Toward X-13?

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Key Words: Model-based signal extraction, seasonal adjustment diagnostics, graphical diagnostics, component time series models.

Abstract:

What further developments can be expected in the X-12-ARIMA seasonal adjustment package? This paper will deal with two areas of development: an experimental version of X-12-ARIMA that produces ARIMA model-based seasonal adjustments from SEATS, and a program that uses alternative, possibly non-Gaussian, component time series models to perform the signal extractions. Examples of adjustments from each of the programs will be shown.

Disclaimer

This paper reports the results of research and analysis undertaken by Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications. This report is released to inform interested parties of ongoing research and to encourage discussion of work in progress.

1. Introduction

The U. S. Census Bureau's X-12-ARIMA seasonal adjustment program, whose basic functions are described in Findley, Monsell, Bell, Otto & Chen (1998), is used as the official seasonal adjustment method of dozens of statistical agencies and central banks around the world. The program has been under development since 1988 (Findley, Monsell, Otto, Bell & Pugh 1988) and will soon have all the features originally conceived for it (as well as others suggested by users and experts). This paper discusses new directions being considered for the Census Bureau's seasonal adjustment software.

An area of continuing research is the use of model-based seasonal adjustment to improve the adjustments of our series. This paper will concentrate on two alternatives dealing with model-based approaches to seasonal adjustment.

The first is an experimental version of X-12-ARIMA that produces model-based seasonal adjustments from the SEATS seasonal adjustment procedure (Gómez & Maravall 1997) and is a collaboration between the Census Bureau with the current developers of SEATS, Agustín Maravall and Gianluca Caporello. This program allows users to generate X-11 and SEATS seasonal adjustments using the same interface and to compare these seasonal adjustments using a common set of diagnostics. This paper will discuss how SEATS adjustments are integrated into the X-12-ARIMA procedure, and show examples of the types of seasonal adjustment and graphical diagnostics available for model-based seasonal adjustments (produced by X-12-Graph (Hood 2002*b*), the graphical companion to X-12-ARIMA).

Another possibility is to use component time series models to perform the signal extraction. Whilst these may be derived from a fitted ARIMA model of the observed data, the method is not restricted to this case alone. Models which can be estimated include structural time series models such as those developed in Kitagawa (1981) and Harvey & Todd (1983). A flexible implementation allowing easy specification of different models has been developed using the SsfPack software module of the Ox matrix programming language. This allows the incorporation of heavy-tailed distributions into certain components within the model. Examples of robust seasonal adjustments using this method will be shown.

2. The X-12-ARIMA/SEATS Prototype

X-12-ARIMA/SEATS is the current name for the product of a collaboration between the developers of X-12-ARIMA and SEATS. It is a prototype of a merged version of the two programs. This prototype was developed to assist in evaluating the effectiveness of model-based seasonal adjustment and to allow for the seamless integration of these adjustments into production processes that currently are designed to use only X-12-ARIMA.

With this prototype, analysts have access to SEATS seasonal adjustments using the familiar X-12-ARIMA input syntax, and can compare SEATS and X-12-ARIMA seasonal adjustments using the seasonal adjustment diagnostics produced by the X-12-ARIMA seasonal adjustment program, most notably the spectrum, sliding spans and history diagnostics (Findley et al.

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1998), as well as the diagnostic graphs of X-12-Graph (Hood 2002*b*).

This program includes all the signal extraction routines from the SEATS seasonal adjustment program. To minimize revisions to the base SEATS code, an interface routine available within the standard SEATS source code is used as an interface between the signal extraction code and source code used to generate seasonal adjustment diagnostics and other special output. Additional routines allow for the transfer of regARIMA model information from the data structures used in X-12-ARIMA's model estimation procedures to the format required for use with SEATS.

The version of X-12-ARIMA used in this prototype has an updated model selection procedure based on the procedure found in the TRAMO time series modeling program (Gómez & Maravall 2000). This automatic model identification procedure uses elementary unit root tests and likelihood statistics to select an appropriate ARIMA model for the series. See Monsell (2002) for more details.

As mentioned previously, the program uses the same user interface conventions as previous versions of X-12-ARIMA. To specify a SEATS seasonal adjustment within the prototype, the user specifies options within a separate `seats` spec. All options deemed useful by the developers of SEATS from the stand-alone SEATS program are available to users of X-12-ARIMA/SEATS; these can be set by specifying arguments within the `seats` spec. Users can save the components of SEATS seasonal adjustments in external files using the save argument in the same format used to save other tables in X-12-ARIMA.

