NIPFP Working paper series

Seasonal adjustment of Indian macroeconomic time-series

No. 160
20-Jan-16

Rudrani Bhattacharya, Radhika Pandey, Ila Patnaik, Ajay Shah

National Institute of Public Finance and Policy
New Delhi

Seasonal adjustment of Indian macroeconomic time-series

Rudrani Bhattacharya, Radhika Pandey* ,
Ila Patnaik, Ajay Shah

Abstract

Macroeconomic analysis benefits from seasonal adjustment. Month- on-month changes of economic time series yield faster information about developments in the economy, but the values have exaggerated variance when annual seasonality is present. In this paper, we show the full process for seasonal adjustment for four important Indian time-series. We find that significant reductions of variance are obtained by using black box seasonal adjustment, at the risk of failure for some time series. Thorough knowledge about seasonal adjustment yields more reliable answers, and a roughly 15% improvement in the volatility of month-on-month changes.

*We are grateful to Montek Singh Ahluwalia and Josh Felman who got us started on these questions. We thank Giovanni Veronese for his valuable suggestions and critical comments. We thank CMIE for providing all the databases used in the paper.

1. Introduction

Macro-economic analysis using monthly or quarterly data in India is primarily conducted using year-on-year growth rates. However, each value for the year-on-year growth of a monthly series is the sum of twelve previous month-on-month changes. Comparing June 2015 to June 2014 fails to see numerous developments which took place in the intervening year. In order to understand June 2015, we have to compare it against May 2015. However, this is not directly feasible owing to seasonality. This motivates 'seasonal adjustment' [Abeln and Jacobs, 2015]. We are permitted to compute month- on-month or quarter-on-quarter growth rates once the raw levels data has been seasonally adjusted.

Seasonally adjusted *levels* are also quite informative. How deep were the drops in exports in 2008 compared to pre-crisis levels? When did exports return to pre-crisis level? These questions can be answered by graphing seasonally adjusted data for the *level* of exports.

In most advanced countries, the statistical system publishes seasonally adjusted data series, in addition to the raw data, but this is not the case in India. Many researchers are doing seasonal adjustment on their own. This is often done by using 'black box' software such as Eviews through which a time-series is blindly processed. The main argument of this paper is that there are problems with such black box seasonal adjustment.

In this paper, we show the complete steps of the seasonal adjustment process for analysing four monthly time-series, the Index of Industrial Production, exports, the Consumer Price Index and the Wholesale Price Index. This involves calendar adjustment, detection and correction for outliers, fitting models, conducting diagnostic tests, etc. We find that Diwali has a significant effect on the IIP, while Eid does not.

We examine the importance of the choice of direct versus indirect seasonal adjustment for some composite series. If a time series is a sum of component series, each component series can be seasonally adjusted and summed to get an indirect adjustment for the aggregate series. On the other hand, we can apply the seasonal adjustment procedure directly to the aggregate series to obtain direct seasonal adjustment. We compare the direct and indirect adjustment of IIP (following the use-based classification) and find that direct adjustment removes noise better compared to indirect adjustment.

In the interests of reproducible research, all the data and the software used in this paper are freely available on the web. This would make it easy for other researchers to utilise this work, and build on it.

The main finding of this paper is that the use of black box seasonal adjustment, e.g. by Eviews, is quite useful when it works. It yields a substantial reduction in the standard deviation of the point-on-point series. However, careful analysis of seasonality is a superior approach: it works reliably for all series (unlike Eviews which is not able to process the CPI series) and it yields improved reductions in the variance of the point-on-point series.

The remainder of this paper is organised as follows. Section 2 outlines the rationale for seasonal adjustment. Section 3 documents the approaches to seasonal adjustment and compares the x-12-arima program with the recently launched x-13-arima-seats program. Section 4 applies the x-13-arima- seats program to seasonally adjust the key Indian macroeconomic series. This section discusses the results for the key series, with a prime focus on the importance of seasonally adjusted point-on-point measure (POP SA), as a foundation for effective policy implementation. Section 4 also discuses the usefulness of seasonally adjusted data in understanding the economy. Section 5 discusses some refinements to the seasonal adjustment methodology. Section 7 shows the outcome of the refinements and concludes the paper.

2. The rationale for seasonal adjustment

When seasonality is present, comparisons between consecutive months are obscured by seasonal effects. This has led to the widespread use of year-on- year changes which are immune to seasonality. However, each year-on-year change is the average of twelve recent month-on-month changes and is thus a sluggish measure. The acronym 'YOY' is used for the year-on-year change and 'POP' for the point-on-point change.

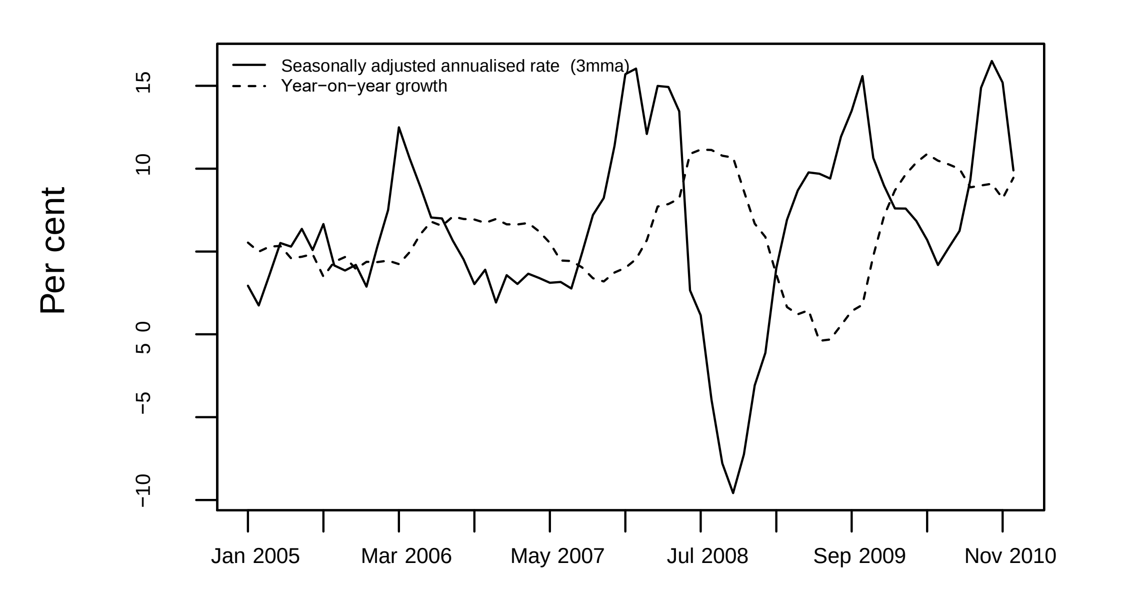
Consider a monthly time series $\{x_t\}$, where t = 0, 1,...∞. Let us define yt = log(xt); then $(1 - L^{12})y_t$ yields the YOY, whereas $(1 - L)y_t$ yields the POP growth rate. The filter $(1 - L^{12})$ can be decomposed as $(1 - L)(1 + L + L^2 + ... + L^{11})$. Comparing the YOY and the POP filter, the presence of the moving average filter, $(1 + L + L^2 + .. + L^{11})$ in the former generates a phase-delay compared to the POP filter [Mak, 2003].

The POP change thus always gives a more timely signal. For instance, the YOY indicator of a monthly series, that captures the 12-month change in a variable, although smooth, lags the POP indicator by 5.5 months [Cristadoro et al., 2005]. Intuitively, the mean lag of the moving average filter of order two.

$(y_t + y_t-1)$ is 0.5. This is because the signal is shifted 0.5 periods backward with respect to y_t. In an analogous manner, the mean lag of the moving average filter of order three is 1 and the one of order eleven is 5.5 periods.

As an example, Figure 1 shows the POP versus the YOY of WPI inflation. The POP inflation shows peaks in August 2006, May 2008, and June 2009. This turns out to be followed by peaks in the YOY numbers in February 2007, July 2008, and October 2009. The POP figures record a sharp fall in November 2006, and October 2008, which preceded the troughs in YOY figures correspondingly in September 2007, and May 2009. Across all these events, the average length of the period by which the YOY lags the POP numbers is 6 months. This lines up nicely, compared with the theoretical prediction of a delay of 5.5 months.

Figure 1: POP (annualised) and YOY growth rate of WPI



Note: This graph shows the seasonally adjusted point on point (POP) growth rate (annualised) and the year on year growth rate of WPI. It shows that the point-on-point indicator gives a timelier signal than the year-on-year indicator. As an example, from November 2007 onwards, inflation pressures were visible in the point-on-point indicator while with the year-on-year indicator the signs of inflationary pressures were visible only since March 2008. The year-on-year indicator lags the point-on-point indicator by five to six months, which is consistent with the theoretical prediction.

