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Abstract

State level unemployment statistics are some of the most important and widely used data sources for local analysts and public officials to gauge the health of their state's economy. We find statistically significant seasonal patterns in the state level seasonally adjusted Local Area Unemployment Statistics (LAUS) released by the U.S. Bureau of Labor Statistics (BLS). We find that the pro-rata factors used in the benchmarking process can invoke spurious seasonal patterns in this data. We also find that the Henderson 13 filter used by the BLS to smooth the seasonally adjusted data may reduce monthly volatility too much in the sense that the aggregated state data is much smoother than the independently estimated national data. To reduce these problems, we suggest that the BLS use seasonally adjusted data when benchmarking regions to national totals.

Keywords: Local Area Unemployment Statistics; Data Revisions; Seasonal Adjustment

JEL Codes: C13, C8

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1. Introduction

The Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS) is a joint Federal-State program which produces monthly estimates of total employed and unemployed for approximately 7,300 areas. At the state level, LAUS reports both the seasonally non-adjusted (NSA) and seasonally adjusted (SA) data. The LAUS estimates provide valuable local labor market information for workers, analysts and policy makers.

In an effort to improve the quality of data produced in previous LAUS models, BLS initiated a major redesign in 2005. One significant change is the introduction of a real-time benchmark where individual state estimates are controlled each month to the Current Population Survey (CPS) national estimate. In practice, the BLS monthly benchmark consists of two steps. First, the US is divided into nine census divisions. Employment and unemployment (and thus labor force as the sum of the two) in these regions are controlled to the national total based on their shares. Second, state employment and unemployment estimates are created with models using input variables such as data from the CPS, establishment survey employment and claims for unemployment insurance. Each state's estimate is then controlled to the regional total. The monthly benchmark insures that state values sum to the region and regions sum to the nation.

The 2005 LAUS redesign implemented the monthly benchmark for the NSA state estimates. However, after the redesign, monthly movements in the state SA series became quite volatile. Because of the increased volatility, in January 2010 the BLS started applying a 13-month Henderson Trend filter to the seasonally adjusted estimates for the states (and D.C.), which is incorporated into the official estimates. They also began benchmarking the state SA data to the nation every month. In the benchmark adjustment for the SA data, the same pro-rata factors computed from the NSA data are used directly to adjust the SA data[2]. Before that, the states SA data were controlled only annually to the census division and the nation for the annual average NSA values.[3]

One would expect the state level seasonally adjusted (SA) estimates to be free of any significant seasonal patterns. However, we find strong evidence indicating there are seasonal movements in many of them. We apply three different seasonality tests to the monthly changes of state SA data using the Census Bureau X-12 ARIMA model[4]. The stable seasonality test assumes the seasonal factors are stable. The moving seasonality test allows the seasonal factors to change over time. The last one combines the first

[2] See answer to question 14 from Bureau of Labor Statistics (2010).
[3] BLS uses the Denton method for the annual benchmark. For more details, readers are referred to BLS website.
[4] We use statistical package SAS for the tests.

two tests, along with a non-parametric Kruskal-Wallis test for stable seasonality, to test the presence of identifiable seasonality. Table 1 summarizes our findings.

Table 1. Seasonality Test for Seasonally Adjusted State Labor Force Data

Variable[5]	**Number of States that Stable Seasonality is found Present at 0.1 Percent Level**[6]	**Number of States that Moving Seasonality is found Present at 1 Percent Level**	**Number of States Showing Presence of Identifiable Seasonality Based on combined test**
Civilian Labor Force	45	37	35
Number of Employed	44	49	39
Number of Unemployed	28	48	9
Unemployment Rate	3	43	0

Notes: The sample period covers from January 1990 to May 2013. The data includes Washington, DC, which is treated as an individual state in this paper.

All three tests unanimously support the strong presence of seasonality in the SA civilian labor force and number of employed, although the evidence is weaker for the number of unemployed and the unemployment rate. For instance, we find identifiable seasonality in 39 out of the 51 state SA employment series. We also tried different sample periods and find the above results are quite robust.

