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Keith R. Phillips and Jack Wang

Federal Reserve Bank of Dallas
Research Department
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Abstract

Rudebush et al (2015a, b) and the Bureau of Economic Analysis find the presence of residual seasonality in the official estimates of U.S. real gross domestic product (GDP). Directly seasonally adjusting official seasonally adjusted GDP, which we refer to as double seasonal adjustment, could revise the first quarter growth in the past several years upward by an average of about 1.5 percentage points. The presence of residual seasonality can significantly distort current analysis of national and regional economies. In this paper we look more closely at the U.S. GDP data and study the quality of the seasonal adjustment when it is applied to data that has already been indirectly seasonally adjusted. We find that double seasonal adjustment can lead to estimates that are of moderate quality. While the optimal method would be to directly seasonally adjust the aggregate not seasonally adjusted data, if this is not possible, double seasonally adjusted data would likely lead to better estimates.

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Introduction

Rudebush, Wilson and Pyle (2015a) first found large residual seasonality in official U.S. GDP, particularly in first quarter estimates. They note that the underlying data used to produce this series is not released in its raw not-seasonally-adjusted form. In order to correct for the seasonal pattern that still existed in the data they used X12-ARIMA to double seasonally adjust this data. Their results showed much different growth rates in RGDP than were being reported. At the time of their study in the Spring of 2015, the current estimates from the Bureau of Economic Analysis (BEA) were that the first quarter GDP growth was 0.2 percent. This very weak pace of growth caused many to be concerned about the strength of the U.S. economy. But with the double seasonal adjustment, the first quarter growth was estimated to be a much stronger 1.8 percent. In response to this and other research, the BEA implemented new procedures to try to reduce the residual seasonality in the data. In general they seasonally adjusted some component series that were not previously seasonally adjusted and implemented some controls for checking for residual seasonality at certain aggregate levels (see McCulla and Smith 2015).

Despite these changes, Rudebush et al. (2015b) found that significant residual seasonality still persists in the U.S. RGDP data. Once again applying a double seasonal adjustment to the data they find that 2015 Q1 GDP data was 1.9 percent instead of the 0.6 percent that was available at the time. Following this analysis, we use standard tests and find strong evidence of residual seasonality in U.S. RGDP data since 1990. We use X-12 ARIMA to double seasonally adjust the data since 1990 and find that U.S. GDP grew at an annualized pace of 2.4 percent in the first quarter of 2016 instead of the 0.8 percent released at the time.

In this article we look at some of the issues involved with the double seasonal adjustment of U.S. GDP data and if the estimates from this procedure are of good quality and tend to be stable over time. Our results show that applying a double seasonal adjustment to the entire time series back to 1947 results in low quality, unstable seasonal estimates. However, applying the double seasonal adjustment just to the period since 1990 results in more stable estimates, which are of moderate quality. While the optimal solution is for the BEA to produce and release the data without seasonal adjustment so that the series can be directly seasonally adjusted, the application of a double seasonal adjustment is likely best performed not on the whole series but on the series since 1990, where evidence of residual seasonality is much stronger .

Literature Review

In a recent article, BEA documents various sources of the (residual) seasonality in officially estimated seasonally adjusted U.S. GDP One of the sources is that in producing aggregate GDP, the BEA prefers to use seasonally adjusted source data at a fine level of detail and aggregate that data up to the total. The BEA prefers this method because "this approach maintains the transparency of BEA's estimating methods, allowing users to trace the estimating process – from the incorporation of the initial source data to the publication of NIPA estimates."[2] In other words, the seasonally adjusted components of GDP are important in and of themselves, and the indirect method allows users to directly determine the sources of changes to aggregate SA GDP. When seasonally adjusting the aggregate GDP separately from the components, there is no direct accounting for the changes in the total.

Also as noted in McCulla and Smith (2015) and BEA (2016), another potential source of the residual seasonality is that when source data are seasonally adjusted at one frequency (such as monthly) they may still exhibit seasonality when aggregated to a different frequency (such as quarterly). Also when

[2] See Box on page 4 of McCulla and Smith (2015).

seasonally adjusted nominal values are deflated by seasonally adjusted price indexes the resulting real estimate can have seasonal patterns.

