EFFECTS OF FORECASTS ON THE REVISIONS OF CONCURRENT SEASONALLY ADJUSTED DATA USING THE X-11 SEASONAL ADJUSTMENT PROCEDURE

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ABSTRACT
Three ARIMA forecast extension procedures for Census Bureau X-11 concurrent seasonal adjustment were empirically tested. Forecasts were obtained from fitted seasonal ARIMA models augmented with regression terms for outliers, trading day effects, and Easter effects. Revisions between initial and final seasonally adjusted values were computed. Ranked ANOVAs were used on various revision measures to determine the statistical significance of the differences between the extension procedures. The main conclusion was that extending the series with enough forecasts to apply a symmetric filter reduced the revisions over not extending the series and using asymmetric filters. This result held whether the model used was one carefully fit by the analyst or was a simple default model. Extension of the series with only one year of forecasts was also examined.

KEYWORDS: Census X-11, X-11-ARIMA, Concurrent seasonal adjustment, Forecasting

Introduction

Seasonal adjustment is the decomposition of a time series into seasonal and non-seasonal components. The additive decomposition is

$$Z_t = N_t + S_t$$

where Z_t is the unadjusted series and N_t and S_t are respectively the non-seasonal and seasonal components. The multiplicative decomposition, more commonly used with economic time series, is

$$Z_t = N_t \cdot S_t$$

or in terms of logs,

$$\log Z_t = \log N_t + \log S_t$$

Only multiplicative seasonal adjustment was used in this study.

In many circumstances all of the data currently available is used to compute the decomposition, in which case the seasonal adjustment is referred to as concurrent (McKenzie, 1984). Prior to the introduction of concurrent seasonal adjustment, the projected factor method was generally used. When using the older method, the seasonal factors S_t were projected and subsequently divided into the new observed Z_t values as they were collected. Thus only the data which had been available when the seasonal factors were projected was used to compute the decomposition. Only concurrent seasonal adjustment is used in this study.

Users of seasonally adjusted data are often most interested in adjustment of the data at the most recent time point. For a given seasonal adjustment procedure, the "final" seasonal adjustment, based upon use of a symmetric moving average filter, is generally considered the best. But this final adjustment can only be made where there is enough data beyond the time period in question to adjust with the symmetric filter. Since obviously there are no available data beyond the most recent time point, initial adjustments are calculated and revised using asymmetric filters until enough future data are collected to produce a final adjustment using a symmetric filter. For Census X-11 this effectively means waiting three years for a final adjustment when a 3x5 seasonal moving average filter is used, and five years when a 3x9 filter is used. (Young 1968). Census X-11 uses a set of asymmetric end filters that depend on the particular final seasonal filter (3x5, 3x9, etc.) and on the amount of data available beyond the time point to be adjusted. These are discussed in Shiskin, Young, and Musgrave (1967) and Wallis (1983). The difference between the initial adjustment of an observation and the final adjustment is called the total revision. For the remainder of this paper the word revision refers to this total revision.

Data users would like the difference between the initial seasonally adjusted values and the final adjusted values (ie., the total revision) to be small. One summary measure of the magnitude of this difference is the mean square of the revisions. Geweke (1978) and Pierce (1980) show that the weighted moving average seasonal adjustment procedure which applies the symmetric filter to the series extended by optimal (minimum mean squared error) forecasts minimizes the mean squared revisions. This suggests that revisions using the Census X-11 procedure could be decreased by extending the unadjusted series with enough forecasts so that a final symmetric filter could be applied to the most recent observation. In this paper we will refer to the process of extending the unadjusted series far enough to use the final symmetric filter as full forecasting, regardless of the method used to extend the series. In practice we need, but do not know, the true covariance structure of the series to produce optimal forecasts, so we must estimate it (say via a model) from the data itself. Thus, we may only approximate the optimal forecasts.

