Does the ABS Henderson-Trending Process Harm Forecasting Accuracy? An Application Using a Selection of Australian Macroeconomic Variables[#]

Liam J. A. Lenten*
Department of Economics and Finance
La Trobe University

Abstract

Using a structural time-series model, the forecasting accuracy of a wide range of 18 Australian macroeconomic variables is investigated. Specifically of importance is whether the Henderson Moving Average procedure used by the Australian Bureau of Statistics (ABS) to generate 'trended' series, distorts the underlying time-series properties of the data for forecasting purposes. Since the ABS regularly publishes both seasonally adjusted *and* trended data along with the original series for many variables, this is an issue of utmost importance. However, given the weight of attention in the literature to the seasonal adjustment processes used by various statistical agencies, it appears that 'trending' procedures have received somewhat less attention, which this study hopes to address.

An unobserved components model is utilised to generate out-of-sample forecasts for each of the 18 series, using both the trended and seasonally adjusted (since the ABS applies the procedure to the seasonally adjusted series, *not* the original) series. The two sets of forecasts are then made comparable by 'detrending' the trended forecasts, and comparing both series to the realised seasonally adjusted values. Forecasting accuracy is measured by a suite of common methods, and a test of significance of difference is applied to the respective Root Mean Squared Errors (*RMSE*s). It is found that, the Henderson procedure applied by the ABS does *not* lead to deterioration in forecasting accuracy in Australian macroeconomic variables on most occasions, though the conclusions are very different between the one-step ahead and multi-step ahead forecasts. Overall therefore, one need not necessarily hesitate to use ABS trended data for forecasting purposes.

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*Contact details: Department of Economics and Finance, La Trobe University, Victoria, 3086, AUSTRALIA. Tel: + 61 3 9479 3607, Fax: + 61 3 9479 1654. E-mail: l.lenten@latrobe.edu.au

1. Introduction

For those well familiar with seasonal adjustment, the process whereby the seasonal component is completely removed from a time series, the debate surrounding the very notion of applying seasonal adjustment to economic variables, macroeconomic and otherwise, is something that comes with that familiarity. Nevertheless, the construction of seasonally adjusted data of these (quarterly or monthly) variables is commonplace in Australia as it is elsewhere for several reasons, not least of all because the ABS often prefers to do so, in line with many of its international contemporaries.[1] It is argued by these agencies that seasonally adjusted data is typically easier for less informed users to interpret, these users including business and political leaders. More importantly, they also argue that seasonal adjustment is necessary because a change in the underlying variable that is caused exclusively by seasonal influences (a temporary change) may be misinterpreted as a fundamental change in the long-term trend.

However, another process that is sometimes applied to time-series data by the ABS that is subject to a lot less attention is the series-trending process of Henderson (1916). While this process is a lot less popular with statistical agencies (the ABS is one of only a few such agencies to publish 'trend' data), it is peculiar in a sense that there is not nearly as much literature on statistical agency trending. For example, so extensive is the debate on seasonal adjustment that it now centres on *four* crucial issues in particular. These issues can be summarised succinctly as thus:

(i) whether or not seasonal adjustment should be applied at all;

[1] These contemporaries include the *Bureau of the Census* (USA), *Office for National Statistics* (UK), *Statistics New Zealand* and *Statistics Canada*.

(ii) the method to be used for seasonal adjustment (presuming the answer to (i) is confirmatory);

(iii) whether seasonally adjusted or unadjusted data should be used for model building, or simply to relate different time series to each other; and

(iv) whether forecasting accuracy is affected adversely by the use of seasonally adjusted as opposed to unadjusted data to estimate the underlying forecasting model

However, issues (i), (ii), (ii) and (iv) are all just as relevant to the debate on trending as well. Yet, there appears to be very little analysis on any of the aspects to this debate as listed above.

The present study, an empirical one, aims to go some way towards rectifying this deficiency by focusing on the final of those four issues – the question of forecasting accuracy. To achieve this aim, this study necessitates the modelling of various economic time series data using unadjusted and adjusted data. To this end, out-of-sample forecasts (both one-period ahead and multi-period ahead) are generated from the estimated model (the one determined to be optimal) such that the trend forecasts are then 'detrended' by restoring the factors originally eliminated by trending, via a simple process.[2] Following that, numerous forecasting accuracy criteria (mostly in terms of magnitude of errors, but also in terms of errors of direction) are evaluated to determine the relative suitability of trended and untrended data to forecast the underlying model.

[2] The term 'detrended' has a very specific meaning here, one that is different to the more common procedure of detrending, whereby the trend of a series is subtracted from the original or seasonally adjusted series.

The subject matter of this paper follows on logically from Lenten (2006), insofar as addressing the fourth issue is concerned. The primary finding there was that trending does not affect forecasting accuracy adversely in the sense that the quantitative measures of forecasting accuracy used were actually superior for the trended series (in aggregate tourism data). However, this finding still leaves an open-ended question as to whether this conclusion can be generalised to all types of time series data or not. Therefore, the purpose of this study is to model a large and varied set of Australian macroeconomic series (18 in total), to see whether trending has an adverse effect on the forecasting properties of this wide variety of alternative variables with different characteristics. The concern is in whether or not forecasting accuracy is affected by the choice between trended and untrended data to estimate the underlying forecasting model. Following this theme, it is the intention of this study to investigate this issue in a similar way to that of Moosa and Ripple (2000), who used US West Coast oil imports data to add their empirical contribution to the seasonal adjustment debate.

In short, the model-based seasonal adjustment, as devised by Harvey (1989), is employed for this purpose. This procedure, which is 'tailor-made' to an individual series, involves fitting a model to the time series, and then obtaining a seasonally adjusted series by subtracting the estimated seasonal component from the observed series. It is invariably the case that the underlying model specification is not the same for all series, since different time series have different properties. This is not a trivial matter, and this point shall be returned to later on.

This paper proceeds in the following manner: next, a short recount of the literature on the effect of seasonal transformation by statistical agencies on forecasting accuracy is provided. Following that, the specification of the general model that can then be used for the purpose of model-based seasonal adjustment is presented. This is the structural time series model suggested by Harvey. Subsequently, the results of the relative forecasting accuracy of the series are presented, along with a brief discussion. The paper concludes with some closing remarks.

2. The Effect of Seasonal Adjustment on Forecasting Accuracy

Similarly with respect to other aspects of the debate over manipulation of economic time series, the literature on forecasting possesses no shortage of contributions in relation to the effect of seasonal adjustment. Among the initial contributions were those of Makridakis and Hibon (1979) and Plosser (1979), from which countless other papers have followed. However, the same stream of research has, by and large, failed to extend to alternative popular methods of series trending by statistical agencies.