The advantages and disadvantages of direct and indirect seasonal adjustment have been discussed in the literature for some time. As noted in Hood and Findley (2003) and others that when the component series that make up the aggregate series have quite distinct seasonal patterns and have adjustments of good quality, indirect seasonal adjustment is usually more appropriate than direct. For example if housing starts have much different seasonal patterns in the north of the country than in the south and through much of the past a majority of the national starts occurred in the south, but if recently they are concentrated in the north, then the recent seasonal pattern would be more accurately measured with the indirect approach. The same can be true of GDP if different components such as consumption and investment have differing seasonal patterns and their share of growth changes sharply in different periods.

On the other hand if the component series have similar seasonal patterns or their shares are fairly constant, then summing the series may result in noise cancelation. The aggregate series can also pick up on patterns that occur infrequently in any given region or sector but which occur consistently in the aggregate data. For example, a big annual trade show that occurs in a given month that moves around the country may spur sales of a product in that month every year – and if the sales are concentrated in the region of the trade show the indirect (by region) seasonal adjustment would not capture this but the direct seasonal adjustment would.

Maravall (2006) looks at the different theoretical arguments for using the direct versus indirect seasonal adjustment and conditions which best suit each adjustment. He states that “the dilemma of direct versus indirect adjustment has not been resolved, despite the fact that the two adjustments may differ substantially. The absence of a definitive solution has fostered a pragmatic approach among users: choose the solution that yields the SA series with the more desirable properties."

The most fundamental property that must be met by any seasonal adjustment, which is agreed upon by all researchers, is that there be no estimable seasonal effects still present in the data. Once that condition is met there are other measures such as the stability and revisions of the seasonal estimates that can be used to determine the quality of one method over another. Hood and Findley (2003), Maravall (2006) and Astolfi, Ladiray and Mazzi (2001 look at different quality measures of direct versus indirect seasonal adjustment once the condition of no residual seasonality has been met. Astolfi, Ladiray and Mazzi (2001) look at the question of which technique is better when producing an aggregate RGDP series for the Euro-zone. Unlike the U.S., the GDP series for these countries are produced and published both seasonally adjusted and not seasonally adjusted. The authors find no residual seasonality with either method and then look at further quality measures to gauge the two methods.

A Closer Look at U.S. GDP

While Rudebush et al.(2015a, b) raised concerns about the validity of the officially released RGDP quarterly growth rates, other researchers questioned the presence of statistically significant seasonal patterns in the data. Gilbert, Morin, Paciorek and Sahm (2015) use the three standard statistical tests in X-12 ARIMA and do not find statistically significant seasonality in U.S. GDP for the periods of 2010 – 2014 and 2005-2014. Groen and Russo (2015) find statistical evidence of residual seasonality for the most recent 10 year period but after adjustment for worse-than-usual weather they find no statistically significant residual seasonality. BEA (2016) conducts tests of residual seasonality in U.S. real GDP over several different periods. They find GDP exhibits residual seasonality when tested over either a 10-year or 30-year time span.

Table 1 highlights how U.S. GDP growth has been weaker on average in the first quarter in the decades beginning with the 1990s, with the weakness particularly pronounced since 2000. In contrast, the second quarter growth in the last two decades has been stronger than the other quarters. This pattern clearly indicates the existence of possible residual seasonality in the seasonally adjusted GDP series. However, since these numbers are averages for long period and can be heavily influenced by large outliers in a few quarters, more formal statistical tests are needed to study if there is actually residual seasonality present in the data.

Table 1. Annualized U.S. GDP Growth by Quarter

Quarter	*1980 to 1989*	*1990-1999*	*2000-2009*	*2010 to Present*
1	3.38	2.65	0.95	0.76
2	2.68	3.92	2.67	3.06
3	3.42	3.32	1.76	2.22
4	3.33	3.67	1.46	2.42

We use the Census-X12 procedure in statistical software package SAS to conduct the test for residual seasonality. In the X12 procedure there are three readily available seasonality tests. 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 combined test contains the same information as the moving seasonality test. Thus here we only report the results from the stable seasonality test and the combined test. In the test for residual seasonality, we consider the full sample period available to us for GDP which starts from 1947Q1 to 2016Q1. In contrast, the longest time span in BEA (2016) study is only 30 years.