In the context of monitoring India's inflationary situation, Bhattacharya et al. [2008] emphasise the importance of POP variation of the seasonally adjusted price level for revealing information about shocks without delay. The authors explore different high inflationary episodes in India to show that monitoring inflation dynamics using seasonally adjusted POP measure would have helped timely monetary policy formulation. In this paper, we conduct seasonal adjustment of the key macroeconomic series in India and analyse the quality of adjustment on the basis of several diagnostic tests. We explore how the important India-specific festivals, such as Diwali, affect the seasonal pattern. We ask whether direct or indirect seasonal adjustment is better for reducing noise and variability in a series.

3. A review of seasonal adjustment procedures

Adjustment for seasonality is a first step towards a meaningful business cycle and macroeconomic research. Seasonal adjustment procedures can be used as 'black boxes'. Very often, these techniques are used with an Eviews interface, where users have little idea of how the seasonal adjustment process works. Alternatively, it is possible to bring greater knowledge to bear on the problem. This involves a number of steps starting from visual inspection to model selection to outlier detection and diagnostic checks. It involves a careful choice of an optimal span of data. Further, it involves checking for festival effects and other special features that may occur in certain months of a year. In this section, we review some of the steps that are used when understanding the seasonality of most series.

When annual seasonality is present with a monthly time series, this disrupts the ability to interpret month-on-month changes. The variance of the month- on-month changes are very large. Seasonal adjustment purges the seasonality and gives a much lower variance of the month-on-month changes, and thus lays bare the month to month changes in the series which are otherwise concealed by the seasonality. While many users of data make do by utilising the year-on-year change, this results in delays in understanding changes in the data.

The first step in exploring the presence of seasonality in a series is by plotting the growth rates in each of the months across the years. The monthly growth rates across years imply, for instance, the growth rate in April over March in each of the years. This gives us some idea of the presence of seasonal peaks, if any, in the series.

As an example, Figure 2 shows the growth rate for Index of industrial production (IIP) for the period from July, 1994 to July, 2015. It shows seasonal peaks in the month of March and December. It also shows that the average POP growth rates are not stable i.e., mean reverting across the years. This clearly suggests that there is annual seasonality in this series.

Seasonal adjustment can be done in a variety of ways. The simplest approach is to include a set of seasonal dummy variables to control for stable seasonality. This approach helps us to assess the presence of seasonal variations in a series. We can estimate:

$$y_t = \beta 0 + \beta 1 Jan_t + \beta 2 Feb_t + \beta 3 Mar_t + \beta 4 Apr_t + \beta 5 May_t + \beta 6 Jun_t + \beta 7 Jul_t + \beta 8 Aug_t + \beta 9 Sep_t + \beta 10 Oct_t + \beta 11 Nov_t + \epsilon_t$$

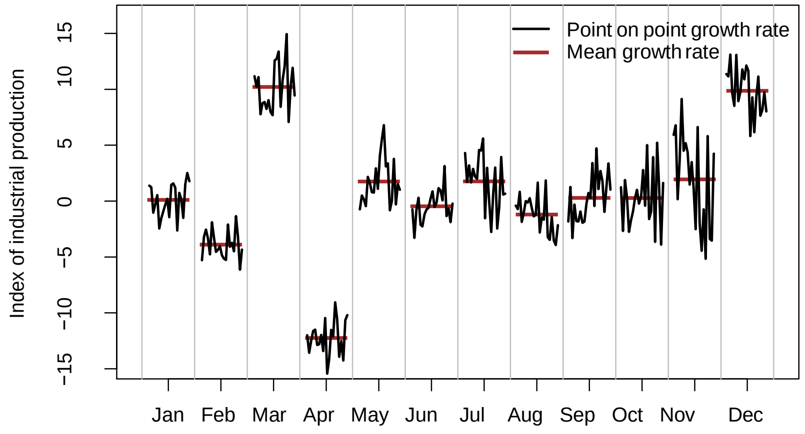
where, Jan_t, Feb_t .... Nov_t are dummy variables. In this formulation, December is the base month. The residual of the regression gives the seasonally adjusted series. Time series can have a trend component as well; in which case, we estimate a regression model with a time trend and seasonal dummy variables. In addition, the changing seasonal patterns over time can be captured by interacting seasonal dummies with trend.

As an example, Table 1 shows that the raw time series of month-on-month changes in the IIP has a standard deviation of 72.05%. The simplest method for seasonal adjustment – a dummy variable regression – brings the standard deviation of the point-on-point growth rate down to 29.06%. In contrast, with the WPI, the gains obtained are much smaller: from 8.76% for the non-seasonally adjusted point-on-point changes to 8.05% for the residuals of the dummy variable regression with a time trend.

While such simple regressions were once the mainstay of seasonal adjustment, a new class of more sophisticated methods have taken over. Seasonal adjustment methods currently in practice can be broadly categorised into filter-based and model-based approaches. The filter-based approach decom- poses a series into a trend, seasonal and irregular components where explicit modeling of each of these components is not required. The model-based approach requires the trend, seasonal and irregular components of the series to be modeled separately.

One element in filter-based approaches is the x-12-arima program of the U.S Census Bureau. It uses regression models with ARIMA errors. The model is used to extend the series with forecasts and backcasts, and to pre-adjust the series for outliers and calendar effects before conducting seasonal adjustment using filters.

Figure 2: Monthly growth rates across the years



Note: This graph shows the growth rate of IIP for each month across different years; for instance, the growth in April over March across years. It also shows the mean growth rate of each month across different years. We can see that the mean growth rate is higher for the months of March and December.

Table 1: Summary statistics of key series

	Std.dev of NSA POP growth rate	Std.dev of YOY growth rate	Std.dev of SA POP growth rate using dummy regression	R2 of regression using seasonal dummies
IIP	72.05	6.15	29.06	0.90
WPI	8.76	3.80	8.05	0.75

Note: This table shows an example of the seasonal variation in two series: the Index of Industrial Production (IIP) and the Wholesale Price Index (WPI). 'Std.dev of NSA POP growth rate' is the standard deviation of the point-on-point growth rate (annualised) of the non- seasonally adjusted series (NSA) and 'Std.dev of YOY growth rate' refers to the standard deviation of the year-on-year growth rate of the respective series. 'Std.dev of SA POP growth rate using dummy regression' shows the standard deviation of the POP growth rate (annualised) of the series, where the series is seasonally adjusted using dummy variable regression.

The table reports the R-square of regression where the series is regressed on its trend and seasonal dummies for each of the series. The table shows that for IIP, there is a significant decline in standard deviation of the residual (adjusted for seasonality) series. In contrast, the WPI series does not show a decline in standard deviation after seasonal dummy regression. This shows that seasonal variations are not prominent in the WPI series.

Among the model based approaches, the most widely used method is tramo-seats developed by Victor Gomez and Augustin Maravall at the Bank of Spain. The programme, seats (Signal Extraction in ARIMA Time Series) estimates and forecasts the trend, seasonal and irregular components of a time series using signal extraction techniques applied to ARIMA models. The programme tramo (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) is used for estimation of regression models with ARIMA errors. The model is used to adjust for missing values and for forecasting in the pre-adjustment stage. The fitted series is then seasonally adjusted by seats.

These two approaches have become more harmonised in recent years, with the x-13-arima-seats program developed and maintained by the US Census Bureau. This program has the capability to generate ARIMA model-based seasonal adjustment using a version of seats as well as nonparametric adjustments from the X-11 procedure [Time Series Research Staff, 2013]. It retains the current filters used in x-12-arima.

The difference between x-12-arima and x-13-arima-seats methods lies in how the filters or moving averages are produced to perform the decomposition of the series into trend, seasonal, and irregular components. The seats filters are derived directly from the ARIMA model and hence are tailored to the specific properties of the series as reflected in the estimated model. In contrast, x-12-arima selects from a set of predetermined filters that have been shown to work well for a wide variety of series [Tiller et al., 2007].

x-12-arima fits what is called the RegARIMA model:

$$y_t = \sum_i \beta_i x_{it} + z_t \quad (1)$$

where, yt is the time series under consideration, xit are explanatory variables observed concurrently with yt, and βi are regression coefficients. The component zt denoting the error term, is assumed to follow a seasonal ARIMA (p, d, q)(P, D, Q)s model, following Box and Jenkins [1970]. The specification of a RegARIMA model requires specification of both the regression variables, (the xit in (1)) and the ARIMA model for the regression errors, zt .

Several regression variables that are frequently used in modeling seasonal economic time series are built into the x-12-arima program, and can be included in the model. The main pre-defined regression variables in x-12-arima include a constant term, fixed seasonal effects, trading day effects, and holiday effects.

Trading day effects occur due to differing day of the week composition of the same calendar month over the years. In some years, the month of January may have more weekends than the other years. This can affect variables such as retail sales. Moving holiday effects arise from holidays whose dates are not fixed over time. The implication of this effect is that economic activity regularly changes during the time of the holiday. The Easter effect is the most common moving holiday effect in U.S. time series.

In addition, x-12-arima provides four other types of regression variables to deal with abrupt changes in the level of a series, depending on the temporary or permanent nature of the change. These are additive outliers (AOs), level shifts (LSs), temporary changes (TCs), and ramps.