The Henderson filter is (while subject to pragmatism) basically an n-period moving average process (where n is an odd number), applied to the already seasonally adjusted series, which has some additional properties. First, it is centred over the current observation, so as to include information from both past and future values. Secondly, it is weighted, such that higher weights are naturally allocated to observations closer to the current period. Thirdly, it is (mostly) symmetric, so that equal weightings are applied to both past and future values. As a standard, $n = 7$ for quarterly series and $n = 13$ for monthly series, though other values of n have also known to be used in cases where the series possesses unusual time-series properties.

The weights themselves are calculated via a process that involves two main criteria; (i) that the series can be tracked by a cubic polynomial without distortion, so that the series can be replicated precisely, and; (ii) the smoothness criteria, specifically minimising the sum of squares of the three-period differences. The only problem that then arises pertains to endpoints, and in particular the $(n-1)/2$ observations at the beginning and end of the sample. This is where a set of surrogate weights correct for endpoints. Consequently, the final $(n-1)/2$ observations need to be updated every period, although this is less dramatic that the revisions required in the seasonal adjustment process. A description of how the surrogate weights are determined can be found in Doherty (2001), while tables of surrogate weights used by the ABS are shown in Australian Bureau of Statistics (1987).

Unlike seasonal adjustment, not many statistical agencies around the world publish trended data like the ABS, but for those that do, the Henderson filter is the standard procedure, being much preferred to other alternatives, such as (for example) Sutcliffe moving averages. While Henderson (1916) is not very clear, suitable representations of the specifics of the procedure can be found in Kenny and Durbin (1982: 26-28), or as applied by the ABS in Australian Bureau of Statistics (2001, section 5.3). The most comprehensive survey with respect to trend filters that one is aware of is Gray and Thompson (1996). Recent research applying the Henderson filter, while scarce, has been undertaken by Dalton and Keogh (1999), who used the Henderson procedure to extract business cycles in Irish business cycle indicators, and Dagum and Luati (2004) in a more evaluative context.

3. Specification and Estimation of Harvey's Structural Time Series Model

This section relates primarily to the econometric methodology utilised for estimating the various forecasting models. The structural time-series model of Harvey (1989), based on the Kalman filter, is called 'structural' in this context because each time series is modelled as a set of components that are not observable directly, however, they still do have a direct economic interpretation. These components can then be aggregated additively (or multiplicatively if specified in logs) to reproduce the actual series. Within the representation of Harvey (1989), the time series, y_t, can be expressed by the equation

$$y_t = \mu_t + \phi_t + \gamma_t + \varepsilon_t \tag{1}$$

whereby μ_t is the trend component, ϕ_t is the cyclical component, γ_t is the seasonal component and ε_t is a white noise random component. Equation (1) is restricted by $\text{cov}(\mu_t, \phi_t, \gamma_t) = 0$ and $\varepsilon_t \sim NID(0, \sigma_\varepsilon^2)$, meaning that the components cannot be correlated and the error term must be normally and independently distributed.

The trend component, representing the long-term movement of the series, is written in its most general form as a stochastic linear process, hence

$$\mu_t = \mu_{t-1} + \lambda_{t-1} + \eta_t \tag{2}$$

$$\lambda_t = \lambda_{t-1} + \zeta_t \tag{3}$$

Equations (2) and (3) are subject to the restrictions: $\eta_t \sim NID\left(0, \sigma_\eta^2\right)$ and $\zeta_t \sim NID\left(0, \sigma_\zeta^2\right)$. The specification in equation (2) reveals that μ_t (known as the 'level') follows a random walk with a drift factor, λ_t (called the 'slope'), which itself follows a first-order autoregressive process (equation 3).[3] Within the context of equations (2) and (3), the μ_t process collapses to a random walk with drift factor if $\sigma_\zeta^2 = 0$, and even further to a random walk with no drift if $\lambda_t = 0$ also, and ultimately to a deterministic linear trend if $\sigma_\eta^2 = 0$. On the other hand, if $\sigma_\eta^2 = 0$ but $\sigma_\zeta^2 \neq 0$, then μ_t follows a smoothly-changing process. To put it another way, both the level and slope components can be modelled with either a stochastic or deterministic (fixed) specification. Alternatively, either or both may be left out altogether.

Also of importance is the form of the cyclical component, which is assumed to follow a stationary linear process, and is represented as thus

$$\phi_t = a \cos \theta_t + b \sin \theta_t \tag{4}$$

For the purposes of allowing the cycle to be stochastic, *a* and *b* (the sensitivity parameters) are allowed to change over time. Establishing a recursion for constructing ϕ prior to introducing the stochastic elements ensures that there is no discontinuation of the series. By introducing disturbances and a damping factor, the following is obtained

$$\phi_t = \rho \cos \theta \phi_{t-1} + \rho \sin \theta \phi_{t-1}^* + \omega_t \tag{5}$$

$$\phi_t^* = -\rho \sin \theta \phi_{t-1} + \rho \cos \theta \phi_{t-1}^* + \omega_t^* \tag{6}$$

[3] These components are equivalent to the intercept and slope (respectively) of a conventional regression.

Within this representation, ϕ_t^* appears by construction, and $\omega_t \sim IID(0, \sigma_\omega^2)$, $\omega_t^* \sim IID(0, \sigma_{\omega^*}^2)$ are requirements of the model. Here, $0 < \rho < 1$ is defined as the damping factor on the amplitude and $0 < \theta < \pi$ is the cycle frequency. The optimal model could include from none up to the entire maximum three stochastic cycles, with the specifications $\rho_1 = \rho_2 = \rho_3 = 0.9$ and $\theta_1 = 2\pi/5$, $\theta_2 = 2\pi/12$, $\theta_3 = 2\pi/20$, as these are the default settings in the modelling software, *STAMP 6.0* (Koopman, Harvey, Doornik and Shephard, 2000).

Additionally, of just as much consequence for this study is the form of the seasonal component. There are three different specifications for seasonality: (i) deterministic; (ii) dummy; and (iii) trigonometric. Alternatively, the seasonal component may be left out altogether - see Harvey (1989), chapter 2, or Koopman, Harvey, Doornik and Shephard (1999) for a formal statistical description.[4] Finally, the irregular component may be included or excluded in the optimal model. As a supplementary possibility, an $AR(1)$ term can also be included should the model require some (albeit limited) dynamics.

