

Technical note on seasonal adjustment for Index of industrial production (Manufacturing)

March 8, 2010

Contents

1	IIP Manufacturing	3
1.1	Additive versus multiplicative seasonality	3
2	Steps in the seasonal adjustment procedure	4
2.1	Tests for identifying the nature of seasonality	5
2.2	Seasonal adjustment of IIP Manufacturing with X-12-ARIMA	5
2.3	Diagnostic checks	6
2.3.1	Validation of the automodel choice by X-12-ARIMA	6
2.3.2	Presence of identifiable seasonality	7
3	Year on year growth versus seasonally adjusted point on point growth	7
4	Spectral representation	9
5	Sliding spans diagnostics	10
6	Revision history diagnostics	11
7	Accounting for India-specific moving holiday effects	13

List of Figures

1	IIP Manufacturing (Non seasonally adusted)	3
2	Monthly growth rates across the years	4
3	IIP Manufacturing (NSA and SA)	6
4	ACF of residuals	7
5	IIP (Manufacturing) Spectral plot (NSA and SA)	10
6	RMSE of revisions	12
7	RMSE of revisions of seasonally adjusted levels	13

List of Tables

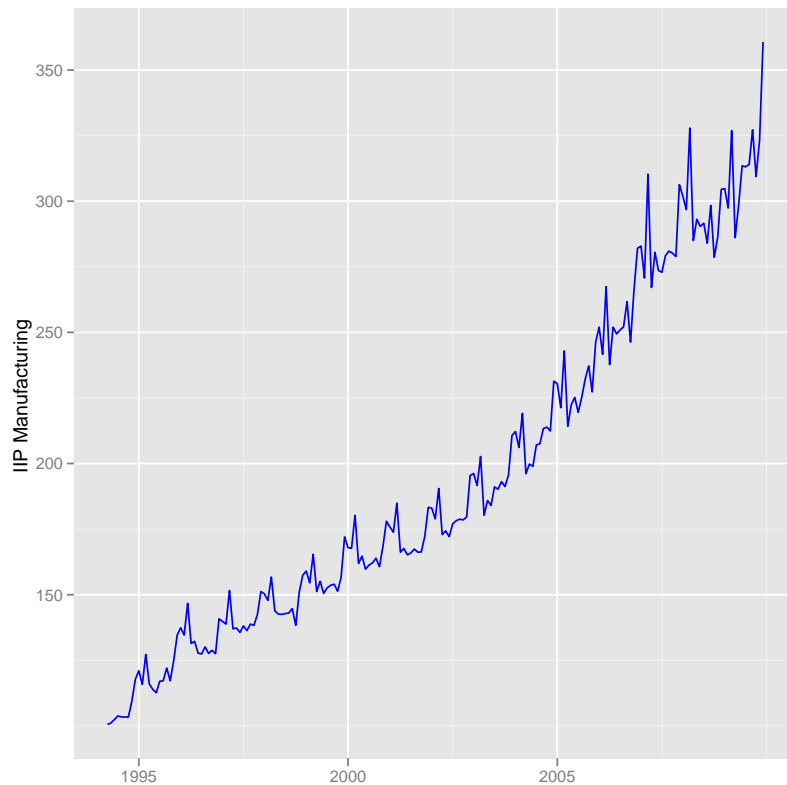
1	HEGY test statistics	5
2	Year on year and point on point growth rates	8
3	Regression model for IIP (Manufacturing)	14

1 IIP Manufacturing

We analyse the monthly data for IIP Manufacturing from April, 1994 onwards. Figure 1 shows the original plot of IIP Manufacturing. The plot shows seasonal peaks. In a non-seasonally adjusted series, it is difficult to discern a trend as the seasonal variations may mask the important characteristics of a time series.

The figure below also shows that the magnitude of the seasonal peaks is increasing with the level of the series.

Figure 1 IIP Manufacturing (Non seasonally adusted)



1.1 Additive versus multiplicative seasonality

X-12-ARIMA has the capability to determine the mode of the seasonal adjustment decomposition to be performed i.e whether multiplicative or additive seasonal adjustment decomposition is appropriate for the series. For Index of industrial production (Manufacturing), multiplicative seasonal adjustment is considered appropriate on the basis of the model selection criteria.

