Seasonal Adjustment of Economic Time Series: Key Challenges and Impact of the COVID-19 Pandemic

by **Leow Geng Hui** and **Koh Yong Siang**
Economic Accounts Division
Singapore Department of Statistics

Introduction

Seasonal adjustment is a process of using statistical techniques to estimate and remove recurring seasonal variations, which are typically observed in economic data. The true underlying trends and short-term movements of a time series may be obscured by the presence of seasonal variations. Seasonally adjusted (SA) data facilitates better assessment and comparison of data across periods and timelier identification of turning points.

This article provides a brief overview of seasonal adjustment and outlines the methodology adopted by the Singapore Department of Statistics (DOS). It discusses several key challenges underlying the seasonal adjustment of economic time series during the COVID-19 pandemic.

Decomposition of Time Series

Under the decomposition model theory, all time series consist of four components, namely, the:

Trend [1] Component

The long-term growth or decline of a time series observed over an extended period of time.

Cyclical Component

The sinusoidal fluctuation [2] observed around the trend that are influenced by economic expansions and contractions.

Irregular Component

The erratic random fluctuations of the short-term movements of a time series.

Seasonal Component

The systematic variations of a time series.

▼ The seasonal component includes the *Regular Seasonal Effect* and *Calendar Effects.*

The ***Regular Seasonal Effect*** refers to the intra-year periodic variation that repeats in the same period every year. For example, the visitor arrival data series exhibit strong regular seasonal effects as the figures tend to be higher in July and December during the peak travel season.

The ***Calendar Effects*** refer to variations resulting from the composition of the calendar. The two main calendar effects are:

Trading Day Effect – arising from the differences in the number of working days in a particular month; and the

Moving Holiday Effect – resulting from shifts in the timing of holidays or festive periods (e.g., Chinese New Year and Hari Raya Puasa) across different years. For example, the retail sales data series are influenced by the timing of festive periods and the number of weekends within a particular month.

In addition to seasonal variations, a time series may also be subjected to structural changes, in view of the evolving economic landscape, technological advancements, and other factors (e.g., policy and legislative changes affecting existing agreements, practices, or preferences). These structural changes can result in *seasonal* and/ or *trend breaks* in a time series. Handling such breaks requires careful consideration during the seasonal adjustment process to ensure reliable results.

[1] Given the difficulties in distinguishing the trend and the cyclical components, most (if not all) of the time, the trend-cycle component, which reflects the combined long-term trend and business cycle movement of the time series is assessed simultaneously.

[2] Sinusoidal fluctuation refers to a variation that follows a sine function, which is a periodic function that smoothly oscillates between its high and low values in a regular manner.

