Pre-adjustment in X12-ARIMA

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Abstract

The X12-ARIMA method, allows modeling either the irregular series or the original series for pre-adjustment. These models are used for outlier detection and correction, for missing observation treatment, for testing and correcting for calendar effects and for forecasting. Being an almost uncorrelated series, the irregular series has the appealing simplicity of being a candidate for ordinary least squares regression estimation of the above components simultaneously. On the other hand, regression models for time series with non-stationary ARIMA residuals enable to model the effects directly rather than as a residual component accounting for the correlation structure of the observed series. The estimation of the moving Jewish festivals and the trading day effects has always posed a difficult problem in Israel. In the past, a special method was developed at the Statistical Analysis Sector of the CBS for the simultaneous estimation of these effects while using X11-ARIMA procedure for seasonal adjustment. Currently, the CBS is in the process of implementing the X12-ARIMA method as the standard method of seasonal adjustment. In this study, we show how these effects can be estimated either modeling the observed series or the irregular series in X12-ARIMA. Selection of number of regressors in the regARIMA model and comparison of several models are based on various statistics such as AICC and out-of-sample forecast performance, and the results are further checked by diagnostic checking statistics including sliding spans analysis. Furthermore, the model is extended to include the estimation of trend breaks as well as outlier detection processes. An empirical study has been carried out for the illustration of the application of this method to three main Israeli indicator series. The empirical results support this approach and use of holiday and trading-day regressors indeed produce a better seasonal decomposition.

Keywords: Seasonal Adjustment, Calendar Effects, RegARIMA Models.

1. Introduction

Festival date movements are typical of festivals whose dates are fixed according to the lunar year, but vary according to the Georgian calendar (e.g., Jewish festivals, Easter, the Chinese New Year). Jewish festivals usually move between two consecutive solar months; the date of the Passover festival moves between March and April, and the dates of the Jewish New Year, the Day of Atonement (Yom Kippur) and the Feast of Tabernacles (Succoth) move between September and October. The Feast of Weeks (Shavuoth) and the Independence Day are another two important lunar holidays with dates moving between April and May, and May and June respectively. A festival falling in a certain month reduces the number of working days in that month. For example, during the holidays the industrial production halts. Furthermore, the trading day effect in a festival month may totally differ from other months that are not affected by festivals. Festival and trading day effects, however, do not necessarily overlap: in many series the occurrence of festivals has an additional effect beyond that of reducing the number of working days, such as increasing the demand for workers prior to the festival or increasing custom clearance of imported goods to compensate for workdays lost. Sometimes, the festival date effect is dominant and the change in the number of working days is of small importance. The importance of pre-adjustments for such effects is clear; it allows more detailed decomposition of a time series into its different components and increases the comparability of data within the series.

Since 1992, the Central Bureau of Statistics of Israel uses a special model in order to estimate the combined effects of the moving festival dates and the trading day variation while using X11-ARIMA procedure for seasonal adjustment. Section 2 overviews briefly this model based on postulating a regression relation between the irregular components and the calendar effects. The X12-ARIMA method, allows modeling either the irregular series or the original series for pre-adjustment. Being an almost uncorrelated series, the irregular series has the appealing simplicity of being a candidate for ordinary least squares regression estimation of the above components simultaneously. On the other hand, regression models for time series with non-stationary ARIMA residuals, i.e. regARIMA models, enable to model the effects directly rather than as a residual component accounting for the correlation structure of the observed series. Hence, in Section 3, the regARIMA modeling is elaborated and various diagnostic checking statistics are introduced. Section 4 provides an empirical study illustrating a variety of issues concerning pre-adjustment. The first real data set is used to show how the combined moving festival dates and trading day effects can be estimated simultaneously by either modeling the irregular series or the original series.

Selection of number of regressors and comparison of several regARIMA models for modeling the observed series, are based on various statistics such as AICC and out-of-sample forecast performance. The results are further checked by diagnostic checking statistics and statistics to assess the quality of seasonal adjustment obtained after adjusting the series for the calendar effects. The second real data example demonstrates how the model can be extended to include trend breaks. Finally, we show, in brief how a user-defined regressor can be included in the model to account for some of the irregularity in the series rather than the automatic outlier detection procedure. Section 5 contains some concluding remarks.