Table 1 shows a sample X-12-ARIMA/SEATS spec file, which generates a default SEATS seasonal adjustment and saves the seasonal component of the SEATS adjustment to a separate file.

```
series{title= "US Imports"
  format="datevalue"
  file="m0.dat"
  name="m0"  }
transform { function=log }
arima{ model=(0 1 1)(0 1 1) }
forecast{ maxlead = 24 }
seats { save = s10 }
slidingspans { savelog = pct }
```

Table 1: X-12-ARIMA/SEATS input file for initial run of U. S. Imports

Note that currently the program can only perform either a SEATS or an X-11 seasonal adjustment from a given spec file. SEATS adjustments generated by the X-12-ARIMA/SEATS prototype can be slightly different from results derived from the stand-alone version of the SEATS program, even if the same model is specified, due to differences in the regARIMA model estimation procedures of TRAMO and X-12-ARIMA.

2.1 Diagnostics

Hood, Ashley & Findley (2000) pointed out that the TRAMO and SEATS programs lack some important diagnostics and can leave users unaware of severe problems in SEATS seasonal adjustments. A critical feature of this prototype is the ability to generate the same seasonal adjustment diagnostics for X-11 seasonal adjustments as well as SEATS model-based seasonal adjustments. This allows for much easier comparison between the two methods. This section briefly describes several of the most important diagnostics produced by the X-12-ARIMA/SEATS prototype.

Sliding spans diagnostics compare seasonal adjustments from overlapping spans of a given time series. Up to four spans of data are chosen, with the final span ending in the last year of the series, and the preceding spans formed by dropping a year of data from the end of the span and adding a year of data to the beginning of the span. Data points common to more than one span are examined to see if their adjustments are stable – observations whose adjustments are too variable from span to span cannot be considered reliable. For more details, see Findley, Monsell, Shulman & Pugh (1990) and Findley et al. (1998).

For X-11 seasonal adjustments, the length of each span is determined by the seasonal adjustment filter used in the adjustment; a longer filter means a longer span will be used in the sliding spans analysis. This determination cannot be done for SEATS seasonal adjustments; instead, research has begun on determining an objective criterion for setting the span length based on the relative standard error of the seasonal component (Aston, Feldpausch, Findley, Hood & Wills 2003). Such a criterion has been implemented into the X-12-ARIMA/SEATS prototype; it uses the estimate of the first order seasonal moving average coefficient of the regARIMA model to determine the span length.

Revisions history diagnostics are another method of assessing the stability of a seasonal adjustment. The basic revision is the difference between the initial seasonal adjustment (often referred to as the *concurrent* adjustment) and the seasonal adjustment with all the data available at the time of the analysis (often referred to as the *final* adjustment). Let $A_{t|t}$ be the seasonal adjustment at time t for data up to time t, and $A_{t|T}$ be the seasonal adjustment at time t for the data up the end of the series at time T. The percent revision for the seasonal adjustment at time t is defined as

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

Similar revisions can be generated for the month-to-month changes in the seasonally adjusted data, the trend estimates, and the trend changes.

Revisions history diagnostics can be useful in comparing different seasonal adjustment methods, checking recent large revisions to see if they are within the range of past large revisions, or deciding whether different seasonal adjustment options can offer improvements to the overall average revision or the revisions in a particular month or year. Graphs of the revisions histories can also be used to detect problems in adjusting specific observations. For more details, see Findley et al. (1998) and Hood (2002*a*).

Graphical diagnostics for the program can be generated from a SAS®[1] software application called X-12-Graph, the companion graphics program for X-12-ARIMA. X-12-Graph uses output from the X-12-ARIMA program to generate several types of graphs useful for seasonal adjustment: overlay graphs of the original series and seasonal adjustment components; component plots of up to 4 components from an X-12-ARIMA seasonal adjustment; special plots of the seasonal component; graphs of the revisions histories of a given adjustment; and many others. An example of a seasonal factor by month plot from a SEATS adjustment is given in Figure 1. For more details on X-12-Graph, see Hood (2002*b*).