The degree to which the trend component and the cyclical component evolve over time depends on the values of the variances σ_η^2, σ_ζ^2 and σ_ω^2, which are known as 'hyperparameters'.[5] To make the numerical estimation easier, it is assumed that $\sigma_{\omega^*}^2 = \sigma_\omega^2$. These hyperparameters and the components can be estimated via maximum

[4] For the sake of keeping this paper as short as possible, the formal representation of these specifications is not covered here, since there are three of them.
[5] The same also applies of the seasonal component, though only if it is specified as trigonometric in the optimal model.

likelihood once the model has been written in a state space representation of equation (1), in which the most compact version of the model is written in matrix form as

$$x_t = \mathbf{Z}_t' \mathbf{A}_t + \varepsilon_t \tag{7}$$

$$\mathbf{A}_t = \mathbf{B}_t \mathbf{A}_{t-1} + \mathbf{v}_t \tag{8}$$

Equations (7) and (8) are the measurement and transition equations, respectively. Here, $\mathbf{Z}_t$ is an $m \times 1$ fixed vector, $\mathbf{A}_t$ is an $m \times 1$ unobservable state vector and $\mathbf{B}_t$ is a non-stochastic $m \times m$ matrix. Equation (8) tells us that the state vector is updated each period, and that it is also subject to serially uncorrelated random disturbances (represented by the $m \times 1$ vector, $\mathbf{v}_t$) with zero mean and variance covariance matrix, $\mathbf{M}_t$. Once the model is written in state space form, parameter estimates can be obtained by maximum likelihood, where the Kalman filter is used to update the unobserved components. If $\mathbf{a}_{t-1}$ is an estimate of $\mathbf{A}_{t-1}$ and $\mathbf{R}_{t-1}$ is its covariance matrix, then the optimal linear projections (i.e. with minimum mean square error) of $\mathbf{a}_t$ and $\mathbf{R}_t$ at time t-1 are given by

$$\mathbf{a}_{t|t-1} = \mathbf{B}\mathbf{a}_{t-1} \tag{9}$$

and

$$\mathbf{R}_{t|t-1} = \mathbf{B}\mathbf{R}_{t-1}\mathbf{B}' + \mathbf{M}_t \tag{10}$$

The Kalman filter updates $\mathbf{a}_{t|t-1}$ with the new information set contained in y_t according to a process that is described by the following equations:

$$\mathbf{a}_t = \mathbf{a}_{t|t-1} + \mathbf{R}_{t|t-1}\mathbf{Z}_t \left(y_t - \mathbf{Z}_t' \mathbf{a}_{t|t-1} \right) / k_t \tag{11}$$

$$\mathbf{R}_t = \mathbf{R}_{t|t-1} - \mathbf{R}_{t|t-1}\mathbf{Z}_t \mathbf{Z}_t' \mathbf{R}_{t|t-1} / k_t \tag{12}$$

where

$$k_t = \mathbf{Z}_t'\mathbf{R}_{t|t-1}\mathbf{Z}_t + \sigma_\varepsilon^2 \quad (13)$$

Equation (11) reveals that the predictor $\mathbf{a}_{t|t-1}$, is updated by incorporating $y_t - \mathbf{Z}_t'\mathbf{a}_{t|t-1}$, the prediction error, weighted by the Kalman gain, $\mathbf{R}_{t|t-1}\mathbf{Z}_t / k_t$. Similarly, equation (12) states that the covariance matrix $\mathbf{R}_t$, is updated so that its new value is equal to the old value minus $\mathbf{Z}_t'\mathbf{R}_{t|t-1}$ weighted again by $\mathbf{R}_{t|t-1}\mathbf{Z}_t / k_t$.

In determining the optimal model for each variable, a general-to-specific methodology is put into operation. In the spirit of this course of action, one begins by estimating the most general model, and then the data is then allowed to 'speak for itself'. Specifically, the version of the model that is estimated in the first instance is the most general version that includes a stochastic trend (stochastic level and stochastic slope), a trigonometric seasonal, the maximum three cycles and an irregular component. Then, several minor variants on this general model are estimated in an attempt to hone in incrementally on the optimal model, which is determined via (a discretionary evaluation of) goodness-of-fit and diagnostic results.[6,7]

4. Data Minutia and Results

In examining the effect of trending on forecasting accuracy, all of the empirical results presented in this study are produced via both seasonally adjusted (untrended) and Henderson-trended data for a total of 18 Australian macroeconomic and industry-level

[6] Since there are a total of 1,152 combinations of settings allowable in the software, this type of approach helps limit the number of regressions required for each variable to about 25-30 on average. In fact, should the values of either ρ_i or θ_i were to be altered from their default settings; there becomes an infinite number of possible combinations.

[7] In model evaluation, some preference was given to more important criteria (for example, serial correlation over normality).

variables. From these 18 series, 10 have a quarterly frequency, and the other 8 have a monthly frequency. Meanwhile, the sample periods extend from between (depending on the variable) 1959 and 1985 at the beginning of the sample, to late 2005 at the end (most recently available observations at the time of writing). The main details of both the untrended (*sa*) and trended (*ss*) series are summarised in table 1, including the full name, three letter abbreviation for all technical material in this paper, units of measurement, frequency and sample range of each variable. The selected variables were not chosen by accident, but rather because they are all from the list of variables used in Moosa and Lenten (2000), in their study of model-based seasonal adjustment.

Both the series are obtained electronically from *ABS Time Series Statistics Plus* via *DX Database 3.0*. The optimal model is determined (for each of the 18 variables) on the basis of the *untrended* series in the first instance. The identical model must then be applied to the trended series for the two sets of forecasts to be directly comparable. There is a specific reason for approaching the problem in this way – since the null hypothesis is that the trending process damages the underlying properties of the data for forecasting purposes, then any rejection of the null is a stronger result if the untrended series was given 'every possible chance' to beat the trended series, yet still fails to do so. The precise characteristics of the structural time-series model for each of the variables (excluding the forecast period) are displayed in full in table 2. As can be seen, the characteristics of the optimal model for the range of alternative time series differ markedly from variable to variable, with the exception of the irregular component (absent in only one series) and the $AR(1)$ term (present in only three series). This multiplicity of alternative specifications demonstrates the versatility of the underlying structural model.

Figure 1 illustrates both the untrended and trended series in the same panel, both measured in levels, for each of the 18 variables. As is shown clearly, in some cases, such as the BRP, CLF, WEC, and DUA series, a large amount of variation in the seasonally adjusted series around the trended series is clearly visible at a casual inspection. However, in other cases, such as in the RTO, GDP, and INV series, the variation in the seasonally adjusted series around the trend is seemingly almost non-existent. While figure 1 does not show the *sa* and *ss* series in relation to the original series, it is clear that most of the variation in all of the original series is eliminated via the seasonal adjustment process alone, a point made by Lenten (2006) in reference to Australian tourist flow figures. Furthermore, it is also clear from figure 1 that much of the variation that still remains is then removed by the Henderson trend.

The model is estimated in levels, implying that the components are additive rather than multiplicative. The estimation is based on both the *sa* and *ss* series over the entire sample period less the forecast period. The forecast period extends from 2000M1 or 2000Q1 to the end of the sample (usually 2005M10 or 2005Q3) for the monthly and quarterly data, respectively.[8] This results in 70 point forecasts for (most of) the monthly series; and 23 point forecasts for (most of) the quarterly series. The loss of observations for the out-of-sample forecast period is undesirable but necessary for generating the out-of-sample

[8] The exceptions are 2005M11 for UNN and PRT; and 2004Q2 for BRP.

forecasts and for determining the possible existence of a structural break. The first set comprises one-period ahead forecasts, whereby the model is estimated over a sample period including the final observation of 1999. The process is then repeated by including one further observation in the estimation sample to generate a forecast for the following month. The second set comprises multi-period ahead forecasts, in which the model is estimated up to the end of 1999, and then used to generate dynamic forecasts.