In this study we use seasonal ARIMA models augmented with regression variables for trading day effects, Easter holiday effects (Bell and Hillmer, 1983) and outliers (Bell, 1984). Having identified and estimated such a model for a given time series, one can use the model to extend the series with enough forecasts so that the final symmetric filter can be applied. We call this procedure X-11-Forecast. The anticipated reduction in the magnitude of revisions for the X-11-Forecast procedure over X-11 may not be realized for several reasons. We may mis-identify the ARIMA structure of the data, or the data may not be well approximated by an ARIMA structure. Also, Geweke and Pierce's theoretical result applies only to linear filters, and there are non-linearities in the Census X-11 multiplicative adjustment procedure (Young 1968, Wallis 1983).

A procedure similar to X-11-Forecast has been studied by Dagum (1975) and implemented in a seasonal adjustment package, X-11-ARIMA. But there are several differences between the procedures. In X-11-ARIMA the series is extended by only one year of ARIMA forecasts, so that the final symmetric filter is not used to adjust the current observation point. The X-11-Forecast procedure responds to Geweke and Pierce's result by extending the series enough to apply the final symmetric filter. X-11-Forecast uses exact likelihood estimation for moving average parameters (Findley, et al., 1988), whereas X-11-ARIMA uses conditional estimation. In contrast to X-11-ARIMA, X-11-Forecast can include regression variables in both modelling and forecasting. Using Census-X-11's concurrent seasonal adjustment method, this study extends the work of Otto (1985) by comparing revisions and final adjustment values obtained using X-11-Forecast to revisions and final adjustment values obtained using X-11 for actual observed time series.

Methods

Forty time series from three Census Bureau economic statistics Divisions (Business, Construction, and Industry) were analyzed. Table 1 lists for each series a brief description of the series, the dates for the period used in the study, and the regression terms and ARIMA model used. Revisions were obtained from three forecast extension procedures (procedure F, procedure 1, and procedure A) and compared to revisions obtained without forecast extension (procedure X). The three extension procedures were: (1) extending the series with a full 3 or 5 year forecast horizon using a user defined model (procedure F); (2) extending the series with one year of forecasts using a user defined model (procedure 1); and (3) extending the series with a full 3 or 5 year forecast horizon using an airline model (0 1 1)(0 1 1)12 as a simple default model (procedure A).

There are two aspects to this study: First, does extending the series, either with enough forecasts to use the X-11 symmetric filter or with some intermediate number of forecasts (one year as is done in X-11 ARIMA) yield lower revisions than not forecasting? Second, how well does the optimal model need to be approximated to decrease revisions? Is a carefully identified user defined model needed, or is some simple default model, possibly from an automatic modelling procedure, adequate? We chose a very simple default model, the airline model. If this does a reasonable job of approximating the optimal model then a richer set of default models should do even better. To summarize: Procedure **F** is our best approximation to the theory. Procedure **1** shows the effect of an intermediate number of forecasts and Procedure **A** uses a less careful approximation of the optimal model. Note that the default airline model is also the most common user defined model. (Table 1)

The revisions for all the treatments were obtained as follows: 1) an experimental period was defined; 2) regression models with ARIMA time series error structures were identified for the full series; 3) the full series were adjusted for outliers and calendar effects; 4) initial and final adjusted values were obtained for time points in the experimental period, for all procedures; 5) Revision measures were calculated; and finally 6) ANOVA's and ranked ANOVA's were done on the revision measures and differences between the final adjustments. Further details concerning these steps follow.

1) Each series was divided into a beginning period of 9 years (which we felt was the smallest time span we would need to identify a seasonal ARIMA model), an experimental period, and an ending period long enough for final seasonally adjusted values to be calculated for each time point in the experimental period. The end period length was chosen according to the seasonal filter used to adjust the series: 3 years for a 3x5 seasonal filter and 5 years for a 3x9 filter.

2) ARIMA models were identified, estimated, and checked, using the Box and Jenkins (1976) approach. Final models are shown in Table 1. We used a version of Census X-12 to estimate regression models with seasonal ARIMA time series error structures using exact likelihood estimation for the moving average parameters (Findley, et al., 1988). Regression variables were included in the model for statistically significant trading day, Easter holiday (Bell & Hillmer 1983), and outlier effects (Bell 1984). We used model-based outlier identification and modeling procedure tests for extreme points (additive outliers) and for permanent shifts in the mean of the series (level shift outliers). We used the whole series to identify the ARIMA model, the outliers, and the calendar effects.

