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SEASONAL ADJUSTMENT FOR FORECASTING

by

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ABSTRACT

This study analyses the effect of seasonal adjustment on the accuracy of forecasts generated from the decomposition method and compares the best against forecasts obtained directly from seasonal ARIMA (SARIMA) models fitted to the original series. Three seasonal adjustment options of the X-11-ARIMA namely: (1) standard; (2) stable and (3) fast-moving seasonality are tested on 35 monthly macroeconomic time series. The MAPE and standardized RMSE of the forecasts from the various methods are calculated for several time horizons.

RESUME

Cette étude analyse les effets de l'ajustement saisonnier sur la précision des prévisions obtenues en utilisant la méthode de décomposition. La meilleurs prévision est ensuite comparée à celle calculée directement à partir de modèles saisonniers ARMMI (SARMMI) appliqués à des séries brutes. Trois types d'ajustement saisonnier couvrant les cas de saisonnalité i) standard ii) stable et iii) mobile sont testés pour 35 séries chronologiques macroéconomiques. Les erreurs de prévision (MAPE et RMSE standardisée) tirées des différentes méthodes sont calculées pour plusieurs horizons temporels.

1- Introduction

The relationship between seasonal adjustment and forecasting has been approached from two main viewpoints: one, the effect of forecasting on the accuracy of seasonal adjustment and two, the effect of seasonal adjustment on the accuracy of forecasting.

Several empirical and theoretical studies (see Dagum 1975 and 1982; Geweke 1978; Kenny and Durbin 1982; Pierce 1980) have shown that moving average seasonal adjustment methods produce more reliable estimates when the series are extented with forecasts. Thus, it was found that forecasting is beneficial for seasonal adjustment and the development of the X-11-ARIMA seasonal adjustment method (Dagum 1980) was based on this assumption.

On the other hand, there is no consensus on the effect of seasonal adjustment on the accuracy of forecasts. Based on a selected sample of 111 series, Makridakis and Hibon (1979) found that forward seasonal factors obtained with Census X-11 or a simple ratio to moving average do not influence significantly the accuracy of the forecasts of the original series using the decomposition method. These authors also found that the forecasting methods that use seasonally adjusted data and reseasonalized with forward factors did better (in the sense of smaller errors) than the methods that estimate seasonality directly, including forecasting with ARIMA models.

Plosser (1979) forecast five economic time series with seasonal ARIMA models and their corresponding seasonally adjusted series by Census X-11 were forecast with non-seasonal ARIMA models. Instead of reseasonalizing the non-seasonal forecasts as Makridakis and Hibon (1979), he transformed the monthly forecasts to annual forecasts and compared to the original observations. Plosser's results were inconclusive, for two series the direct forecasts gave both smaller mean absolute error (MAE) and root mean square error (RMSE); for two other series, the differences were negligent and for one series the forecasts from seasonally adjusted series were better than from the original series. Plosser observed that the ARIMA models for seasonal series did not deteriorate over time. On the other hand, model inadequacies according to the diagnostic checks for the randomness of the residuals were often found for the models of the seasonally adjusted series when using the multiplicative form.

Cholette (1983) found that the forecast accuracy of seasonally adjusted data was larger when the series were extended with forecasts from seasonal ARIMA models than when the forecasts were obtained directly from non-seasonal ARIMA models applied to the seasonally adjusted series. The first approach is the one of X-11-ARIMA but where instead of obtaining forward seasonal factors, one is interested in forecasting seasonally adjusted values. The second approach is ARIMA-X-11 in the sense that the seasonally adjusted series are first obtained with Census X-11 and then forecast with non-seasonal ARIMA models.

The main purposes of this study are: one, to assess the extent to which the accuracy of the seasonal factor forecasts affects the accuracy of the original series forecasts when using the decomposition procedure and two, to compare the accuracy of forecasts obtained directly with seasonal ARIMA models with those from the best decomposition method.