2 Steps in the seasonal adjustment procedure

Given that seasonality exists, it is important to model seasonality before the application of seasonal adjustment procedure. Seasonality in time series can be deterministic or stochastic. Stochastic seasonality can be stationary or non-stationary.

A visually appealing way of looking at the raw data is to plot the growth rates in each of the months across the years i.e the growth of April over March in each of the years from 1994 onwards. This gives us some idea of the presence of seasonal peaks, if any in the series. The nature of seasonality can also be inferred intuitively from the plot before the application of the testing procedures.

Figure 2 Monthly growth rates across the years

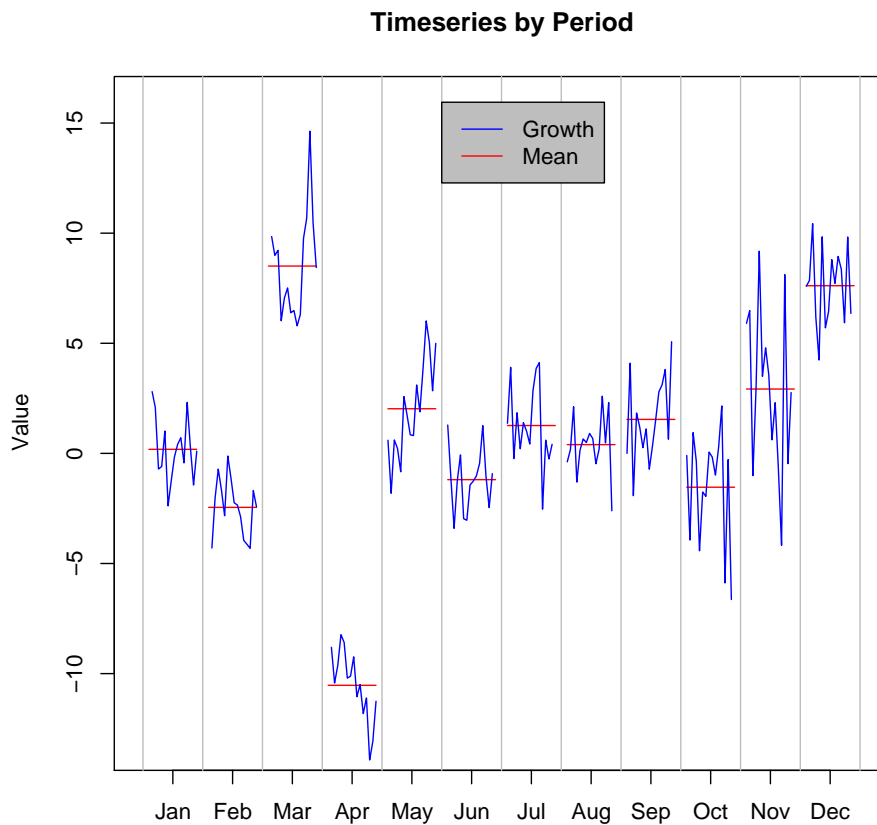


Figure 2 shows seasonal peaks in the month of March and December. The growth rates in each of the months across the years are not stable. Intuitively, seasonality in the series cannot be captured by seasonal dummy.

2.1 Tests for identifying the nature of seasonality

We test for the nature of seasonality using HEGY and Canova Hansen test.

Under the null hypothesis of the HEGY test, nonstationary unit root behavior exists not only at the long run (or zero) frequency, but also at some or all of the seasonal frequencies.

The Canova Hansen test takes the opposite approach. The null hypothesis is stationarity with deterministic seasonality.

Table 1 HEGY test statistics

	Stat.	p-value
tpi_1	0.74	0.10
tpi_2	-1.69	0.10
Fpi_3:4	15.01	0.10
Fpi_5:6	0.95	0.01
Fpi_7:8	0.94	0.01
Fpi_9:10	5.05	0.01
Fpi_11:12	4.64	0.01
Fpi_2:12	7.02	
Fpi_1:12	6.93	

 Canova & Hansen test

Null hypothesis: Stationarity.