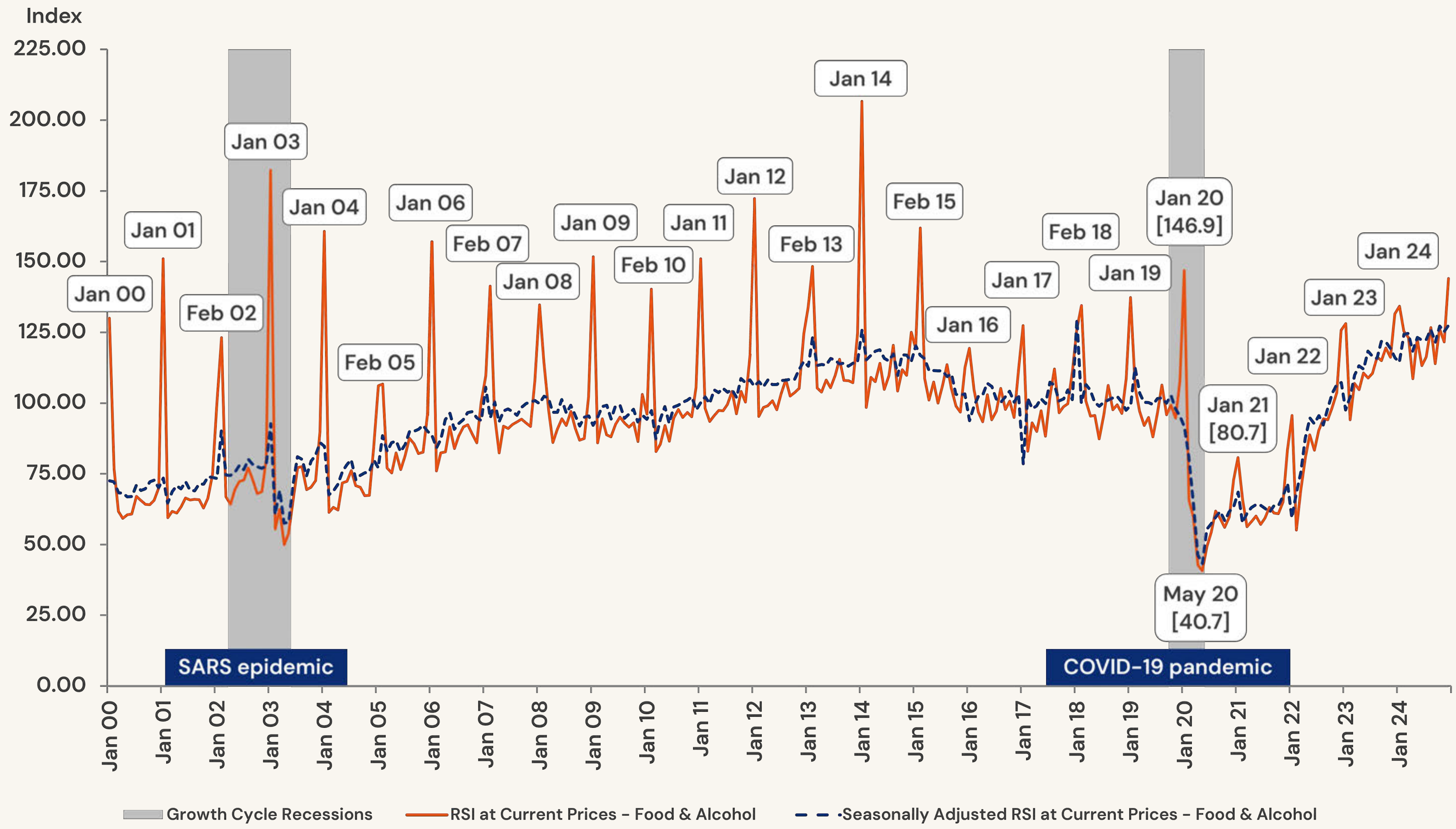
Did you know?

DOS compiles and publishes the Retail Sales Index (RSI) which measures the short-term performance of the retail trade industry on a monthly basis. In addition to the Regular Seasonal Effect, most of the RSI series exhibit variations due to the Calendar Effects.

For instance, the RSI of the Food & Alcohol segment typically rises sharply in January or February, depending on when Chinese New Year falls. This increase occurs as families stock up ahead of the festive celebrations.

While retail sales for the Food & Alcohol segment were relatively unaffected during the Severe Acute Respiratory Syndrome (SARS) outbreak in 2002-2003, this segment recorded a sharp plunge in sales in early 2020 due to the implementation of the Circuit Breaker and strict safe distancing measures during COVID-19. As such, the segment's sales index declined 45% year-on-year from January 2020 (146.9) to January 2021 (80.7), as illustrated in Chart 1.

Chart 1: Retail Sales Index at Current Prices - Food & Alcohol



Seasonal Adjustment Methodologies

DOS utilises the X12-ARIMA [3] procedure for seasonal adjustment, a method developed by the United States Census Bureau. This procedure is widely adopted by many advanced National Statistical Offices (NSOs) such as the United Kingdom's Office for National Statistics and Statistics New Zealand, and international organisations such as the Organisation for Economic Co-operation and Development and the World Bank). X12-ARIMA works based on an iterative process, which alternately estimates the trend-cycle and seasonal components of a time series using various moving average filters, ultimately producing the SA data as the resultant.

There are two approaches to seasonal adjustment – the ***Concurrent Adjustment* Approach** and the ***Forward Adjustment* Approach**.