Table 2 also brings to attention one noteworthy issue. It could be argued that there is no need to include a seasonal component at all, since both the *sa* and *ss* series have both already been seasonally adjusted. However, this position is debatable on particularly credible grounds: if the X-11 seasonal adjustment procedure used by the ABS is truly robust, then the seasonal component and the individual seasonals should be insignificant anyway. Therefore, including the seasonal component is only necessary when the optimal model dictates that the best specification for the seasonal component is something other than 'none', which ends up being the case for 17 out of 18 cases anyway. This point is also important in relation to the use of the 'general-to-specific' methodology, as mentioned previously. This argument is also consistent with the assertion that any conventional regression equation should always contain an intercept term, leaving the data to determine whether it is significant or not.

Table 2 outlines both the goodness-of-fit and diagnostic results for the univariate estimation of equation (1) for both series and all variables. In terms of the former, both the standard error of the estimated equation, $\tilde{\sigma}$, and either (whichever is the most appropriate for any given variable, given the optimal model outlined in table 2) of two modified coefficients of determination, R_s^2 or R_d^2, are reported. The reason for the use of $R_s^2 \left(R_d^2\right)$ is that for data where y_t exhibits seasonality (trend movements), it is more appropriate to compare the prediction error variance with the variance of y_t, making it preferable to the conventional R^2 (see Koopman *et al.*, 1999, chapter 11).

The diagnostic tests include the most conventional serial correlation test, the Durbin-Watson (*DW*) statistic, which is simply the ratio of the sum of squared differences in successive residuals to the residual sum of squares. An alternative serial correlation test, the Ljung and Box (1978) *Q* statistic, is also reported. The *Q* test is based on the first *n* autocorrelation coefficients, distributed as $\chi^2(n+1-k)$, where k is the number of estimated parameters. In testing for normality, the Bowman and Shenton (1975) test is used, distributed as $\chi^2(2)$, *N*. The *N* test is based on the joint departures of the third and fourth moments (measures of skewness and kurtosis respectively) from their predicted values under normality (0 and 3 respectively). The presence of heteroscedasticity is also tested for, specifically via the $H(h)$ test. This test follows an $F(h,h)$ distribution (henceforth denoted as *H*), and is calculated as the ratio of the squares of the last *h* residuals to the squares of the first *h* residuals, where *h* is the closest integer to $T/3$. A high (low) *H* value means an increase (decrease) in the variance over time.

Finally, in order to test for structural stability of the various models, both the predictive failure (*PF*) and *CUSUM* (*CUS*) statistics are used to determine how well the model forecasts out-of-sample. Both of these test statistics are calculated ultimately from the derived out-of-sample forecast errors. For a formal representation of these test statistics, see Koopman *et al.* (1999). The critical values are not reported here because (using *Q* and *H* as examples) they vary widely from variable to variable, however, significant values are marked with an asterisk.

Concentrating initially on each of the untrended series only (the unshaded rows of the table), it is seen that the results overall indicate a range of reasonably well-specified models, by structural time-series standards. The goodness-of-fit results are of a wide variety, depending on the variable concerned and the specification of the optimal model. Diagnostically, the various models fail the *Q* test for serial correlation in 4 cases; however, none of the models fail the *DW* test.[9] The *N* test surpasses the critical value on no less than 10 occasions, however, this merely indicates the presence of outliers. The test for *H* fails for 8 variables, although the main implication here is for the validity of the standard errors, which are not being used here for any purpose, rather than for the estimates themselves. In terms of structural stability, the *PF* test is worryingly significant on 11 occasions, although the *CUS* test provides more assuring evidence, failing only in the case of LBP.

Turning our attention now to the trended series (the shaded rows), one can detect that the raw goodness-of-fit measures indicate the same models, despite being fitted to the untrended data specifically, appear to better fit the trended series. However, it is

[9] It must be noted, however, that the *DW* test is invalid in three cases, including one where the *Q* statistic is failed, due to the inclusion of the first-order autoregressive term.

erroneous at this point to compare the results directly at this stage, as the two models are not equivalent because the dependent variable is different. Analogously, with respect to diagnostics and structural stability, it is clear that the trended series are much more likely to fail the test statistics, especially the *DW* statistic (significant on 13 occasions as opposed to 0 for the untrended series), the *Q* test (17 as opposed to 4) and the *CUS* test (4 compared to 1). Again, while a direct comparison is not possible, it does confirm generally how the models (better suited to the untrended series) have not really been fitted with the unique characteristics of the trended data in mind.

Figures 2 and 3 reveal the one-period and multi-period ahead forecasts respectively, compared to the actual values, based on both untrended and trended data. The raw forecast errors derived from the untrended data $\left(\xi_t^{sa}\right)$ are obtained simply by subtracting the raw forecast, $\hat{y}_t^{sa}$, from the realised value, y_t^{sa}, as in equation (14). However, the raw forecast errors for the trended series (same notation again, but with an *ss* superscript instead) need to be detrended by taking back out the trend factors, that had been previously built into the series via the Henderson process. If this correction is not made, then the two sets of forecasts are not comparable directly, because $y_t^{sa} \neq y_t^{ss}$ on the left-hand side of equation (1) in the separate models for each variable. In summary, the two sets of forecasts are derived according to the formulae

$$\xi_t^{sa} = y_t^{sa} - \hat{y}_t^{sa} \tag{14}$$

$$\xi_t^{ss} = y_t^{ss} - \left[\frac{\left(\hat{y}_t^{ss}\right)}{y_t^{ss} / y_t^{sa}}\right] \tag{15}$$

From a quick visual inspection of figure 2, it does not appear totally obvious that the trended series systematically underperforms (nor outperforms) the trended data for forecasting purposes, nor is it obvious on a systematic basis in figure 3. With this in mind, we look towards more formal statistical evidence for further indication.

