Seasonal Adjustment in Volatile Economic Situations – Statistics Canada's Experience

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Seasonal adjustment is an important process applied to most sub-annual economic indicator programs at Statistics Canada, notably those that support the production of the Gross Domestic Product. Seasonal adjustment offers a timelier picture of the current economic situation than analysis such as year-over-year comparisons based on unadjusted data. The seasonal adjustment process highlights the underlying trend-cycle by filtering out systematic movement due to both seasonal and calendar effects, and taking outliers or irregular events into consideration. In volatile economic times, producing seasonally adjusted data may be challenging. In this paper, we will present recent examples of seasonal adjustments where interesting results were obtained by going beyond the usual options. We will also illustrate simple diagnostics which can be useful to detect structural changes in seasonal patterns.

Key Words: REGARIMA, Seasonal Adjustment, X12-ARIMA

1 Concurrent Seasonal Adjustment at Statistics Canada

Producing estimates for sub-annual surveys at Statistics Canada is a collaborative effort which involves the co-operation of many groups within the agency, who each bring their experience in different areas including data collection, survey methodology, economics and computer programming. Ultimately, subject matter analysts are responsible for analysis of the survey outputs; including both unadjusted (raw) and seasonally adjusted estimates. The subject matter analysts also manage the survey process in general and typically have an educational background in economics.

As with most survey related processes at Statistics Canada, a set of guidelines have been developed to outline general principals related to creating, maintaining and publishing seasonally adjusted data (Statistics Canada, 2009). A number of key guidelines are listed below:

- Use the X-12-ARIMA methodology (Findley et al., 1998) for seasonal adjustment
- Use extrapolations based on the ARIMA model to extend the series. This is encouraged to reduce the use of asymmetric filters but has also been found to reduce the size of revisions when seasonally adjusted estimates are benchmarked to the raw estimates for each calendar year.
- Estimate seasonal factors concurrently. With this approach, the seasonal factors for the entire series are re-estimated based on the current data each time an additional reference period is added to the series.

- Include adjustments for calendar effects (such as trading day and holiday effects) where appropriate. In practice, the decision on whether or not to include these regressors with the ARIMA model is determined on a series-by-series basis.
- Restore additivity in the seasonally adjusted series. In cases where a number of sub-series which add up to an aggregated series are seasonally adjusted, we apply a reconciliation step to ensure that the relationship is respected.

The Time Series Research and Analysis Centre (TSRAC) is a section within the Business Survey Methods Division at Statistics Canada that provides support throughout the agency for the application of seasonal adjustment of sub-annual surveys as well as back-casting and other related processes. With regard to the production of survey outputs, TSRAC is responsible for developing and maintaining the processing systems that are used for seasonal adjustment, as well as ensuring the quality of the seasonally adjusted estimates.

In general, the approach taken to maintain the processing systems at Statistics Canada is for TSRAC to review the options used in seasonal adjustment for each series on an annual basis, and to set the options for the upcoming year time based on this analysis. The seasonal adjustment is then applied by the subject matter areas as part of their monthly process, and TSRAC is consulted when any issues arise. When feasible, the TSRAC has access to the diagnostic reports that are created each time that seasonal adjustment is run to proactively identify areas where special attention is required, or where changes may need to be made to the seasonal adjustment options in advance of the next scheduled review. This type of treatment and ad-hoc on-going reviews is thought to yield the best results for seasonal adjustment as suggested by the simulations presented in Ciammola *et al* (2010)

Seasonal adjustment at Statistics Canada is carried out using a SAS-based modular processing system, the Time Series Processing System (TSPS) which has been developed to apply seasonal adjustment to sub-annual surveys within the agency. This processing system is based on custom SAS macros to verify files and derive variables, the PROC X12 procedure for seasonal adjustment as well as available SAS processes from the agency's Generalized Software for benchmarking and raking, G-Series. For more information on the TSPS, refer to Ferland and Fortier (2010) and for details on G-Series see Quenneville and Fortier (2011) or contact G-series@statcan.gc.ca.

When estimates are regularly published by Statistics Canada for a given survey program, revisions are often made to previously released estimates for prior reference periods. These revisions can be made to both unadjusted estimates and seasonally adjusted estimates for a number of reasons which are outlined for individual surveys at http://www23.statcan.gc.ca/imdb-bmdi/pub/indexth-eng.htm. The seasonally adjusted estimates are revised to take into account the updates to the unadjusted values, but also to reflect the impact of adding periods to the end of the series. Revised values that are notably different from the previously released values are problematic, and if these revisions are unexpected given the changes in the raw series, TSRAC works together with subject matter analysts to ensure that the seasonally adjusted results are indicative of the economic conditions.