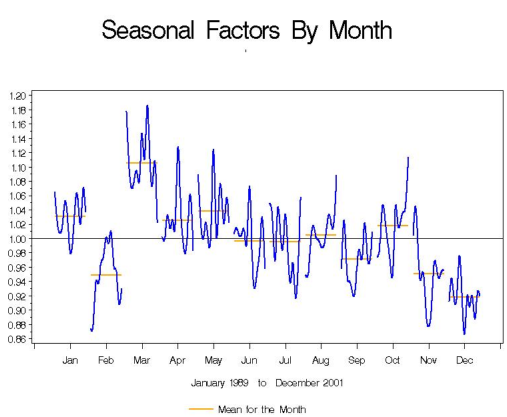

Figure 1: Seasonal factor by month plot from a SEATS adjustment of Imports of Rubber Products (source: U. S. Census Bureau).

Spectral graphs are another important form of graphical diagnostic that is produced both in the X-12-ARIMA output and by X-12-Graph. The prototype produces spectral plots of the regARIMA residuals, the final SEATS seasonal adjustment and the final irregular component from a SEATS seasonal adjustment. The plots are marked at frequencies commonly associated with seasonal and trading day variation, so the user can easily check for residual effects in the model residuals or seasonal adjustment. The alias frequencies for trading day variation were first documented by Cleveland & Devlin (1980).

The program also searches each of the spectra for peaks at the seasonal and trading day frequencies. A warning message is printed out if visually significant peaks are found, and the plot in which a peak was found is printed out. For more information on this procedure, see Soukup & Findley (1999).

2.2 Example: Retail Sales of Shoe Stores

To show some of the features of the current prototype and X-12-Graph, we will examine a Census Bureau series which measures monthly retail sales of shoe stores from January 1984 to February 1998. The X-12-ARIMA spec shown in Table 2 appears to be a reasonable start – the program identifies an ARIMA model using the automatic model identification routine, and generates a default SEATS seasonal adjustment using the identified model.

```
series{
  title= "Retail sales shoe stores"
# automatic ARIMA model and
# transformation identification,
# default SEATS adjustment
  format="2L"
  span=(1984.1,1998.2)
  file="shoers.dat"
  name="S0B566" }
transform { function=auto }
automdl { }
check { }
seats { }
```

Table 2: X-12-ARIMA/SEATS input file for initial run of U. S. Retail Sales of Shoe Stores (Jan 1984-Feb 1998, source: U. S. Census Bureau)

In this run, the automatic transformation procedure determines that the series requires a log transformation, and the automatic model identification procedure selects an ARIMA (0 1 1)(0 1 1) model (referred to as the "airline model" in Box & Jenkins (1976)). The SEATS routines within the prototype use the Ljung-Box Q statistic of the regARIMA residuals as a check the adequacy of the model, see Ljung & Box (1978). The Ljung-Box Q

[1]SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ®indicates USA registration.

```
series{
  title= "Retail sales shoe stores"
# final ARIMA model, default SEATS adjustment
# sliding spans and revisions history
  format="2L" file="shoers.dat"
  span=(1984.1,1998.2) name="S0B566"
}
transform { function=log }
regression { variables = ( td easter[8] AO1995.Feb ) }
arima { model = ( 0 1 1 )( 0 1 1 ) }
check { }
forecast{ maxlead=24 }
seats{ }
slidingspans{ fixmdl = no savelog = pct }
history { estimates = ( sadj trend sadjchng ) }
```

Table 3: X-12-ARIMA/SEATS input file with final regARIMA model of Retail Shoe Store Sales. This spec file generates the sliding spans and revisions history results for SEATS found in Table 4.

statistic at lag 24 is 23.02 (with a p-value of 0.4), and the model is accepted. However, Figure 2 shows that there is significant residual trading day variation in the regARIMA model residuals, (and the Q-statistics at lags 3, 4, and 5 are unsatisfactory).

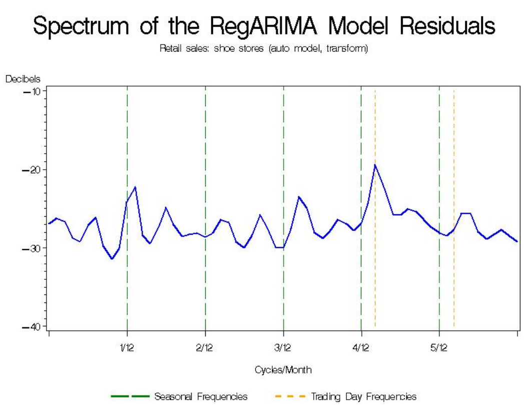

Figure 2: Spectrum plot of the final 8 years of the regARIMA residuals, Retail Shoe Store Sales. Note the peak at the first trading day frequency.