The selected quantitative measures of forecasting accuracy are displayed in tables 4 and 5. The measures are as follows: (i) sum of absolute errors (*SAE*); (ii) mean absolute error (*MAE*); (iii) sum of squared errors (*SSE*); (iv) mean squared error (*MSE*); (v) root mean square error (*RMSE*); (vi) mean absolute percentage error (*MAPE*); and (vii) Theil's inequality coefficient (*TIC*), which is simply the quotient of the root mean square error divided by the notional root mean square error from using naïve forecasts. In addition to the quantitative measures, the number of turning point errors (*TPE*) is reported. A directional turning point error occurs if the actual (one-period) change in the variable has the alternate sign to that of the predicted change. More formally, we have

$$\text{either} \quad \begin{cases} y_t - y_{t-1} > 0 \quad \text{and} \\ \hat{y}_t - y_{t-1} < 0 \end{cases} \quad \text{or} \quad \begin{cases} y_t - y_{t-1} < 0 \quad \text{and} \\ \hat{y}_t - y_{t-1} > 0 \end{cases} \tag{16}$$

Starting with the one-period ahead forecasts, the various measures of forecasting accuracy are exposed in panel (a) of table 4. It can be gleaned from this panel that the *RMSE* in particular (the benchmark measure) from the trended data is quantitatively smaller than those derived from the untrended data in each case in the 18 variables. This finding is reinforced unanimously by all of the other measures of forecasting accuracy. Furthermore, the number of *TPE*s from the trended data do not exceed the number from the untrended data in any case (they are equal in one case, INV).

However, without applying actual tests of significance, it is not obvious whether the differences are statistically different in a qualitative sense. In the endeavour to overcome this problem, the Ashley, Granger and Schmalensee (1980) *AGS* test is employed to test for the difference in the *RMSE*s between the two models. The *AGS* test requires the estimation of the following linear regression

$$D_t = \kappa_0 + \kappa_1\left(S_t - \overline{S}\right) + u_t \tag{17}$$

where

$$D_t = \begin{cases} w_{1t} - w_{2t} & : \text{if } \left\{\overline{w_1}, \overline{w_2} > 0\right. \\ -w_{1t} - w_{2t} & : \text{if } \left\{\overline{w_1} < 0 < \overline{w_2}\right. \\ w_{1t} + w_{2t} & : \text{if } \left\{\overline{w_2} < 0 < \overline{w_1}\right. \\ -w_{1t} + w_{2t} & : \text{if } \left\{\overline{w_1}, \overline{w_2} < 0\right. \end{cases} \tag{18}$$

and

$$S_t = \begin{cases} w_{1t} + w_{2t} & : \text{if } \left\{\overline{w_1}, \overline{w_2} > 0\right. \\ -w_{1t} + w_{2t} & : \text{if } \left\{\overline{w_1} < 0 < \overline{w_2}\right. \\ w_{1t} - w_{2t} & : \text{if } \left\{\overline{w_2} < 0 < \overline{w_1}\right. \\ -w_{1t} - w_{2t} & : \text{if } \left\{\overline{w_1}, \overline{w_2} < 0\right. \end{cases} \tag{19}$$

Further, $\overline{S}$ is the mean of *S*, $w_{1t}\ \left(w_{2t}\right)$ is the out-of-sample error at *t* of the model with the higher (lower) *RMSE*, and $t = T+1,\ldots,T+\ell$.

The statistical difference between the *RMSE*s of the two models using untrended data and the trended data is tested using the estimates of κ_0 and κ_1 in equation (17). In all, three scenarios are possible: (i) the estimates of κ_0 and κ_1 are both positive. In this case, significance is determined by the Wald coefficient restriction test (distributed as $\chi^2(s)$, where s is the number of restrictions) of the joint restriction $\kappa_0 = \kappa_1 = 0$, henceforth referred to as *CR*. Scenario (ii) is where one of the estimates is significantly negative, in which case the test is inconclusive; and (iii) is where the estimate is negative but statistically insignificant, in which event the test will still be conclusive, with significance being determined by an upper-tail *t*-test on the positive coefficient estimate.

The results of the *AGS* test for the one-step ahead forecasts are displayed in panel (a) of table 5. First of all, there was an inability to obtain a *CR* test statistics for both the CLF and PLF series, since the restrictions were near linearly dependent. However, for each of the remaining 16 series, the differences between the two *RMSE*s were statistically significant, indicating a qualitative (as well as quantitative) superiority of the trended series over the untrended series for forecasting.[10] For 12 of these series, significance was determined via the *CR* test, whereas the *t*-test determined significance for the other 4. In no case was the test inconclusive.

The analogous results for the multi-period ahead forecasts (shown in panel b from each of tables 4 and 5) tell an exceptionally dissimilar story. Here, the number of smaller *RMSE*s is split evenly between the untrended and trended forecasts, at 9 from 18 cases each. Furthermore, the other forecasting accuracy measures unfortunately shed no further light on these findings, with the results again mixed across the board. The *CR* statistics were again unobtainable for the CLF and PLF series, both for which the *RMSE*s were lower for trended data, and the test was inconclusive in the case of LBP, for which the untrended data had the lower *RMSE*. For the remaining 15 variables, the difference

[10] Judging from the large relative differences between the *RMSE*s of the untrended and trended series for both the CLF and PLF variables, significance would not appear to be a problem, despite being unable to conclude formally via the *AGS* test. The same applies for CLF for the multi-step ahead forecasts.

between the *RMSE*s was found to be statistically insignificant in 4 cases, out of which 2 each favoured each of the *sa* and *ss* series quantitatively. In the remaining 11 cases, the difference between the *RMSE* of the two models was significant at the five per cent level, with 6 of these cases favouring the *ss* series as the better forecasting model, and the *sa* series being favoured for the other 5. Despite these results, a brief numeric analysis of the *TPE*s reveals the trended series to produce less (quantitative) *TPE*s than the untrended series in 11 cases, whereas the opposite is true in only 3 cases, with 5 'ties'.

5. Conclusion

This study has attempted to cast some assertions regarding the suitability of using data which has already been trended (prior to reporting) by the ABS using the Henderson moving average procedure, for the purposes of forecasting. The focus of this objective has been a comparative one in relation to the seasonally adjusted (but untrended) data, via the fitting of models and the adjustment of the forecast error series wherever necessary, in order to make the two sets of forecasts comparable in a direct sense.

This study goes above and beyond the scope of much of the previous work in the area of statistical manipulation of economic and financial time series by statistical agencies, in the sense that most of the antecedents have examined only the process of seasonal adjustment, rather than this further manipulation process. Despite the difference, many of the key issues surrounding the trending process are still the same as for seasonal adjustment, as stated earlier. Not only are quantitative measures considered here, whereby measured accuracy depends on the deviation of the forecasts from their realised values, but also included is a *TPE* measure which captures the ability of the estimated model to predict the direction of one-period change. Another feature of this paper is the use of both one-period ahead and multi-period ahead forecasts.

The results that are presented here allow us to conclude that the trending process does not generally compromise forecasting accuracy, a result demonstrated by the comparative values for the various forecasting accuracy measures between the untrended and trended data. The results, however, are very different between the one-step and multi-step forecasts. For the former, in fact, the trended series outperforms the untrended series unanimously, although for the latter, the evidence is approximately equally supportive of both series, still not allowing us to conclude that the trending process causes detriment to the series for forecasting purposes.