Table 2 highlights the statistical tests starting from the beginning of the data in 1947 and for the period since 1990, for both U.S. GDP and its three major components, namely, consumption, investment and government spending. The second shorter period is chosen based on graphical evidence of persistent weakness in growth during the first quarter. For the period since 1947 the results are mixed. The F-test for stable seasonality is not significant at the 1 percent level of significance but it is significant at the 5 percent level. Using the combined test, we do not find any statistically significant seasonality at the 0.1 percent level of significance, which is the conventional level used for this type of test. For the components that make up a large share of GDP, only government has strongly statistically significant seasonality. Looking at the period since 1990, however, the results show strong evidence of residual seasonality. The F test for stable seasonality and the combined test shows statistically significant seasonality in GDP. In terms of the major components, the results for government are similar to total GDP. In addition, the F-test for stable seasonality is significant at the 5 percent level for investment, while consumption shows no significant seasonality. In short, the results in Table 2 echo the findings in BEA (2016) and provide further evidence of the residual seasonality that exist in the U.S. GDP data.

Table 2. Test for Residual Seasonality in U.S. GDP

Sample Period 1990Q1 to 2016Q1

Variable	F-stat for Stable Seasonality	Combined Test(*)	1% CV for F-stat for Stable Seasonality	5% CV for F-stat for Stable Seasonality
GDP	12.50	Present	3.85	2.64

Consumption	1.35	Not Present	3.85	2.64
Investment	2.93	Not Present	3.85	2.64
Government	18.50	Present	3.85	2.64

Sample Period 1947Q1 to 2016Q1

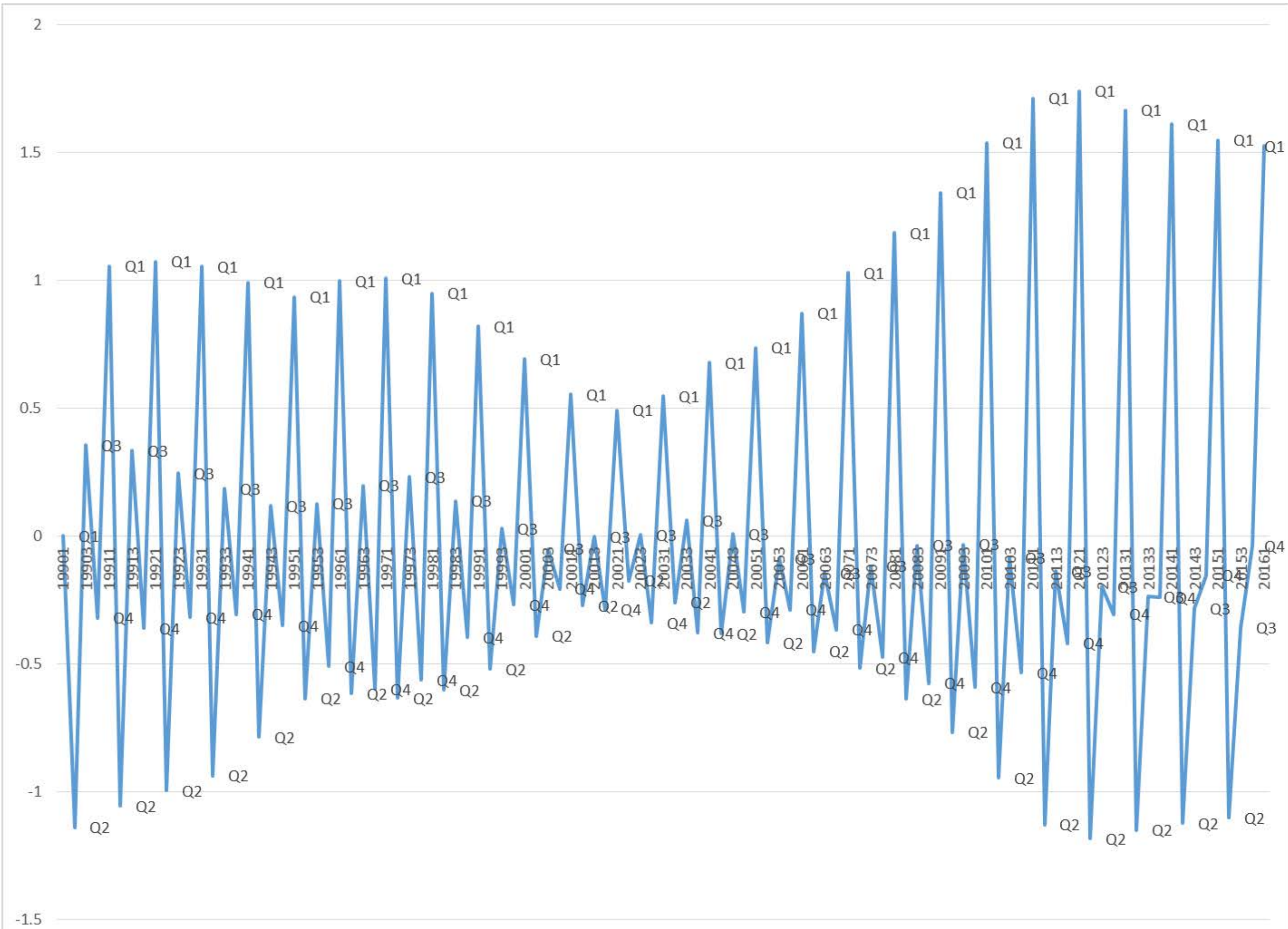
Variable	F-stat for Stable Seasonality	Combined Test(*)	1% CV for F-stat for Stable Seasonality	5% CV for F-stat for Stable Seasonality
GDP	3.04	Not Present	3.97	2.69
Consumption	1.24	Not Present	3.97	2.69
Investment	0.58	Not Present	3.97	2.69
Government	7.60	Present	3.97	2.69