Alternative hypothesis: Unit root.

Frequency of the tested cycles: $\pi/6$, $\pi/3$, $\pi/2$, $2\pi/3$, $5\pi/6$, π ,

L-statistic: 1.914

Lag truncation parameter: 14

Critical values:

0.10 0.05 0.025 0.01

2.49 2.75 2.99 3.27

Although the HEGY and Canova Hansen test point towards deterministic seasonal pattern, the model without the seasonal dummy gives better results in terms of the autocorrelations of the residuals.

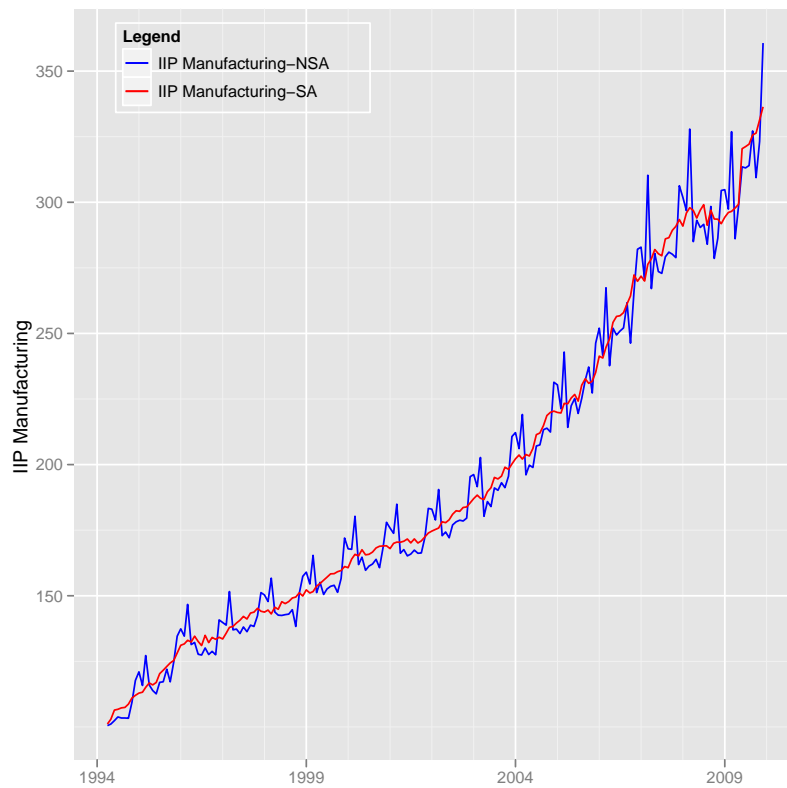
The nature of seasonality in IIP Manufacturing is taken to be stochastic.

2.2 Seasonal adjustment of IIP Manufacturing with X-12-ARIMA

Seasonal adjustment of is done with X-12-ARIMA method.

Figure 3 shows the non-seasonally and seasonally adjusted IIP Manufacturing. The plot reveals that the seasonal peaks are dampened after seasonal adjustment.

Figure 3 IIP Manufacturing (NSA and SA)