2. The Currently used Method

Let $\{ O_t : t = 1,...,T \}$ denote the observed series. First, we assume the multiplicative decomposition model

$$O_t = T_t * S_t * I_t \tag{1}$$

where T_t is the trend-cycle level, S_t the seasonal effect and I_t the irregular factor expressed as percentage points. It is assumed that $\{ I_t : t = 1,...,T \}$ are random variables with $E(I_t) = 100$ and constant variance σ^2. In addition they are assumed to be uncorrelated. Equation (1) can be extended by assuming that $I_t = P_t * \varepsilon_t$ as

$$O_t = T_t * S_t * P_t * \varepsilon_t$$

where P_t is the measurable part of the irregularity that includes calendar effects and ε_t is the remaining irregularity.

To estimate the overall calendar effect P_{ij}, for month j of year i, assuming an additive relationship with its components we write the following model for the estimator of I_{ij}:

$$N_{ij}^{*} (\hat{I}_{ij} / 100) - N_{ij} = \sum_{l=1}^{6} \beta_{lj} (D_{lj} - D_{7j}) + \gamma_j F_i + \delta_j H_{ij} + e_{ij} \tag{2}$$

where N_{ij} and N_{ij}^{*} are the number of days and average number of days in month j of year i, respectively, $D_{1j},..., D_{7j}$ are the number of Sundays, the number of Mondays,..., the number of Saturdays in month j, F_i denotes the festival date in year i, measured as the number of days between the actual starting date and the earliest possible starting date of the festival, H_{ij} is the number of intermediate festival days (hol hamoed) in month j of year i and e_{ij} is the random error term with expectation 0 and constant variance. The coefficient γ_j of the festival effect for month j and is equal 0 for months j not affected by festivals. Note that $D_{1k},..., D_{7k}$ are not the traditional daily activity variables; they are recalculated after adjustments for festival dates. For example, if the festival eve and the festival dates fall on Wednesday and Thursday respectively, the number of Wednesdays and Thursdays are reduced by 1 and the number of Fridays and Saturdays are each increased by 1. As a result, we might have months, such as October, with 6 or 7 Fridays and Saturdays. Equation (2) implies that the calendar effects should be estimated separately for every month. This is problematic because of the limited number of observations available for each month. Our earlier studies have shown that we can group months that share similar calendar effects. For example, winter months (November, December, January and February) have similar daily activity effects and are unaffected by festivals. For short series, the trading day effects are estimated based on data for all months (one group). In general, the decision concerning the number of groups of months is based on the length of the series and on statistical testing. The above model is estimated separately for each group of months by ordinary least squares using an external program to X11-ARIMA. It should be mentioned that the currently used method includes some enhancements mainly dealing with the identification and the treatment of the outliers.

3. Calendar Effect Estimation in X12-ARIMA

As mentioned above, the X12-ARIMA method allows modeling either the irregular series or the original series for pre-adjustment. Application of the model for the irregular series defined by equation (2) is straightforward as X12-ARIMA allows the provision of used-defined regressors. Modeling the original series is carried out through regARIMA models.
<u>RegARIMA models</u>:
It is sometimes useful to transform the series prior to estimating a regARIMA model mainly to stabilize the variance. More specifically, transformations that change smoothly in λ maybe used, such as

$$y_t^{(\lambda)} = f(O_t) = \begin{cases} O_t / d_t, & \lambda = 1 \\ \lambda^2 + \left[(O_t / d_t)^{\lambda} - 1\right]/\lambda, & \lambda \neq 0,1 \\ \log(O_t / d_t), & \lambda = 0 \end{cases}$$

where d_t is some appropriate sequence of divisors. The regARIMA model for $\lambda = 1,0$ then becomes:

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B)^D(y_t - \beta' X_t) = \theta_q(B)\Theta_Q(B^s)a_t \tag{3}$$

where $\phi_p(B)$ and $\Phi_P(B^s)$ are the autoregressive polynomials in B and B^s of degree p and P, respectively, with roots outside the unit circle, $\theta_q(B)$ and $\Theta_Q(B^s)$ are the moving average polynomials of degree q and Q respectively, with roots outside the unit circle, d and D are the order of regular and seasonal differencing respectively, s is the seasonal parameter, equals to 12 or 4, X_t is the matrix of regressors, and a_t is white noise with mean 0 and variance σ_a^2. It follows that:

$$w_t = (1-B)^d(1-B)^D(y_t - \beta' X_t)$$

is a covariance stationary series that satisfies:

$$\phi_p(B)\Phi_P(B^s)w_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{4}$$

Consequently, the model (3) can be rewritten as

$$(1-B)^d(1-B)^D y_t = \sum_i^r \beta_i \left\{(1-B)^d(1-B)^D x_{it}\right\} + w_t$$

This is a regression model for differenced y_t with stationary ARMA errors w_t. If we assume that a_t in (4) are i.i.d. and normally distributed with expectation 0 and variance σ^2, all the model parameters can be estimated by maximizing the likelihood function.