3) The estimated calendar and outlier effects were removed from the original series. The previously identified ARIMA models were then re-estimated without the regression variables prior to forecasting. The resulting adjusted data Z_t and associated ARIMA models were used for all subsequent analysis. The X-11 outlier procedure was used at its default sigma-limit setting when the seasonal adjustments were calculated for the adjusted data (X-11 finds considerably more outliers than the model-based approach).

4) Initial and final concurrent season adjustments for each of the four procedures were obtained for each time point t in the experimental period. For the no forecasting procedure, procedure **X**, we computed initial seasonal adjustments for each time point t as follows: a) X-11 was run on the subseries consisting of all time points from time point 1 to time point t (including the beginning period of 9 years); b) the seasonal factor for time point **t** was obtained and divided into z_t, the regression adjusted series, to produce an initial seasonal adjustment $n_t^{(x,i)}$. We computed final seasonal adjustments $n_t^{(x,f)}$ for each time point t in the experimental period by applying X-11 to the full series.

The process for the procedure **F** was the same as that for the procedure **X** outlined above except that at each time point t: a) before each X-11 run the ARIMA model was re-estimated using the current span of data (time points 1 through t) and enough forecasts were generated to use the full symmetric seasonal filter to obtain the initial adjustments, $n_t^{(F,i)}$; b) X-11 was applied to the series extended by the forecasts. The final adjustments, $n_t^{(F,f)}$, were obtained using a forecast extended series.

The process for procedure **1** was the same as for procedure **F** except that the series was extended by only one year of ARIMA forecasts to obtain $n_t^{(1,i)}$ and $n_t^{(1,f)}$. Finally, the process for the procedure **A** was the same as for procedure **F** except that the airline model was used as the ARIMA model to generate the forecasts.

5) We calculated four different types of total revisions, where total revision is defined as the difference between the initial seasonal adjustment and the final adjustment. The four types of revisions calculated were series-level, log-level, month-to-month change, and year-to-year change.

An analysis of revisions does not make sense unless the revisions go to the same final value. We chose $n_t^{(x,f)}$ as the final estimate for revisions since the **X** procedure is currently used by the Census Bureau and we wished to avoid favoring any of the forecast extension procedures by using their final estimates. This decision biases our results toward procedure **X** whenever the finals are not equal.

The series-level revision is the difference between the initial seasonal adjustment at a given time point using the k[th] procedure and the final adjustment using the **X** procedure. The series-level revisions for the four procedures are therefore:

$$r_t^{(X)} = n_t^{(X,i)} - n_t^{(X,f)}$$
$$r_t^{(1)} = n_t^{(1,i)} - n_t^{(X,f)}$$
$$r_t^{(A)} = n_t^{(A,i)} - n_t^{(X,f)}$$
$$r_t^{(F)} = n_t^{(F,i)} - n_t^{(X,f)}$$

For all the series in this study, the variance increases directly with the mean, so the logs of the series are modeled and a multiplicative X-11 seasonal adjustment is done. When the log transform of the time series is modeled then the revisions of the log-levels are a more sensible revision to examine. Therefore the log level revisions

$$r_t^{log} = ln\left(n_t^{(i)}\right) - ln\left(n_t^{(X,f)}\right),$$

were calculated for each procedure.

Since month-to-month changes are the values the public most often studies, we included the revisions of the month-to-month changes in our study. The month-to-month changes are the ratio of the current seasonally adjusted value over last month's adjusted value and the total revision is the difference between the initial change and the final change at each time point. Total revisions in the month-to-month changes,

$$r_t^{month} = n_t^{(i)} / n_{t-1}^{(i)} - n_t^{(X,f)} / n_{t-1}^{(X,f)},$$

were computed for all four procedures. Note that there is no revision value for the first time point in the experimental period of the series because there is no month-to-month change for the first time point.

Year-to-year changes are also often studied, although such changes can be misleading when used to indicate trends. (Findley, et al., 1990) The year-to-year changes are the ratio of the current seasonally adjusted value over last years seasonally adjusted value and again the total revision is the difference between the initial change and the final change at each time point. For each procedure, revisions in the year to year changes,

$$r_t^{year} = n_t^{(i)} / n_{t-12}^{(i)} - n_t^{(X,f)} / n_{t-12}^{(X,f)},$$

were calculated. There is no year-to-year revision for the first year of the experimental period. Since year-to-year changes appear to be inherently more stable than month-to-month changes (Findley, et al., 1990), we expected the three forecast extension procedures to affect them less.