ARIMA identification is done automatically by analysing the autocorrelation function

(ACF) and the partial autocorrelation function (PACF) of a time series, yt, and its differences. An iterative generalised least squares (GLS) algorithm is then used, which works in two consecutive steps. In step 1, given values of AR and MA parameters of the error term, coefficients of regressors are estimated by GLS using the covariance structure of the regression errors determined by the ARIMA model. In step 2, given estimates of regression parameters, regression errors are calculated and the ARIMA model is estimated using maximum likelihood estimation (MLE). These two steps are iterated till convergence is achieved. The fitted series, adjusted for effects of regressors, including outliers, is passed through seasonal and trend filters to obtain the seasonally adjusted series, the trend-cyclical and the irregular component.

x-13-arima-seats combines the current filters used in x-12-arima with arima-model-based adjustment as implemented in the program seats. In seats, the seasonal and trend filters are estimated simultaneously based on the ARIMA model. seats uses signal extraction with filters derived from an ARIMA-type time series model that describes the behavior of the series. x-12-arima uses signal-to-noise ratios to choose between a fixed set of moving-average filters, often called X-11-type filters. The new program still provides access to all of x-12-arima's seasonal and trend filters and to the diagnostics. arima-model-based adjustments work very well for series with a large irregular component. However, this is only true when the series are long enough. For series with only four years of data, for example, it is difficult to get an accurate arima model.

x-13-arima-seats and x-12-arima are designed to pre-adjust a series be- fore the seasonal adjustment by removing some deterministic effects such as trading day, moving holidays, and outliers. x-13-arima-seats and x-12-arima also contain similar model diagnostics.

In this paper, we conduct seasonal adjustment of the key macroeconomic series with the x-13-arima-seats system. After seasonal adjustment, we perform a series of diagnostic checks using relevant tests and quality assessment statistics provided by the x-13-arima-seat program to judge the quality of seasonal adjustment. In addition to the diagnostic checks pro- vided by x-13-arima-seats, we analyse spectral plots[1] of the growth rates of seasonally adjusted and unadjusted series. A good seasonal adjustment procedure should eliminate peaks at seasonal frequencies.

4. Examples of four important series in India

We now illustrate seasonal adjustment procedures for four key Indian macroeconomic series.

4.1 Index of industrial production

The x-13-arima-seats program gives the user the option to choose the seasonal adjustment procedure–x11 or seats. We check the volatility of the point-on-point growth of the seasonally adjusted series obtained through x- 11 and seats and find that the volatility is lower with seats adjustment program. We use seats for seasonal adjustment. The next step is to identify outliers and to check for the significance of other regressors like the trading day- effects. Table 2 shows the outliers identified by the seasonal adjustment program in the IIP series.

Table 2: Outliers identified in the IIP series

Date	Type of outlier
October 2011	Additive Outliers
November 2008	Level Shift

[1] The spectral plot is an important tool of frequency domain analysis. It shows the portion of variance of the series, contributed by cycles of different frequencies.

Table 3: Five best models identified by the x-13-arima-seats program

arima models	BIC
1 (0 1 1)(0 1 1)	-4.985
2 (1 1 0)(0 1 1)	-4.971
3 (1 1 1)(0 1 1)	-4.969
4 (0 1 2)(0 1 1)	-4.969
5 (2 1 0)(0 1 1)	-4.968

We add these outliers to the regression part of the specification and perform seasonal adjustment. The x-13-arima-seats chooses the arima model for identification of seasonal and trend components. The five best models identified by the BIC criterion are shown in Table 3

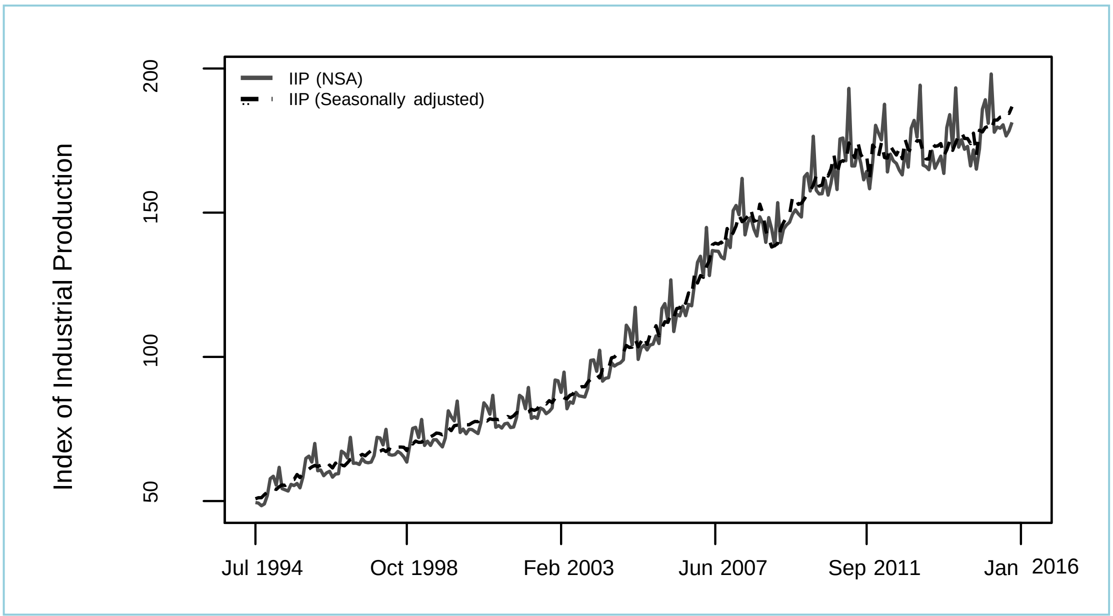
Figure 3 shows the raw and seasonally adjusted IIP. The raw series shows seasonal peaks which are increasing with the level of the series.

A summary of important diagnostic statistics, reflecting the quality of seasonal adjustment is reported in Table 4. The standard deviation of the POP growth rate of the seasonally adjusted series declines significantly. This shows that a considerable amount of variability in the series is on account of seasonal variations (see column 1 of Table 1 and Table 4). Although, the approach of seasonal adjustment using dummy variable regression removes some noise in the series, a much smoother series is obtained through application of the x-13-arima-seats program. A comparison of the standard deviation of the POP growth of the deseasonalised series, derived from dummy variable regression with that from x-13-arima-seats program reveals that the x-13-arima-seats program outperforms dummy variable regression in removing seasonal variation. This can be seen by comparing column 3 of Table 1 and column 1 of Table 4.

Table 4 reports the statistic M 7. It is a measure of the amount of moving seasonality present relative to the amount of stable seasonality. A value less than 1 is desirable to show identifiable seasonality in the series.

The following paragraphs discuss some of the key diagnostic checks provided by the x-13-arima-seats program.

Figure 3: IIP (NSA and SA)



Note: This graph shows the non-seasonally adjusted (NSA) and seasonally adjusted IIP.

Table 4: x-13-arima-seats diagnostic statistics for IIP

	Std.dev of SA POP using x-12-arima	*M* 7	Sliding span (*A*%)
IIP	21.16	0.2	0%

Note: This table shows the diagnostic statistics after the application of the x-13-arima-seats program. Here 'Std.dev of SA POP is the standard deviation of the POP growth rate (annualised) of the seasonally adjusted IIP using x-13-arima-seats program. It shows the values for *M*7 and sliding spans, two important diagnostic statistics reported by the x-13-arima-seats program.

Sliding span diagnostics: The sliding span diagnostics show how the quality of seasonal adjustment procedure is affected when the span of data is altered in a systematic way[2] for the series. Table 4 shows that for the IIP, no month shows unstable adjustment i.e., the percentage difference between the seasonally adjusted values does not exceed the threshold value of 3, for any month belonging to overlapping spans.

Revision history: An important criterion to evaluate the quality of seasonal adjustment is the revision history diagnostic. It shows how close the initial estimate of the seasonally adjusted value of a particular data point is, to the most recent estimate of the same data point, as more data becomes available. Users of seasonally adjusted data are often most interested in current information; thus, it is desirable that the initial seasonally adjusted estimates be as close as possible to the improved estimates made, after more data becomes available.

Table 5 shows the concurrent and most recent estimates of the seasonally adjusted value. As an example, say for August 2014, the first column shows the seasonally adjusted value for IIP when the series for IIP is available till August 2014. The second column shows the seasonally adjusted value for IIP when the data is available till the latest available period. Table 6 shows the average absolute percentage revision across the years. The table shows that the extent of revision declines as the data approaches the current period.

QS statistic: QS is a statistic that provides a test of the hypothesis of no seasonality. It is applied to appropriate series associated with the modeling and the seasonal adjustment of a given series. These include the original series (log transformed, regression and/or extreme-value adjusted as appropriate) and various output series, most importantly the seasonally adjusted series (log transformed, etc. as appropriate). The statistic QS is assumed to be adequately approximated by a chi-squared.