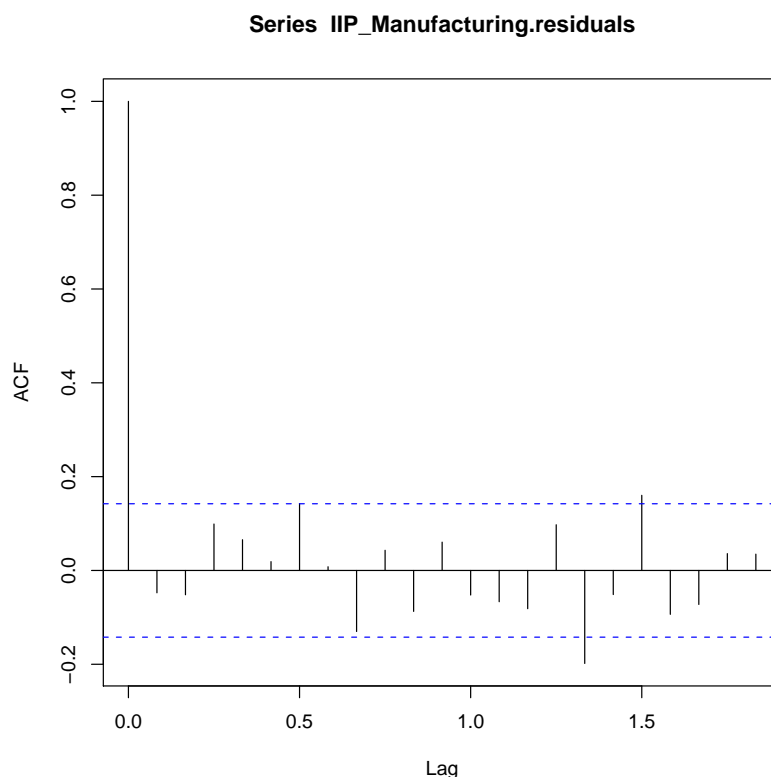
2.3 Diagnostic checks

After seasonal adjustment, a series of diagnostic checks are performed through relevant tests and quality assessment statistics.

2.3.1 Validation of the automodel choice by X-12-ARIMA

A test of validation of the auto model choice by X-12-ARIMA is the randomness of the residuals of the ARIMA model. The Ljung-Box test is conducted on the residuals of the fitted ARIMA model to check whether or not the residuals are white noise. The ACFs of the residuals are plotted to check for randomness.

Figure 4 ACF of residuals



The figure 4 does not reveal significant autocorrelation amongst the residuals.

2.3.2 Presence of identifiable seasonality

The statistic M7 shows the amount of moving seasonality present relative to stable seasonality. It shows the combined result for the test of stable and moving seasonality in the series. A value lesser than 0.7 is desirable to show identifiable seasonality in the series. The value of M7 is 0.172 for IIP Manufacturing

IIP Manufacturing series show identifiable seasonality on the basis of M7 statistic.

3 Year on year growth versus seasonally adjusted point on point growth

Growth rates can be computed either year on year or point on point. The year on year growth rate is computed as the percentage change with respect to the corresponding month (or quarter) in the preceding year, while the point on point growth rate is computed as the percentage change with respect to the preceding period.

Table 2 shows the year on year growth and seasonally adjusted annualized rate in percent, point on point.

Table 2 Year on year and point on point growth rates

	YoY growth	Point on point growth
2006 Jan	9.37	31.10
2006 Feb	9.17	-4.44
2006 Mar	10.09	21.81
2006 Apr	10.97	15.35
2006 May	13.31	29.81
2006 Jun	10.75	10.52
2006 Jul	14.31	-0.34
2006 Aug	11.94	6.12
2006 Sep	12.70	15.42
2006 Oct	3.84	14.25
2006 Nov	17.16	12.10
2006 Dec	14.54	14.11
2007 Jan	12.26	8.27
2007 Feb	12.04	-9.01
2007 Mar	16.04	29.49
2007 Apr	12.37	8.58
2007 May	11.31	15.15
2007 Jun	9.70	-7.24
2007 Jul	8.77	-4.52
2007 Aug	10.75	26.80
2007 Sep	7.37	3.28
2007 Oct	13.76	11.24
2007 Nov	4.73	6.30
2007 Dec	8.58	12.81
2008 Jan	6.72	-11.22
2008 Feb	9.64	19.81
2008 Mar	5.67	9.49
2008 Apr	6.70	-4.91
2008 May	4.49	-11.85
2008 Jun	6.14	11.70
2008 Jul	6.85	7.64
2008 Aug	1.72	-11.27
2008 Sep	6.19	1.97
2008 Oct	-0.57	-13.08
2008 Nov	2.65	-0.61
2008 Dec	-0.59	-3.56
2009 Jan	0.96	8.75
2009 Feb	0.20	7.29
2009 Mar	-0.30	2.70
2009 Apr	0.39	4.02
2009 May	1.84	5.45
2009 Jun	7.95	81.66
2009 Jul	7.37	2.47
2009 Aug	10.99	6.06
2009 Sep	9.95	12.48
2009 Oct	11.13	0.93
2009 Nov		