Next, for each of the four types of revisions we calculated three revision measures: mean square revisions, maximum absolute revisions, and absolute revisions. The absolute revisions were calculated for each time point in the experimental period of each series. In contrast the mean square and maximum absolute revisions are summary statistics calculated for the entire experimental period for each series.

Since all the series were log transformed, the theory suggests that the mean square of the log-level revisions will be minimized by the F procedure. To determine if mean squares are empirically minimized for any of the types of revisions, mean square revisions were computed as follows:

$$\sum_{t \in \left(\substack{experimental \\ period}\right)} \frac{r_t^2}{nexp}$$

where the mean of the sum of squared revisions is taken separately for each method and series over the number **nexp** of time points in the experimental period for the given series.

One approach to final method selection is to choose the method that minimizes the maximum absolute revision. The maximum absolute revision is defined as follows:

$$\max_{t \in \left(\substack{experimental \\ period}\right)} |r_t|$$

where the maximum is taken over all the time points for each method applied to each series.

Lastly, the absolute revisions themselves were analyzed so that revisions could be compared at each time point. For each time point in the experimental period for each series and method combination the absolute revisions are defined as follows:

$$|r_t|$$

6) ANOVA's were done to test the differences in revision measures between the three forecast extension procedures. The hypotheses we were trying to test were: 1) Does extending a series using a full forecast horizon or some smaller number of forecasts yield smaller revisions, and 2) Must a user specified model be identified? That is, is there an appreciable difference in revisions between the simple default model and a custom fit model?

To test the first hypothesis, we looked at the differences between the **X** and **F**, **X** and **1**, and **1** and **F** treatments. We expected procedure **F** to have the smallest revisions, followed procedure **1**. To test the second hypothesis, we looked at the **X** and **F**, **X** and **A**, and **A** and **F** treatment differences. We expected the **F** method to have the smallest revisions, the **X** method to have the largest revisions, and the **A** method to have revisions intermediate between the other two methods.

Because of the substantial heteroscedasticity of the data, the analyses were done on the ranks of the revision measures rather than on the revision measures themselves. Also, we blocked on series for all the analyses and we blocked on time nested within series for the analysis of the absolute revisions. Unfortunately the rank transformation and the blocking do not solve the problem of autocorrelation of the revisions over time for the analyses of the absolute revisions. Since blocking was performed on each time point within series, autocorrelation explainable by relationships between mean revisions at different time points was accounted for but any other form of correlation was not and could corrupt results. However, we think the results are so strong that the lack of independence is not a crucial problem.

The model for the ANOVA's of the ranked mean square revisions and the ranked maximum absolute revisions was, $\mathbf{rank}\ (R_{s,m}) = \mu + S_s + T_m + \varepsilon_{s,m}$, where $\mathbf{rank}\ (R_{s,m})$ is the rank of the revision measure for the s^{th} series and the m^{th} method and m ranges over the treatments X, 1, A, or F. μ is the overall mean, S_s is the series mean which is our blocking factor, T_m is the method effect, and $\varepsilon_{s,m}$ is the error. The analyses of the absolute revisions included a nested blocking effect of time within series, $\tau_t\ (S_s)$, where the time index t runs from 1 to the number of points in the experimental period of series S_s. The model was $\mathbf{rank}\ (R_{s,m,t}) = \mu + S_s + \tau_t(S_s) + T_m + \varepsilon_{s,m,t}$. The percentage differences are taken from analyses of the original data but the tests of significance are taken from the above analyses of the ranked data.

Results

We are interested in testing two hypotheses: 1) which forecast horizon will minimize the revisions, and 2) how well do we need to approximate the optimal model to obtain lower revisions than X-11 without forecast extension. As shown in Table 2 all the overall differences in methods are significant, but to test our two hypotheses we are interested in only certain comparisons.