***** Default 0.1% critical value (CV) used in the Combined Test

As shown in Chart 1, double seasonal adjustment of the already seasonally adjusted U.S. GDP data by applying the X-12 ARIMA procedure results in large upward revisions to first quarter growth and downward revisions to growth in the second quarter. The revisions to the annualized growth rate in the first quarter were about one percent in the 1990s, fell to less than 0.5 percent from 2002 to 2005 and then increased to a range of 1.5 percent to 2 percent beginning in 2007. In recent years, the low estimate of U.S. GDP in the first quarter concerned many analysts and suggested that the U.S. economy had slowed sharply. For instance, in the first quarter of 2016, a very different picture is given by the 2.36 percent annualized growth rate from the double-seasonally adjusted data than the official estimate of 0.8 percent.

Chart 1. Difference between Double SA and BEA official SA U.S RGDP Growth

Annualized percentage



Quality of Double Seasonally Adjusted U.S. GDP

Directly seasonally adjusting a series that was indirectly seasonally adjusted but contained residual seasonality is likely a suboptimal way to remove seasonality. However, the optimal method of directly seasonally adjusting the not seasonally adjusted aggregate data may not be feasible if the data is not available in this form. This is the case for US GDP for now, although BEA recently announced that they will release the non-seasonally adjusted GDP data by July 2018. An important question then is what is the quality of the double seasonally adjusted data? In other words, is the 2.36 percent annualized growth estimated for Q1 2016 a good measure of the trend, cycle, noise in GDP?

