Seasonal Adjustments: Causes of Revisions

Øyvind Langsrud
Statistics Norway, Oyvind.Langsrud@ssb.no

August 15, 2011

ABSTRACT

X-12-ARIMA is a frequently used tool for seasonal adjustment. To find the best decomposition into trend, seasonal and irregular components several modeling decisions have to be taken. When a new data point is available we also have new information about the seasonal pattern and the decomposition model can be updated. The consequence is that seasonally adjusted data are revised. Choosing seasonal adjustment methodology can be viewed as a question of balancing the requirement of optimal seasonal adjustment at each time point against the requirement of minimal revisions.

In this paper history analysis of 52 Norwegian economic time series has been conducted. Seasonal adjustment revisions are mainly caused by revisions of seasonal factors. Revisions of prior adjustments (calendar effects) are less important. This paper demonstrates how several modeling choices (ARIMA model, trading day, holiday treatment) affect revisions. The treatment of outliers (extreme observations and level shifts) is related to both prior adjustments and seasonal factors. When a completely automatic procedure for detecting outliers is applied, re-identification of outliers leads to big revisions. This paper demonstrates how revisions and out-of-sample forecasts (quality of model) are affected by the outlier detection limit. The analyses were made by running X-12-ARIMA via the R programming language.

Introduction

Times series analysis by using regARIMA models (linear regression models with ARIMA time series errors) is an important part of seasonal adjustment methodology. Alternative modeling variants can be compared fairly by looking at out-of-sample forecasts and revisions. How well the regARIMA models describe the data can be evaluated by out-of-sample forecast diagnostics. Since the model changes over time, the level of revisions is another important quality aspect.

In X-12-ARIMA revision diagnostics are based on absolute values of relative differences. On the other hand, the history analysis of X-12-ARIMA produces sums of squared out-of-sample forecast errors based on log-transformed data. However, in this paper, revision

Table 1: *Difference measures used to calculate root mean square error (RMSE).*

	Difference measure
One-month revisions of seasonally adjusted data	$\log(A_{t\|t+1}) - \log(A_{t\|t})$
One-year revisions of seasonally adjusted data	$\log(A_{t\|t+12}) - \log(A_{t\|t})$
First-year average absolute month-to-month revisions of seasonally adjusted data	$\frac{1}{12}\sum_{h=1}^{12}\left\|\log(A_{t\|t+h}) - \log(A_{t\|t+h-1})\right\|$
One-month out-of-sample forecasts	$\log(Y_{t+1\|t}) - \log(Y_{t+1})$

differences and forecast errors will be treated in a similar way. Technical details are described in the next section. The later section will illustrate how ARIMA model selection procedures and outlier detection procedures affect revisions and forecasts.

A unified approach for forecast errors and revisions

Assume a time series Y_t where $t = 1, 2, \dots, N$. By using time series modeling, an h-step ahead forecast, $Y_{t+h|t}$, can be produced. The relative forecasting error on the original scale is approximately equal to the absolute error on the log scale (natural logarithm). More precisely we have the inequality

$$\frac{Y_{t+h|t} - Y_{t+h}}{Y_{t+h|t}} \le \Big(\log(Y_{t+h|t}) - \log(Y_{t+h})\Big) \le \frac{Y_{t+h|t} - Y_{t+h}}{Y_{t+h}} \tag{1}$$

Thus, the log-scale difference can be interpreted as a relative difference. Furthermore, it can be viewed as a compromise between $Y_{t+h|t}$ and Y_{t+h} as the denominator when calculating the relative difference.

The forecasting errors on a time interval can be summarized as the root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N_1 - N_0 + 1}\sum_{t=N_0}^{N_1}\Big(\log(Y_{t+h|t}) - \log(Y_{t+h})\Big)^2} \tag{2}$$

The relation between relative difference and log-scale difference can be expressed similarly for seasonal adjusted data. That is

$$\frac{A_{t|t+h} - A_{t|t}}{A_{t|t}} \approx \Big(\log(A_{t|t+h}) - \log(A_{t|t})\Big) \tag{3}$$

where $A_{t|t+h}$ is the seasonal adjustment of Y_t calculated from the series where Y_{t+h} is the last observation. Commonly, percentage revisions (multiply by 100%) are based on the left