Including trading day regressors in the model eliminates the trading day spectral peak in Figure 3, and the estimates for the ARIMA model coefficients change substantially when trading day and holiday regressors are included in the model. For example, the estimate for the seasonal MA parameter Θ_{12} changes from 0.54 without trading day and Easter regressors to 0.33 with these effects included in the model, and all Q-statistics for the model residuals are satisfactory when they are included.

After determining the final form of the model, sliding

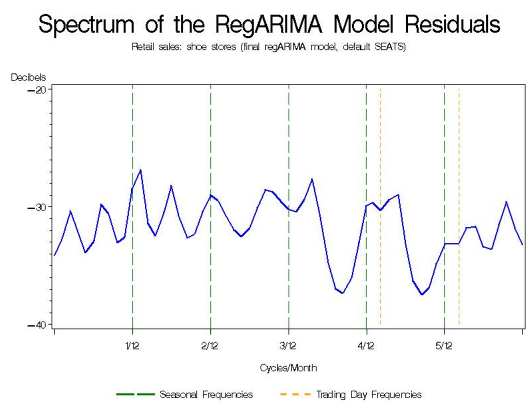

Figure 3: Spectrum plot of the final 8 years of the regARIMA residuals with trading day regressors included in the model of Retail Shoe Store Sales.

spans and revision history diagnostics were generated for default X-11 and SEATS seasonal adjustments. The span length used in the sliding spans analysis for both adjustments was set based on the value of the seasonal MA coefficient estimate for the regARIMA model as described in Aston et al. (2003).

These diagnostics are summarized in Table 4. The first three diagnostics listed are the percentage of months flagged for unstable seasonal factors (S(%)), seasonal adjustments (A(%)), and month-to-month changes in the adjustments (M(%)). While both adjustments are well within the acceptance criteria given in Findley et al. (1990), the SEATS adjustment is clearly more stable than the default X-11 adjustment.

Similarly, the revisions measures given in the table show that the SEATS adjustments have slightly more stable revisions measures than those for default X-11.

Diagnostic	X-11	SEATS
S(%)	3.5	1.2
A(%)	8.5	1.2
M(%)	10.2	1.2
AAR - Adjusted Data	0.848	0.773
AAR - Change in Adjusted Data	0.757	0.700
AAR - Trend	0.839	0.753

Table 4: Seasonal Adjustment Diagnostics for Default X-11 and SEATS (AAR = Average Absolute Revision)

2.3 Future Plans

There are several areas of development for the X-12-ARIMA/SEATS prototype to be completed before its release.

- Seasonal outlier effects will be added to the predefined regression variables that can be specified in regARIMA models, and the automatic outlier identification procedure will identify seasonal outliers. The seasonal outlier to be implemented is equivalent to the Seasonal Level Shift outliers described in Kaiser & Maravall (2002) as well as the seasonal outlier of Bell (1983).

- Pulse and intervention regressors of the same type as are currently in TRAMO will be added to the regARIMA modeling procedure. These regressors make it possible to perform intervention analysis of the type outlined in Box & Tiao (1975).

- Spectral diagnostics for the infinite concurrent adjustment filter will be added to the software, and plots of this diagnostic will be made available so that properties of these filters can be studied (see Findley & Martin (2003) for more information).

- Currently, the format of the SEATS output of the program is identical to that produced by the DOS version of SEATS, which is different than the X-12-ARIMA output format of the rest of the program. The tabular output of the program will be standardized, with labels assigned to each of the tables. The user will be given more control over which output tables can be stored or saved than SEATS currently offers.

- New or modified diagnostics resulting from ongoing research on diagnostics for model-based seasonal adjustments will be incorporated into the X-12-ARIMA/SEATS prototype.

3. Component Modeling

After log or other transformation, if needed, seasonal time series are commonly regarded as having a seasonal-trend-irregular decomposition of the form . Sometimes there are additional additive components, for transitory effects, sampling errors, etc. For nonseasonal series, decompositions not involving a seasonal component are frequently used. Modeling of a series that has a decomposition into unobserved components often involves, directly or indirectly, the assignment of a model form to each decomposition component, usually a regression or ARIMA model or a combination of the two (a regARIMA model). Kitagawa & Gersch (1984) and Harvey (1989) describe structural models based on directly specified component model types. Linear models with drift are used for trend components and, in the latter reference, trigonometric models for the seasonal components. Hillmer & Tiao (1982) developed different specifications of component models tied to a fitted ARIMA model. This allowed traditional ARIMA type structures such as the airline model (Box & Jenkins 1976) to be considered with reference to separate seasonal, trend, and irregular components, facilitating for example, seasonal adjustment of the series with these models.