Section 2 deals with the design of the experiment; Section 3 describes a case study of the series Canada Unemployed Males 25 years old and over; Section 4 analyses the results of the adjustment for a sample of 35 monthly macroeconomic time series and section 5 gives the conclusions of this investigation.

2- Design of the Experiment.

A sample of thirty five monthly series from Labour, Imports and Exports, Finance, Prices, Retail Trade, Gross National Product and Industry Product are used in this study. All series have a significant amount of seasonality according to both the F-tests of the X-11-ARIMA program and the analysis of their corresponding spectra. Series affected by trading day variations, e.g. retail trade, are first trading day adjusted and then the experiment proceeds as for the remaining series. The appropriate seasonal

adjustment of all these series is the standard option of the X-11-ARIMA package with ARIMA extrapolation. The selection of the standard seasonal adjustment option which implies the use of a 5-term (3 X 3) and of a 7-term (3 X 5) weighted moving averages for the estimation of the seasonalcomponent is made in agreement with the I/S ratio printed by the X-11-ARIMA package which is a measure of the relative contribution of the irregular component with respect to the seasonal variations (Lothian, 1982). The selection of the ARIMA models is made according to the following criteria of goodness of fit and of extrapolation (Dagum, 1981):
(1) the probability value of the portmanteau statistic to test the randomness of the residuals is at least 5% and (2) the mean absolute percentage error of the forecasts for the last three years is no greater than 15%.

For each of the sample series three seasonal adjustments are done with: (1) the standard option; (2) the stable seasonality option (a simple arithmetic mean of the seasonal-irregular ratios for each month over all the years); and (3) the fast moving seasonality option which consists of applying a 5-term (3 X 3) weighted moving average in all the iterations of the program.

For each of the three seasonal adjustment options, seasonal factor forecasts are generated up to 12 months ahead.

For each of the three corresponding seasonally adjusted outputs, non-seasonal ARIMA models are identified and retained if they pass the criterion of goodness of fit mentioned above. The non-seasonal ARIMA models retained are used to forecast up to 12 months ahead. These forecasts are then combined with the corresponding forward seasonal factors to obtain forecasts for the original series.

The mean absolute percentage error (MAPE) and the standardized root mean square error (SRMSE) of the forecasts from each of the three decomposition methods described above are calculated for time horizons 1, 6 and 12 and cumulative time horizons 1 to 3, 1 to 6 and 1 to 12. Then MAPE and SRMSE are compared with those obtained for forecasts from seasonal ARIMA (SARIMA) models applied directly to the original series.

3- A Case Study: Canada, Unemployed Males 25 years old and over.

A case study of the series of Canada Unemployed Males 25 years old and over is here discussed to illustrate better the experiment done with the sample of thirty five series.

First, four SARIMA models were automatically fitted to this sèries. These models are currently available in the automatic option of an experimental version of the X-11-ARIMA computer package. Their incorporation into the program is based on a study by Chiu, Higginson and Huot (1985) that evaluated the forecasting performance of ARIMA models on a sample of 200 series according to eight criteria. These models are:[1]

(1) (0,1,1)(0,1,1)s;

(2) (0,1,2)(0,1,1)s;

(3) (0,2,2)(0,1,1)s and,

(4) (2,1,0)(0,1,1)s

For the Canada unemployed series analysed here, the model selected is a $(2,1,0)(0,1,1)_{12}$. This model gives the best fit in terms of the randomness of the residuals, significance of the parameter values and no overdifferentiation.

Table 1 shows the model selected and the forecast accuracy measures for year 1985.

(place Table 1 about here)

The MAPE and SRMSE are shown only for the cumulative forecasts 1 to 12. This same model is used to extend the series with 12 months forecasts before seasonally adjusting with the X-11-ARIMA program in order to generate forward seasonal factors for the decomposition method.

Table 2 shows three types of decomposition that enable us to assess the impact of the seasonal adjustment on the accuracy of the forecasts of the original series, namely:

(1) We are using the standard (p,d,q)(P,D,Q)s symbolic notation for the general multiplicative seasonal ARIMA model (Box and Jenkins, 1970).