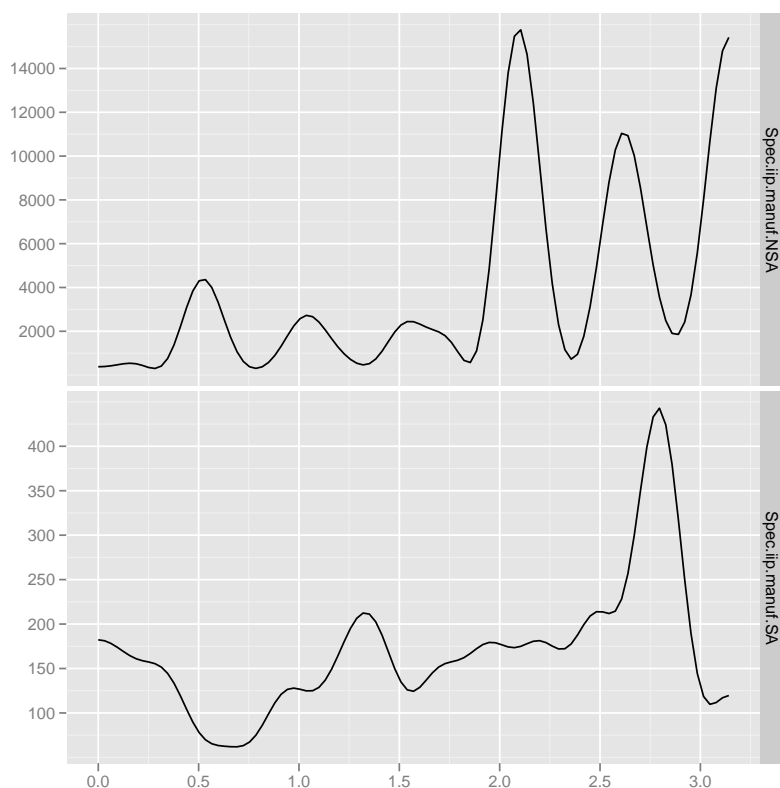
4 Spectral representation

Figure 5 shows the spectral plot of the growth rate of the unadjusted and seasonally adjusted series. Spectral plot, an important tool of the frequency domain analysis shows the portion of variance contributed by cycles of different frequencies.

The x-axis represent frequency from 0 to π (3.14). 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). In terms of periods (months); they are 12 months, 6 months, 4 months, 3 months and 2.4 months.

The figure at the lower panel shows that peaks at seasonal frequencies are eliminated after seasonal adjustment. For example the first peak at 0.52 correspond to 12 months which is eliminated after seasonal adjustment. Other peaks seen in the lower panel of the figure are not at seasonal frequencies.

Figure 5 IIP (Manufacturing) Spectral plot (NSA and SA)



5 Sliding spans diagnostics

Sliding span diagnostics are descriptive statistics of how the seasonal adjustments and their month-to-month changes vary when the span of data used to calculate them is altered in a systematic way.

It is based on the idea that for a month common to more than one overlapping spans, the percent change of its adjusted value from the different spans should not exceed the threshold value and for a month common to more than one span, the difference between the month on month change from the different spans should not exceed the threshold value (the threshold value being 0.03).

Sliding span gives the percentage of months ($A\%$) for which the seasonal adjustment is unstable (the difference in the seasonally adjusted values for a particular month from more than one span should not exceed 0.03). It also gives the percentage of months ($MM\%$) for which the month on month changes of the seasonally adjusted values is unstable i.e exceeding the threshold value. The seasonal adjustment produced by the procedure chosen should not be used if $A\% > 25.0$ (> 15.0 is considered problematic) or if $MM\% > 40.0$.

For Index of industrial production (Manufacturing) both $A\%$ and $MM\%$ is 0.