2 Challenges with Seasonal Adjustment in Volatile Economic Situations

A review of seasonal adjustment basic concepts and of how it can help analysts hone in on the underlying economic trend is presented in Wyman (2010). The process of seasonal adjustment is more difficult than usual during times where the economy is particularly volatile. For the purposes of this article, we define volatile as being characterized by or subject to rapid or unexpected change. This volatility can manifest itself in a number of ways, but some of the more common impacts on a time series include an increased number of one-time outliers or extreme values, sudden shifts in the level of a series, and changes to seasonal patterns that had previously been stable. Depending on the characteristics of the volatility when estimating the decomposition of a time series, the increased volatility can be attributed to many components: the trend-cycle, calendar effects, seasonal component, and irregular component (including different types of outliers). In most cases, the volatility will be divided among several of the components. As a result, when analysing the seasonally adjusted series, we should be prepared for volatile month-to-month movements. In addition, this instability can lead to large revisions to previously published estimates as subsequent months' estimates are added to the series.

We regularly implement what we will refer to as practical seasonal adjustment in order to reduce some of these undesirable effects. Increased variability in parts of the data and the presence of potential outliers could lead to unusual movements in the seasonally adjusted data if system generated specifications were left intact. *Practical seasonal adjustment* means modifying automatically generated options to come up with a customized set of options that fit the data better, both statistically and from a common sense point of view with emphasis on reducing the severity of month-to-month fluctuations while maintaining the fundamental quality of the adjustment. Practical seasonal adjustment is often applied during the annual review of each series, as well as in the ad hoc analysis that is conducted between annual review periods.

2.1 Impacts of economic volatility on seasonally adjusted data

Considering that the primary aim of seasonal adjustment is to remove the trading day, holiday and seasonal components from the raw data series, we now examine the ways in which these components are affected during a period of increased volatility. The X12-ARIMA method includes a regression model (REGARIMA) followed by a non-linear filtering step (the X11 algorithm) and each are affected by increased volatility. The trading day and holiday effects are estimated during the REGARIMA portion and the seasonal factors are estimated within the X11 algorithm which is applied to the calendar and outlier adjusted series.

During periods of economic volatility, the estimation of the ARIMA model can be affected in a number of ways. First of all, we anticipate an increased level of apparent noise that makes it more difficult to estimate both the order and the parameter values of the ARIMA model. As well, in cases where there are outliers, they should be properly identified and treated in order to not have undue influence on the model. Similarly, if there are sudden or gradual shifts to the level of the series, they need to be treated in order to properly identify other outliers. Further, once the ARIMA model is estimated, the increased level of error in the model will make it more difficult to estimate trading day factors and holiday effects using the available data. If the trading day or holiday effects themselves are affected by the volatility, we note that the estimated factors will be affected over the entire span of the series as they are used throughout to adjust the raw series for calendar effects. Finally, the ARIMA model is used to extend the series into the future to reduce the usage of asymmetric filters in the subsequent X11 algorithm.

In the X11 algorithm, an increased magnitude of irregular components make it more difficult to accurately estimate the other components of the model (seasonal and trend-cycle components). In cases where there is some pattern underlying the increase in the irregularity it may be unclear which component should absorb the increased deviations. For example, a series of suddenly lower than expected observations could either be a sequence of negative irregular components being realised, or could be due to a temporary change in the trend of the series. If there is an apparent seasonal pattern to the increased irregular component, it will not be distinguishable from the long-term seasonal component and will pollute the estimates of seasonal factors.

2.2 Signals of economic volatility

A number of signals are used to determine when a series is particularly volatile and may require some attention. The most important signal is based on feedback from subject matter experts. Given their knowledge of the economic conditions relevant to a particular industry or data series, this insight into the presence of volatility as well as its underlying causes and expected effects is extremely valuable.

In the context of an ever increasing number of time series to analyse and adjust within a typical set of resource constraints, developing a set of diagnostics that would identify the subset of series that gives you the most *bang for your buck* becomes more and more important (*bang* representing improvement in quality of the adjustment and *buck* representing analytical time). For example, it makes sense to invest analytical time in series that display residual seasonality.

The X-12-ARIMA methodology lends itself to many diagnostic measures which can be monitored to indicate when we are encountering volatility. Many of the standard diagnostics will help indicate when there are unexpected changes (for example the F-test for stable seasonality, the Ljung-Box q statistic for autocorrelation, the forecast error of the ARIMA model and the tests for residual seasonality) and provide an early indication that the results of the seasonal adjustment should be verified.

A number of practical diagnostics are also used, such as the size of the month-to-month movements in the seasonally adjusted data and the size of revisions introduced with the addition of a new reference period. When these movements or revisions are large, they serve as an indication that something unexpected has occurred, and are signals to initiate a review process. Another practical diagnostic that has been developed to indicate volatility and changes in seasonal or calendar effects is the outlier and extreme values report.

To this aim, we recently added a new diagnostic to our set: the number of outliers in the last 5 years for a given month or quarter. Three types of outliers are considered here: a) REGARIMA additive outliers (AOs), b) REGARIMA temporary changes (TCs) and c) down-weighted data points in the final irregular component (weights smaller than 1.0 in X-12-ARIMA's table C17). This diagnostic may be useful in identifying series that recently went through sudden changes affecting data patterns for specific months or quarters and where the adjustment may no longer be optimal.

2.3 Practical Seasonal Adjustment to limit the impacts of economic volatility

In order to consider the different approaches to limit the impacts of this instability, we divide the seasonal adjustment process into three stages and consider potential interventions that could be made at each.