(A) ARIMA extrapolation and standard seasonal adjustment; (B) ARIMA extrapolation and stable seasonality option and (C) ARIMA extrapolation and fast moving seasonality option.

(place Table 2 about here)

For each of the three seasonally adjusted output we first fitted the same ARIMA model where the seasonal part was dropped. In this case it is the non-seasonal ARIMA model (2,1,0)(0,0,0). If the non-seasonal ARIMA model identified in this simple way was found inadequate for the seasonally adjusted series, then other non-seasonal ARIMA models were identified. In this case, we observe in Table 2 that the non-seasonal model is inadequate for the seasonally adjusted series obtained with the stable seasonality option i.e., case B. We then checked whether the high autocorrelations of the residuals was due to some seasonality left and then fitted the same model with a seasonal parameter (one autoregressive or one moving average as shown in Table 3.

(place Table 3 about here)

We observe that the (2,1,0)(1,0,0) model for the seasonally adjusted output from the stable seasonality option is now adequate but the χ^2 probability value for the randomness of the residuals of the other two cases dropped to non-acceptance levels.

Looking at the MAPE and SRMSE we can draw interesting conclusions. First, if a non-seasonal model is used to extrapolate the seasonally adjusted series even though the model may be inadequate as in case (B), then the decomposition method gives poor forecasting accuracy measures. Particularly, the MAPE and the SRMSE are much larger than those obtained with the correct seasonal adjustment (ARIMA extrapolation and standard option) and an adequate ARIMA model (case A).

However, if the seasonality left in case B is picked up with a SARIMA model (see Table 3) then the forecasting accuracy measures of this decomposition approach are the best. We wonder whether it was then preferable to forecast directly from a SARIMA model but as can be seen from Table 1 the MAPE and SRMSE measures are the highest of the four cases. In fact, the results show that the decomposition method gives better forecast than the direct even if the non-seasonal ARIMA model is inadequate for one case. It also shows that if we fit an adequate SARIMA model to the seasonally adjusted series obtained with the less reliable forward seasonal factors we can obtain forecasts which are even better than those from the preferred decomposition method (case A). We then looked at the pattern of the monthly forecasts. Figure 1 compares the forecasts from the three decomposition methods with the observed values of the original series.

(place Figure 1 about here)

It can be observed that the forecasts from the decomposition method using stable seasonality option overestimates the seasonality from June to October and also misses the level of the series. On the other hand, case (A) and case (C) tend to underestimate the seasonality particularly that of the month of September but by a much smaller amount and do not miss the level. These two procedures give very close results with the one using the standard option being slightly better.

Figure 2 compares the best of the decomposition method (case A) with the forecasts obtained directly from a SARIMA model and the original values. It can be observed that the direct approach underestimates significantly the seasonality from June to October.

(place Figure 2 about here)

This experiment was performed for other time origins of the same series. For year 1984, the (2,1,0)(0,1,1) model is still adequate for direct extrapolation as shown in Table 4. The non-seasonal part, however, can no longer be applied to the corresponding seasonally adjusted series since the χ^2 probability value for the test of randomness of the residuals is too low as indicated in Table 5.

(place Tables 4, 5 and 6 about here)

Similarly to year 1985, we then fitted the same model with a seasonal parameter but still none of the models are adequate as shown in Table 6. We proceeded to identify new ARIMA models for the seasonally adjusted output. Table 7 shows that cases (A) and (C) are fitted with a (0,1,3) model and case (B) with a (0,1,3)(1,0,0) model. The corresponding MAPE and SRMSE measures are now larger than the direct approach, being the highest those of case (B).

(place Table 7 about here)

The non-seasonal ARIMA models have to be changed frequently to fit the data adequately whereas the same (2,1,0)(0,1,1) SARIMA model was still correct.