The sliding span diagnostics is not reliable when the range of the seasonal factors in a particular span is low (less than 5).

6 Revision history diagnostics

We generate the revision history diagnostics for different series. For a given series y_t where $t = 1, \dots, T$, we define $A_{t|n}$ to be the seasonal adjustment of y_t calculated from the series y_1, y_2, \dots, y_n , where $t \leq n \leq T$. The concurrent seasonal adjustment of observation t is $A_{t|t}$ and the most final adjustment of observation t is $A_{t|T}$. The percent revision of the seasonally adjusted series is defined to be:

$$R_t = \frac{A_{t|T} - A_{t|t}}{A_{t|t}}$$

This revision in the levels is reported by the X-12-ARIMA programme. The programme also reports the revisions in the month on month change in the seasonally adjusted values. Let $C_{t|n}$ denote the month to month change in the seasonally adjusted series at time t calculated from the series y_1, y_2, \dots, y_n . $C_{t|n}$ is calculated as:

$$C_{t|n} = \frac{A_{t|n} - A_{t-1|n}}{A_{t-1|n}}$$

The revision for these changes is:

$$R_t = C_{t|T} - C_{t|t}$$

We find the revisions of the levels and the month on month changes in the seasonally adjusted values of IIP (Manufacturing) and calculate the root mean square error (RMSE) of the revisions. We normalize it by the standard deviation of the seasonally adjusted series and of the month on month change in the seasonally adjusted series respectively.

Figure 6 shows the root mean square error of the revisions of the month on month changes of the seasonally adjusted values normalized by the standard deviation of the month on month change in the seasonally adjusted values. The figures range from 0.42 to 0.53.

Figure 6 RMSE of revisions

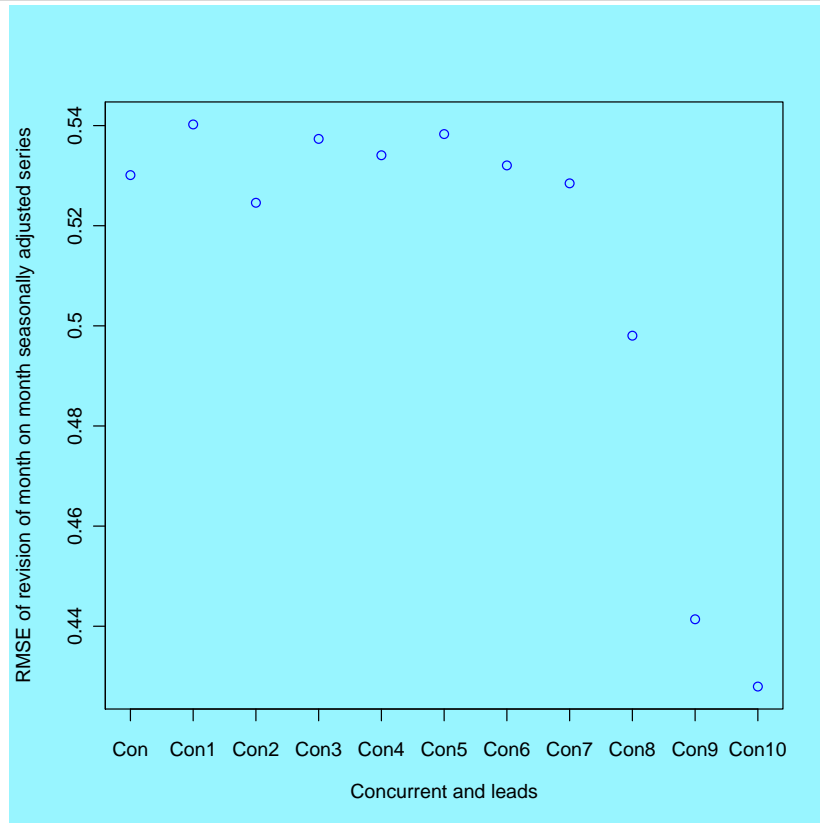
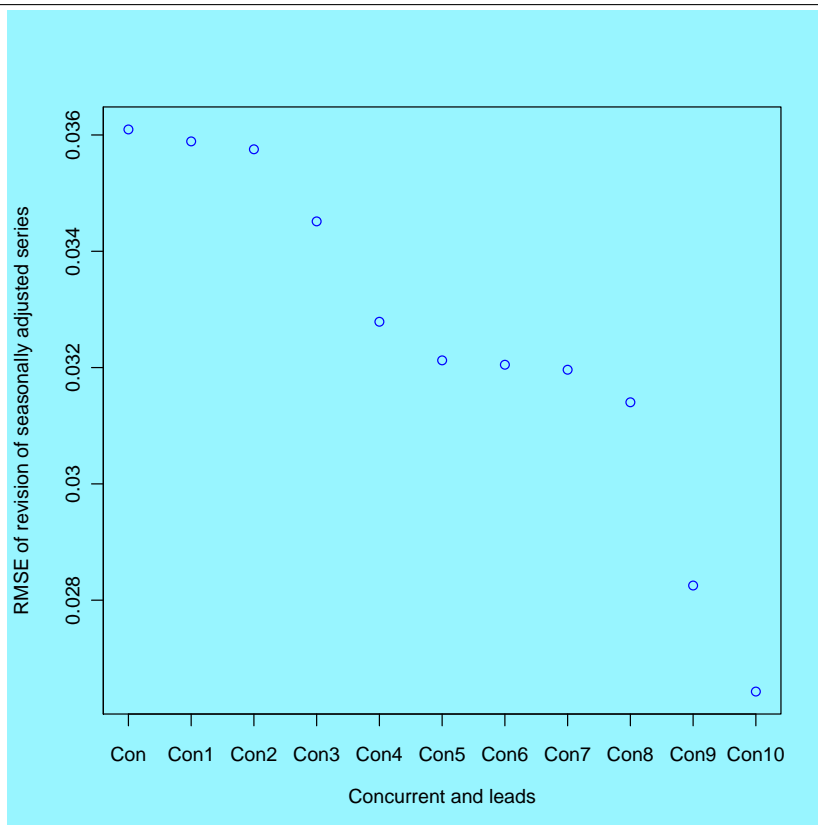