[2] The sliding span diagnostic statistics are calculated as follows: let A_t denote the seasonally adjusted value for a month t in a particular year obtained from the complete series. Let month t belongs to at least two overlapping spans, j. Also let A_j^t denote the seasonally adjusted value obtained when the seasonal adjustment procedure is applied to data in the j-th span only. The seasonal adjustment is called unstable if the percentage difference between the maximum and minimum value of A_j^t, obtained from different overlapping spans, exceeds 3. x-13-arima-seats reports the percentage of such months in the series, for which the adjustment is unstable. This percentage is denoted by A%. According to the U.S. Census Bureau, the adjustment procedure should not be relied upon if A% is more than 25.

Table 5: Concurrent and most recent revision in seasonally adjusted figures

	Concurrent SA	Final SA
2014 Jul	175.79	175.68
2014 Aug	173.96	174.01
2014 Sep	177.06	177.08
2014 Oct	168.31	168.69
2014 Nov	178.85	179.46
2014 Dec	178.22	178.50
2015 Jan	179.26	179.34
2015 Feb	179.86	179.90
2015 Mar	178.37	178.70
2015 Apr	181.64	181.91
2015 May	181.75	182.05
2015 Jun	183.69	183.80
2015 Jul	182.63	182.88

Note: This table shows the concurrent and final seasonally adjusted figures for IIP. This measure shows how close the initial estimate of seasonally adjusted figure is to the final estimate.

Table 6: Average absolute percentage revisions across the years

Years	Concurrent-Final
2002	0.71
2003	0.63
2004	0.73
2005	0.67
2006	0.59
2007	0.56
2008	0.74
2009	0.84
2010	0.65
2011	0.40
2012	0.35
2013	0.35
2014	0.21
2015	0.07
Total	0.54

Note: This table shows the average absolute percentage revisions across the years in the con- current and final seasonally adjusted numbers for IIP. The table shows that the extent of revision declines as the concurrent observation year approaches the final observation year.

Table 7: Q-S test statistic for IIP–NSA and SA

Original Series	353.15	(P-Value = 0.0000)
Original Series (EV adj)	378.93	(P-Value = 0.0000)
Residuals	0.00	(P-Value = 1.0000)
Seasonally Adjusted Series	0.00	(P-Value = 1.0000)
Seasonally Adjusted Series (EV	0.00	(P-Value = 1.0000)
Irregular Series	0.00	(P-Value = 1.0000)
Irregular Series (EV adj)	0.00	(P-Value = 1.0000)

Table 8: Ljung-Box test

Test statistic: 38.8812
Degrees of freedom = 24
p-value = 0.0281

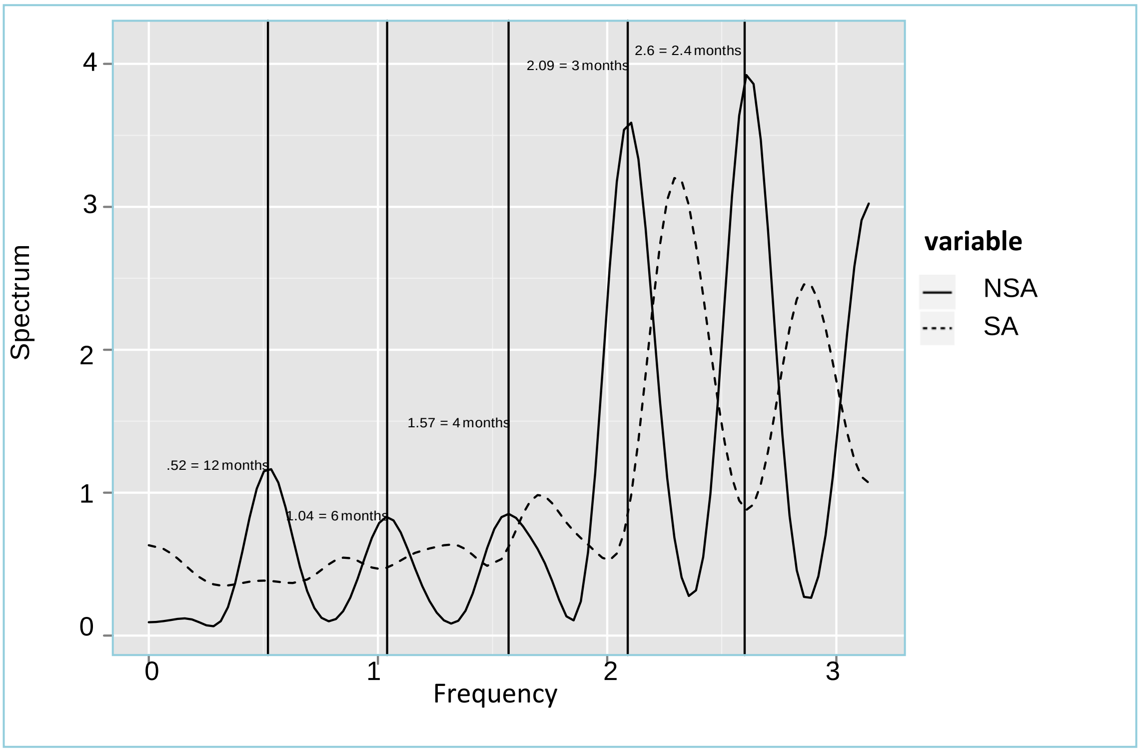
distribution with two degrees of freedom. Only when QS is larger than a preset critical value for this distribution, usually that for a .01 significance level, does the QS output indicate that seasonality is present.

Box - Ljung: It is a test for the fitted model. The residuals of the fitted model must be white noise. The null hypothesis is that there is no autocorrelation in residuals. The significant codes are shown if the null hypothesis is rejected.

Spectral plots: An important diagnostic check using the frequency domain analysis is examining spectral plots of the growth rates of differenced non-seasonally adjusted and seasonally adjusted series. A spectral plot shows the portion of variance contributed by cycles of different frequencies.

Figure 4 shows the spectral plot of the POP growth rate (annualised) of the unadjusted and seasonally adjusted series. The x-axis represents frequency from 0 to π. The seasonal frequencies are π/6 (0.52 on the x-axis), π/3 (1.04 on the x-axis), π/2 (1.57 on the x-axis), 2π/3 (2.09 on the x-axis) and 5π/6 (2.6 on the x-axis). Expressed as periods (months); they are 12 months, 6 months, 4 months, 3 months, and 2.4 months. The plot of the unadjusted series shows peaks at seasonal frequencies. These are eliminated after seasonal adjustment. For example, the first peak at 0.52 corresponds to 12 months. This is eliminated after seasonal adjustment

Figure 4: Spectrum of SA and NSA IIP

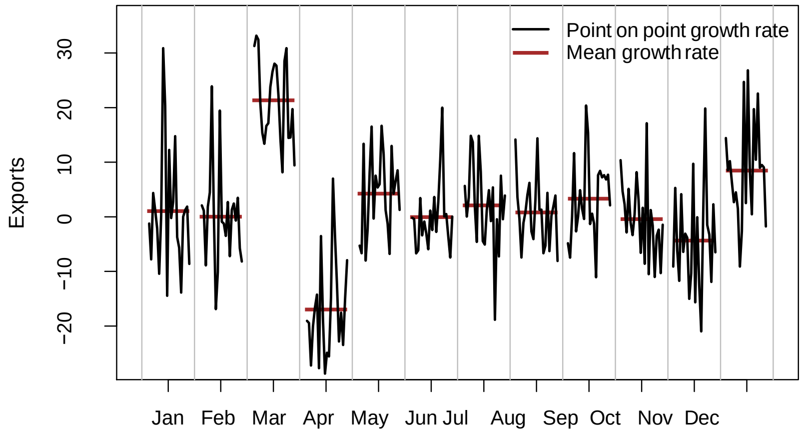


Note: This figure shows the spectral plot of the POP growth (annualised) of IIP before and after seasonal adjustment. Here 'NSA' and 'SA' refer to spectral plots of the POP growth rate of the non-seasonally adjusted (NSA) and seasonally adjusted series. The annotations show seasonal frequencies. The seasonal frequencies are $\pi/6$ (0.52 on the x-axis), $\pi/3$ (1.04 on the x-axis), $\pi/2$ (1.57 on the x-axis), $2\pi/3$ (2.09 on the x-axis) and $5\pi/6$ (2.6 on the x-axis). The non-seasonally adjusted series shows peaks at seasonal frequencies which are suppressed after seasonal adjustment. As an example, the NSA series shows a peak at 0.52 corresponding to 12 months. This peak is suppressed after seasonal adjustment.

4.2 Exports

Exports is another key macro series that shows seasonal fluctuations. Figure 5 shows the monthly growth rates across the years for exports. The mean growth rates vary across the months. This shows the presence of seasonal peaks in the series. We perform the same steps i.e. choice between x11 and seats seasonal adjustment program, detection of trading-day effect and outliers and accounting for these regressors in the specification. We find a significant trading day effect.

Figure 5: Monthly growth rates across the years



Note: This graph shows the growth rate of exports for each month across different years; for instance, the growth in April over March across years. It also shows the mean growth rate of each month across different years.

Table 9: Outliers in the exports series

Date	Type of outlier
September 2008	Level shift
November 2010	Level shift

Table 9 shows the outliers identified by the x-13-arima-seats program.