The information drawn from this case study helped us to decide how our experiment would proceed for the larger sample. Our main question was to determine whether we would fit non-seasonal ARIMA models to all the seasonally adjusted outputs or not. We had observed that even if some amount of seasonality was left in the seasonally adjusted data, it was often possible to find non-seasonal ARIMA models that would pass the fitting criterion. Since one of the main purposes of using the decomposition method is to be able to apply non-seasonal forecasting methods to the seasonally adjusted series we decided to follow the latter approach, that is, to find non-seasonal ARIMA models for the three types of seasonally adjusted outputs.

4- Comparison of Forecasting Accuracy of Seasonal ARIMA Models versus Three Decomposition Methods that Use Non-Seasonal ARIMA Models.

Tables 8, 9, 10 and 11 summarize the results of the experiment described in section 2 and applied to a sample of thirty-five monthly economic time series. Because we are working with series that end in a given calendar year, the one step ahead forecast corresponds to the month of January, the six-step ahead to June and the 12-step ahead to December. The 1 to 3 step ahead cumulative forecast goes from January to March, the 1 to 6 step-ahead from January to June and the 1 to 12 step-ahead for the whole year. For the four methods analysed, the forecasts associated with the month of June (six-step ahead) are worse than those associated with the month of December (12-step ahead). This observation is difficult to explain for generally the forecast error increases with the time-horizon. We can only attribute this unusual finding to the seasonal characteristics of the sample series. The standard deviations for the six-step ahead forecasts are also the highest.

Looking at the cumulative time horizon forecasts, no contradicting results are shown by the MAPE and SRMSE measures. The values of these measures increase as the time horizons increase.

Table 8 shows that the forecasts of the original series obtained from the decomposition method that uses the standard seasonality option and non-seasonal ARIMA models have the smallest MAPE and SRMSE for all the horizons analysed. This is the preferred method.

(place Table 8 about here)

On the other hand, Table 9 shows that the forecasts from the decomposition method that uses the stable seasonality option and non-seasonal ARIMA models have the highest MAPE and SRMSE for all the time horizons analysed. The forecast errors are between 21% up to 40% higher than those of the preferred method depending on the forecasts lead time.

(place Table 9 about here)

Table 10 shows that the forecasts from the decomposition method that uses the fast moving seasonality option have MAPE and SRMSE about 10% higher than those of the preferred approach. It should be noted that the only difference between the standard and the fast moving seasonality options is that instead of a 7-term a 5-term weighted moving average is applied to the seasonal-irregular ratios in all the interations.

(place Table 10 about here)

Table 11 shows that the direct forecasts from SARIMA models have MAPE and SRMSE of 12% up to 27% higher than those of the preferred decomposition method Table 8 for all time horizons except for the one-step ahead where both procedures give similar results in terms of MAPE. The direct forecasts, however have always smaller forecast errors than those of the decomposition method that uses the stable seasonality option.

(place Table 11 about here)

5- Conclusions.

This study showed that there are large differences in the forecasting errors from decomposition methods that use different seasonal adjustment options and extrapolate the corresponding seasonally adjusted outputs with non-seasonal ARIMA models. These results do not agree with those obtained by Makridakis and Hibon (1979) where the authors used the naive method for forecasting.

On the other hand, similar to Makridakis and Hibon (1979) this study also found that the decomposition method that use the correct seasonal adjustment option and an adequate non-seasonal ARIMA model produces smaller forecasting errors than those obtained directly from SARIMA models for all time horizons with the only exception of the one-step ahead forecast. In general, however, the same SARIMA model passed the diagnostic checks of randomness of the residuals over several years whereas the non-seasonal ARIMA model fitted to the seasonally adjusted series had to be re-identified frequently.

