased.

4. BLS 2-step V.S. BP 2-step Seasonal Adjustment

Realizing the potential bias in standard seasonal adjustment procedure, Berger and Phillips (1993, 1994) proposed a two-step seasonal adjustment process that estimates and applies two separate seasonal adjustment factors for the two parts of the data. In early 1994 the BLS, partly in response to the research by Berger and Phillips (BP), adopted a two-step adjustment procedure for the state employment data published at the one-digit SIC level. The methods used by both agencies essentially followed the same procedure. Both estimate separate seasonal factors for the benchmark part of the data and the survey part and then apply the seasonal factors to the two separate parts of the hybrid series. Therefore, both methods help correct the potential bias caused by applying the standard seasonal adjustment method. It is worthwhile to mention that, even when a time series is not a hybrid series, that is, there is only one source of seasonality, doing a 2-step seasonal adjustment shall allow us to achieve the same adjustment as the standard seasonal adjustment method would do.

The procedure used by the BLS, however, differs from the procedure used by BP in an important way. At the transition month (T_0)where the survey data starts, often October, BP extrapolates the seasonal factors using the percent change in the survey data seasonal factors from September to October and then multiply this change by the September benchmark seasonal factor. In contrast, the BLS simply divides the September benchmark value by the benchmark seasonal factor and then divides the October survey value by the survey seasonal factor – in essence they simply juxtaposes the two different sets of seasonal factors.

In practice, CES employment series is usually adjusted using multiplicative seasonal decomposition. Therefore, in this section, we use the multiplicative decomposition representation to specifically show how the BLS 2-step differs from BP 2-step seasonal adjustment method. In the multiplicative seasonality setting for any seasonally unadjusted series Y_t, the relationship between the seasonally adjusted series and the raw series can be described as $Y_t^{sa} = Y_t / m_{S_t}$ where m_{S_t} is the seasonal factor for time t. The 12 month averages of m_{S_t} are restricted to be 1.

Recall from Section 1 that the seasonally unadjusted hybrid CES series $H_t \, (1 \le t \le T)$

$H_t = \begin{cases} B_t, & if \quad t \le T_0 \\ S_t, & if \quad t \ge T_0 \end{cases}$ where B_t is the CES benchmarked employment data so that it ends at the last benchmark date T_0 and S_t be the sample survey data. The hybrid series H_t has been benchmarked up to T_0, therefore $H_{T_0} = B_{T_0} = S_{T_0}$.

If we adopt the BLS 2-step seasonal adjustment method, it is not hard to see that the change in the seasonally adjusted hybrid series from T_0 to $T_0 + 1$, calculated as the growth rate from prior period, $\Delta H_{T_0+1}^{sa}$ can be expressed as

$$\Delta H_{T_0+1}^{sa} = \frac{H_{T_0+1} / \mathrm{m}_{\mathrm{S,T_0+1}}}{H_{T_0} / \mathrm{m}_{\mathrm{B,T_0}}} = \frac{S_{T_0+1} / \mathrm{m}_{\mathrm{S,T_0+1}}}{S_{T_0} / \mathrm{m}_{\mathrm{B,T_0}}} = \frac{\mathrm{m}_{\mathrm{B,T_0}}}{\mathrm{m}_{\mathrm{S,T_0+1}}} \Delta S_{T_0+1} \quad (4)$$

Where ΔS_{T_0+1} is the growth rate in the original seasonally unadjusted sample series from T_0 to $T_0 + 1$. $\mathrm{m}_{\mathrm{B,T_0}}$ is the estimated seasonal factor at T_0 using the benchmark component while $\mathrm{m}_{\mathrm{S,T_0+1}}$ is the estimated seasonal factor at $T_0 + 1$ using sample series.

In contrast, when using the BP 2-step seasonal adjustment method, the change in the seasonally adjusted hybrid series from T_0 to $T_0 + 1$, can simply be described as