Diagnostics

Checking regARIMA modeling. ACF, PACF and ACF of the squared residuals from a fitted regARIMA model together with associated Box-Ljung portmanteau statistics, histogram of the residuals and normality statistics for the residuals are used for diagnostically checking regARIMA modeling. The spectrum is used to detect remaining seasonal effects in the residuals.

Checking the quality of seasonal adjustment. F-test for the presence of seasonality from Table D8A of the X11 output, comparison between the standard deviations of the seasonal factors and the irregular factors from Tables D10 and D13, M1-M11, Q and Q without M2 statistics are used to check the quality of seasonal adjustment. The spectrum is used to detect residual seasonality remaining in the seasonally adjusted series.

Checking the stability of seasonal adjustment. Findley, et al. (1990) describe in detail the sliding span statistics and propose their use to analyze the stability of the seasonal adjustment. First, the whole sample is divided into four overlapping spans. The basic diagnostics are descriptive and reflect how the seasonal factors, trading day factors, seasonally adjusted series and their month to month and year to year percent changes vary when the span is altered systematically. Denote by S_t^j and TD_t^j the seasonal factor and the trading day factor for month t estimated from data in the jth span respectively, A_t^j be the seasonally adjusted value for month t estimated from data in jth span, MM_t^j and YY_t^j denote the month to month change and year to year change in the seasonally adjusted series. A month t belonging to at least two spans is considered to have unstable seasonal factors, trading day factors and seasonal adjustments if:

$$\frac{\max_j S_t^j - \min_j S_t^j}{\min_j S_t^j} > .03,$$

$$\frac{\max_j TD_t^j - \min_j TD_t^j}{\min_j TD_t^j} > .02,$$

and

$$\frac{\max_j A_t^j - \min_j A_t^j}{\min_j A_t^j} > .03,$$

respectively. Furthermore, for months t such that both t and $t-1$ belong to at least two spans, the seasonally adjusted month to month percent change is considered as unstable if

$$\max_j MM_t^j - \min_j MM_t^j > .03.$$

For month t such that both t and $t-12$ belong to at least two spans the seasonally adjusted year to year percent change is considered as unstable if

$$\max_j YY_t^j - \min_j YY_t^j > .03.$$

S(%), TD(%), A(%), MM(%) and YY(%) are used to denote the percent of unstable months with respect to the number of months for which the left hand side of the above inequalities hold.

Another type of stability diagnostic associated with continuous seasonal adjustment over a period of time is revision histories. Let $A_{t\backslash u}$ and $T_{t\backslash u}$ denote the seasonally adjusted and trend values for month t respectively obtained from data up to time u, $1 \le t \le u \le T$. The values $A_{t\backslash t}$ and $T_{t\backslash t}$ obtained from data up to time t are called the concurrent estimates and it is the first adjustment obtained for month t. Similarly, $A_{t\backslash T}$ and $T_{t\backslash T}$ are the most recent estimates for month t. The revision from the concurrent to the most recent adjustment of the seasonally adjusted series expressed as a percentage of the concurrent adjustment is calculated by

$$R_{t\backslash T}^{A} = 100 * \frac{A_{t\backslash T} - A_{t\backslash t}}{A_{t\backslash t}}.$$

Similarly, revisions for month to month percent changes in the seasonally adjusted data $R_{t\backslash T}^{A\%}$ as well as their analogous quantities for trend data, $R_{t\backslash T}^{T}$ and $R_{t\backslash T}^{T\%}$, are calculated.