To test the first hypothesis on the length of the forecast horizon we consider which of the **X**,**1**, and **F** methods minimizes the revisions. We do this with the planned paired comparisons **X-F**, **X-1**, and **1-F**. As shown in Table 2 for the **X-F** and **X-1** comparisons, extending the series with forecasts causes a decrease in the revisions which is significant at the .001 level for all measures, except that the **1** procedure shows no improvement for mean square year-to-year and absolute year-to-year changes. The average for all series of the decrease in revisions for the **F** procedure over the **X** procedure was 15.1% for log-level absolute revisions, 14.9% for absolute revisions, 0.28% for year-to-year changes, and 0.21% for month-to-month changes. Although the average decrease was quite small for year-to-year and month-to-month changes, in contrast the decreases in maximum absolute revisions were 9.81% and 5.44% respectively. The maximum absolute revisions in month-to-month changes were smaller for procedure **F** for 38 of the 40 series. The same measure applied to year-to-year changes was smaller for **F** for 34 of the 40 series.

Procedure **F** had significantly lower revisions than procedure **1** for all measures except the absolute revisions of the levels and of the month-to-month changes. On average, 80% of the improvement in absolute revisions occurred by extending the series one year and 20% by extending the series beyond one year to the full forecast horizon. A careful study of the summary measures for each series for procedure **X**, procedure **F**, and procedure **1** showed that procedure **X** consistently produced the worst results of the three procedures for a large majority of the series.

To test the second hypothesis concerning how much care needs to be taken to identify an ARIMA model for the series we determined which of the **X**, **A**, and **F** methods minimized the revisions. For this we performed the comparisons **X-A** and **A-F**. As shown in Table 2 there are significantly smaller revisions, at the .001 level, using forecasts from the default model (method **A**) compared to not forecasting (method **X**), for all measures for all types of revisions. Concerning the **A-F** comparison, it is surprising that in none of the measures is there a significant difference between using the default model (method **A**) and the user defined model (method **F**).

Conclusions

We conclude that revisions are significantly smaller when a time series is extended with enough forecasts to use a final symmetric filter compared to when the series is not extended or is extended by only one year. We recommend extending the series to the full forecast horizon as was done with procedure **F** and procedure **A**. When this full forecasting approach was used, we found that revisions achieved using a very simple automatic modelling procedure were not significantly less than those achieved using individually fitted ARIMA models.