The data transformation stage - If an additive decomposition is well-suited to the data series and the magnitude of each component is time invariant, no prior data transformation is generally needed. If a multiplicative decomposition is preferred, a log transformation is typically applied to the data series for REGARIMA modelling. We may also consider other data transformations that bear different impacts on the series in terms of correction of outliers, and the magnitude of various components over the entire series.

The REGARIMA stage - When the REGARIMA model is estimated, a number of types of regressors can be included to represent outliers with different impacts, such as an additive outlier, a level shift, a ramp or a temporary change. These typically need to be specified by the user as the automatic detection is generally limited to additive outliers or one-time shocks. In addition, seasonal outliers (Monsell, 2007) can be included in the REGARIMA model to represent sudden changes to the seasonal pattern.

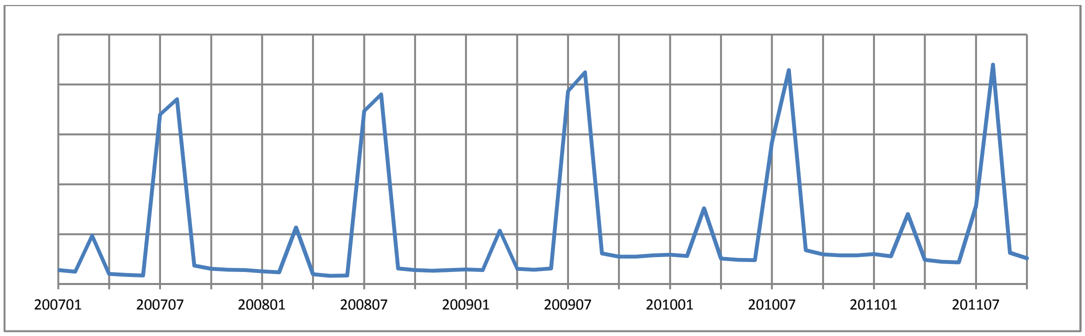
The X11 algorithm stage - The X11 algorithm involves a number of parameters, including the critical values for identification of extreme values, and the length of seasonal and trend filters. Each parameter affects the seasonal adjustment differently, and customizing their values is one way to control the seasonally adjusted results.

3 Recent examples of interventions to address volatility

In this section, five examples are presented where different approaches are used to limit the impacts of volatility in sub-annual data series.

Example 1: Use of a 4th root transformation. This example is based on a series representing regular beneficiaries of employment insurance (EI) in a particular occupation group. The series is characterized by a modest upward trend with small spikes in March and two large spikes in July and August. The spikes are not unusual given the nature of the occupation. Seasonality appears to be moving somewhat but no more so than other series related to this sector. Figure 1 below shows the last 5 years of the series.

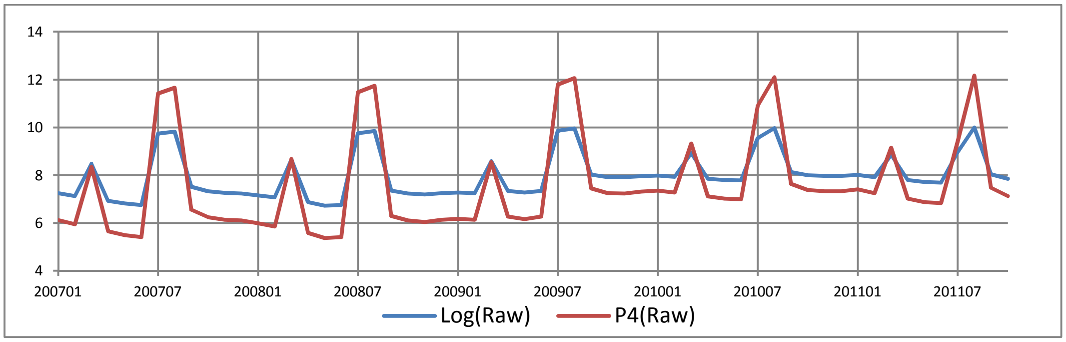
Figure 1: Number of regular EI beneficiaries in Selected Occupation Group



The series fans out somewhat over time so the log transformation corresponding to a multiplicative model seems appropriate. It also reduces the magnitude of seasonal extremes (July and August observations) shrinking them closer to the main data cloud. Despite this, a large number of outliers, level shifts, and temporary changes were identified leading to a high degree of jaggedness in the deseasonalized series. This in turn led to extremely large relative month-to-month changes ranging from -90% to +1900%. The seasonally adjusted series shows a trend towards levelling off but the monthly movement in the recent past is still unusually erratic and was flagged by subject matter for further evaluation.