2. Tracing the Source of Seasonality

What is the main source of seasonality found in the state level SA labor force estimates? One obvious possibility is the residual seasonality inherited from the corresponding NSA data. However, there is another important possible source; the pro-rata factors computed from the NSA data that are used in benchmarking the SA data.

To show the second possibility, consider the following hypothetical scenario where a census division only consists of two states, A and B. Assume the labor force in A and B are stationary over time and their movement can fully be described by their seasonal changes. Assume the (stable) seasonal

[5] All tests are applied to the monthly changes of the interested variables. We have also tested the presence of seasonality in the SA labor force estimates using the level data. Our main conclusion remains largely the same.
[6] Notice that the significant levels of the seasonality tests are much smaller than the conventional values used in many other tests. For more information on the seasonality tests, see, for example, Lothian and Morry (1978).

components of two NSA labor force data series for the two states are X and Y respectively. For a given year, X and Y can be represented as $X=\sum_{i=1}^{12} a_i D_i$ and $Y=\sum_{i=1}^{12} b_i D_i$, where D_i are seasonal dummies for the 12 months within the year; $\{a_i\}$ and $\{b_i\}$ are the seasonal factors. Based on the two seasonal components, the proportion of state A in this hypothetical division, or the pro-rata factor for state A becomes

$$prf(A)=\frac{X}{X+Y}=\frac{\sum_{i=1}^{12} a_i D_i}{\sum_{i=1}^{12}(a_i+b_i)D_i} \qquad (1)$$

It is not hard to see that the $prf(A)$ can be simplified to

$$prf(A)=\sum_{i=1}^{12}\frac{a_i}{a_i+b_i}D_i \qquad (2)$$

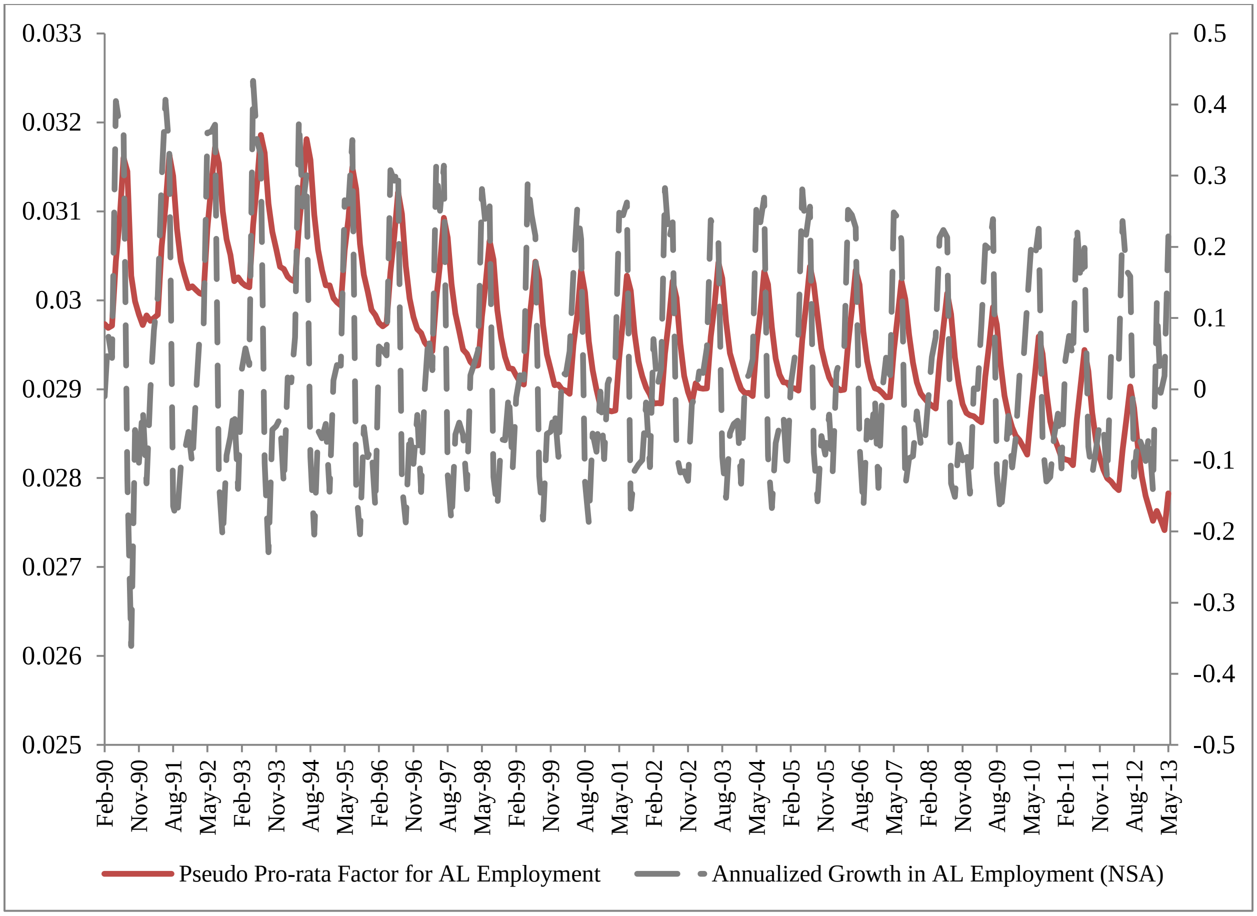
Equation (2) shows that, in general the pro-rata factor for state A will display seasonal patterns, with seasonal factors being $\{a_i/(a_i+b_i)\}_{i=1,\dots12}$. Only under the special circumstance that state A and state B have identical seasonal factors will $prf(A)$ be a constant. To see this, assume state A and state B have identical seasonal pattern, then for any month in the year the two seasonal factors are proportional to each other $b_i=\theta a_i$ where $\theta \neq -1$[7]. In this case $a_i/(a_i+b_i)$ becomes $1/(1+\theta)$, a constant that does not vary from month to month. It should be noted that the seasonal pattern for $prf(A)$ is in general different from the original seasonal pattern for the NSA data X.