More generally, the findings support the evidence of Moosa and Ripple (2000) and Lenten and Moosa (2006), who both utilise a very similar methodology, insofar that the forecasting accuracy is not affected adversely by the use of data that has been manipulated by statistical agencies using common procedures. Further, this paper effectively overcomes one of the key questions raised by Lenten (2006), which pertains to whether those results for aggregate tourism data could be generalised over a wide variety of time series. Therefore, these results amount to quite significant support of the manipulation of Australian economic data by the ABS for reporting purposes, at least of the grounds of forecasting accuracy.

Table 1: Australian Macroeconomic Series Used in this Study

Time Series	Abbreviation	Units	Frequency and Sample Range
Total Motor Vehicle Registrations*#	MVR	Number	1962M1-2005M10
Beer Production (Including Ale and Stout)	BRP	$\times 10^6$L	1965Q1-2004Q2
Industrial Gross Product	IGP	89/90=100	1974Q3-2005Q3
Unemployment Rate	UNN	%	1978M2-2005M11
Participation Rate	PRT	%	1978M2-2005M11
Retail Turnover#	RTO	$\times 10^6$$	1962M4-2005M10
Total Personal Finance Commitments	PLF	$\times 10^3$$	1985M1-2005M10
Total Commercial Finance Commitments	CLF	$\times 10^3$$	1985M1-2005M10
Current Account Balance¶	CAB	$\times 10^6$$	1959Q3-2005Q3
Beef Production	BFP	Tonnes	1979Q3-2005Q3
Lamb Production	LBP	Tonnes	1979Q3-2005Q3
Exports of Goods and Services	EXP	$\times 10^6$$	1959Q3-2005Q3
Imports of Goods and Services	IMP	$\times 10^6$$	1959Q3-2005Q3
Gross Domestic Product	GDP	$\times 10^6$$	1959Q3-2005Q3
Inventories: Current Prices	INV	$\times 10^6$$	1984Q2-2005Q3
Company Profits: Before Income Tax	COP	$\times 10^6$$	1985Q3-2005Q3
Total Wine Consumption	WEC	$\times 10^3$L	1975M7-2005M10
Total Dwelling Units Approved	DUA	Number	1983M7-2005M10

*The ABS discontinued the MVR series after 2001M12, instead continuing with 'Total Motor Vehicle Sales', which closely resembles MVR.

#To ensure continuity, the MVR series is spliced with the Sales series at 2001M12. A trend break was inserted between June and July 2000 as a result of the introduction of the new tax system.

¶A trend break correction of $1.8bn was applied to the *ss* series in June 2005 quarter due to an increase of some non-rural export commodities ($1.0bn to coal and $0.8bn to iron ore).

GDP is at constant (2003/4) prices, whereas the other dollar series are measured at current prices.

Note: BRP was discontinued after 2004Q2.

Figure 1: Seasonally Adjusted (Thin Line) and Trended (Bold Line) Data for All Series

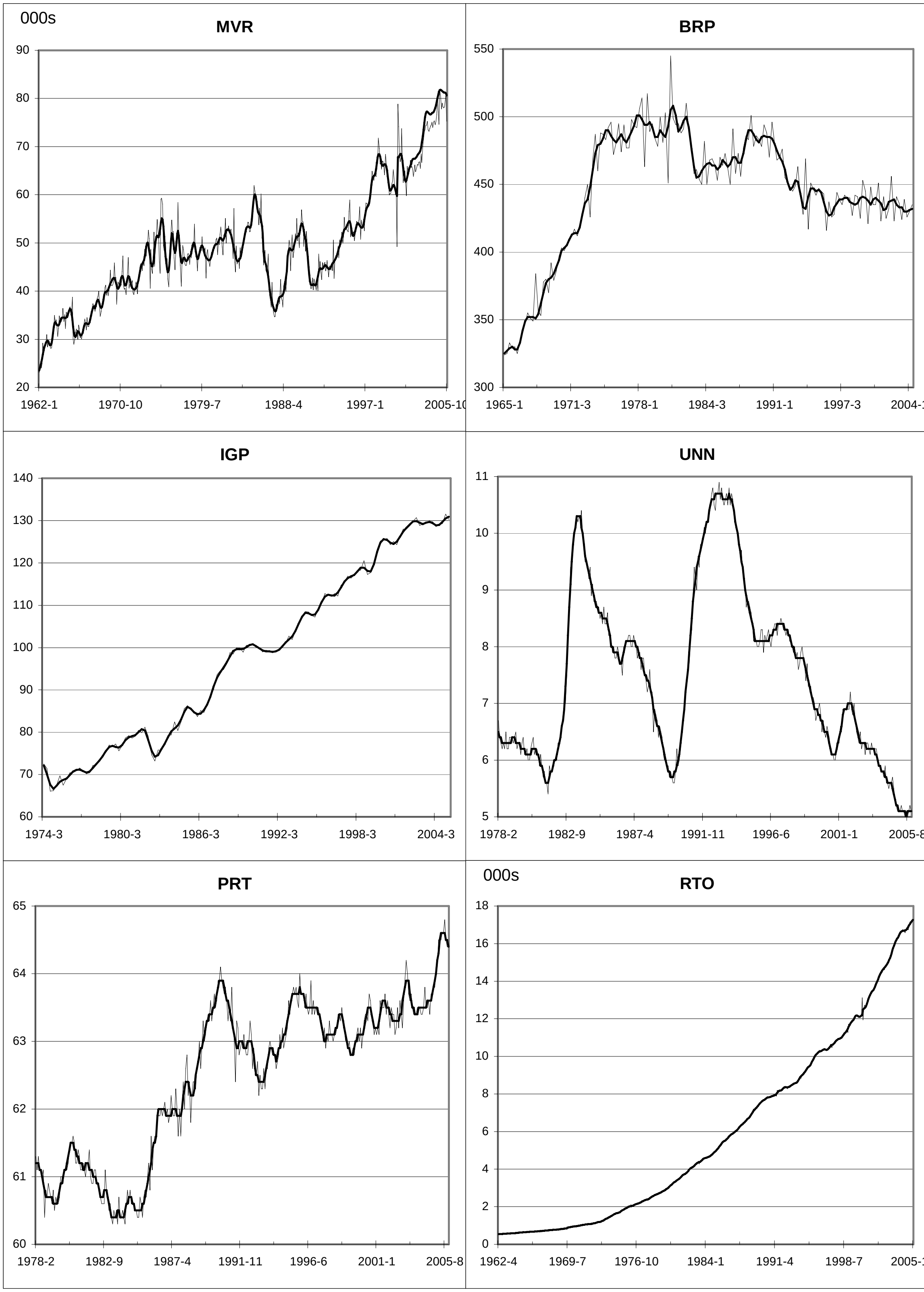

Figure 1 (Con't): Seasonally Adjusted (Thin Line) and Trended (Bold Line) Data for All Series