Table 10: Five best models identified by the x-13-arima-seats program

arima	BIC criterion
(0 1 1)(0 1 1)	-2.362
2 (2 1 0)(0 1 1)	-2.359
3 (0 1 2)(0 1 1)	-2.355
4 (1 1 0)(0 1 1)	-2.351
5 (1 1 1)(0 1 1)	-2.350

Table 11: Average absolute percentage revisions across the years

Years	Concurrent- Final
2002	2.29
2003	2.41
2004	1.56
2005	1.84
2006	1.39
2007	1.22
2008	2.02
2009	1.93
2010	0.71
2011	0.78
2012	0.62
2013	0.58
2014	0.61
2015	0.31

Note: This table shows the average absolute revision across the years in the concurrent and final seasonally adjusted numbers for exports. The table shows that the extent of revision declines as the concurrent year approaches the final year. As an example the average absolute revision from concurrent to final observation is 2.29 in 2002. This falls to 0.61 in 2014.

Table 10 shows the five best models identified by the x-13-arima-seats program on the basis of the BIC criterion.

There is a considerable reduction in the standard deviation of the point- on-point growth (annualised) of the series after seasonal adjustment. The standard deviation of the raw series was 137.8, after seasonal adjustment it reduces to 83.77

A key statistic of interest reported by the x-13-arima-seats program is the extent to which the seasonally adjusted figures are revised across months and across years. As we approach the end of the series, the average absolute percentage revision in the seasonally adjusted figures fall (See Table 11). This is intuitive as the concurrent and the final values of the series approach convergence.

4.3 When did exports return to pre-crisis levels?

The seasonally adjusted numbers help us in addressing critical questions about the state of the economy. We know that exports were adversely affected during the global financial crisis. When did exports return to the pre-crisis levels? A glance at the seasonally adjusted figures help us in understanding the trends.

Table 12: Exports: NSA, SA (levels) and year-on-year growth

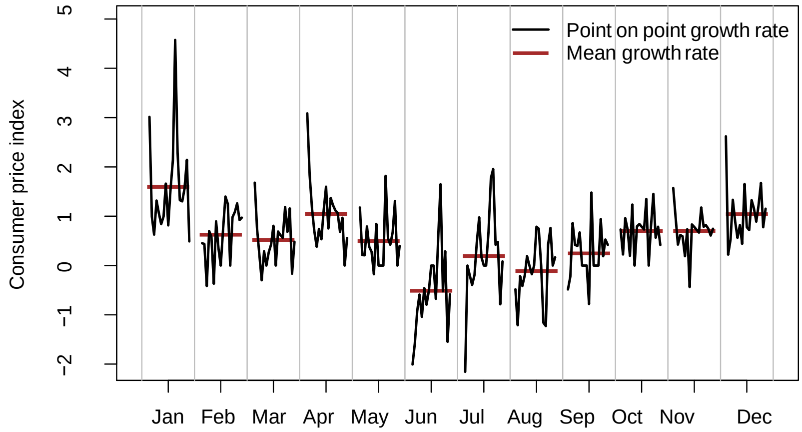
	Exports (NSA)	Exports (SA)	Year-on-year change in exports
2008 Jan	14718.70	14580.50	34.93
2008 Feb	15117.20	15025.10	43.61
2008 Mar	17252.30	15221.57	34.14
2008 Apr	18461.50	18942.05	68.56
2008 May	18684.40	18758.71	53.02
2008 Jun	19181.00	19409.48	61.57
2008 Jul	19029.50	18895.94	52.82
2008 Aug	17758.20	18540.56	40.78
2008 Sep	15790.30	15212.55	26.78
2008 Oct	14129.50	13900.67	-3.15
2008 Nov	11163.10	12442.29	-12.56
2008 Dec	13366.70	13137.62	4.23
2009 Jan	12870.00	13036.52	-12.56
2009 Feb	11941.20	12391.85	-21.01
2009 Mar	12916.00	11196.95	-25.13
2009 Apr	12475.30	12812.35	-32.43
2009 May	12317.20	12642.05	-34.08
2009 Jun	13606.70	13449.06	-29.06
2009 Jul	14340.80	14255.67	-24.64
2009 Aug	13584.90	14199.94	-23.50
2009 Sep	14623.90	14079.11	-7.39
2009 Oct	14806.40	14903.41	4.79
2009 Nov	14931.80	16262.65	33.76
2009 Dec	16493.00	16154.42	23.39
2010 Jan	15557.00	16101.59	20.88
2010 Feb	15757.00	16355.53	31.95
2010 Mar	20252.60	17193.59	56.80
2010 Apr	17738.90	18234.22	42.19
2010 May	16534.80	16965.21	34.24
2010 Jun	19840.00	19581.61	45.81
2010 Jul	16099.40	16366.29	12.26
2010 Aug	16806.60	17216.12	23.72
2010 Sep	18223.90	17535.95	24.62
2010 Oct	17929.90	18473.67	21.10
2010 Nov	21488.70	22879.83	43.91
2010 Dec	26343.50	25744.52	59.73

Using the SA level data in Table 12 we see:

1. The bottom of the post-Lehman crash was March 2009; and
2. Only by late 2010 were we clearly above the pre-crisis values.

Neither of these two statements can be made using the YOY data or using the NSA levels data.

Figure 6: Monthly growth rates across the years



Note: This graph shows the growth rate of CPI for each month across different years; for instance, the growth in April over March across years. It also shows the mean growth rate of each month across different years. The graph shows that the mean growth rates do not vary across the years. This indicates that seasonal fluctuations do not matter much for CPI.

Table 13: Outliers identified in the CPI series

Date	Type of outlier
January 2006	Level shift
July 2006	Additive outlier
June 2007	Level shift

4.4 CPI

In contrast to IIP and exports, the CPI series does not show significant seasonal spikes. Figure 6 shows monthly growth rates across the years for CPI. We do not see major variation across the years. We now turn to a formal investigation of seasonality in the series. We perform the same steps i.e. pre-adjustment of the series through detection of outliers and trading day effects, accounting for these regressors in the specification and determination of the optimal arima model.

Table 13 shows the outliers identified by the x-13-arima-seats. We account for these outliers in the regression part of the specification and perform seasonal adjustment. The x-13-arima-seats chooses the arima model for identification of seasonal and trend components. The five best models identified by the BIC criterion are shown in Table 14.

There is a moderate reduction in the standard deviation of the point- on-point growth (annualised) of the series after seasonal adjustment. The standard deviation of the raw series was 9.92, after seasonal adjustment it reduces to 7.16.

Table 14: Five best models identified by the x-13-arima-seats program

arima	BIC
(0 1 1)(0 1 1)	-7.386
(1 1 0)(0 1 1)	-7.385
(2 1 0)(0 1 1)	-7.362
(1 1 1)(0 1 1)	-7.362
(0 1 2)(0 1 1)	-7.362

4.5 When did CPI inflation collapse in the recent period?

Figure 7 shows the recent trends in CPI inflation. The point-point seasonally adjusted rate (annualised, 3 months moving average) shows a moderation in inflation since November 2013. However RBI actions continued to remain hawkish. RBI raised the repo rate in October 2013 and Jan 2014. The cycle of reduction in rates started only since the beginning of 2015.

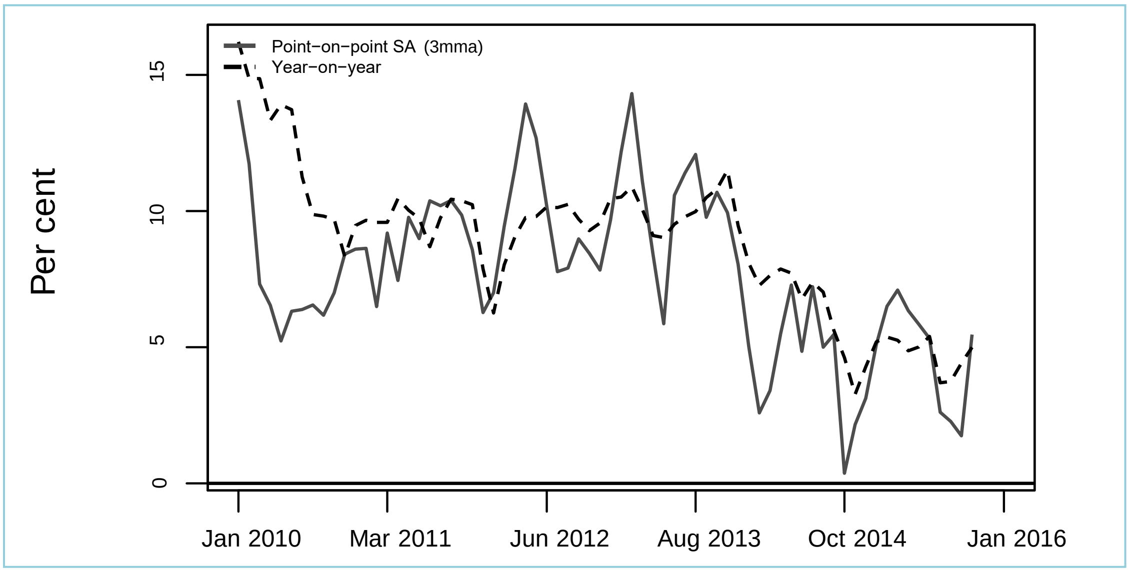
These examples underscore the importance of seasonally adjusted levels and growth rates in gaining useful insights about the state of economy.