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TABLE 1

AVERAGE FORECAST ERROR OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS OLD AND OVER USING A SEASONAL ARIMA MODEL (YEAR 1985)

SEASONAL ARIMA MODEL	MAPE	SRMSE
(2,1,0)(0,1,1) $\phi_1 = .035$ $\phi_2 = .240$ $\Theta = .35$ $P(\chi^2) = 58.4\%$	9.82	11.35

TABLE 2

AVERAGE FORECAST ERRORS OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS OLD AND OVER USING THE DECOMPOSITION METHOD (YEAR 1985)

SEASONAL FACTOR FORECASTS FROM X-11-ARIMA (1)	FORECASTS OF SEASONALLY ADJUSTED SERIES WITH NON-SEASONAL ARIMA MODELS (2)	MAPE OF COMBINED FORECASTS (1) AND (2)	SRMSE OF COMBINED FORECASTS (1) AND (2)
(A) ARIMA EXTRAPOLATION FROM (2,1,0) (0,1,1) AND STANDARD SEASONAL ADJUSTMENT	(2,1,0)(0,0,0) $\phi_1 = -.028$ $\phi_2 = .290$ $P(X^2) = 7.3\%$	5.34	6.16
(B) SAME AS (A) BUT STABLE SEASONALITY OPTION	(2,1,0)(0,0,0) $\phi_1 = .276$ $\phi_2 = .151$ $P(X^2) = 0.00\%$ (MODEL NOT ADEQUATE)	7.92	9.2
(C) SAME AS (A) BUT FAST MOVING SEASONALITY OPTION	(2,1,0)(0,0,0) $\phi_1 = 0.041$ $\phi_2 = .298$ $P(X^2) = 7.8\%$	5.72	6.45

TABLE 3

AVERAGE FORECAST ERRORS OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS AND OVER USING THE DECOMPOSITION METHOD
(1985)

SEASONAL FACTOR FORECASTS FROM X-11-ARIMA (1)	FORECASTS OF SEASONALLY ADJUSTED SERIES WITH SEASONAL ARIMA MODELS (2)	MAPE OF COMBINED FORECASTS (1) & (2)	SRMSE OF COMBINED FORECASTS (1) & (2)
(A) ARIMA EXTRAPOLATION FROM (2,1,0)(0,1,1) AND STANDARD SEASONAL ADJUSTMENT	(2,1,0)(1,0,0) $\phi_1=.011$ $\phi_2=.294$ $\Phi=-.113$ $P(\chi^2)=3.7\%$	5.00	5.65
	(2,1,0)(0,0,1) $\phi_1=.004$ $\phi_2=.303$ $\Theta=.151$ $P(\chi^2)=3.3\%$	4.95	5.60
(B) SAME AS (A) BUT STABLE SEASONALITY OPTION	(2,1,0)(1,0,0) $\phi_1=.218$ $\Phi_2=.180$ $\Phi=.343$ $P(\chi^2)=11.4\%$	3.17	4.21
	(2,1,0)(0,0,1) $\phi_1=.249$ $\phi_2=.167$ $\Theta=-.263$ $P(\chi^2)=11.3\%$	4.2	5.45
(C) SAME AS (A) BUT FAST MOVING SEASONALITY OPTION	(2,1,0)(1,0,0) $\phi_1=.024$ $\phi_2=.308$ $\Phi=-.146$ $P(\chi^2)=4.4\%$	5.32	5.81
	(2,1,0)(0,0,1) $\phi_1=.020$ $\phi_2=.317$ $\Theta=.172$ $P(\chi^2)=3.2\%$	5.32	5.83

TABLE 4

AVERAGE FORECAST ERROR OVER 12 MONTHS OF CANADA UNEMPLOYED MALE 25 YEARS OLD AND OVER

USING A SEASONAL ARIMA MODEL (YEAR 1984)

SEASONAL ARIMA MODEL	MAPE	SRMSE
(2,1,0)(0,1,1)		
ϕ_1 =.079 ϕ_2 =.207 Θ=.75	3.65	4.10
$P(\chi^2)$ =16.2%		

TABLE 5

AVERAGE FORECAST ERRORS OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS OL
AND OVER USING THE DECOMPOSITION METHOD (YEAR 1984)