Concurrent Adjustment Approach

The time series is re-analysed and the seasonal component is re-estimated whenever a new data point becomes available. While this approach is intuitively appealing and more reflective of the prevailing state of the economy, it suffers from the drawback of frequent revisions to the entire SA data series whenever a new data point becomes available.

Forward Adjustment Approach

Seasonal adjustment analysis is conducted annually when the latest full-year data becomes available. Forward seasonal factors for the upcoming year are projected using the X12-ARIMA procedure. When a new data point becomes available, the SA data is then derived using these forward seasonal factors.

DOS leverages both the Concurrent Adjustment and Forward Adjustment Approaches. The Concurrent Adjustment Approach is usually adopted for quarterly time series, which generally have a more stable seasonal component. Hence, data revisions for the entire series are more manageable. The Forward Adjustment Approach is generally adopted by DOS for monthly time series, which are typically more volatile, to minimise potential distortions caused by fluctuations in the irregular component. However, for closely monitored quarterly Gross Domestic Product (GDP) estimates, its seasonal adjustment uses the Forward Adjustment Approach to avoid frequent revisions to the historical data series.

[3] X12-ARIMA is a statistical procedure with Auto-Regressive Integrated Moving Average (ARIMA) modelling as one of its key features.

Table 1: Seasonal Adjustment Approaches - Concurrent Adjustment versus Forward Adjustment

	Concurrent Adjustment Approach	Forward Adjustment Approach
Advantages	• Incorporates latest information whenever available ◦ New data points ◦ Revisions to existing data	• Minimises frequency of SA data revisions • Revisions only occur during annual seasonal adjustment re-analysis
Disadvantages	• Requires frequent revisions to entire SA data series	• Slower to incorporate latest available information

Did you know?

Uses of Non-Seasonally Adjusted versus Seasonally Adjusted Data

Non-seasonally adjusted (NSA) data reflects the actual characteristics and fluctuations of the time series, while the SA data reveals the underlying movements that may be hidden by seasonal variations. SA data is developed to supplement, not replace, the information presented by the NSA data.

SA data will be analytically useful when strong seasonal patterns in the NSA data hinders detailed, in-depth data analyses. For example, with NSA data, only year-on-year growth rates can be quoted for analytical reporting as period-on-period growth rates may be masked by seasonal fluctuations. While year-on-year growth rates implicitly account for Regular Seasonal Effects, they may still be affected by the Calendar Effects. This can be significant for selected series, such as the RSI – Food & Alcohol segment due to shifts in Chinese New Year dates. Moreover, year-on-year growth rates are relatively less sensitive to short-term changes in growth momentum compared to higher-frequency period-on-period growth rates computed using the SA data.

Table 2: Analysis on NSA versus SA data

	Non-Seasonally Adjusted	Seasonally Adjusted
Advantages	• Reflects actual data characteristics and fluctuations • Preserves raw data without additional treatment or pre-adjustments	• Facilitates uncovering true underlying trends and in-depth analyses • Allows for period-on-period comparisons, which facilitates faster identification of turning points
Disadvantages	• Difficult to identify non-seasonal effects (e.g., long-term movements, cyclical variations), which are important economic signals	• Potential for judgement or treatment bias in seasonal adjustment procedure
Applications	• Year-on-year growth rates	• Period-on-period growth rates

Challenges of Seasonal Adjustment: Impact of the COVID-19 Pandemic

The X12-ARIMA procedure estimates the seasonal and trend-cycle components via iterative moving average filters. It implicitly assumes that the characteristics of the data series remain largely similar over time, and that the irregular component can be eliminated through the iterative process.

These assumptions and resultant models from the X12-ARIMA procedure are generally valid and accurate under normal circumstances. However, ARIMA models can be severely influenced by extreme observations, outliers, structural breaks, and unexpected fluctuations to the data. An example of such anomaly is the COVID-19 pandemic, which led to an abrupt and sharp decline in economic activities. Hence, it is crucial to identify such anomalies and introduce appropriate pre-treatments and adjustments to specific data point(s) to account for these unusual data trends and observations prior to the seasonal adjustment process, to ensure more accurate and meaningful results.