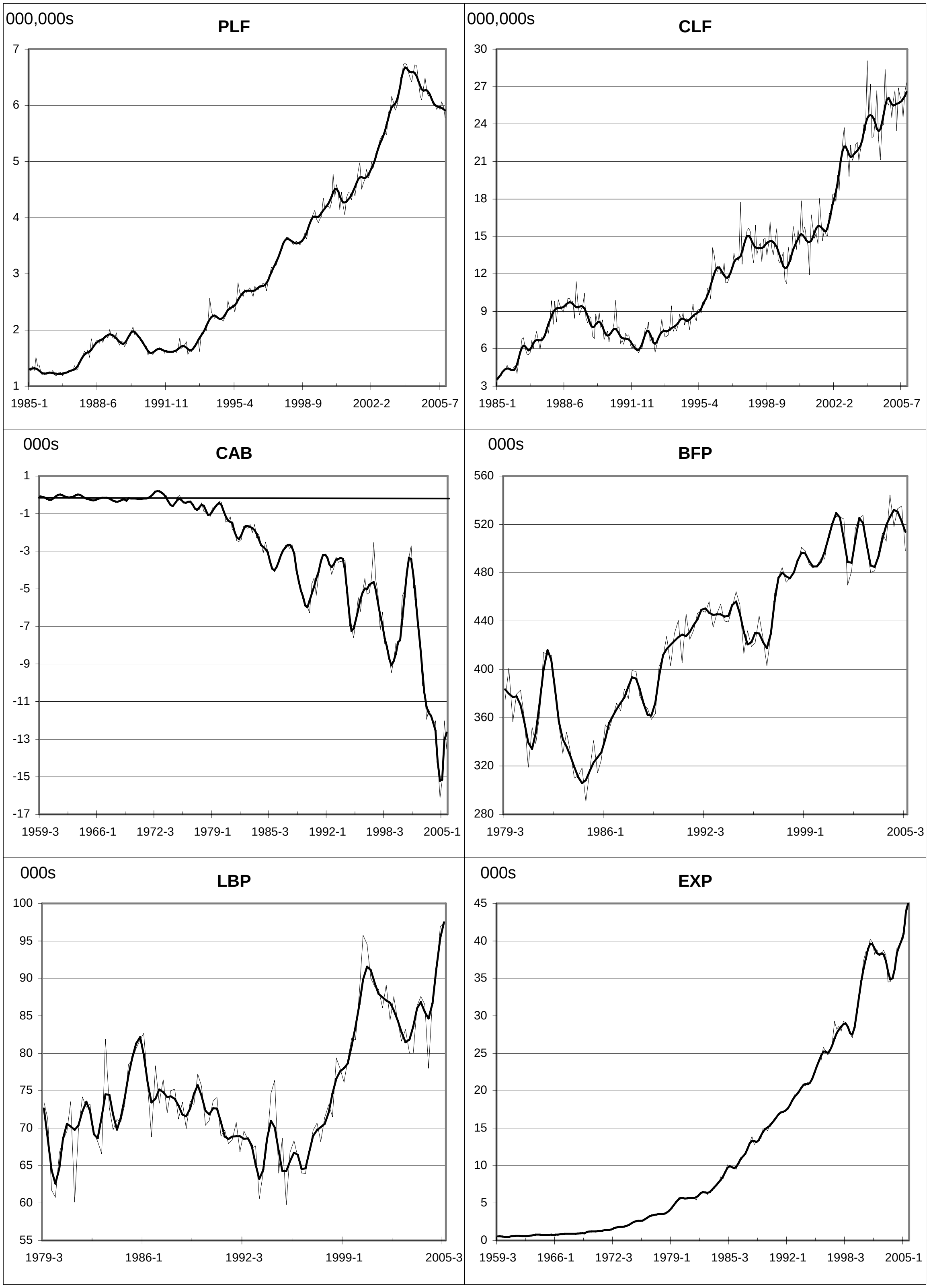

Figure 1 (Con't): Seasonally Adjusted (Thin Line) and Trended (Bold Line) Data for All Series