4.6 WPI

Similar to the CPI series, the WPI also does not show significant seasonal variations. We perform the same steps i.e. choice between x11 and seats seasonal adjustment program, identification of outliers and trading-day effects and accounting for the outliers in the pre-adjustment stage of seasonal adjustment. The x-13-arima-seats identified June 2008 as a level shift outlier in the series.

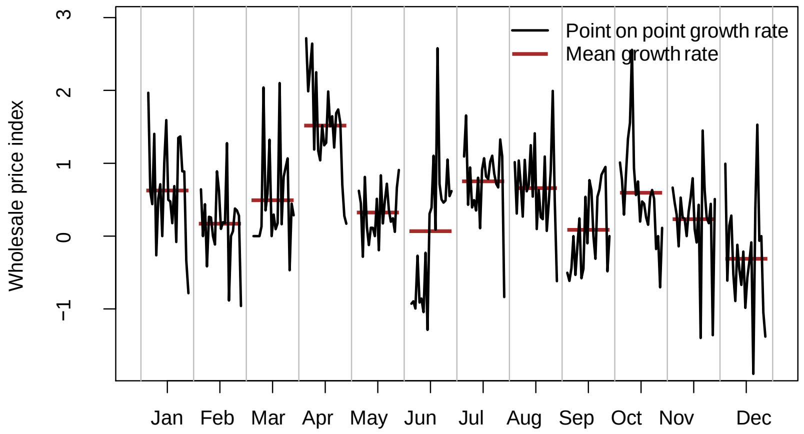
The application of the x-13-arima-seats using both seats and x11 seasonal adjustment procedure gives the warning that the "series should not be a candidate for seasonal adjustment." We further examine this warning by looking at the monthly growth rates across the years and by analysing the spectral plots of the non-seasonally and seasonally adjusted series.

Figure 7: Recent trends in CPI inflation



Note: The above figure shows the seasonally adjusted point-on-point growth (3 months moving aver- age) and year-on-year growth in CPI. The graph shows that the point-on-point indicator gives early signals of the surge, and then the moderation, in inflation. As an example, while the point-on-point indicator signalled a moderation in inflation since November 2013, RBI's stance continued to remain hawkish for an extended period.

Figure 8: Monthly growth rates across the years



Note: This graph shows the growth rate of WPI for each month across different years; for in- stance, the growth in April over March across years. It also shows the mean growth rate of each month across different years. The graph shows that the mean growth rates do not vary across the years. This indicates that seasonal fluctuations do not matter for WPI.

Figure 8 shows monthly growth rates across the years for WPI. We do not see major variation in the monthly growth rates across the years. As an example, the growth rates across the years for January do not differ much from the growth rates in February. Similarly, Figure 9 does not show distinct peaks at annual seasonal frequency (at 0.52). Also, if we compare the point-on-point growth of the raw and seasonally adjusted series, we do not see a major difference in their standard deviation. This analysis shows the importance of thorough analysis of the series before making the key decision of whether to adjust the series for seasonality or not.

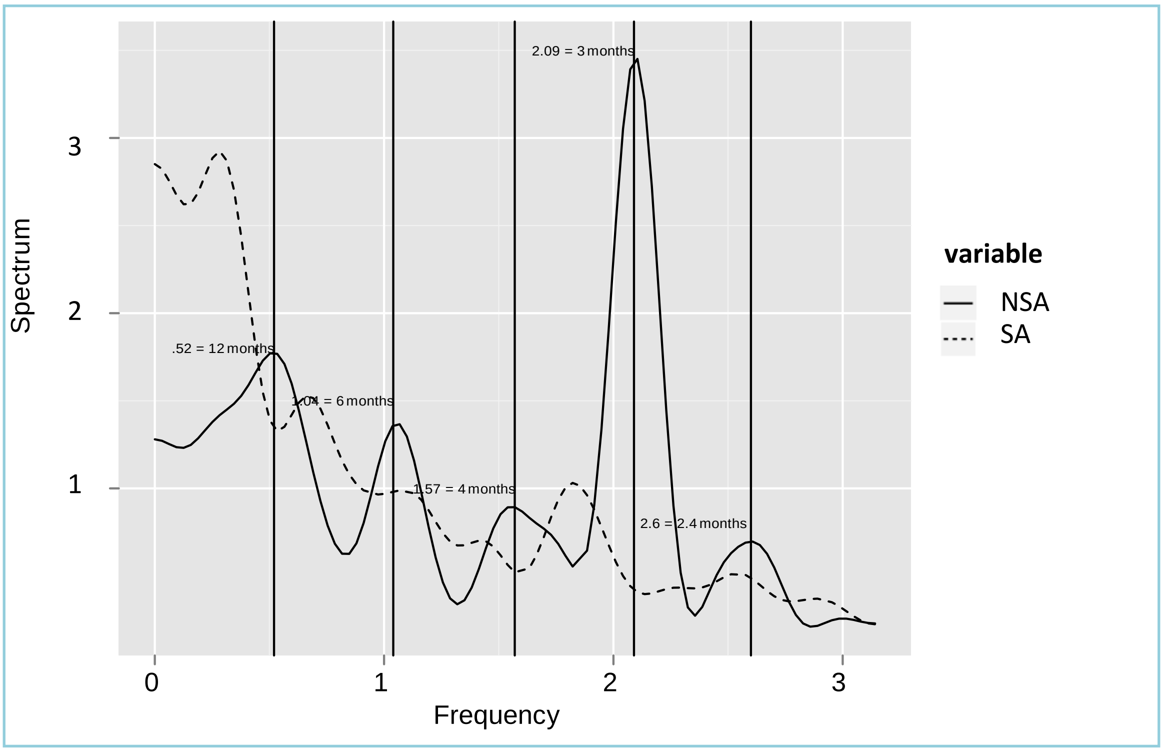
5. Refinements of the seasonal adjustment procedures

In this section we examine three refinements to the routine procedures of seasonal adjustment. First, we test for the impact of India-specific moving holiday such as Diwali. We show the importance of adjusting for moving holidays as they have a bearing on our assessment of the series. Second, using IIP as an example we examine whether direct or indirect seasonal adjustment is better at reducing variability in the series. Third, we examine how the span of data can influence the quality of seasonal adjustment.

5.1 Accounting for India-specific moving holidays

x-13-arima-seats is capable of handling the moving holiday effects through the inclusion of regressors for Easter Sunday, Labor Day, and Thanksgiving Day. For our analysis, we have focused on Diwali and Eid. We model the effect of these holidays following the concepts used to model moving holidays such as Easter and Labour Day effects in the x-13-arima-seats program [Time Series Research Staff, 2013].

Figure 9: Spectrum of SA and NSA WPI



Note: This figure shows the spectral plot of the POP growth (annualised) of WPI before and after seasonal adjustment. Here 'NSA' and 'SA' refer to spectral plots of the POP growth rate of the raw and seasonally adjusted series. The vertical lines correspond to seasonal frequencies. The seasonal frequencies are $\pi/6$ (0.52 on the x-axis), $\pi/3$ (1.04 on the x-axis), $\pi/2$ (1.57 on the x-axis), $2\pi/3$ (2.09 on the x-axis) and $5\pi/6$ (2.6 on the x-axis). Expressed as periods (months); they are 12 months, 6 months, 4 months, 3 months, and 2.4 months. The figure does not show visible spikes at all seasonal frequencies. As an example, the figure does not show spike at 0.52 corresponding to the 12 month seasonality.

As an example, to account for the Diwali effect, the basic assumption is that the level of activity changes on the w-th day before Diwali and remains at the new level until the day before Diwali. Here w is taken to be 5 days including the Diwali day. Diwali falls either in the month of October or November. Its effect on economic activity may be visible in the month of September, October and November depending on its date. We take the Diwali dates from 1999 to 2015 to estimate the effect of the festival.

In the x-13-arima-seats system, we use the genhol program to account for the moving holiday effect. The program generates regressor matrices from holiday date file to enable x-13-arima-seats estimate moving holiday effects. The genhol program has the capability to generate regressors for before the holiday interval, surrounding the holiday interval and past the holiday interval.