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Table 1

Description of Series and Models

Series	Dates	ARIMA+Regression Model*
Business RETAIL INVENTORIES		
GENERAL MERCHANDISE	76-83	$(013)(011)_{12}+TD+O$
TOTAL APPAREL	76-83	$(010)(011)_{12}+TD+O$
TOTAL NONDURABLE GOODS	76-83	$(010)(011)_{12}+TD+O$
Business RETAIL SALES		
HOUSEHOLD APPLIANCES	67-89.10	$(010)(011)_{12}+TD+O$
AUTO AND HOME SUPPLY	67-88	$(210)(011)_{12}+TD+O$
DEPT STORES W/0 LEASED DEPTS	67-89.10	$(011(011)_{12}+TD+E+O$
FURNITURE STORES	67-88	$(011)(011)_{12}+TD+O$
GAS STATIONS	67-89.10	$(01[15])(011)_{12}+TD+O$
GROCERY STORES	67-89.10	$(310)(011)_{12}+TD+E+O$
HARDWARE	67-88	$(01[134])(011)_{12}+TD+O$
LIQUOR STORES	67-88	$(012)(011)_{12}+TD+O$
MEN'S STORES	67-88	$(012)(011)_{12}+TD+O$
SHOE STORES	67-89.10	$(011)(011)_{12}+TD+E+O$
VARIETY STORES	67-88	$(210)(011)_{12}+TD+E+O$
WOMEN'S APPAREL	67-88	$(012)(011)_{12}+TD+E+O$
Business WHOLESALE SALES		
ELECTRICAL GOODS	67-89.10	$(011)(011)_{12}+TD+O$
FURNITURE	67-88	$(011)(011)_{12}+TD+O$
GROCERIES	67-88	$(013)(011)_{12}+TD+O$
HARDWARE	67-88	$(011)(011)_{12}+TD+O$
SPORTING GOODS	67-88	$(012)(011)_{12}+TD+O$
Construction TOTAL U.S. HOUSING STARTS		
TOTAL	64-88	$(013)(011)_{12}+TD+O$
HOUSING WITH 2 TO 4 UNITS	64-88	$(101)(011)_{12}+O$
HOUSING WITH 5 OR MORE UNITS	64-88	$(103)(011)_{12}+O$
Construction SINGLE FAMILY HOUSING STARTS		
MID-WEST	64-88	$(011)(011)_{12}+O$
NORTH-EAST	64-88	$(012)(011)_{12}+O$
SOUTH	64-88	$(101)_{12}+MU+SE+TD+O$
WEST	64-88	$(101)_{12}+MU+SE+O$
Construction TOTAL HOUSING STARTS		
MID-WEST	64-88	$(101)(011)_{12}+TD+O$
NORTH-EAST	64-88	$(101)(011)_{12}+O$
SOUTH	64-88	$(102)_{12}+MU+SE+O$
WEST	64-88	$(10[13])(011)_{12}+O$
Industry TOTAL INVENTORIES		
COMMUNICATION EQUIPMENT	68-88	$(013)(011)_{12}+O$
FATS AND OILS	64-88	$(01[16])(011)_{12}+O$
BEVERAGES	64-88	$(01[14])(011)_{12}+O$
FARM MACHINERY & EQUIPMENT	62-88	$(01[2])(011)_{12}+O$
GLASS CONTAINERS	62-88	$(01)(011)_{12}+O$
HOUSEHOLD APPLIANCES	62-88	$([14]10)(011)_{12}+O$
TOTAL TELEVISION & RADIOS	64-88	$([156]10)(011)_{12}+O$
Industry UNFILLED ORDERS		
TOTAL TELEVISION & RADIO	64-88	$(010)(011)_{12}+O$
NEWSPAPER, PERIODICAL & MAGAZINE	64-88	$(10[1346])(011)_{12}+O$

* Explanation of Regression Codes
- TD Trading Day
- O Outlier(s)
- E Easter holiday
- MU mean effect
- SE fixed seasonal

Table 2

Treatment Differences between different forecast horizons and ARIMA models

Mean Square Revisions

	F	p	X-F	p	X-A	p	A-F	p	X-1	p	F-1	p
Level	48.2	0	10.7	0	9.9	0	.7	.4	7.6	0	3.1	.002
Log-level	61.1	0	12.1	0	11.1	0	1.1	.3	9.1	0	3.0	.003
Month-to-Month	57.6	0	11.6	0	11.3	0	.4	.7	8.3	0	3.3	.001
Year-to-Year	20.3	0	6.1	0	9.1	0	.3	.8	1.0	.3	8.0	0

Maximum Absolute Revisions

	F	p	X-F	p	X-A	p	A-F	p	X-1	p	F-1	p
Level	24.1	0	7.6	0	7.1	0	.5	.6	4.9	0	2.7	.009
Log-level	30.2	0	8.2	0	8.3	0	.03	.9	4.9	0	3.3	.001
Month-to-Month	34.3	0	9.1	0	8.3	0	.8	.4	4.8	0	4.4	0
Year-to-Year	18.4	0	6.7	0	6.0	0	.7	.5	3.7	0	3.0	.003

Absolute Revisions

	F	p	X-F	p	X-A	p	A-F	p	X-1	p	F-1	p
Level	85.4	0	14.0	0	13.0	0	1.0	.3	11.9	0	2.1	.03
Log-level	106.1	0	15.9	0	14.5	0	1.4	.1	12.7	0	3.2	.001
Month-to-Month	58.1	0	11.4	0	10.9	0	.5	.7	9.9	0	1.5	.14
Year-to-Year	78.8	0	10.9	0	10.0	0	.9	.4	-.8	.4	11.7	0

The first column, labeled **F**, is the F-statistic for the method effect; the second column, labeled **p**, is the associated p-value. The remaining columns show alternately the t-statistic for the relevant contrast (labeled **X-F**, **X-A**, etc.) followed by the associated p-value **p**.

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[1] This paper reports the general results of research undertaken by Census Bureau staff. The views expressed are attributable to the author(s) and do not necessarily reflect those of the Census Bureau.