SEASONAL FACTOR FORECASTS FROM X-11-ARIMA (1)	FORECASTS OF SEASONALLY ADJUSTED SERIES WITH NON-SEASONAL ARIMA (2)	MAPE OF COMBINED FORECASTS (1)&(2)	SRMSE OF COM FORECA (1)&(2
(A) ARIMA EXTRAPOLATION FROM (2,1,0)(0,1,1) AND STANDARD SEASONAL ADJUSTMENT	(2,1,0)(0,0,0) $\phi_1=.075$ $\phi_2=.320$ $P(\chi^2)=.05\%$	6.78	7.4
(B) SAME AS (A) BUT WITH STABLE SEASONALITY OPTION	(2,1,0)(0,0,0) $\phi_1=.278$ $\phi_2=.191$ $P(\chi^2)=.03\%$	15.05	17.
(C) SAME AS (A) BUT WITH FAST MOVING SEASONALITY OPTION	(2,1,0)(0,0,0) $\phi_1=.101$ $\phi_2=.333$ $P(\chi^2)=.01\%$	7.24	7.

TABLE 6

AVERAGE FORECAST ERRORS OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS OLD AND OVER USING THE DECOMPOSITION METHOD (YEAR 1984)

Seasonal Factor forecasts from X-11-ARIMA (1)	Forecasts of Seasonally Adjusted Series with Seasonal ARIMA Models (2)	MAPE of combined forecast (1)&(2)	SRMSE of combined forecast (1)&(2)
(A) ARIMA extrapolation from (2,1,0)(0,1,1) and standard seasonal adjustment	(2,1,0)(1,0,0) $\phi_1=.066$ $\phi_2=.345$ $\Phi=-.123$ $P(\chi^2)=.12\%$	5.77	6.52
	(2,1,0)(0,0,1) $\phi_1=.065$ $\phi_2=.341$ $\Theta=.211$ $P(\chi^2)=.06\%$	5.98	6.78
(B) Same as (A) but with stable seasonality option	(2,1,0)(1,0,0) $\phi_1=.248$ $\phi_2=.224$ $\Phi=.271$ $P(\chi^2)=1.5\%$	14.90	17.72
	(2,1,0)(0,0,1) $\phi_1=.253$ $\phi_2=.209$ $\Theta=-.244$ $P(\chi^2)=.74\%$	16.03	18.67
(C) Same as (A) but with Fast Moving Seasonality Option	(2,1,0)(1,0,0) $\phi_1=.088$ $\phi_2=.353$ $\Phi=-.143$ $P(\chi^2)=.02\%$	6.10	6.75
	(2,1,0)(0,0,1) $\phi_1=.088$ $\phi_2=.350$ $\Theta=.202$ $P(\chi^2)=.01\%$	6.49	7.11

TABLE 7

AVERAGE FORECAST ERRORS OVER 12 MONTHS OF CANADA UNEMPLOYED MALES 25 YEARS OLD AND OVER USING THE DECOMPOSITION METHOD (YEAR 1984)

SEASONAL FACTOR FORECASTS FROM X-11-ARIMA (1)	FORECASTS OF SEASONALLY ADJUSTED SERIES FROM ARIMA MODELS (2)	MAPE OF COMBINED FORECAST (1)&(2)	SRMSE OF COMBINED FORECAST (1)&(2)
(A) ARIMA EXTRAPOLATION FROM (2,1,0)(0,1,1) AND STANDARD SEASONAL ADJUSTMENT	(0,1,3)(0,0,0) $\theta_1=.06$ $\theta_2=-.30$ $\theta_3=-.357$ $P(\chi^2)=52.59\%$	4.03	4.99
(B) SAME AS (A) BUT WITH STABLE SEASONALITY OPTION	(0,1,3)(1,0,0) $\theta_1=-.166$ $\theta_2=-.304$ $\theta_3=-.345$ $\Phi=.29$ $P(\chi^2)=22.13\%$	13.06	15.29
(C) SAME AS (A) BUT WITH FAST MOVING SEASONALITY OPTION	(0,1,3)(0,0,0) $\theta_1=.06$ $\theta_2=-.273$ $\theta_3=-.413$ $P(\chi^2)=27.48\%$	4.88	5.65