Choosing between competing models. Suppose there are competing regARIMA models that differ in the choice of regressors, or in the choice of transformations or in the choice of ARMA model (4). For competing regARIMA models whose diagnostics seem to be adequate, X12-ARIMA produces likelihood-based model selection criteria: AIC, AICC (F-adjusted AIC), Hannan-Quinn and BIC. One advantage to these criteria over standard t-statistic, χ^2-statistics and the likelihood ratio test is that they may be used to compare nonnested models (one model cannot be obtained simply by removing parameters from another model). AICC criterion proposed by Hurvich and Tsai (1989) and the Schwarz BIC criterion are defined as:

AICC = -2*L + 2m / {1 – (m+1)/(T – d –sD)}

BIC = -2*L + m* log (T- d – sD)

respectively, where L is the log likelihood and m is the number of estimated parameters. For each of these statistics, the model producing a lower value is preferred.

An alternative approach to model selection is to compare the out-of-sample forecast performance. Assume we are interested in h-step ahead forecasting of the time series O_t. For each t in $T_0 \le t \le T-h$, let $y_{t+h\backslash t}$ denote the forecast of y_{t+h} obtained by estimating the regARIMA model using only the data up to time t. The out-of-sample h-step forecast of O_{t+h} is defined as $O_{t+h\backslash t} = f^{-1}(y_{t+h\backslash t})$ and the associated forecast error as $e_{t+h\backslash t} = O_{t+h} - O_{t+h\backslash t}$. Consider the sequence of accumulating sum of squared out-of-sample forecast errors

$$SS_{h,M} = \sum_{t=T_0}^{M} e_{t+h\backslash t}^2, \qquad M = T_0,\dots,T-h.$$

The weighted differences between $SS_{h,M}^1$ and $SS_{h,M}^2$ from two competing models, defined by

$$SS_{h,M}^{1,2} = \frac{SS_{h,M}^1 - SS_{h,M}^2}{SS_{h,T-h}^2 / (T-h-T_0)}$$

can be used for model selection. Let us emphasize that this diagnostic does not require the assumption that any of the models being compared is correct. When model selection diagnostics based on the log likelihood, such as AICC, are inapplicable because the models are fit to different time series, forecast comparisons are still possible. For example, out-of-sample forecast performance can be used to compare the regression models of the irregular component with regARIMA models of the observed series. In addition, the smoothness statistic for the series calculated as the square root of the sum of the squared first differences can be used to favor one of the competing models.

4. Empirical Results

This section contains three real data examples to illustrate a variety of issues concerning pre-adjustment in X12-ARIMA. The first example demonstrates how the diagnostics described above can help with decisions about what kind of trading day adjustment to use. The second example is an extension of the model to include trend breaks. The third example shows how some other user-defined regressors can be included in the regARIMA models, instead of the automatic outlier detection procedures, to account for some irregularity in the series.

Total Industrial Production Index. An important source of the month-to-month fluctuations in the Total Industrial Production Index is trading day variation. The model used today for the estimation of these effects together with the moving festival effects in X11-ARIMA is given in equation (2). RegARIMA modeling capabilities in X12-ARIMA lead to the dilemma whether to model the irregulars or the original series and this is our concern here. The data was processed through

Table 1: RegARIMA Model Statistics and Statistics Related to Seasonal Adjustment

		Regression on Y			Regression on I		
	Model 1	**Model 5**	**Model 6**	**Model 7**	**Model 2**	**Model 3**	**Model 4**
	without user-defined variables	**one group**	**three groups**	**five groups**	**one group**	**three groups**	**five groups**
RegARIMA Related Statistics							
Number of parameters estimated	3	14	27	39	3	3	3
Log Likelihood	194.31	284.99	297.16	305.21	279.37	292.68	303.66
AICC (F-corrected AIC)	776.58	620.88	634.42	663.72	606.47	579.84	557.88
BIC	784.85	656.51	694.82	736.57	614.73	588.10	566.14
Residual Normality							
Skewness	0.760	0.811	0.771	0.764	0.817	0.804	0.779
Kurtosis	4.457	2.738	3.780	3.596	2.724	2.754	3.191
Forecasting Performance							
Average absolute percentage error in out-of-sample forecasts (last 3 years)	4.62	4.20	3.91	4.65	3.73	3.71	3.24
Statistics Related to Seasonal Adjustment							
D8A F-value - test for seasonality	22.19	66.71	73.34	79.67	98.37	110.77	127.23
std(D10)	4.90	3.63	3.46	3.46	4.88	4.90	4.76
std(D13)	3.37	1.36	1.19	1.09	1.43	1.23	1.17
Q	0.66	0.29	0.29	0.25	0.31	0.27	0.22
Relative Contributions (F2.B)							
I (E3)	8.58	2.14	1.14	1.35	2.28	1.77	1.00
C (D12)	0.70	0.60	0.63	0.57	0.50	0.48	0.43
S (D10)	90.74	49.36	44.08	40.27	77.09	78.25	75.36
TD&Holiday (D18)	0.00	47.90	54.15	57.87	20.14	19.50	23.21
Sliding Spans Statistics							
S(%)	0% (0/113)	2.7% (3/113)	5.3% (6/113)	12.4% (14/113)	0% (0/113)	0% (0/113)	0% (0/113)
TD(%)	0% (0/106)	0% (0/106)	12.3% (13/106)	36.8% (39/106)	0% (0/106)	0% (0/106)	0% (0/106)
A(%)	0.9% (1/113)	0% (0/113)	0.9% (1/113)	0.9% (1/113)	0% (0/113)	0% (0/113)	0% (0/113)
MM(%)	4.5% (5/112)	0% (0/112)	2.7% (3/112)	2.7% (3/112)	0% (0/112)	0% (0/112)	0% (0/112)
YY(%)	0% (0/101)	0% (0/101)	1% (1/101)	7.9% (8/101)	0% (0/101)	0% (0/101)	0% (0/101)