Table 15: Regression model for IIP

Variable	Parameter estimate	Standard error	z-value	P-value
Diwali	-0.016181	0.005093	-3.85	0.00149**

Table 16: Moving holiday effect in IIP: Key diagnostic summary

Variable	Std.dev of SA POP
IIP	22.74
IIP with diwali regressor	21.23

Note: Here "Std.dev of SA POP" refers to the standard deviation of the point on point growth rate of the seasonally adjusted series. The variability reduces after the incorporation of Diwali regressor. The Diwali regressor is found to be significant for IIP. Table 15 shows significant trading day effect on IIP on account of Diwali.[3]

Table 16 reports the standard deviation of the point-on-point growth of the seasonally adjusted series before and after the incorporation of Diwali regressors. There is a reduction in the volatility after the incorporation of the Diwali effect. Table 17 shows the month-on-month growth in IIP in Diwali months with and without adjusting for Diwali effect. As an example, October 2009 was a month of festivities with fewer working days but enhanced purchases prior to Diwali. The month-on-month annualised growth was a dismal -28% in October 2009, but when we adjust the series for Diwali effect, the month- on-month growth numbers improve to -13%. Similarly in November 2015, adjusting for Diwali yields an improvement in month-on-month growth from -71.01% to -39.44%.[4]

Table 17: Month-on-month annualised growth rates for seasonally adjusted IIP with and without adjusting for Diwali

	Growth without Diwali adjustment	Growth with Diwali adjustment
2009 Oct	-28.6	**-12.98**
2010 Nov	-20.66	**-16.47**
2011 Oct	-64.06	**-52.3**
2012 Nov	-3.85	**9.19**
2013 Nov	-7.72	**-22.35**
2014 Oct	-58.24	**-47.87**
2015 Nov	**-71.01**	**-39.44**

5.2 Direct and indirect seasonal adjustment of aggregate series

A critical issue in the field of seasonal adjustment is the choice of direct versus indirect seasonal adjustment of a composite series. If a time series is a sum (or the composite) of component series, we can seasonally adjust each of the component series and sum them to get an indirect adjustment for the aggregate series. This kind of adjustment is called an indirect adjustment of the aggregate series. On the other hand, application of seasonal adjustment procedure directly to the aggregate series is called direct seasonal adjustment [Hood and Findley, 2003].

[3] We also find significant trading day impact of Diwali on IIP (Manufacturing) and IIP (Consumer goods).
[4] http://ajayshahblog.blogspot.in/2016/01/how-bad-is-iip-growth-after-controlling.html

The choice between direct and indirect adjustment depends on how similar or distinct are the seasonal patterns of the component series. In general, when component series have distinct seasonal patterns, indirect adjustment is more appropriate than direct adjustment. On the other hand, when component series are noisy, but have similar seasonal patterns, aggregation of the series may cancel out noise and direct seasonal adjustment may be of better quality.

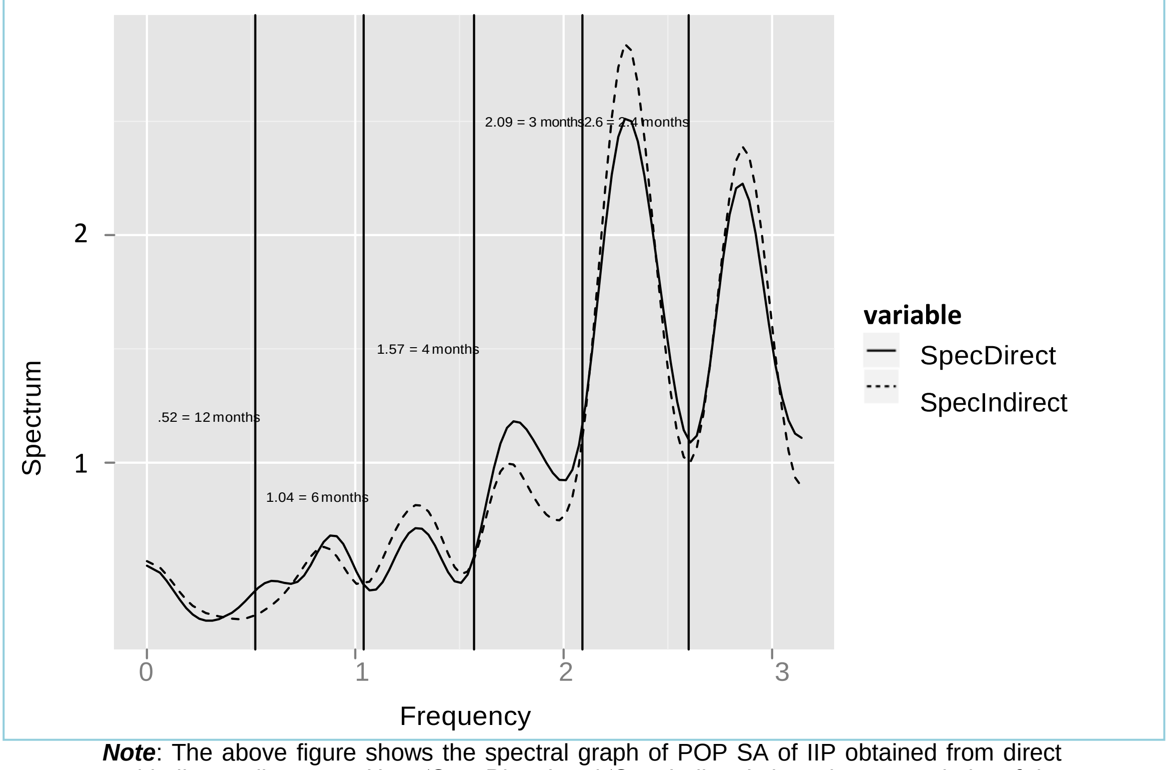
We look at the diagnostics to check the quality of direct and indirect seasonal adjustment procedure. The most fundamental requirement is that there should not be any estimable seasonal effect in the seasonally adjusted series.

We analyse the data for IIP which is a composite of basic, capital, inter- mediate and consumer goods to check for the quality of direct and indirect seasonal adjustment. Each of the component series has distinct seasonal pat- terns hence we seasonally adjust each individual component and check for the quality of seasonal adjustment with direct and indirect method. We find that the standard deviation of the point-on-point growth of the seasonally adjusted series obtained through direct adjustment is lower than that obtained through indirect adjustment (See Table 18). This finding is further validated if we observe the spectral plots of the point-on-point growth of the seasonally adjusted series obtained through direct and indirect methods.

Table 18: Standard deviation of the point-on-point growth rate of the IIP series obtained through direct and indirect adjustment

Direct adjustment	21.19
Indirect adjustment	22.76

Figure 10: Spectral plot of direct and indirect seasonal adjustment through use based classification of IIP



Note: The above figure shows the spectral graph of POP SA of IIP obtained from direct and indirect adjustment. Here 'SpecDirect' and 'SpecIndirect' show the spectral plot of the POP growth rate of the series obtained through direct and indirect seasonal adjustment respectively. The figure shows that the spectral plot of the series obtained through direct adjustment exhibits lesser variability than the spectral plot of the series obtained through indirect adjustment.

Figure 10 shows the spectral plot of the POP growth of IIP obtained from direct and indirect seasonal adjustment. The variability of the series is lower in case of direct seasonal adjustment.

Table 19: Outliers identified in the series starting from January 1994

Date	Type of outlier
November 2008	Level shift
October 2011	Additive outlier
October 2014	Additive outlier

Table 20: Regression estimates with series starting from January 1994

	Estimate	Std. Error	z value	Pr(>|z|)
LS2008.11	-0.07	0.02	-4.57	0.00
AO2011.10	-0.07	0.01	-4.48	0.00
AO2014.10	-0.06	0.02	-3.79	0.00
MA-Nonseasonal-01	0.46	0.06	8.12	0.00
MA-Seasonal-12	0.65	0.05	13.46	0.00

5.3 Optimal span of data

An important issue in seasonal adjustment is the optimal span of data to be considered for adjustment. In the context of seasonal adjustment of macroeconomic series, there is a trade-off between the need for a longer time series in order to get a better estimate of the ARIMA model, and the necessity to avoid modeling a time series containing a structural break [Bruno and Otranto, 2000]. A very long series will have data which will not relate to the pattern of the current series. On the other extreme, a short series may be highly unstable and be subject to frequent revisions.

The length of the series may be shortened owing to changes in methodologies, definitions, moving to new statistical classifications, the use of new sources of information [Mazzi and Giovanni., 2005]. An important principle in this regard is that seasonal adjustment should not be performed if the size of data is less than 3 years [Eurostat, 2009]. Seasonal factors of series with 3-7 years duration are quite unstable. The specification of the parameters used for pretreatment and seasonal adjustment has to be checked more often (e.g. twice a year) in order to deal with the higher degree of instability of such series [Eurostat, 2009].

To demonstrate the issues with the seasonal adjustment of a shorter time- series, we compare the model parameters and statistics obtained from the seasonal adjustment of different time-spans of IIP series. We consider three spans of IIP series: starting from January 1994 (long series), starting from January 2005 (medium series) and starting from January 2011 (short series). We find that the model parameters and statistics are similar in the case of long and medium time series. Both identify identical arima model and similar outliers in the two series (See Tables 19 and 21). The seasonal adjustment of IIP with short time series is not reliable as it is not able to identify outliers in the series. Further, the x-13-arima-seats program does not report revision history diagnostics with the short time series. Tables 20, 22 and 23 show the model parameters with different spans of IIP series. While Tables 20 and 22 report the estimates associated with outliers in the series, Table 23 does not report the outlier estimates.