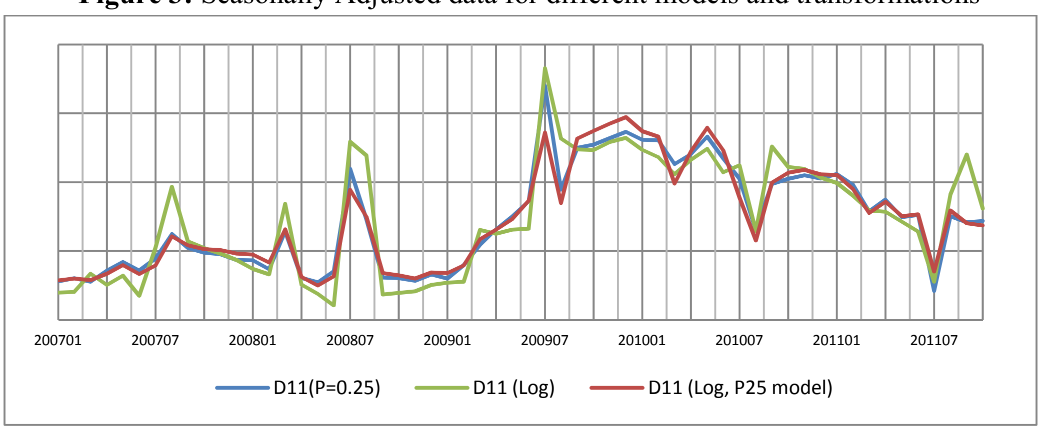
The series possesses a strong seasonal pattern that is rapidly evolving as relative movements since 2009 are much less extreme. Critical values for REGARIMA outliers and extreme values identified in the X11 algorithm were raised to adapt more rapidly to the change. By doing so, the evolving seasonally pattern is modelled in the seasonal contribution instead of the irregular. And when the seasonal component was removed, the magnitude of the remaining irregular component is reduced which makes it easier to decipher trend-cycle information from the seasonally adjusted series. Unfortunately, the log transformation is too aggressive in that it shrinks seemingly extreme observations to the point where they are almost indistinguishable from the rest of the series. Over-shrinking causes the seasonal factors to be underestimated, which still leaves large (fewer than before), intuitively hard to justify, month-to-month jumps in the seasonally adjusted series. To resolve this issue, one needs a transformation that reduces the range of the data without wiping out its intrinsic patterns. For the series shown here the fourth root is such a transformation. Figure 2 illustrates why it retains some of the larger seasonal peaks better than its log counterpart.

Figure 2: Comparison of log versus 4th root transformations



For large seasonal peaks the 4th root transformation retains much more of the original uniqueness. When the outlier limits are extended, more of the natural fluctuation in the data goes into the computation of the seasonal factors. This reduces the month-to-month changes. The figure below compares seasonally adjusted data using log and 4th root transformations, two different models, and default versus extended outlier limits. The four different seasonally adjusted series are: (i) D11(P=0.25) – 4th root transformation with outlier limits extended, (ii) D11(Log) – default set of options generated by the system, and (iii) D11(Log, P25 model) – log transformation with the same options as (i). Option (iii) is included to gauge the performance of a log transformation relative to the 4th root transformation while all other parameters are being kept the same. Options sets (i) and (iii) produce similar results in terms of the overall trend yet, judging by the raw data, the level generated by (i) is much more in line with expectations and the seasonal peaks are not as pronounced.

Figure 3: Seasonally Adjusted data for different models and transformations

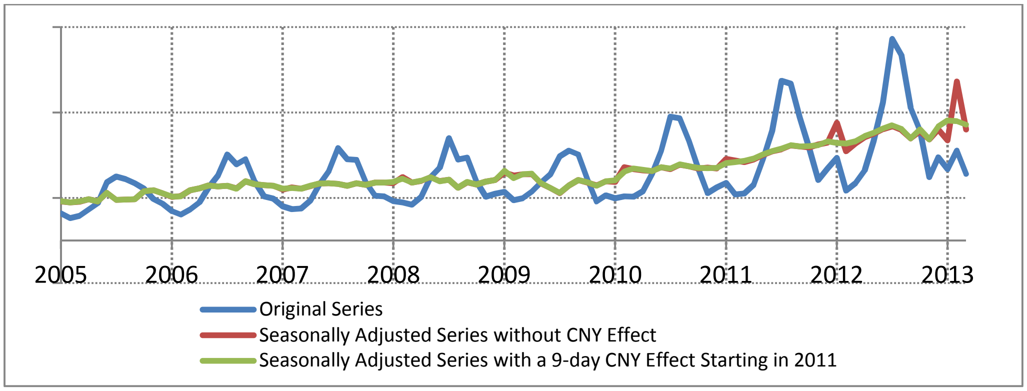


Example 2: New Calendar Effect. A monthly series tracking the number of visitors from an Asian country travelling to Canada started to act unexpectedly for the months of January and February, as illustrated by the red line in Figure 4. This came to our attention

as two of the last five January and three of the last five February data points were identified as outliers.