X12-ARIMA program for the time span from January 1990 to May 2001 (125 observations) using multiplicative decomposition model. All the values of the likelihood-based model selection criteria, such as AICC, were lower for the model with log transformation. Thus, all the models checked hereafter use log data transformations. We systematically applied the following models: (1) no regressors for trading day and festival effects. (2) OLS regression model of the irregulars for trading day effects for all months (one group), and festival effects. (3) OLS regression model of the irregulars for trading day effects for three groups of months (three groups), and festival effects. (4) OLS regression model of the irregulars for trading day effects for five groups of months (five groups), and festival effects. The analogous regARIMA models (2), (3) and (4) will be referred in the following as models (5), (6) and (7).

Table 1 summarizes the statistics related to model selection and quality of the seasonal adjustment. The comparison of the regARIMA models when modeling the original series, reveals that model (5) has the lowest AICC and BIC values. The seasonal patterns for models (5), (6) and (7) are similar, but the prior adjustment factors have different intensity especially for festival months. However, model (6) has the lowest average percent out-of-sample forecast for the last three years and outperforms the other two models for one period ahead forecast, based on accumulated forecast errors. The sliding span statistics show that the percentage of unstable months is relatively high for model (7). This is probably due to the large number of regressors in the model in respect to the number of observations. It is an open question how long a series is needed for reliable estimation of trading day and moving festival effects and we will pursue it in the future. When comparing the regressions on the irregulars, all the statistics favor model (4). Model (4) has the lowest average percent out-of-sample forecast error for the last three years and outperforms all the other models for one period ahead forecast. It should be mentioned that this model is almost identical to the currently used model. Figures 1, 2 and 3 present the comparison of the prior adjustment factors, seasonal factors and the combined factors for model (4), model (6) and the currently used model, respectively. The months that are greatly affected by moving festival dates such as April and October have different decompositions in models (4) and (6). Model (6) has produced much larger prior adjustment factors and has compensated for this with much smaller seasonal factors. This can also be seen from the high relative contributions of the trading day and festival effects to the month-to-month variance in the original series for model (6). As a result, although the seasonal factors and the prior adjustment factors differ for models (4) and (6) the combined factors obtained from these models are similar.