Table 3. Quality Measures for Double Seasonally Adjust U.S. GDP

M and Q Statistics

Indicator	***Value for Sample from 1947Q1 to 2016Q1***	***Value for Sample from 1990Q1 to 2016Q1***
M1	0.46	0.47
M2	0.01	0.01
M3	0.00	0.00
M4	1.48	0.85
M5	0.20	0.20
M6	0.79	1.03
M7	1.43	0.71
M8	2.53	1.01
M9	0.08	0.26
M10	1.12	0.84
M11	1.03	0.64
Q	0.79	0.46

In order to answer this question we first look at the quality measures that we get when we apply the X-12 ARIMA procedure to the U.S. GDP data. Shown in Table 3 are the M and Q statistics produced by the

X-12 ARIMA procedure in SAS. Two versions are shown – one is when you apply the double seasonal adjustment to the entire series beginning in 1947 and the other is to apply the double seasonal adjustment to the series beginning in 1990. In order for the seasonal adjustment to be of high quality these values should be less than one[3]. As shown in the table, for the long sample period , five out of the 11 M values are greater than one – indicating a seasonal adjustment of low quality. M8, which looks at the size of the fluctuations in the seasonal components throughout the whole series, is particularly significant. The large value of M4 indicates significant autocorrelation in the irregular and M7 the amount of moving seasonality present relative to the amount of stable seasonality. In general these results suggest that, where applied to the full sample period where only little evidence of residual seasonality is found, the double seasonal adjusted estimate are of low quality.

For the series that is double seasonally adjusted beginning in 1990, the results are much better, but still show some instability. In particular, the values of M6 and M8 are slightly above one - indicating some instability in the seasonal adjustment.

Table 4. Summary Analysis of Quarterly

Revisions to Double Seasonally Adjusted U.S. GDP Growth

	Sample Period from 1947Q1 to 2016Q1				Sample Period from 1990Q1 to 2016Q1			
Date	*16 Q Mean*	*16 Q STD*	*32 Q Mean*	*32 Q STD*	*16 Q Mean*	*16 Q STD*	*32 Q Mean*	*32 Q STD*
200401	-0.31	0.21	-0.29	0.15	-0.37	0.29	-0.25	0.24
200402	0.14	0.11	0.16	0.07	0.24	0.14	0.17	0.14
200403	0.25	0.11	0.30	0.09	0.20	0.09	0.19	0.09

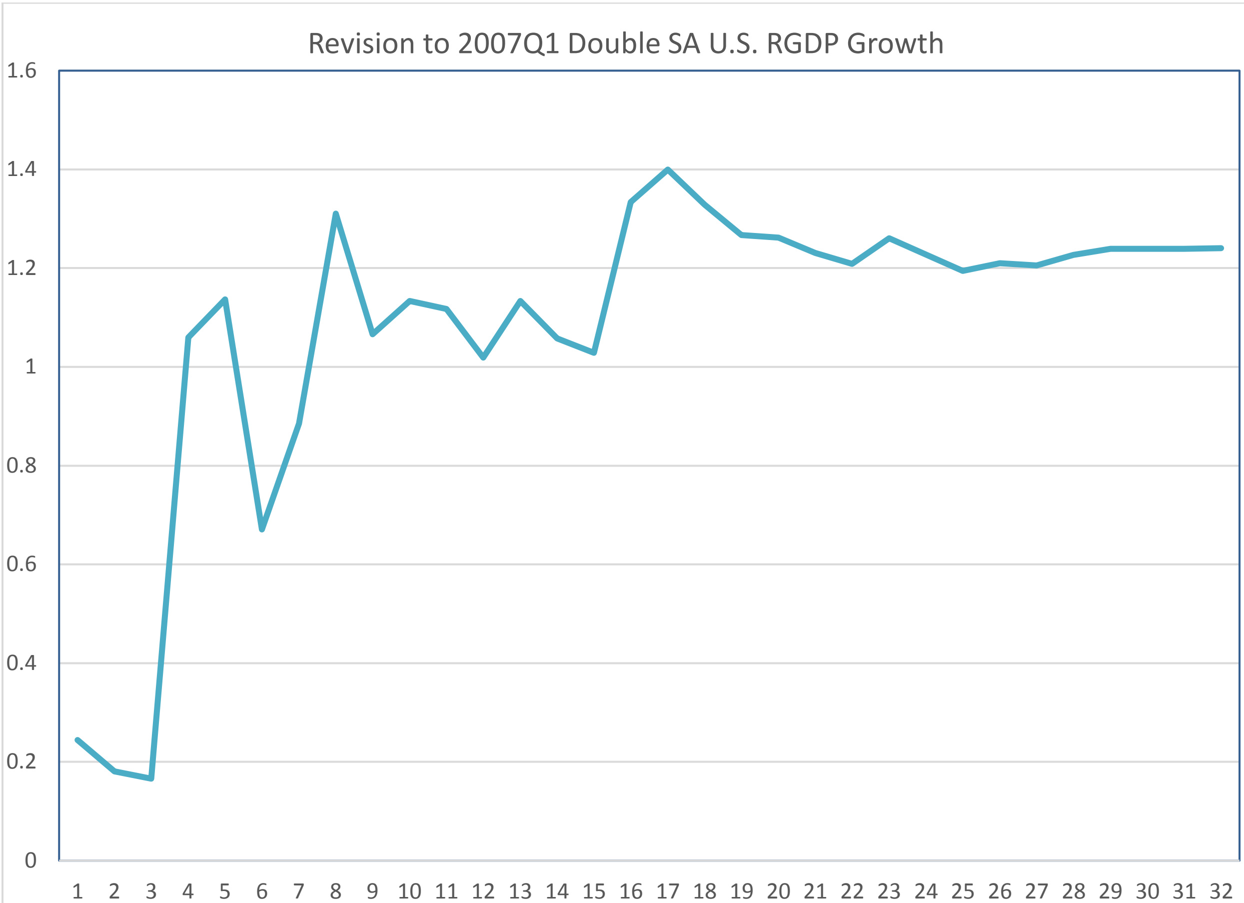
[3] For a much more detailed discussion for these quality measures, readers are referred to Ladiray, D. and Quenneville, B., 2002.