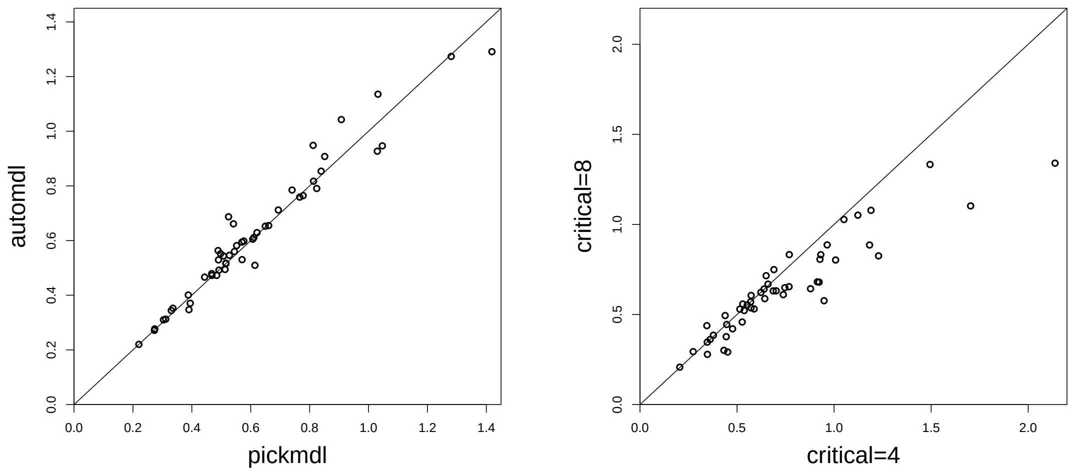

Figure 1: *RMSE of* ***one-month revisions*** *of seasonally adjusted data. Results from the history analysis of 51 series are plotted. Two ARIMA model selection procedures (left panel) and two outlier detection limits (right panel) are compared. The diagonal line represents equal values.*

side of this expression. However, in this paper, the log-scale difference is used (right side). Note that in practice the difference between the two approaches are almost negligible.

Below, monthly data will be analyzed and three types of revision measures will be considered. In addition we will look at one-month out-of-sample forecasts. All four measures are described in Table 1. The RMSE in equation (2) corresponds to the last line in Table 1 ($h = 1$). Below we also summarize revisions by calculating the RMSE similar to equation (2). Then, the expression inside the brackets is replaced by a difference measure in Table 1.

History analysis of 52 series

We consider 52 Norwegian economic time series. There are 32 series that are related to the production index (years 1989-2009). The addtional 20 series are related to the index of household consumption of goods (years 1979-2009). The time intervals for the history analyses are set to the last 14 and 20 years, respectively.

Two ARIMA model selection procedures were compared; `automdl` (default) and `pickmdl`. When using `pickmdl` only five model candidates were allowed. The `automdl` procedure selects the model from a broader range of candidates. To ensure that the ARIMA model was the only modeling difference, fixed outliers were used. These outliers were found from a single analysis of the whole series by using the ARIMA model according to `automdl`. Effects of trading days and moving holidays were included in the regression specification.

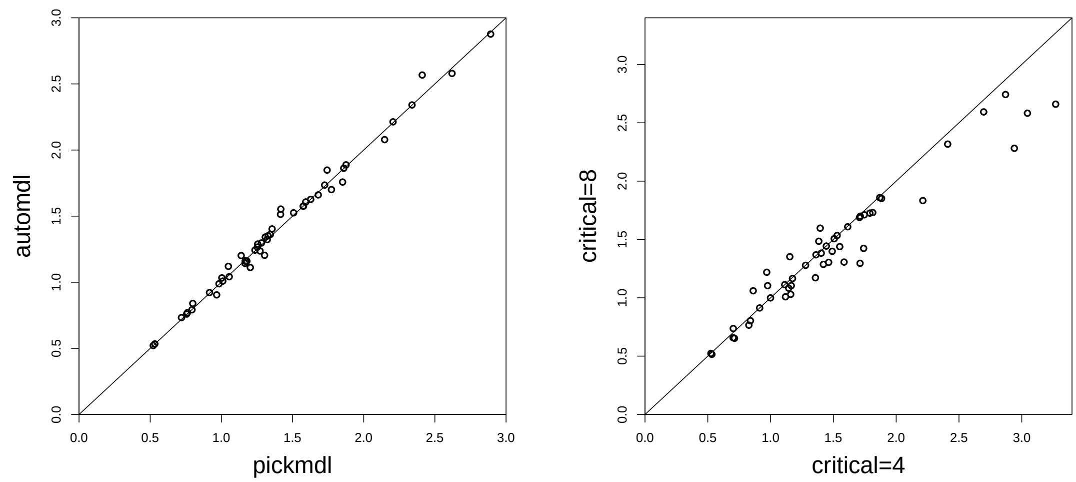

Figure 2: *RMSE of* ***one-year revisions*** *of seasonally adjusted data. Results from the history analysis of 51 series are plotted. Two ARIMA model selection procedures (left panel) and two outlier detection limits (right panel) are compared. The diagonal line represents equal values.*

Two outlier detection limits ($t = 4$ and $t = 8$) were compared in a similar way. Both additive outliers and level shifts were allowed. The results are given in Figures 1-4. Each point in each scatter plot represent the results from one series and RMSE were calculated as described above. The values of the axes are percentages. One series with extreme behaviour was omitted from the plotting (because of axis limits).