TABLE 8

MEASURES OF FORECASTING ERRORS FROM THE DECOMPOSITION METHOD USING STANDARD SEASONAL ADJUSTMENT AND NON-SEASONAL ARIMA MODELS FOR VARIOUS TIME HORIZONS

FORECAST HORIZONS	MAPE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1	4.56	7.25	.19	30.16
6	7.51	15.09	.17	79.43
12	5.96	6.23	.25	26.13
1 TO 3	5.26	9.43	.16	39.04
1 TO 6	5.96	8.58	.26	31.62
1 TO 12	7.03	8.63	.19	28.54

FORECAST HORIZON	SRMSE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1 TO 3	6.08	11.03	.18	46.00
1 TO 6	7.32	11.02	.28	39.03
1 TO 12	8.45	10.60	.24	34.99

TABLE 9

MEASURES OF FORECASTING ERRORS FROM THE DECOMPOSITION METHOD USING STABLE SEASONALITY OPTION AND NON-SEASONAL ARIMA MODELS FOR VARIOUS TIME HORIZONS

FORECAST HORIZONS	MAPE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1	6.48	9.46	.01	38.02
6	8.87	10.96	.07	38.39
12	8.37	7.27	.33	27.21
1 TO 3	7.38	10.88	.23	42.46
1 TO 6	7.33	9.13	.19	33.67
1 TO 12	8.52	8.58	.16	29.23

FORECAST HORIZONS	SRMSE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1 TO 3	8.30	12.23	.25	48.50
1 TO 6	8.97	10.76	.23	39.03
1 TO 12	10.02	10.19	.20	37.37

TABLE 10

MEASURES OF FORECASTING ERRORS FROM THE DECOMPOSITION METHOD USING FAST MOVING SEASONALITY OPTION AND NON-SEASONAL ARIMA MODELS FOR VARIOUS TIME HORIZONS

FORECAST HORIZONS	MAPE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1	4.72	7.62	.05	29.16
6	8.65	15.97	.23	79.37
12	6.33	6.89	.06	25.86
1 TO 3	5.82	9.91	.19	36.04
1 TO 6	6.52	9.08	.29	30.58
1 TO 12	7.51	8.84	.24	28.76

FORECAST HORIZONS	SRMSE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1 TO 3	6.73	11.41	.21	44.26
1 TO 6	7.94	11.37	.31	37.43
1 TO 12	9.03	10.80	.27	34.20

TABLE 11

MEASURES OF FORECASTING ERRORS FROM SEASONAL ARIMA MODELS FOR VARIOUS TIME HORIZONS (DIRECT APPROACH)

FORECAST HORIZONS	MAPE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1	4.57	6.88	0.14	27.98
6	8.98	13.01	0.14	60.73
12	7.60	8.54	0.08	41.45
1 TO 3	6.16	10.59	0.22	43.41
1 TO 6	6.77	9.21	0.23	37.51
1 TO 12	7.88	8.90	0.54	31.71

FORECAST HORIZONS	SRMSE	STANDARD DEVIATION	MINIMUM VALUE	MAXIMUM VALUE
1 TO 3	6.99	12.06	.23	49.09
1 TO 6	8.12	10.95	.26	43.30
1 TO 12	9.45	10.85	.60	37.54