200404	0.03	0.23	-0.13	0.23	0.06	0.18	0.00	0.19
200501	-0.28	0.28	-0.10	0.28	-0.15	0.31	0.07	0.32
200502	-0.10	0.13	-0.18	0.12	-0.15	0.27	-0.28	0.23
200503	0.15	0.14	0.19	0.10	0.10	0.17	0.13	0.13
200504	-0.18	0.34	-0.39	0.31	-0.03	0.28	-0.21	0.27
200601	0.47	0.52	0.75	0.46	0.50	0.44	0.75	0.40
200602	-0.36	0.30	-0.48	0.22	-0.43	0.38	-0.53	0.29
200603	-0.44	0.15	-0.39	0.12	-0.24	0.21	-0.18	0.16
200604	-0.53	0.40	-0.76	0.35	-0.27	0.37	-0.47	0.33
200701	1.24	0.56	1.49	0.41	0.91	0.38	1.08	0.32
200702	-0.66	0.38	-0.73	0.25	-0.50	0.37	-0.53	0.26
200703	-0.06	0.23	0.01	0.18	-0.32	0.22	-0.19	0.20
200704	-1.04	0.38	-1.22	0.33	-0.36	0.48	-0.56	0.39

To further analyze the quality of the double seasonally adjusted data we looked at how adding more data impacts the revisions to the current values. We focus on the 16 quarters of data from the first quarter of 2004 to the fourth quarter of 2007. We analyze a single vintage of data and how the seasonally adjusted data gets revised over the following 32 quarters as new data are added to the series (but the old data is not revised). This allows us to look at the stability of the seasonal adjustment to the data. In looking at the revisions to the annualized percentage change in the double-seasonally adjusted data most seemed to flatten out at about 16 quarters out. Shown in Table 4 is the mean and standard deviation of the revisions from the first estimate to the 16 and 32 estimates for each quarter from 2004 to 2007. Seasonal adjustment applied to the entire period from 1947 and from the period since 1990. As shown here, the average revisions and the standard deviation of the revisions tend to be highest for the first quarter estimates and second highest for fourth quarter estimates. Also, the magnitude of revisions tend to be larger in the immediate following quarters. For instance, if using the first 16 quarters, the standard deviations of the revisions are consistently larger.