Concluding remarks

The above plots illustrate overall differences between two methods. Note that these overall differences are caused by important single-observation differences (e.g. when the model changes). The results illustrate that purely automatic use of X-12-ARIMA leads to revision problems. These problems can be reduced by using `pickmdl` instead of `automdl` and by increasing the outlier detection limit. However, a better solution is to handle these problems in a non-automatic way.

The analyses were done by running X-12-ARIMA several times using the R programming language. This is more flexible than the built-in history procedure. We now use this program system to investigate the treatment of holidays at Statistics Norway.

The oral presentation will contain additional results. The treatment of trading days and holidays will be analysed. Furthermore, plots based on non-squared differences will also be shown.

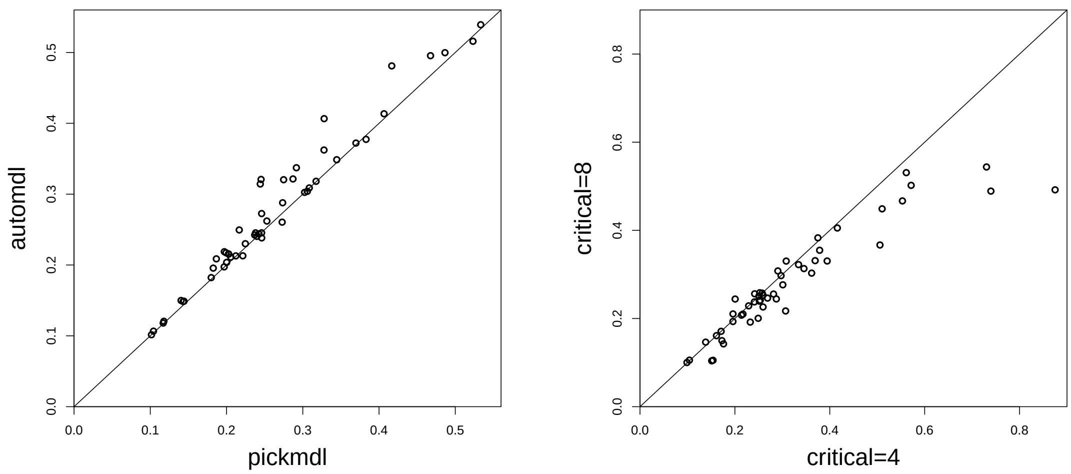

Figure 3: *RMSE of* ***first-year average absolute month-to-month revisions*** *of seasonally adjusted data. Results from the history analysis of 51 series are plotted. Two ARIMA model selection procedures (left panel) and two outlier detection limits (right panel) are compared. The diagonal line represents equal values.*

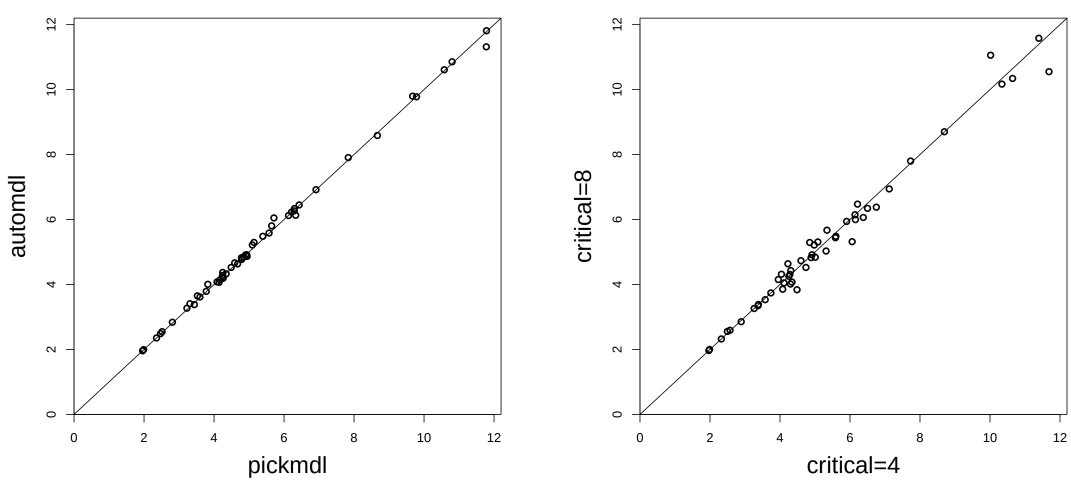

Figure 4: *RMSE of* ***one-month out-of-sample forecasts****. Results from the history analysis of 51 series are plotted. Two ARIMA model selection procedures (left panel) and two outlier detection limits (right panel) are compared. The diagonal line represents equal values.*