3.1 Software for Model-Based Seasonal Adjustment

Harvey's approach is implemented in STAMP (Koopman, Harvey, Doornik & Shephard 2000), and the Hillmer and Tiao approach is implemented in SEATS (Gómez & Maravall 1997). These two programs are often seen as fundamentally different, but the methods they use are just part of a wider class of component models. If a state-space representation is used for both types of model, it can easily be seen just how similar they are. The approach of Kitagawa & Gersch (1984) was also specified in state space form. Its latest software implementation, Web Decomp, can be accessed directly at *http://ssnt.ism.ac.jp/inets2/title.html*.

3.2 RegComponent

Bell (2003) provides the first extensive formal discussion of time series models with a regression mean function and an error process that is sum of independent component time series, each being a known scalar multiple (e.g. 1.0) of a time series that follows an individual ARIMA model. This reference also describe a software program developed at the Census Bureau for estimating the unknown parameters of these RegComponent models, as they are called. Such models obviously include the structural models of Kitagawa & Gersch (1984) and Harvey (1989), but the paper describes three other kinds of examples, including model with time varying trading day regression coefficients. Once all parameters are specified, for example after parameter estimation or by inputting the parameter values of the canonical seasonal decomposition models of an estimated regARIMA model following Hillmer & Tiao (1982), this program, named RegCMPNT, can calculate the optimal linear estimates of the unobserved components using a state space smoothing algorithm. (RegCMNT does not calculate the parameter values of the component models of the canonical decomposition itself, so these must be obtained externally.)

3.3 Gaussian vs. Non-Gaussian

So far all the methods considered are based on assuming Gaussian disturbances for the components. However, there are instances where departures from this assumption would be preferred. One major application of non-Gaussian models is to help in the modeling of outliers. Seasonal adjustment can be affected by outliers in the data. Whilst additive outliers are essentially associated with the irregular component, they can lead to changes in other components. As most series are constantly being updated with further data, if Gaussian outlier detection methods are used, based on a cutoff threshold for deciding whether an outlier has occurred, outliers can come into and out of a model of a time series as time passes and observations are added to the series. This can lead to instabilities in all components. If, however, a non-Gaussian distribution, e.g. a t-distribution, is used, no threshold is needed and each datum is weighted according to the probability of its being an outlier. This allows a more continuous approach to the modeling of outliers in time series, and hence more robust seasonal adjustments.

However, adding non-Gaussian components increases the computational burden as the likelihood now need to be computationally assessed as opposed to their being explicit analytical solutions. However, recent advances in state space modeling with non-Gaussian disturbances through the use of importance sampling (Durbin & Koopman 2000) has helped to make this task easier.

3.4 The Implementation

A program implementing models with non-Gaussian components has been designed in the object-oriented matrix programming environment of `Ox`, see Doornik (2001). Extensive use is made of the state space functions in the `SsfPack` library, see Koopman, Shephard & Doornik (1999). For Gaussian models, once the model is in state space form, the Kalman filter can be used to construct the exact likelihood function. By contrast, non-Gaussian estimation of the model is carried out using the importance sampling and simulation methods described in detail in Durbin & Koopman (2000) and Durbin & Koopman (2001).

The fundamental idea behind the program is to incorporate different parts of the above ideas into a single program. Firstly it allows the model flexibility of RegComponent to handle many types of component models rather than choosing one of either SEATS or STAMP. Also, it is able to calculate the ARIMA component model decompositions used in SEATS and thus apply non-Gaussian error terms to components. This flexibility allows an integrated approach to seasonal time series modeling.

3.5 Example: U. S. Automobile Retail Series

The U. S. Census Bureau series, Retail Sales of Automobiles January 1967 to March 1988, was examined. It was determined that there were outliers present using the full data set. However when a shortened subset of the data was taken (Jan 1977-Mar 1988), it was found that the outliers, assumed to be in the data, depended on the threshold that was chosen for outlier detection. If a relatively small threshold was used (that is 3.0) then just two of the three outliers determined were found, whilst if this number was larger (that is 4.5) then none of the outliers were detected. Typical values of thresholds used in seasonal adjustment tend to be high due to the large number of tests being performed. The difference in the seasonals found allows illustration of the advantages of using a t-distribution, as a predetermined threshold for the detection of the outliers is not required.