To highlight the potential instability of the seasonal estimates, in Chart 2, we plot the following 32 quarters' revisions to the double seasonally adjusted 2007Q1 GDP growth with the seasonal adjustment beginning in 1990. These revisions are due solely to the addition of new data – no revisions occur to past data. As shown in the chart, revisions to the seasonal adjustment can be substantial. For example, the initial estimate of the first quarter of 2007 was annualized growth of -0.03 percent – a year later that was revised to positive 1.3 percent and then later revised up to as much as 1.4 percent 17 quarters after the initial estimate. The revision gradually stabilizes after 17 quarters.

Chart 2. (In)Stability of Double Seasonal Adjustment to U.S. GDP - An Example



While this analysis suggests that the double seasonal adjustment may result in poor quality adjustment, it does suggest that improvement can occur if the seasonal adjustment is only applied to the period where statistically significant residual seasonality is found in the data. Also, since direct seasonal adjustment is not possible for U.S. GDP we cannot compare the double seasonally adjusted data to a direct seasonally adjusted series. Therefore, we look to other series where we can look at direct, indirect and double seasonal adjustment to give us some clues as to whether the double seasonal adjustment typically results in low quality adjustment relative to direct adjustment.

What can we learn from U.S. State Employment Data?

The U.S. Bureau of Labor Statistics (BLS) releases employment data for every state in the country in its Current Employment Statistics program. Although these employment data are available back in the early 20th century, we use the more recent sample period starting from January 1990, where the BLS provides seasonally adjusted data. The BLS seasonally adjusts this data using the indirect method but also release the data not seasonally adjusted. We tested this data using the standard test in X-12 ARIMA and found statistically significant residual seasonality in the employment series for the state of Alabama. To correct for the residual seasonality we use two methods and compare the quality of the two adjustments. That is, we directly seasonally adjust the raw total nonfarm data and we also apply a double seasonal adjustment to the data that was indirectly seasonally adjusted.

Chart 3 shows the annualized growth rates in the three series for Alabama since 2010. Notice that the double seasonally adjusted series can differ sharply from the direct seasonally adjusted series. To give one example, in May 2015, according to the direct seasonally adjusted number, Alabama employment grew at an annualized rate of 2.7 percent. In contrast, the indirectly seasonally adjusted and double seasonally adjusted series both suggest a growth rate of around 4 percent.

Chart 3. Annualized Growth Rate of Alabama Employment

Table 5 highlights the M and Q statistics for the direct and double seasonally adjusted series. All of the values are less than one for the direct seasonally adjusted series while the double seasonally adjusted series shows three M statistics greater than one. Interestingly M8, which looks at the size of the fluctuations in the seasonal components throughout the whole series is above one in the double seasonally adjusted series and was above one for the two time periods applied to the double seasonal adjustment to U.S. GDP. If we assume the optimal series is the one that is directly seasonally adjusted (no residual seasonality and high quality) than we might ask which of the suboptimal series moves the closest to the optimal series. The RMSE of the monthly annualized growth rate of the indirect seasonally adjusted series from the direct seasonally adjusted series is 2.73 while the same statistic for the double seasonally adjusted series is 1.08. Since the double seasonally adjusted series has no residual seasonality and moves more similarly to the optimal series, we conclude that it is better than just using the indirect seasonally adjusted series that contains residual seasonality.

While employment in Alabama likely differs in many regards to U.S. GDP this experiment gives further support that applying a double seasonal adjustment to data which is indirectly seasonally adjusted could possibly lead to low quality estimates. Once again this suggests that statistical agencies that release data in seasonally adjusted form should also release the data not seasonally adjusted to give the user options to correct for any issues they have with the seasonal adjustment. However, even with the lower quality of adjustment, the double seasonally adjusted data is likely a better estimate of the true seasonally adjusted series than the indirectly estimated series.