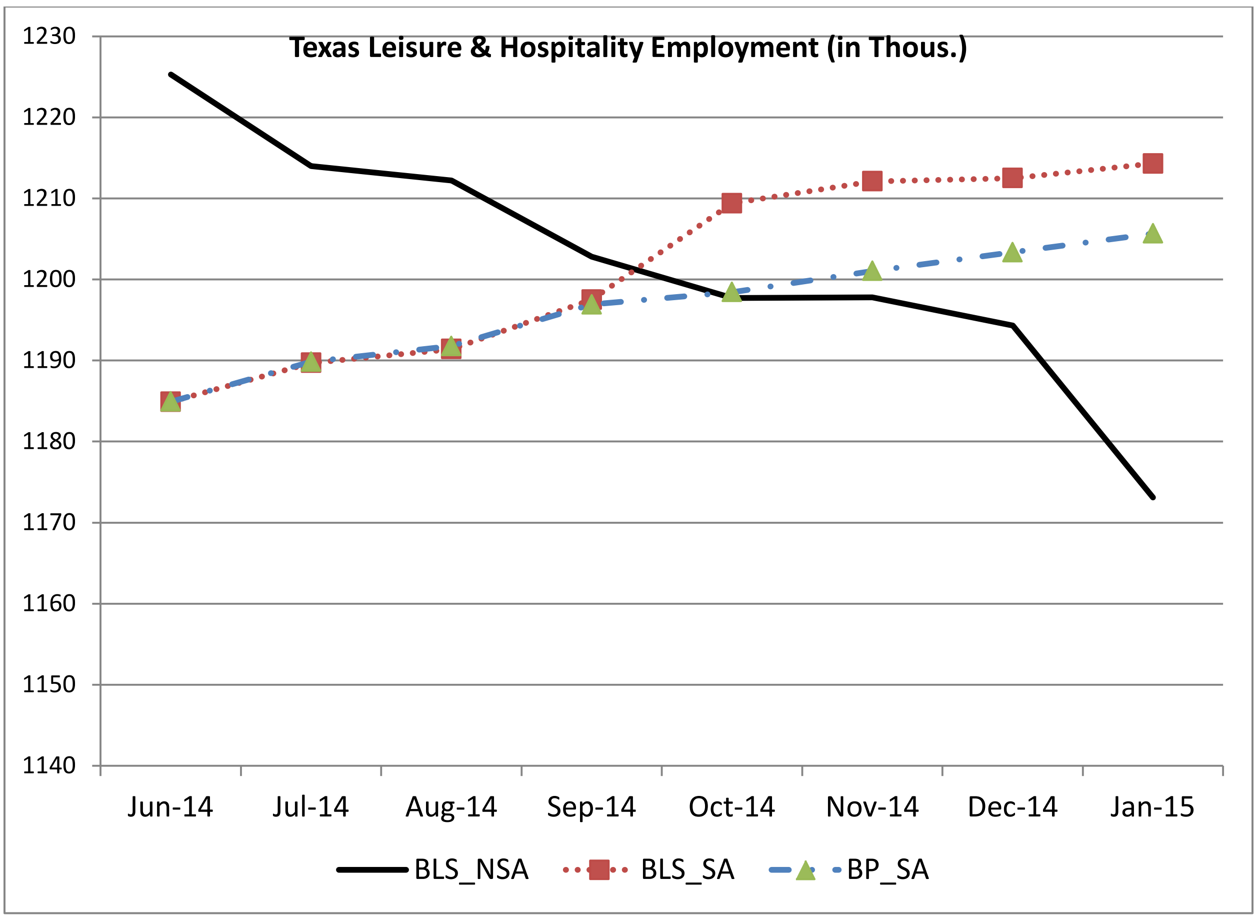
$$\Delta H_{T_0+1}^{sa} = \frac{H_{T_0+1} / \mathrm{m}_{\mathrm{S,T_0+1}}}{H_{T_0} / \mathrm{m}_{\mathrm{S,T_0}}} = \frac{S_{T_0+1} / \mathrm{m}_{\mathrm{S,T_0+1}}}{S_{T_0} / \mathrm{m}_{\mathrm{S,T_0}}} = \frac{\mathrm{m}_{\mathrm{S,T_0}}}{\mathrm{m}_{\mathrm{S,T_0+1}}} \Delta S_{T_0+1} \quad (5)$$

Unless $m_{B,T_0} = m_{S,T_0}$, (4) and (5) will differ. In particular, from equation (4) we can see that, if using the BLS 2-step seasonal adjustment method, the change in estimated seasonal factor from T_0 to $T_0 + 1$ $\frac{m_{B,T_0}}{m_{S,T_0+1}}$ could possibly introduce unwanted shift in $\Delta H^{sa}_{T_0+1}$ because m_{B,T_0} is estimated from the benchmark series but m_{S,T_0+1} is estimated from the sample series. By comparison, in the BP 2-step method, the seasonal factors for time T_0 and $T_0 + 1$ are both estimated from the sample series. Therefore, the BP 2-step method avoids any irregular seasonal movement at the transition point where the two source components with different seasonality join.