To further illustrate possible seasonality caused by pro-rata factors computed from NSA data, we take the LAUS NSA employment data for the states of Alaska (AL) and Texas, whose seasonal patterns are very different due to obvious reasons such as climate and geographical location. Assuming Alaska and Texas were the only two states in the same census division, we construct the pseudo pro-rata factor for Alaska through dividing the NSA employment series of Alaska by the sum of the two states' NSA employment series. Figure 1 shows the constructed pro-rata factors along with the original NSA employment series of Alaska. The pseudo pro-rata factors clearly display a seasonal pattern. In addition, the peaks and troughs of the two series differ substantially.

[7] θ equals -1 in the polar case where the two states have exactly the opposite seasonal patterns.

Figure 1. Seasonal Pattern in AL Employment

BLS NSA Employment vs. the Constructed Pseudo Pro-rata Factor



The example here shows that adjusting SA data using the pro-rata factors based on the NSA data may introduce undesirable seasonality. This secondary seasonal pattern invoked in the benchmarked data may differ dramatically from the original seasonal pattern in the NSA data.

3. Some Empirical Evidence

As discussed in the previous section, theoretically there are various possible causes of seasonality in the SA state labor force data, thus it is worthwhile to carry out an empirical exercise to see which one is more important.

For this purpose, we first estimate the stable seasonal factors using the annualized monthly growth rates of the following 1) The SA labor force data in those states where the combined test showing presence of identifiable seasonality; 2) The NSA labor force data in the same states as in 1); 3) The US national NSA labor force data; 4) NSA labor force data for the nine census divisions. We then run the following regression, which is intended to decompose the variation of seasonality detected in the state level SA labor force data.

$$SF\_state\_SA_{jt} = \alpha + \beta_1 SF\_state\_NSA_{jt} + \beta_2 SF\_US\_NSA_{jt} + \beta_3 SF\_Division\_NSA_{jt} + \varepsilon_{jt}$$

Here *j* refers to the state of interest and $t = 1,2,...,12$ denotes the twelve months. The dependent variable is the seasonal factors estimated from the state level SA data. The three independent variables are the seasonal factors estimated from the state level NSA data, the seasonal factors estimated from the national NSA data and the seasonal factors estimated from the associated census division NSA data. Table 2 reports the results.