Figure 1: Total Industrial Production- Prior Adjustment Factors

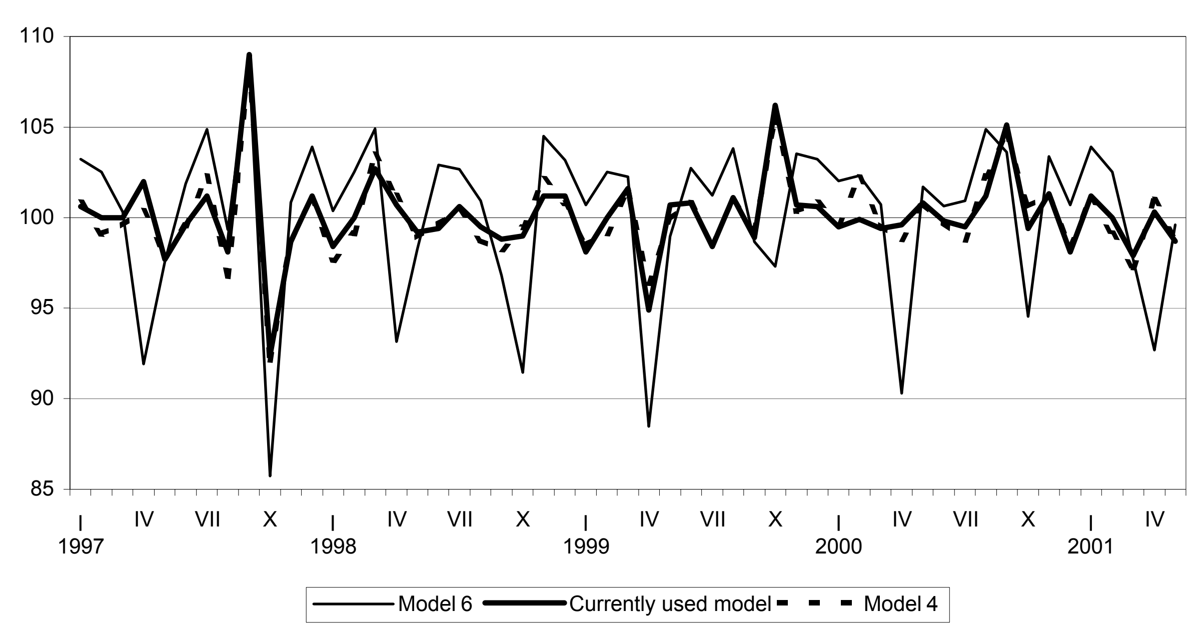


Figure 2: Total Industrial Production- Seasonal Factors