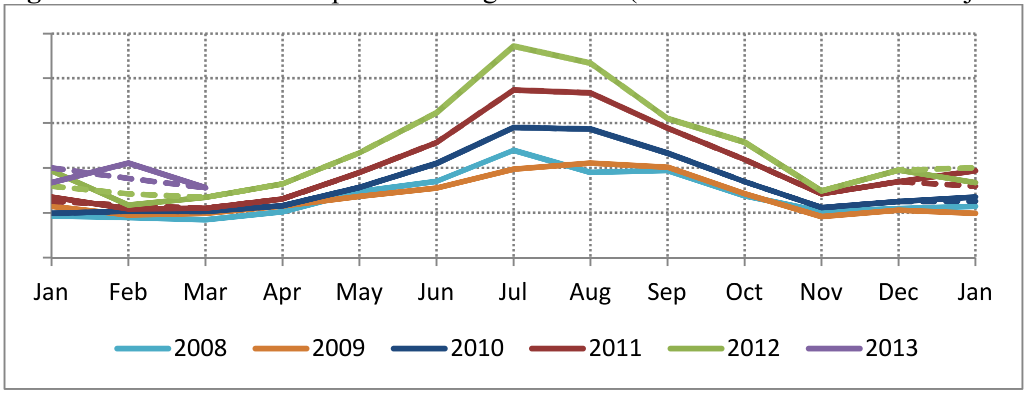
The Chinese New Year, which is a moving holiday that falls between January 21 and February 20 in the Gregorian calendar, may affect travel flows in the months of January and February for travelers coming from Asian countries that have adopted the *lunisolar* Chinese calendar. While this particular series was not affected by the Chinese New Year moving holiday (Lin and Liu, 2002) before, it now appears to be strongly influenced by it in recent years. After investigation, a 9-day Chinese New Year (CNY) effect starting in 2011 gave the best results, as illustrated by the green line in Figure 4. Although improvements in the adjustment are most apparent in 2012 and 2013, the seasonally adjusted series is also slightly smoother around January and February in 2010 and 2011.

Figure 4: Improvement to the Adjustment by Adding a New Calendar Effect



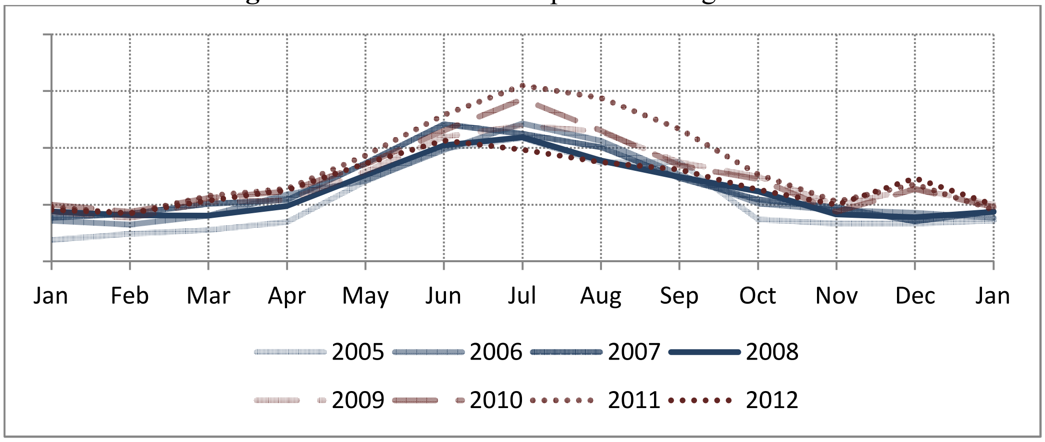
Improvements to the year on year lines for the calendar adjusted original data are also noticeable in Figure 5. With this new calendar effect, only one of the last five January and none of the last five February data points ended up being identified as an outlier. The newly introduced moving holiday effect, whose current *t*-value is 6.6, is in line with recent changes in the country's travelling policy that simplifies travel to Canada for its citizens. This being said, the effect will continue to be closely evaluated in the upcoming years.

Figure 5: Year on Year Graph of the Original Series (dashed lines are calendar adjusted)



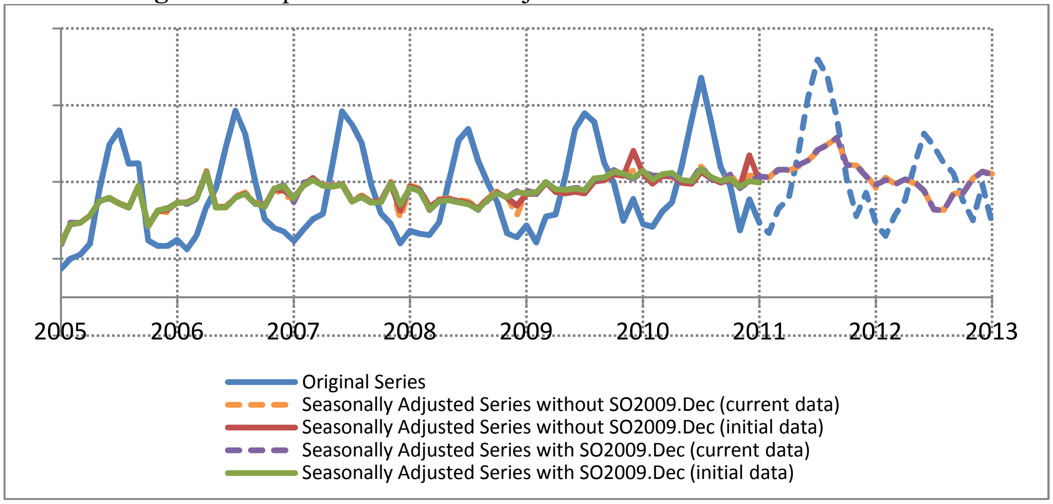
<u>Example 3: Sudden Change in the Seasonal Pattern.</u> Another interesting case was noticed in an international travel series using the new diagnostic on outliers in early 2011. At that time, four of the last five December series data points from 2006 to 2010 were identified as outliers. As the year on year graph illustrates (see Figure 6), a change in the seasonal pattern for December appeared to occur in 2009 for that series. The solid lines in Figure 6 illustrate the situation prior to 2009 while the dashed lines show the pattern change for December in 2009 and 2010. The dotted lines represent data for 2011 and 2012 that were not available at the time and seem to confirm the new pattern.