The seasonal pattern in the US national data are found to be the most important single factor explaining the seasonal movements in the state level SA civilian labor force and employment. Statistically the coefficient estimates on the national seasonal factors are highly significant. Take January as an example, if on average the seasonal factor drives up the annualized growth rate in US civilian labor force by 4.9% when compared to other months, there will be a 0.2% upward seasonal adjustment for January (4.9%*0.041) in the annualized growth rate for state level civilian labor force. For the number of unemployed, the seasonal pattern in the regional NSA data is found to be correlated with the seasonality in the SA state unemployment, albeit marginally significant. The negative sign of the coefficient estimates is consistent with fact that the NSA benchmark total enters the denominator when computing the shares. The small magnitude of the coefficient estimates is also expected if the seasonality in the state level SA data mainly comes from the pro-rata factors.

In contrast, the seasonal pattern in the state level SA data is found to be very different from that in the state level NSA data. Only in the number of employed series we find the two are marginally correlated; and the coefficient estimate is less than one third of the coefficient estimate on the national NSA employment. Thus, empirically the seasonality from the pro-rata factors seems to be the dominant source of seasonality found in the SA state labor force data.

Table 2. Decomposing the Seasonality in the SA State Labor Force Data[8]

	Seasonal Factors Estimated from State SA Data		
	Civilian Labor Force	**Employment**	**Unemployment**
	Adj. R-sq = 0.2575	Adj. R-sq = 0.2985	Adj. R-sq = 0.0438
Seasonal Factors Estimated from associated Census Division NSA data	0.00204 (0.00795)	0.00404 (0.00738)	-0.0061* (0.00341)
Seasonal Factors Estimated from US national NSA data	-0.04128*** (0.00808)	-0.03513*** (0.00762)	0.00681 (0.00422)
Seasonal Factors Estimated from state NSA data	-0.00219 (0.005)	-0.01202* (0.00429)	0.000949 (0.00142)

Notes: Standard errors in parentheses

*** Significant at 1 percent level

** Significant at 5 percent level

* Significant at 10 percent level

4. Use of the Henderson Filter

Because of the volatility caused by the monthly benchmark the BLS applies a Henderson trend filter to the SA data before they release the official estimates. While this causes the state data to look very smooth the filter may misrepresent actual volatility in the series. To better illustrate this problem, we calculate a different version of US national unemployment rate than the one published by BLS. More specifically, we divide the sum of all state SA unemployment by the sum of all state SA civilian labor force. Figure 2 compares the monthly changes in the derived SA unemployment rate with those of the official BLS SA unemployment rate. Not surprisingly, the derived SA US unemployment is much

[8] We have also tried incorporating the state fixed effect. It turns out the results are basically the same as the ones reported in Table 2.

smoother because of the Henderson trend filter. When we study the month-to-month changes, in 99 out of the total 281 months (or about 35 % of the time) , the official BLS SA estimate moves in the opposite direction as the derived SA estimate. This discrepancy between the two estimates implies that the SA state level labor markets often show an inconsistent or even conflicting view than the national labor market does. This is surprising since the benchmark process was supposed to make the states and regions more consistent with the nation.