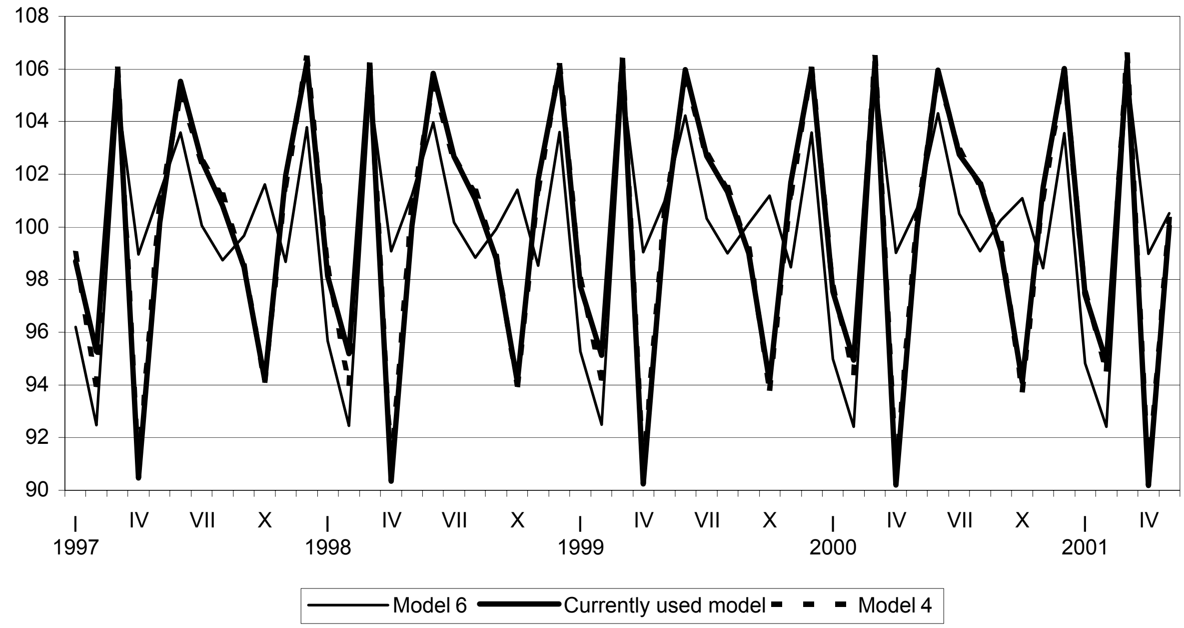
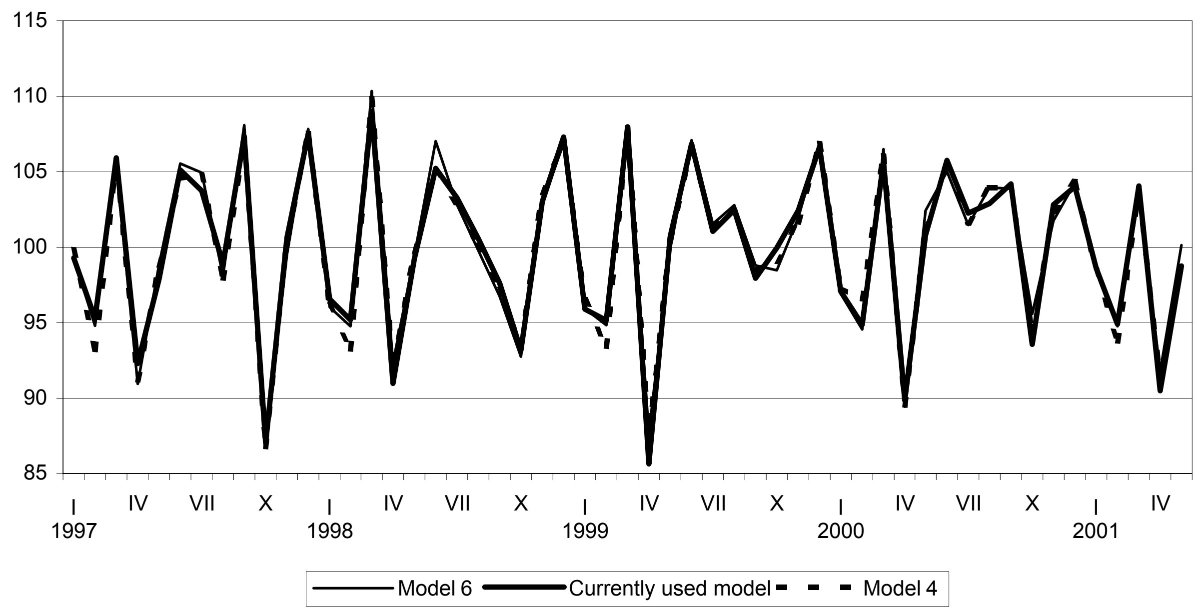
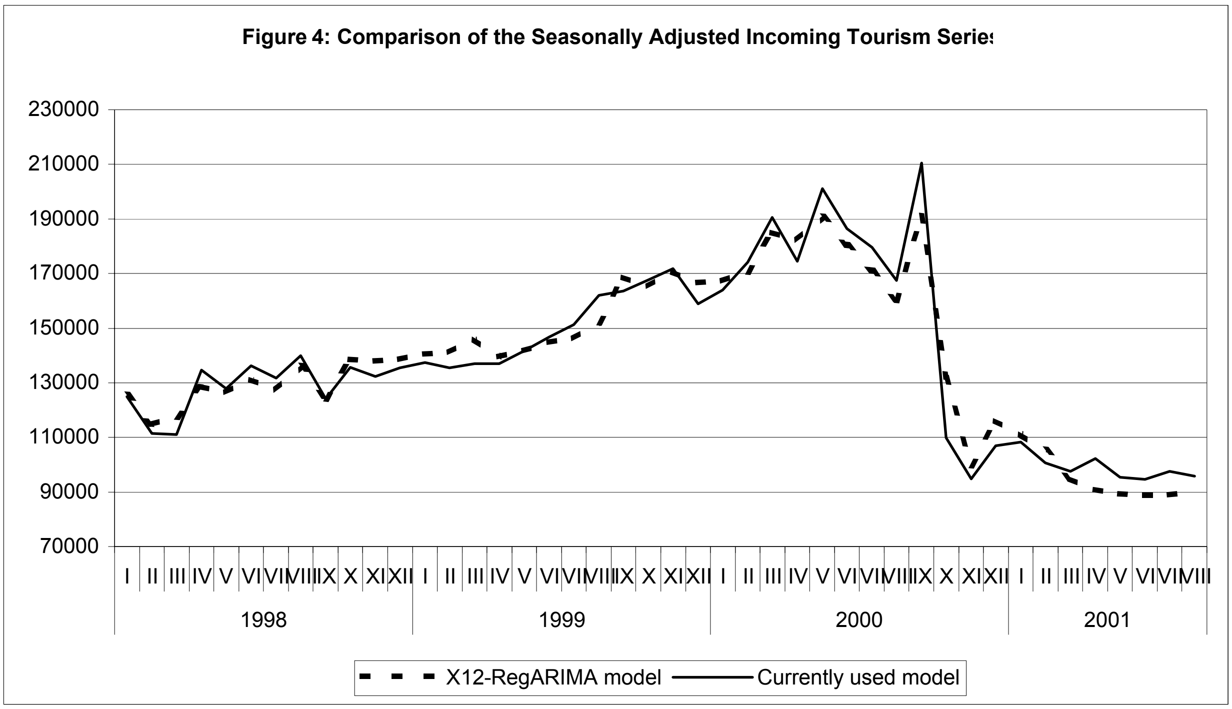