Figure 6: Year on Year Graph of the Original Series



After applying a REGARIMA seasonal outlier (SO) in December 2009, none of the five December data points from 2006 to 2010 were identified as outliers. The solid lines in Figure 7 show the improvement to the adjustment after implementing the seasonal outlier whose initial *t*-value was 3.03 back in 2011. The seasonally adjusted series is clearly smoother around December from 2008 to 2010, corresponding to three of the four December data points that were initially identified as outliers. The dashed lines in Figure 7 represent the adjustments with and without the SO, with data up to January 2013. A couple of points are worth mentioning here. First, the dashed line with the SO continues to perform well, confirming the adequacy of the seasonal outlier implemented in 2011. The SO's current *t*-value even slightly increases to 3.49. Second, the dashed line without the SO performs reasonably well around December from 2009 onwards, especially after 2010. This illustrates that even without the SO the seasonal filters do indeed eventually adapt to the new pattern. The situation is slightly different though around December 2007 and 2008 where the seasonally adjusted series with the SO clearly outperforms the one without the SO. This is explained by the fact that the 2007 and 2008 December data points are identified as outliers without the SO while they are not with the SO.

Figure 7: Improvement to the Adjustment with the Seasonal Outlier



This example clearly illustrates the power of the new diagnostic: identify problems while they are impacting the quality of the adjustment and allow for timely solutions.

<u>Example 4: Adding regressors to ARIMA model.</u> In this example, we consider a series representing the sales of a particular group of retail stores in Canada. The series is characterized by a general upward trend typical of retail trade, with a repeating seasonal pattern that includes elevated levels from July onwards, typically peaking in December. Seasonality appears to be fairly stable over time. The graph below shows the series from 2004 through to the end of 2010. What we notice in this period is a notable drop towards the end of 2008, when the economic downturn began. The level does appear to rebound in early 2009 not quite returning to the level from early 2008. However the usual seasonal pattern seems to be re-established by the middle of 2009. Based on information from analysts at Statistics Canada, the series was expected to be affected by the economic downturn during this period. Ideally, we wish to take steps to ensure that this unusual event not unduly affect the seasonal factors for this year and surrounding years.

Using the default tolerances for detection of outliers and extreme values as the series evolves, the X-12 ARIMA algorithm identifies very few REGARIMA outliers during this period. Instead, the unusual seasonal pattern leads to a number of months identified as extreme values and the values are down-weighted for October and December of 2008 when calculating seasonal factors. Based on information from analysts, a relatively gradual decline was expected in this series during the economic downturn. This pattern also seems plausible based on the graph of the series. The regressor that best represents this pattern and fits the data was found to be a ramp from September of 2008 to February of 2009. Once this relatively simple adjustment is applied to the data, the outlier-corrected series shows a much more consistent seasonal pattern in 2008 and 2009 relative to the other years in the series, with October and December 2008 data points no longer identified as extreme values.

Figure 8: Total sales of selected retail industry – raw (left) and outlier adjusted (right)