Table 5. Quality Measures for Seasonally Adjust AL Employment

Indicator	Direct SA AL Employment	Double SA AL Employment
M1	0.07	0.27
M2	0.00	0.00
M3	0.00	0.00
M4	0.61	0.09
M5	0.11	0.03
M6	0.04	0.37
M7	0.12	0.82
M8	0.35	1.62
M9	0.16	0.39
M10	0.31	1.42

M11	0.25	1.15
Q	0.15	0.47

Summary and Conclusion

In this paper we address a fundamental question about U.S. GDP data - can we trust that the estimates are truly free from seasonal patterns? In other words, was the first estimate of 0.8 percent growth in the first quarter of 2015 indicative of a sharp slowing of US growth? Or was the growth rate of 2.4 percent from the double seasonally adjusted data better reflective of trend/cycle growth? Analyzing the data from 1990 shows a strong seasonal pattern. The optimal solution of directly seasonally adjusting the data is not feasible now since the data is not available without seasonal adjustment (at least until mid-2018), so users are faced with applying a direct seasonal adjustment to data that has already been seasonally adjusted with the indirect method.

We find that double seasonally adjusting data can lead to very different results than directly seasonally adjusting the raw data. Using payroll employment data as an example, in one U.S. state, namely, Alabama, where there is strong residual seasonality in data using indirect seasonal adjustment, we find the direct method produces high quality seasonal adjustment while the double seasonally adjusted method does not. However, we find that the double seasonally adjusted data tracks more closely to the direct seasonally adjusted data than the original indirect seasonally adjusted data and thus the double seasonal adjustment represents an improvement to the original data. For the U.S. GDP data we find that narrowing down the period to apply the double seasonal adjustment produces higher quality adjustment although several of the M statistics were still slightly higher than one – suggesting some remaining instability of the seasonal adjustment.

We conclude that the double seasonal adjustment is a suboptimal method of removing residual seasonality – although it represents an improvement from data that is indirectly seasonally adjusted but contains statistically significant residual seasonality. If there is no other alternative, we recommend users to formally test residual seasonality in the data before they apply double seasonal adjustment. Double seasonal adjusted numbers should be interpreted with some caution since they may be of low quality. Optimally, statistical agencies such as BEA should release the data in both seasonally and not seasonally adjusted forms. We are glad to see that currently BEA is working to do this by mid-2018.

References

Astolfi, R., Ladiray, D. and Mazzi, G.L., 2001. Seasonal adjustment of European aggregates: Direct versus indirect approach. *Eurostat, WP17*.

Bureau of Economic Analysis, 2016, Residual Seasonality in GDP and GDI: Findings and Next.

Gilbert, C., Morin, J., Paciorek, A and Sahm, C. 2015, "Residual Seasonality in GDP", FEDS Note, May 14, Board of Governors of the Federal Reserve.

Groen, J., Russo, P. 2015, "The Myth of First-Quarter Residual Seasonality", Federal Reserve Bank of New York.

Hood, C.C. and Findley, D.F., 2001, August. Comparing direct and indirect seasonal adjustments of aggregate series. In *Proceedings of the Annual Meeting of the American Statistical Association*.

Ladiray, D. and Quenneville, B., 2002. *Seasonal adjustment with the X-11 method* (Vol. 158). Springer Science & Business Media.

Ladiray, D. and Mazzi, G.L., 2003. Seasonal adjustment of European aggregates: direct versus indirect approach. *Seasonal Adjustment*, p.37.

Maravall, A., 2006. An application of the TRAMO-SEATS automatic procedure; direct versus indirect adjustment. *Computational Statistics & Data Analysis*, *50*(9), pp.2167-2190.

McCulla, Stephanie H. and Shelly Smith. 2015, "Preview of the 2015 Annual Revision of the National Income and Product Accounts." Survey of Current Business (June 2015), pp 1 -8.

Rudebusch, G.D., Wilson, D.J. and Pyle, B., 2015. Residual seasonality and monetary policy. *FRBSF Economic Letter*, *2015*, p.27.

Rudebusch, G.D., Wilson, D. and Mahedy, T., 2015. The puzzle of weak first-quarter GDP growth. *Puzzle*, *2015*, p.16.

Silvia, J., Bullard, S., Iqbal, Azhar. Pugliese, M., 2016. Residual Seasonality in GDP: Mirage or Real? Wells Fargo Securities Commentary.