Figure 7 shows the root mean square error of the revisions of the seasonally adjusted values. The RMSE is normalized by the standard deviation of the seasonally adjusted series. The figures range from 0.027 to 0.038.

Figure 7 RMSE of revisions of seasonally adjusted levels



7 Accounting for India-specific moving holiday effects

Accounting for moving holiday effect is a crucial component of pre-treatment of the series before the application of seasonal adjustment method. X-12-ARIMA is capable of handling the moving holiday effects through the inclusion of regressors for Easter Sunday, Labor Day, and Thanksgiving Day. These are important moving holidays for U.S time series.

We use the GENHOL program of X-12-ARIMA to analyse India-specific moving holiday effect. The program generates regressor matrices from holiday date file to enable X-12-ARIMA, estimation of complex moving holiday effects. It has the capability to generate regressors for before the holiday interval, surrounding the holiday interval and past the holiday interval.

The key assumption is that the fundamental structure of a time series changes for a fixed number of days before, after or for a fixed interval surrounding the holidays. We estimate the effect of Diwali which is an important moving holiday in Indian scenario. For estimating

Table 3 Regression model for IIP (Manufacturing)

Variable	Parameter estimate	Standard error	t-value
User defined			
Diwali	-0.0179	0.00382	-4.68

Diwali effect, we assume that the level of economic activity changes 5 days before Diwali (including the day on which Diwali falls). Regression variable for Diwali is found to be significant for IIP (Manufacturing).

The results in Table 3 show significant trading day effect on IIP (Manufacturing) on account of Diwali. There is a significant drop in IIP (Manufacturing) around Diwali on account of loss of working days. This can be seen with the latest October numbers for the series. If we do not take Diwali effect into account, the seasonally adjusted annualised rate (SAAR) is -2.27. After accounting for Diwali, the SAAR number for IIP (Manufacturing) improve to 0.93.