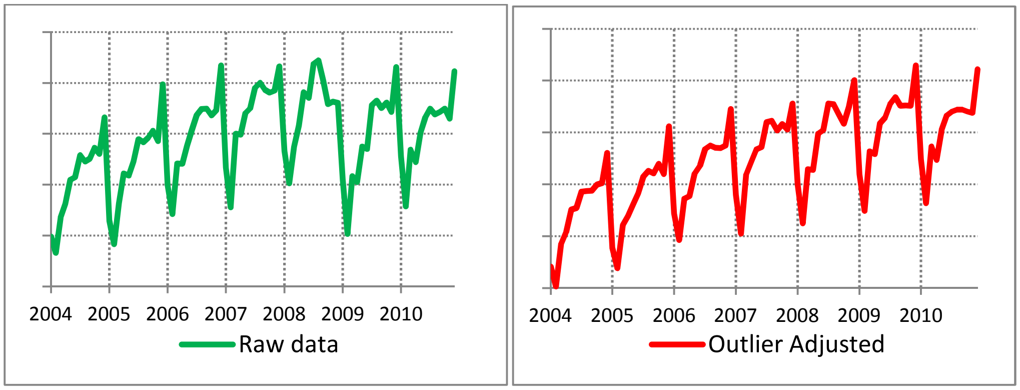
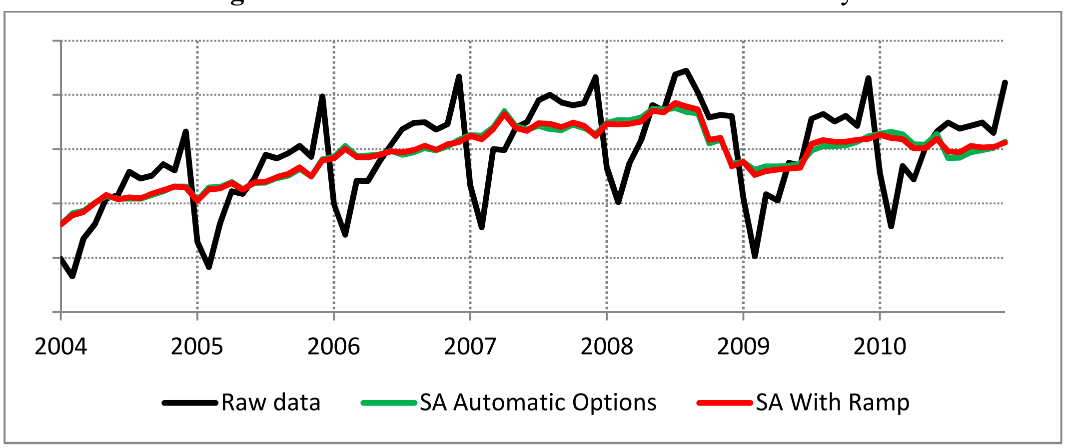


Figure 9 below shows the raw series, in addition to seasonally adjusted series that results from using two strategies for seasonal adjustment of the raw series extended through the end of 2010; one scenario represents default options for outlier detection and the second includes the effects of specifying the ramp regressor described above.

Figure 9: Total Retail Sales of Selected Retail Industry



Although the results are quite similar, the adjusted series with the ramp included appears to be somewhat smoother from mid-2008 onwards. By including this ramp regressor in the specifications for the seasonal adjustment of the series, a number of desirable outcomes were achieved:

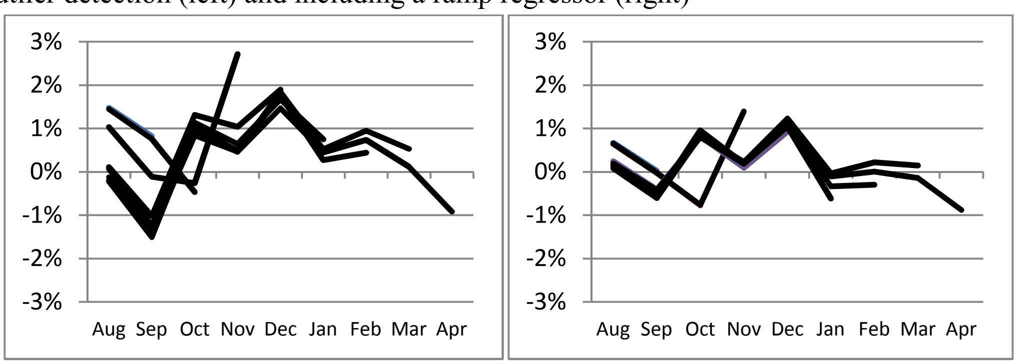
- The ARIMA model used in the algorithm is more stable. The model diagnostics are improved for the model that includes the ramp regressor. Note that this model is used to estimate trading day and Easter effects, in addition to forecasts.
- Protection against explainable economic events having undue influence on the estimated trading day and Easter regressors used throughout the series, as well as the estimated seasonal factors, particularly in years surrounding the event. This was evident as the seasonal factors estimated in the X11 algorithm vary less over time.

Based on these criteria, it seems that including the ramp regressor is preferable in terms of the overall seasonally adjusted series, once a number of subsequent observations are included. We now consider how the use of the ramp will affect the seasonally adjusted series as it is initially published during and immediately following the economic change. In particular, these types of economic changes can lead to significant revisions to the concurrent estimates, and we would like to minimize these revisions if possible.

To evaluate the options for doing so, we consider one scenario where the automatic outlier detection options are used as the series evolves and one where a ramp regressor is implemented gradually, beginning with the second month of the economic change, and extending the ramp month-by-month until the end of the economic change. Obviously, the level of subject matter knowledge required is different for the two scenarios: automatic outlier detection requires no subject matter knowledge whatsoever as any outlier regressors are automatically detected and tested for significance. The ramp regressor on the other hand requires fairly extensive subject matter knowledge as the economic event must be recognized almost immediately. Ideally the beginning and end of the event would be identified immediately, but once the beginning of the event has been identified, the extension of the ramp can be evaluated each month by examining the results of the statistics that are produced in the ARIMA modelling stage.

Figure 10 presents the series resulting from each of these scenarios, where the seasonally adjusted series for each reference month are expressed as a ratio with the corresponding month of the final seasonally adjusted series. By final seasonally adjusted series, we refer to the series that is estimated using the same model, but applied to the data extending to the end of 2010 as the expected revisions beyond this point should be negligible.