Figure 1 shows an example of how BLS's 2-step seasonal adjustment method may cause unwanted level shift in seasonally adjusted hybrid series at the transition point. The three series shown in the chart are the real time data for Texas Leisure and Hospitality CES employment when the January 2015 data was first released. The seasonally unadjusted data (series 'BLS_NSA' in the chart) is benchmarked up to September 2014. If we use the BLS 2-step seasonal adjustment method (series 'BLS_SA' in the chart), from September 2014 to October 2014, the Texas leisure and hospitality employment grows at annualized rate of 13%. In contrast, when using the BP 2-step method (series 'BP_SA' in the chart), the number drops to only about 2%. We also computed the annualized growth rates in seasonally adjusted Texas leisure and hospitality employment in the six months preceding and following October 2014. The average annualized growth rate is 3.8% (4.3% when averaging the absolute change) and the standard deviation is 2.9%. Therefore, according to recent growth patterns, a 2% growth rate in October 2014 seems to be more reasonable than a 12.6% growth rate. Moreover, there seem to be very little anecdote evidence supporting such a strong growth in Texas leisure and hospitality employment around October 2014 as suggested by the BLS seasonally adjusted number.

It should be noted that, as shown in equation (4) and (5), it is the difference between m_{S,T_0} and m_{B,T_0} for Texas leisure and hospitality employment at $T_0 =$ September 2014 that primarily causes the difference between the BLS 2-step seasonally adjusted and the BP 2-step seasonally adjusted October growth. If there does not exist notable difference in m_{S,T_0} and m_{B,T_0} for other sectors, we would not find a jump in the series at the transition month like we did in the BLS Texas leisure and hospitality employment series.

Figure 1. BLS 2-step Seasonal Adjustment VS. BP 2-step Seasonal Adjustment – An example



In a BLS working paper, Scott, Stamas, Sullivan and Chester (1994) note that the when using the BP method, the mean of the seasonally adjusted series deviates from the unadjusted series and using the BLS method, the seasonally adjusted series "goes through" the center of the non-adjusted series and thus better conforms to what a seasonally adjusted series is supposed to look like. They conclude that the Berger-Phillips procedure contains a bias that throws off the average level of the seasonally adjusted series. The authors conclude that "the potential for distortions across the seam deserves more study, but that the bias in the Berger-Phillips formula is unacceptable." What the authors do not discuss is the bias in the unadjusted survey data caused by the differences in the seasonal pattern at the transition month. The "bias" in the BP method is simply an adjustment for the shift in the unadjusted data at T_0.

To see this, re-arrange equation (5) slightly we get

$$\Delta H^{sa}_{T_0+1} = \frac{\mathrm{m}_{\mathrm{S,T_0}}}{\mathrm{m}_{\mathrm{S,T_0+1}}} \Delta S_{T_0+1} = \frac{\mathrm{m}_{\mathrm{B,T_0}}}{\mathrm{m}_{\mathrm{S,T_0+1}}} \left(\frac{\mathrm{m}_{\mathrm{S,T_0}}}{\mathrm{m}_{\mathrm{B,T_0}}} \Delta S_{T_0+1} \right) \quad (5')$$

When compared to equation (4), we clearly see the extra adjusting term $\frac{\mathrm{m}_{\mathrm{S,T_0}}}{\mathrm{m}_{\mathrm{B,T_0}}}$ in the BP method. To make the levels of the BP seasonally adjusted series and the seasonally unadjusted series more compatible (have their averages equal), the best adjustment would be to multiply the seasonally unadjusted survey part of the series at the start of the survey data (time T_0 +1) by a factor of $\frac{\mathrm{m}_{\mathrm{S,T_0}}}{\mathrm{m}_{\mathrm{B,T_0}}}$.

This would correct for the level shift in the unadjusted series at the transition point and make it average to the BP seasonally adjusted series. If we use this adjustment on the BLS non-seasonally adjusted data for leisure and hospitality employment shown as the solid line in Figure 1 and then apply the BLS seasonal factors that were used to calculate the BLS seasonally adjusted series shown in the same chart, then the October growth rate would go from the current estimate of 12.6 % to a more reasonable 4.6 %.

5. Conclusion

In this paper we examine the issues surrounding the seasonal adjustment of hybrid time series. This unique type of series is due to the combination of two different series that may have different seasonal patterns. We first present a simple test for different seasonality in the two different parts of the series. We apply this test to Texas nonfarm employment and its super sectors and find strong evidence of separate seasonal factors in them. We then discuss the bias caused by assuming that the seasonal factors are the same. Finally, we discuss two different methods currently being used to apply the two separate sets of seasonal factors to the hybrid series. We argue that the appropriate method is to extrapolate the seasonal factors in the second part of the series rather than to juxtapose the two differing sets of seasonal factors. Alternatively, a level adjustment can be made to the non-seasonally adjusted survey data that makes the BLS process of juxtaposing the seasonal factors equivalent to extrapolating the seasonal factors but also ensures that the seasonally adjusted data averages to the non-seasonally adjusted data.

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