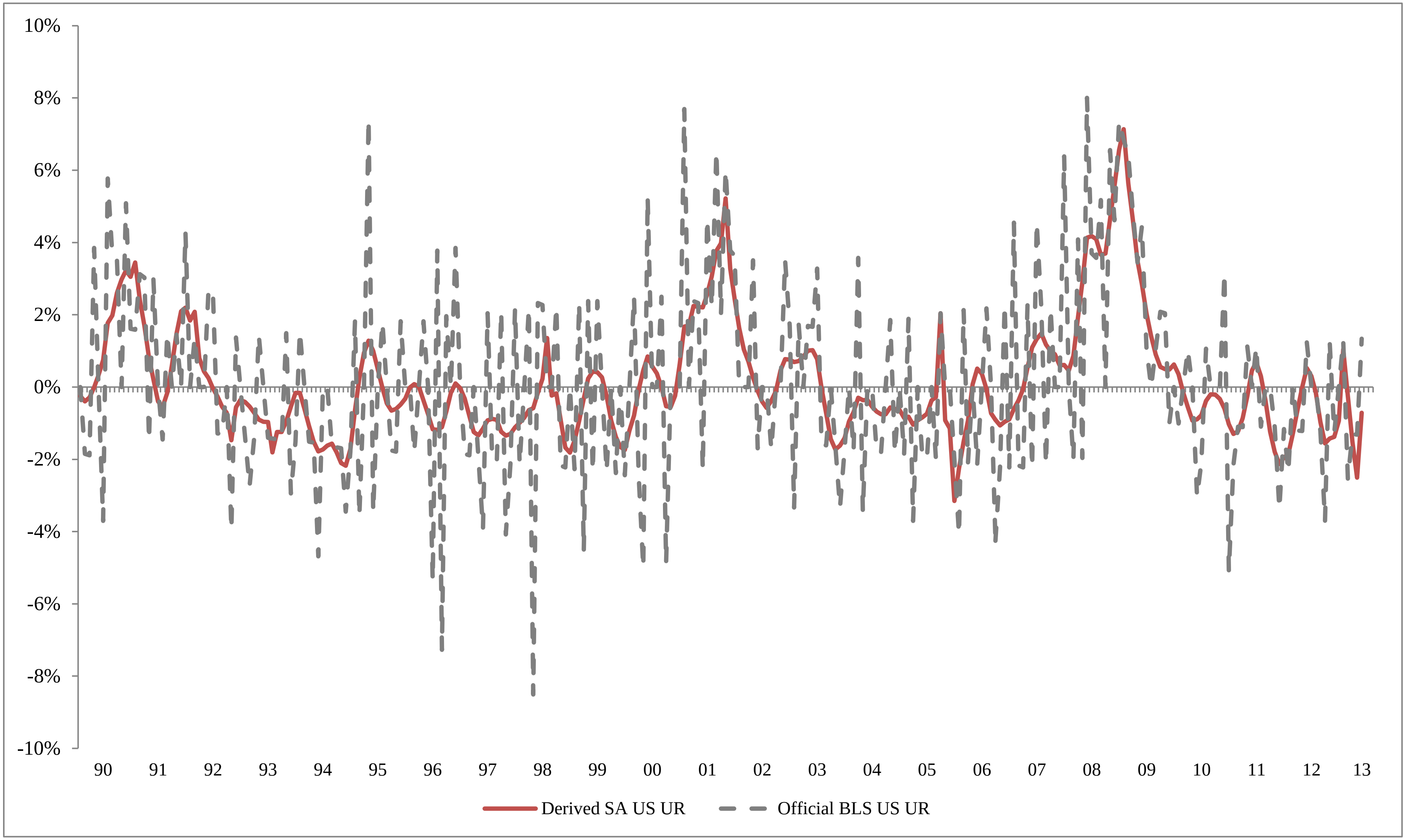
5. Concluding Remarks

We find statistically significant seasonality in the many of the seasonally adjusted state LAUS series. We also find that the seasonality is possibly driven by pro-rata factors used in the benchmarking process. This implies these seasonal changes are spurious and do not represent true regional dynamics.

If, as the present paper suggests, the seasonality in the SA state level LAUS data truly comes from the pro-rata factors, one straightforward remedy would be to compute the pro-rata factors based on SA data instead of the NSA data. To get the NSA data for each state, the BLS can multiply the SA adjusted data by the state seasonal factors. Doing benchmark adjustment in this manner may reduce the volatility in the state SA estimates and may reduce the need for the Henderson trend filter which seems to be creating too much smoothness in the state estimates.

Figure 2. US Unemployment Rate

Official BLS V.S. Derived SA estimate



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