However, the challenge lies in identifying these anomalous and 'unusual' observations. It may not be apparent when such data are first observed. When these 'unusual' observations are identified, professional judgement from statisticians is often required due to limited information available to provide evidence-based decisions on the appropriate treatment to undertake.

In the earlier example of the RSI – Food & Alcohol series, the annual seasonal adjustment review was conducted in early 2021 with data up to December 2020. While an abrupt fall in series was recorded in May 2020, it was unclear at the time whether the plunge was temporary or permanent, and if the impact of COVID-19 would lead to structural changes to the underlying data patterns. Given that these data points were significantly different from the historical series, they did not fit well with the underlying model. Hence, direct intervention was necessary to ensure that the SA series reliably reflected the underlying economic reality during COVID-19. In the case, the 2020 data were treated as outliers and excluded from the annual seasonal adjustment review as they were deemed 'unusual'. Such an approach is consistent with international practices and norms.

Did you know?

DOS Adopts an Agile Approach to Promptly Tackle the Impact of COVID-19 on Data Series

DOS adopts an agile approach in the seasonal adjustment process to promptly review and intervene in view of the impact of COVID-19 on affected data series. Without direct intervention, the quality of the SA series may be compromised, potentially distorting SA trends.

Three broad options (Table 3) are identified to determine the appropriate intervention techniques to undertake in the seasonal adjustment procedure. Given the unstable behaviour underlying the seasonal and trend-cycle components of selected data series, some NSOs have opted to temporarily suspend the release of such affected series.

Table 3: Seasonal Adjustment Procedures with Intervention

	Option 1	Option 2	Option 3
Assumptions	Seasonal patterns are largely unaffected by COVID-19 after accounting for extreme and influential observations.	Changes or shifts in seasonal patterns arising from COVID-19 are temporary; seasonal fluctuations are expected to return to normal when the situation stabilises.	Changes or shifts in seasonal patterns arising from COVID-19 are both significant and permanent, i.e., new seasonal patterns following COVID-19 are distinctly different from pre-COVID periods.
Treatment	Identify and account for extreme and influential observations as outliers.	Project forward SA factors for the affected periods using pre-COVID historical NSA data.	Analyse data series pre-, during, and post- COVID separately to capture their respective seasonal patterns.
Advantages	Incorporates latest available NSA data for seasonal adjustment analysis and modelling. Model is self-correcting in nature as more data becomes available.	Pre-COVID SA data trends will not be influenced by COVID-impacted NSA data.	Seasonal adjustment analyses which are separately conducted, will more accurately capture and reflect the appropriate seasonal patterns for the respective periods.
Disadvantages	Incorporation of latest NSA data during the COVID-impacted periods, which are more volatile, may lead to drastic revisions to the SA data.	Does not incorporate latest available NSA data in a timely manner.	Requires sufficient data points for rigorous seasonal adjustment analyses; during- and post- COVID data are limited and pose challenges in modelling and estimation.

Conclusion

Seasonal adjustment is a statistical procedure to estimate and remove the recurring seasonal and calendar effects from a time series. This enables the uncovering of true underlying trends and short-term movements of a time series, facilitating in-depth assessment and timelier identification of turning points. SA data provides an additional lens and perspective and is developed to supplement the NSA data.

Similar to other econometric and statistical modelling techniques, the X12-ARIMA seasonal adjustment procedure works on the basis of iterative estimation. It implicitly assumes that the characteristics of the data will remain largely similar, and historical patterns are likely to remain and repeat.

To obtain more reflective SA trends, particularly in the face of unprecedented events like the COVID-19 pandemic, it is therefore necessary to intervene and incorporate pre-treatments or adjustments to the NSA data to account and adjust for any 'unusual' data prior to the seasonal adjustment process. This ensures that the resulting SA series accurately reflects underlying economic realities.

DOS remains committed to providing high-quality, relevant statistical information by continuously adapting and improving its methodologies in line with international best practices.