Table 21: Outliers identified in the series starting from January 2005

Date	Type of outlier
November 2006	Level shift
December 2008	Level shift
October 2011	Additive outlier
October 2014	Additive outlier

Table 22: Regression estimates with series starting from January 2005

	Estimate	Std. Error	z value	Pr(>|z|)
Constant	-0.00	0.00	-2.44	0.01
LS2006.11	0.06	0.02	3.96	0.00
LS2008.12	-0.06	0.02	-3.99	0.00
AO2011.10	-0.06	0.01	-4.00	0.00
AO2014.10	-0.06	0.01	-4.45	0.00
Weekday	0.00	0.00	3.18	0.00
MA-Nonseasonal-01	0.42	0.07	5.67	0.00
MA-Seasonal-12	1.00	0.07	14.81	0.00

6. Reproducible research

The data and source code that implement the methods of this paper are freely available on the web to enable reproducible research. This would make it easy for other researchers to utilise this work, and build on it.

7. Conclusion

The year-on-year change is the average of the latest 12 values of the month- on-month changes. It is thus, inevitably, a poor measure of current developments in the economy. However, the month-on-month change is often contaminated by seasonality. It has a very high volatility which reflects the combination of the true change and seasonal effects.

The promise of seasonal adjustment procedures lies in being able to purge the seasonal effects, and uncover a month-on-month series with much lower variance. Table 24 shows the outcome of these refinements for IIP, exports and CPI. Seasonal adjustment can be done using a black box such as Eviews. Alternatively, a full knowledge about seasonal adjustment can be applied to obtain improved results.

For the IIP, the raw series (non-seasonally adjusted) has a standard deviation of the point-on-point change of 73.26%. If Eviews is used as a black box, a sharp gain is obtained, and the volatility drops to 25.73. Our procedures add value, getting the standard deviation down to 23.12.

For the exports series, the raw data has a standard deviation of the point- on-point change of 132.53%. This drops to 89.4% using Eviews as a black box, and improves further to 78.01% using our best methods.

In the case of the CPI, the raw series has a standard deviation of point-on- point changes of 9.22%. Eviews as a black box is unable to process this series. Our best procedures get the standard deviation down to 7.28%.

Table 23: Regression estimates with series starting from January 2011

	Estimate	Std. Error	z value	Pr(>|z|)
Constant	0.00	0.00	3.22	0.00
MA-Nonseasonal-01	0.99	0.06	17.11	0.00
MA-Seasonal-12	1.00	0.17	5.99	0.00

Table 24: Reduction in standard deviation obtained with our methods

(a) IIP

Method	Std.dev of PoP growth rate over 2005-2015
Raw series	73.26
SA with eviews (1994-2015)	26.79
SA with our approach (taking an optimal span, adjusting for outliers and trading day effect)	25.73
SA after adjusting for diwali effect	23.23
SA after adjusting for diwali effect and adjusting for outliers and trading day effect	23.12

(b) Exports

Method	Std.dev of PoP growth rate over 2005-2015
Raw series	132.53
SA with eviews (1994-2015)	89.40
SA with our approach (taking an optimal span, adjusting for outliers and trading day effect)	78.01

(c) CPI

Method	Std.dev of PoP growth rate over 2005-2015
Raw series	9.22
SA with eviews (1994-2015)	Failure
SA with our approach (taking an optimal span, adjusting for outliers and trading day effect)	7.28

References

Barend Abeln and Jan P.A.M. Jacobs. 2015. "Seasonal adjustment with and without re- visions: A comparison of X-13ARIMA-SEATS and CAMPLET." CAMA Working Papers 2015-25, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University, July. http://ideas.repec.org/p/een/camaaa/2015-25.html.

C. Hood. 2002 "Comparison of time series characteristics for seasonal adjustments from SEATS and X-12-ARIMA". Technical report, U.S. Census Bureau.

C. Hood and D. Findley. 2003. Comparing Direct and Indirect Seasonal Adjustment of Aggregate Series. in (eds.) M. Manna and R. Peronaci, *Seasonal Adjustment. European Central Bank*.

D. Mak. 2003. The Science of Financial Market Trading. World Scientific.

European Commission Eurostat. 2009. "ESS Guidelines on Seasonal Adjustment". Technical report, Eurostat: Methodologies and Working Papers.

F. Canova and B. E. Hansen. 1995. "Are Seasonal Patterns Constant over Time? A Test for Seasonal Stability". *Journal of Business and Economics Statistics*, 13 (3):237–252.

G.E.P Box and G.M. Jenkins. 1970. "Time Series Analysis: Forecasting and Control." Wiley.

G. Bruno and E. Otranto. 2000. "The choice of time interval in seasonal adjustment: A heuristic approach." In XL scientific meeting of the Italian statistical society, 26-28 April, Florence.

Gian Luigi. Mazzi and Savio Giovanni. "The Seasonal Adjustment of Short Time Series." Technical report, Office for Official Publications of the European Com- munities, 2005.

Ila Patnaik and R. Sharma. "Business Cycles in the Indian Economy.Technical report," National Council of Applied Economic Research, 2001.

----------2002. "Business cycles in the Indian economy." *Margin,* 35(1):71–79, October–December.

J.J. Beaulieu and J. A. Miron. 1992. Seasonal Unit Root in Aggregate U.S. Data. Technical report, NBER, Technical Paper No. 126.

O.P. Mall. 1999. "Composite index of leading indicators for business cycles in India." Reserve Bank of India, Occasional Papers.

P. Dua and A. Banerjee. 2001. "An indicator approach to business and growth rate cycles: The case of India." *Indian Economic Review.*

R. Bhattacharya, I. Patnaik, and A. Shah. 2008. "Early Warnings of Inflation in India." *Economic and Political Weekly*, XLIII(49):62–67, December.

R. Cristadoro, M. Forni, L. Reichlin, and G. Veronese. 2005. "A Core Inflation Indicator for the Euro Area." *Journal of Money Credit and Banking*, 27(3).

R. Kaiser and A. Maravall. 2000. Notes on Time Series Analysis, ARIMA Models and Signal Extraction. Technical report, Bank of Spain, Documentation No.0012,

Reserve Bank of India. 2006.Leading Indicators for the Indian Economy. Technical report, Reserve Bank of India.

R. Tiller, D. Chow, and S. Scott. 2007. "Empirical Evaluation of X-11 and Model based Seasonal

Adjustment Methods. Technical report, Bureau of Labour Statistics.

Sandip Mazumder and Soumya Chakraborty. 2013. "Study on seasonal adjustment of IIP using x-12-arima". *The Journal of Industrial Statistics*, 2(1):37–67.

S. Hylleberg, R. Engle, C.W.J. Granger, and B.S. Yoo. 1990. "Seasonal Integration and Co-integration". *Journal of Econometrics*, 44:215–238.

S. Jayaram, I. Patnaik, and A. Shah. "Examining the decoupling hypothesis for India. *Economic and Political Weekly"*, XLIV(44):109–116, October 2009.

Shah. Ajay. 2008. "New issues in macroeconomic policy", in (ed.) T. N. Ninan, *Business Standard India*, chapter 2: 26–54. Business Standard Books, http://www.mayin.org/ajayshah/PDFDOCS/Shah2008_whatchanged.pdf.

Statistical Research Division. U.S. Census Bureau Time Series Research Staff. 2011. X- 12-ARIMA Reference Manual. Technical report, U.S. Census Bureau.

Statistical Research Division U.S. Census Bureau Time Series Research Staff. 2013. X-13ARIMA-SEATS Reference Manual. Technical report, U.S. Census Bureau.

V. Chitre. 2001. Indicators of business recessions and revivals in India: 1951-1982. *Indian Economic Review*.

W. R. Bell and S.C. Hilmer. 1984. "Issues involved with the seasonal adjustment of economic time series". *Journal of Business and Economics Statistics*, 2(4):291– 320.

MORE FROM THE AUTHORS

- Rudrani Bhattacharya, Ila Patnaik, 2013. "Credit Constraints, Productivity Shocks and Consumption Volatility in Emerging Economies", NIPFP Working Paper no. 121 (March)
- Ila Patnaik and Ajay Shah, 2013. "The Investment Technology of Foreign and Domestic Institutional Investors in an Emerging Market", NIPFP Working Paper no. 124 (June)
- Rudrani Bhattacharya, Radhika Pandey and Giovanni Veronese, 2011. "Tracking India Growth in Real Time". NIPFP Working Paper No. 90 (Jul)

Link to detailed profile of authors:

Rudrani Bhattacharya

Radhika Pandey is a Consultant at NIPFP.

Ila Patnaik

Ajay Shah

MORE IN THE SERIES

- Ila Patnaik, Madhavi Pundit, 2016. Where is India's Growth Headed? No. 159.
- Kausik K. Bhadra, 2015. "Inequality Effects for Fiscal Policy: Analysing the Benefit Incidence on Health Sector in India", No. 158

National Institute of Public Finance and Policy,
18/2, Satsang Vihar Marg,
Special Institutional Area (Near JNU),
New Delhi 110067
Tel. No. 26569303, 26569780, 26569784
Fax: 91-11-26852548
www.nipfp.org.in