Figure 10: Revisions required from concurrent SA to final SA estimates under automatic outlier detection (left) and including a ramp regressor (right)



Clearly, the scenario where the ramp outlier is used allows us to track closer to the final seasonally adjusted values with our concurrent estimates, that is, it requires smaller revisions in order to arrive at the final seasonally adjusted series than does the use of automatic outlier options. We note that if a regressor was introduced that was later found to be inappropriate, these gains would presumable not be made, and in fact large revisions may be necessary to produce a reliable seasonally adjusted series. In order to introduce an appropriate regressor, we note that this does require information on the economic events as well as their exact timing, but we observe that making use of this information at an earlier time leads to smaller revisions to the series.

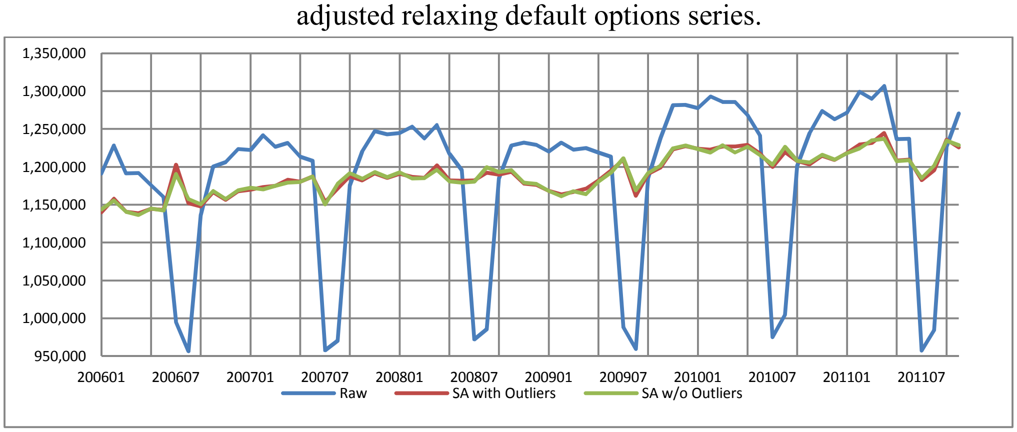
<u>Example 5: Uncertainty in seasonal pattern addressed by critical values for outlier detection.</u> The final example is a national employment series for a selected industry. It is relatively stable for most part with a large dip in July and August, when a lot of contract workers are being let go for the summer hoping to be rehired in September. This is not a recent trend but one that is more pronounced in the last 10 years. Anecdotal evidence and discussions with industry experts suggest that the industry is undergoing a restructuring where more and more workers are signed to 10-month contracts.

As this trend continues to strengthen, there is a corresponding increase in volatility of the counts in July and August. This manifests itself in employment going up somewhat in August after a large dip in July in some years, or going down marginally in others. This added volatility translates into identifying outliers either in July or August, depending on the dominant movement in the recent past. This, unfortunately, leads to some large month-to-month changes that are hard to explain to the end user.

Relaxing the outlier tolerance criteria allows for more of the summer volatility to become part of the seasonal factors. This has a positive dampening effect on the seasonally adjusted data, reducing the magnitude of monthly fluctuations. Recognizing that the industry may be undergoing an accelerated shift towards hiring workers on a contractual basis has enabled us to better understand the nature of the data and to explain the recent trends.

Figure 11 below presents a raw employment series showing the summer pattern visibly "*flip-flopping*", a seasonally adjusted series using default options, and a seasonally adjusted series with relaxed outlier detection and extreme values identification criteria. These changes allow some of the volatility present in the estimates in the summer months to move into the seasonal factors. As a result, residual seasonality overall and in the last three years is reduced. Other pertinent statistics remain largely unchanged. From Figure 11, it is evident that month-to-month movement is reduced as the series shrinks towards the trend.

Figure 11: Raw employment, seasonally adjusted using default options, and seasonally adjusted relaxing default options series.



4 Conclusions

This paper presents a number of recent examples of practical seasonal adjustment where interventions were made to address instability that was caused by volatility in the economy. A number of different approaches were used to address this volatility, and different outcomes were achieved. A few summary observations are given below:

- A number of signals are available to identify volatile periods, and in many cases these can be helpful to determine the type of intervention that is most appropriate.
- In general, the default approach appears to be somewhat robust to economic volatility. In most examples, the resulting seasonally adjusted series will be relatively similar whether or not we intervene, particularly after some time has elapsed after the intervention. The algorithm appears to produce logical results in response to this volatility either within the trend component, the seasonal component or the irregular component, depending on the pattern of volatility.
- In different contexts of volatility, different types of interventions appear to be appropriate. In some cases including specific regressors with the REGARIMA model gives good results and allows us to produce seasonally adjusted series that reflect economic events in a more timely fashion. In other cases fine-tuning parameters in the X11 algorithm allows us to be more conservative and avoid large revisions after the initial release.

Based on the examples presented in this article as well as other experience with seasonal adjustment at Statistics Canada, we continue to believe in the added value of practical seasonal adjustment. Although in some cases it can be fairly time consuming to develop the approach for an individual case, this investment leads to generally preferable results and less important revisions.

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