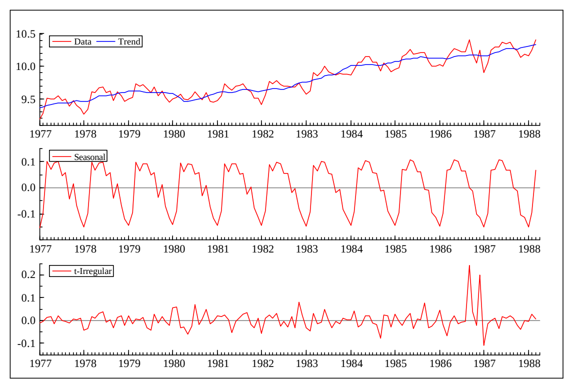

Figure 4: U. S. Retail Sales of Automobiles (Jan 1977-Mar 1988, source: U. S. Census Bureau) and estimated components from a three-components model with t-distribution for outlier component: (top) series y_t and trend T_t; (middle) seasonal component S_t; (bottom) outlier component O_t.

The components resulting from fitting the model with the t-distribution to account for outliers can be seen in Figure 4. This is a SEATS type decomposition of the airline model. However, the irregular term is modeled using a t-distribution, and thus the decomposition is done within each maximum likelihood estimation step, as opposed to the SEATS method of estimating the final ARIMA model and then performing the decomposition.

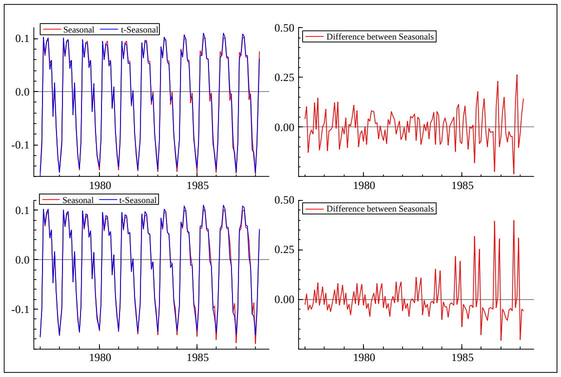

Figure 5: U. S. Retail Sales of Automobiles (Jan 1977-Mar 1988, source: U. S. Census Bureau) and estimated components from a Gaussian model and a three-components model with t-distribution for the irregular component: (top) seasonal component from Gaussian model with outlier threshold value of 3.0 (seasonal) and seasonal from three-components t-model (t-seasonal) and the difference between the two series; (bottom) seasonal component from Gaussian model with outlier threshold value of 4.5 (seasonal) and seasonal from three-components t-model (t-seasonal) and the difference between the two series. The differences are normalized to the root mean square of the seasonal signal.

In Figure 5, the seasonal components from the two different models are overlayed with the two different threshold levels on the subsequent graphs. As can be seen, if the threshold is set too high, in this case, the seasonality is markedly different from the seasonality determined using the three component t-distributed model as the presence of the outliers is not detected. It is most noticeable towards the end of the series. This can be more easily seen in the difference between the two. It should also be noted that even though the changes in seasonality are largest (up to 40% of the root mean square of the seasonal signal) near the outliers, they are still present even in months much earlier than the outliers. However, as can also be seen, if the outliers are detected then the seasonal components in the Gaussian and t-case are much more alike. Even subtle changes can have a big effect, especially on yearly changes of seasonally adjusted data. Thus it is likely that the problem of where to set the threshold, so that only outliers are removed and not actual data, can be ignored if a t-distribution is used, where no predetermined threshold is needed.

3.6 Conclusion

The program described here allows for the use of different modeling procedures in a single framework. It gives a flexibility to the modeling procedure whilst also adding an ease of use through the common interface to all the different model types.

4. Acknowledgements

The X-12-ARIMA/SEATS prototype would not be possible without the assistance of Gianluca Caporello and Agustín Maravall, who made the source code of SEATS programs available for study and implementation and generously shared their expertise.

The authors are also grateful to Bill Bell, David Findley, Donald Martin, and Kellie Wills for their collaboration and assistance in developing both the X-12-ARIMA/SEATS prototype and the Ox component modeling module; to Catherine Hood, Golam Farooque, Roxanne Feldpausch and Kathleen McDonald-Johnson of the Time Series Methods Staff for their work developing X-12-Graph and other utility programs for X-12-ARIMA, testing various versions of the X-12-ARIMA software, and making suggestions that continue to help shape X-12-ARIMA/SEATS; and to Trang Nguyen and Michael Furchtgott for data and testing of the Ox component modeling module.

We thank Kathleen McDonald-Johnson and David Findley for their careful reading of a draft of this document.

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