FIGURE 1. STEP-AHEAD FORECASTS FOR 1 TO 12 MONTHS
CANADA, UNEMPLOYED MALE 25 YEARS & OVER

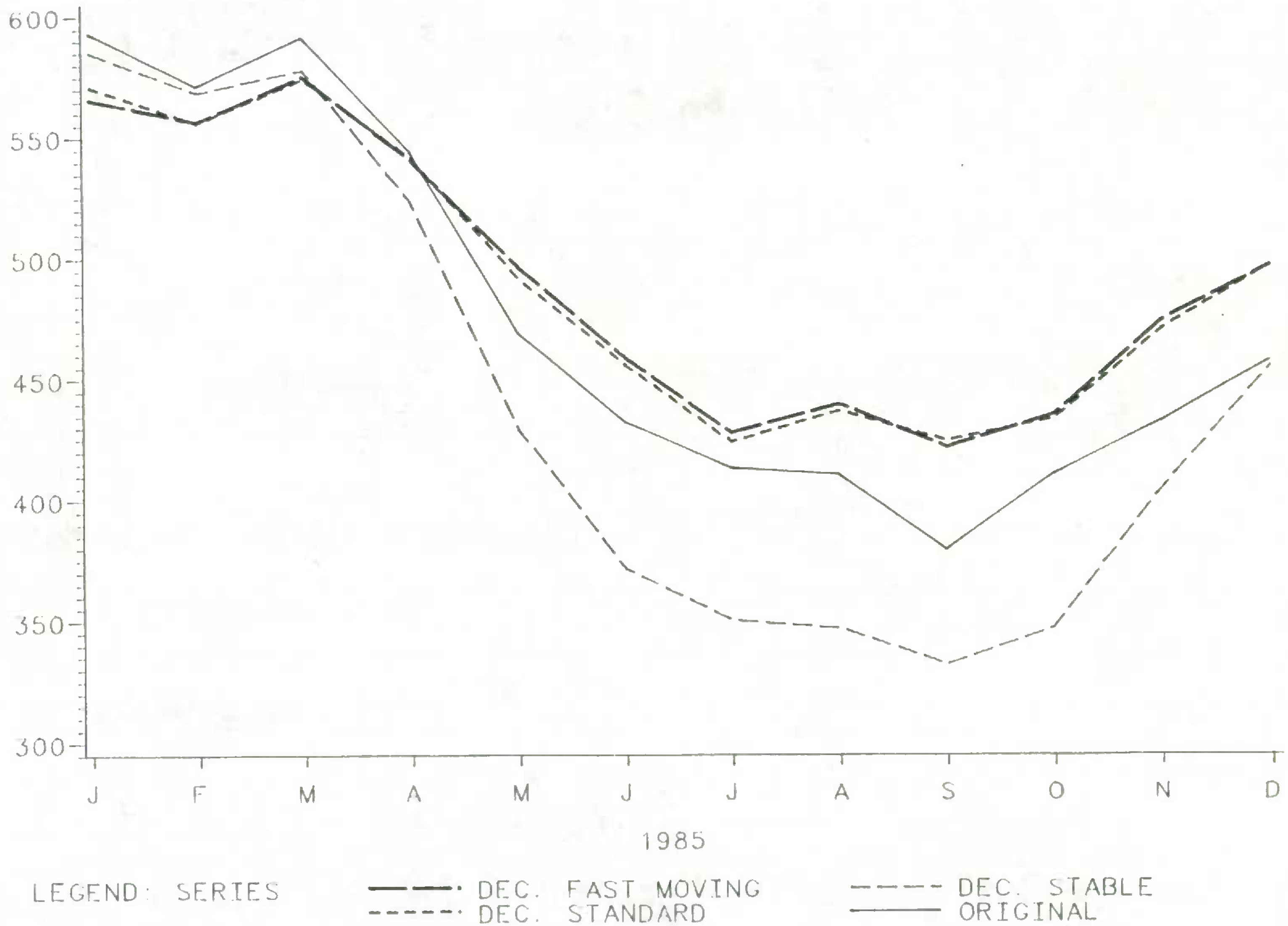

FIGURE 2. STEP-AHEAD FORECASTS FOR 1 TO 12 MONTHS CANADA, UNEMPLOYED MALE 25 YEARS & OVER