Figure 3: Total Industrial Production- Combined Factors (Seasonal and Prior Adjustment)



Total Tourist Arrivals by Air. As of October 2000, due to the security situation in Israel, a change in the level of the series of incoming tourism was detected. Therefore, calculation of seasonally adjusted data and trend data since October 2000 was carried out after adjusting the data up to September 2000 to the low level observed during the first six months of the crisis. The change in level was estimated as the ratio of the average of the original series between October 2000 and March 2001 to the average of the ARIMA forecasts for the same period obtained from the X11-ARIMA run on data till September 2000. Here, the data was processed through the X12-ARIMA program for the time span from January 1990 to August 2001 (140 observations), using multiplicative decomposition model. The trading day and the festival effects were estimated from the irregulars. The model is slightly different than the one used for the Total Industrial Production series as it includes extra variables to account for the Easter effects and has no variables for the effect of the intermediate festival days. First, we applied the automatic outlier identification procedure of the program with a critical value 5.00. The program detected one level shift outlier for October 2000 with t-value=-6.47. The resulting AICC values for models excluding and including the level shift variable were 2305.21 and 2192.2 respectively. Obviously, level shift variable should be included in the model. Also, all the other statistics related to the quality of the seasonal adjustment were far better for the model including the level shift variable for October 2000. Figure 4 compares the X12-ARIMA adjustment to the X11-ARIMA adjustment with level shift estimated as described above. The figure indicates that the size of the change in the level of the series estimated from X12-ARIMA seem to be slightly smaller than our current estimation. Also, the seasonally adjusted series from X12-ARIMA is smoother.



Total Electricity Generation. Total Electricity Generation in Israel is highly seasonal as this series is strongly dependent on weather conditions. The increasing amount of air-conditioning devices purchased over the past years, has changed the seasonal pattern of the series as the peak in January, a cold month, has moved to August, the hottest month. The data was processed through the X12-ARIMA program for the time span from January 1990 to April 2003 (148 observations) using multiplicative decomposition model. The trading day and the festival effects were estimated from the observed series. The sliding span analysis showed that there are not many unstable months, but the maximum percent difference in the seasonal factors occur in August, July, November, December and January as expected. The outliers detected by the program occur usually on the winter months, November, January and February. For instance, the harsh winter in 1992 lead to the detection of January and February 1992 as extreme outliers. We introduced into the model a new variable: the tenth percentile of the average temperature measured at 8 p.m. each month. The inclusion of this variable slightly improved most of the statistics such as the AICC in the regARIMA models for the observed series, the standard deviation of the irregulars and the relative contribution of the irregulars. We are aware that the inclusion of such a variable does not help forecasting but might achieve a better decomposition of the time series with the available data.

5. Concluding Remarks

In this study, we have addressed various issues concerning pre-adjustment. We have shown how the impact of moving festival dates and trading days in Israel can be estimated by either modeling the irregular series or the observed series in X12-

ARIMA. In general, the better inference properties of regARIMA models added to the performance of its estimates lead us usually to prefer the regARIMA modeling of the original series for pre-adjustment. However, we have found that some series are not modeled well by regARIMA modeling. For example, the Total Industrial Production series, that is greatly affected by the moving festival dates and trading day, seem to be better modeled from the irregular series. This conclusion is based on out-of-sample forecast performance, accumulated forecast errors and other diagnostic statistics. On the other hand, for the Total Tourist Arrivals and the Total Electricity Consumption series the performance of the regARIMA modeling seems to be superior or equal, based on the same statistics. Our analysis has also shown that adding other regressors such as those associated with trend breaks improves the seasonal decomposition. AICC, accumulated forecast error and sliding-span statistics are useful in choosing between different competing methods.

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