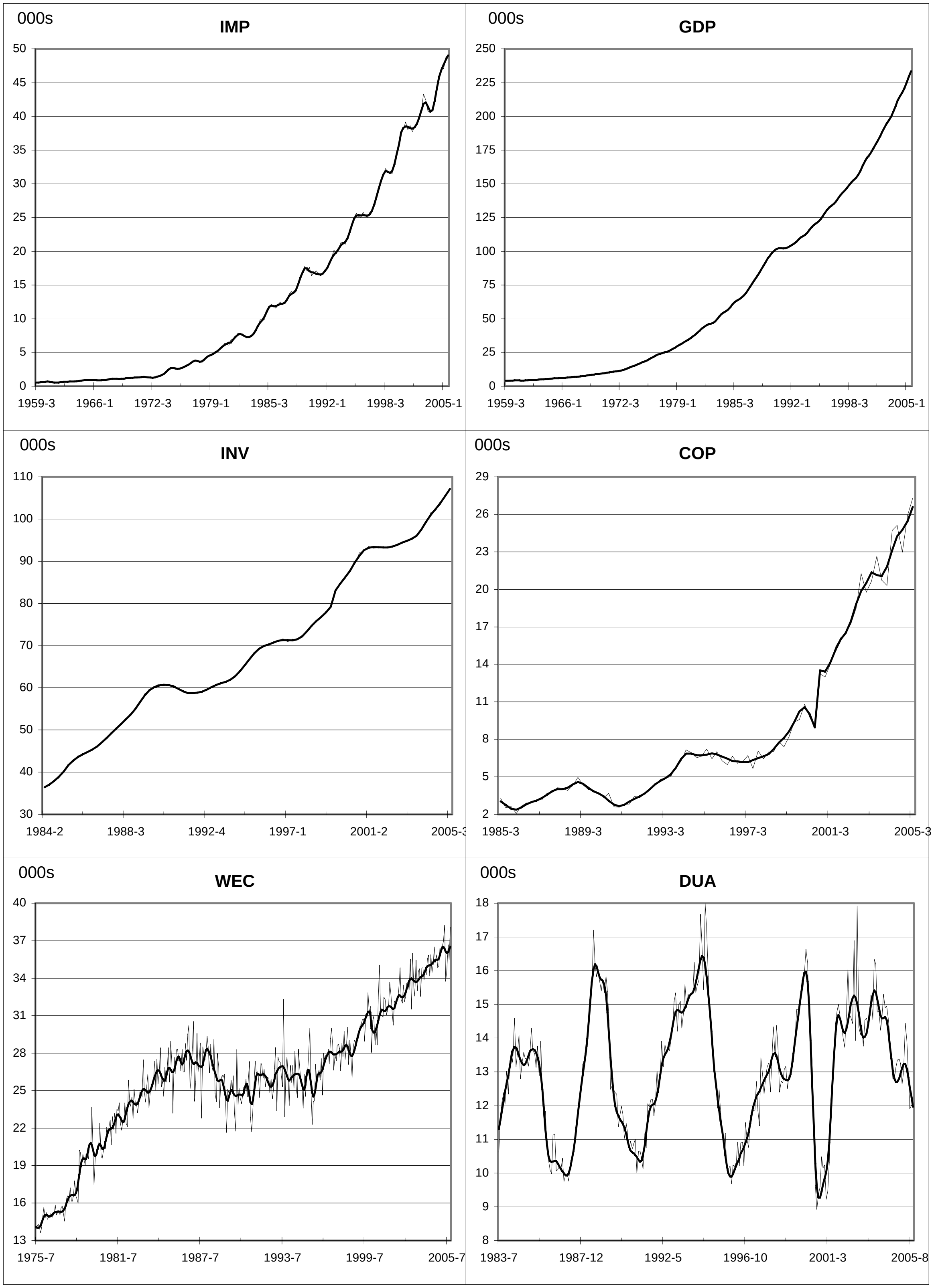

Table 2: Main Characteristics of the Optimal Model for Each Variable

Variable	Level	Slope	Seasonal	Irregular	*AR*(1)	Cycles
MVR	Stochastic	Fixed	Dummy	Yes	No	1,2
BRP	Stochastic	Stochastic	Fixed	Yes	Yes	2
IGP	Stochastic	Fixed	Fixed	Yes	No	1,2,3
UNN	Fixed	Stochastic	Trig	Yes	No	2
PRT	Fixed	Stochastic	Trig	Yes	No	3
RTO	Stochastic	Stochastic	Trig	Yes	No	1,2,3
PLF	Stochastic	Stochastic	Trig	Yes	No	3
CLF	Stochastic	Stochastic	Dummy	Yes	No	1,2,3
CAB	Stochastic	None	None	Yes	No	1,2,3
BFP	Fixed	Fixed	Fixed	Yes	No	3
LBP	Fixed	None	Dummy	Yes	No	1,2,3
EXP	Fixed	Stochastic	Dummy	Yes	No	1,2,3
IMP	Fixed	Stochastic	Fixed	Yes	No	3
GDP	Stochastic	Stochastic	Dummy	Yes	No	1,2
INV	Stochastic	Stochastic	None	No	Yes	3
COP	Stochastic	Stochastic	Trig	Yes	No	None
WEC	Fixed	Fixed	Dummy	Yes	No	1,2,3
DUA	Fixed	Stochastic	Trig	Yes	Yes	1,2,3

Table 3: Goodness-of-Fit and Diagnostic Test Statistics For all Variables (Untrended and Trended)

	$\tilde{\sigma}$	R_s^2/R_d^2	*DW*	*Q*	*N*	*H*	*PF*	*CUS*
MVR(U)	2,557	0.1865	2.0365	14.68	42.28*	0.9751	176.61*	0.7487
MVR(T)	688.29	0.1424	0.2695*	706.91*	44.46*	1.7132*	179.55*	2.3239*
BRP(U)	14.35	0.4594	N/A	19.96*	5.1099	1.0524	10.74	-0.5202
BRP(T)	4.3360	0.2561	N/A	100.56*	1.7043	1.2600	10.10	0.1281
IGP(U)	1.4311	0.0279	1.7656	5.4976	4.3582	0.5390	18.48	-0.0087
IGP(T)	0.7313	0.3278	0.6368*	65.53*	7.1443*	0.8389	21.70	0.6377
UNN(U)	0.1997	0.1494	1.9674	17.16	1.4935	0.6172	37.19	0.1427
UNN(T)	0.0649	0.7133	2.1033	18.66*	1.0130	0.8246	61.06	0.2200
PRT(U)	0.2151	0.1824	2.0465	18.07	4.2491	0.8108	60.39	0.5950
PRT(T)	0.0693	0.2739	1.9532	28.83*	2.1337	0.8271	70.81	0.1375
RTO(U)	46.96	0.1679	2.0108	39.59*	239.72*	39.49*	1,037*	0.1365
RTO(T)	5.4259	0.9281	1.3079*	146.61*	877.23*	1.6022*	4,348*	1.2075
PLF(U)	95,843	0.1154	1.9654	8.4041	20.09*	1.4760	251.33*	-1.2391
PLF(T)	10,627	0.8746	0.3809*	257.55*	0.8566	1.4077	338.06*	-0.7626
CLF(U)	934,740	0.2989	2.0032	4.9381	12.04*	2.2589*	249.95*	0.6224
CLF(T)	79,611	0.8552	0.5440*	230.91*	0.8589	2.6232*	306.54*	0.2335
CAB(U)	494.61	0.9569	1.9908	9.2490	39.97*	125.10*	203.60*	-5.7789
CAB(T)	243.20	0.9896	0.5026*	132.21*	63.37*	58.88*	322.63*	-6.1670
BFP(U)	18,858	0.1039	1.8952	9.3018	0.0406	0.4410	25.93	0.0934
BFP(T)	9,227	0.1771	0.5748*	62.92*	7.7134*	0.5334	30.92	0.4972
LBP(U)	3,927	0.2999	1.9918	10.83	1.9414	0.6496	60.61*	4.9846*
LBP(T)	1,845	0.0145	0.8943*	57.86*	0.4167	0.8681	113.09*	9.8608*
EXP(U)	439.02	0.2304	2.0375	21.90*	72.93*	146.60*	540.77*	1.5476
EXP(T)	187.64	0.5761	0.6286*	121.96*	106.39*	48.02*	1,646*	5.7514*
IMP(U)	405.00	0.1686	1.9070	9.4304	20.76*	55.20*	156.33*	0.3030
IMP(T)	211.24	0.5651	0.6006*	94.40*	21.99*	78.57*	186.37*	-0.2335
GDP(U)	586.49	0.5721	2.0112	11.53	14.44*	48.15*	158.15*	1.2771
GDP(T)	237.42	0.9143	0.7393*	126.69*	8.5489*	45.73*	78.77*	1.4468*
INV(U)	582.94	0.3747	N/A	4.1963	15.62*	2.8938*	29.56	-0.5102
INV(T)	473.65	0.5095	N/A	3.5548	53.56*	9.5070*	15.64	-0.2107
COP(U)	493.10	0.0892	2.0506	7.8204	0.6193	1.7209	249.00*	0.7724
COP(T)	143.21	0.6911	1.2275*	42.64*	3.4503	0.7373	2,545*	0.5213
WEC(U)	1,447	0.4617	1.9637	18.19*	18.08*	2.0259*	51.59	-0.5101
WEC(T)	233.78	0.0476	0.4139*	414.53*	1.9793	1.4694*	62.92	-0.2994
DUA(U)	631.89	0.1240	N/A	9.9734	2.9769	0.7503	233.55*	-0.7822
DUA(T)	65.73	0.9325	N/A	175.41*	11.12*	0.5574	382.91*	-1.1583

*Significant at the 5 per cent level.

Figure 2: One-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

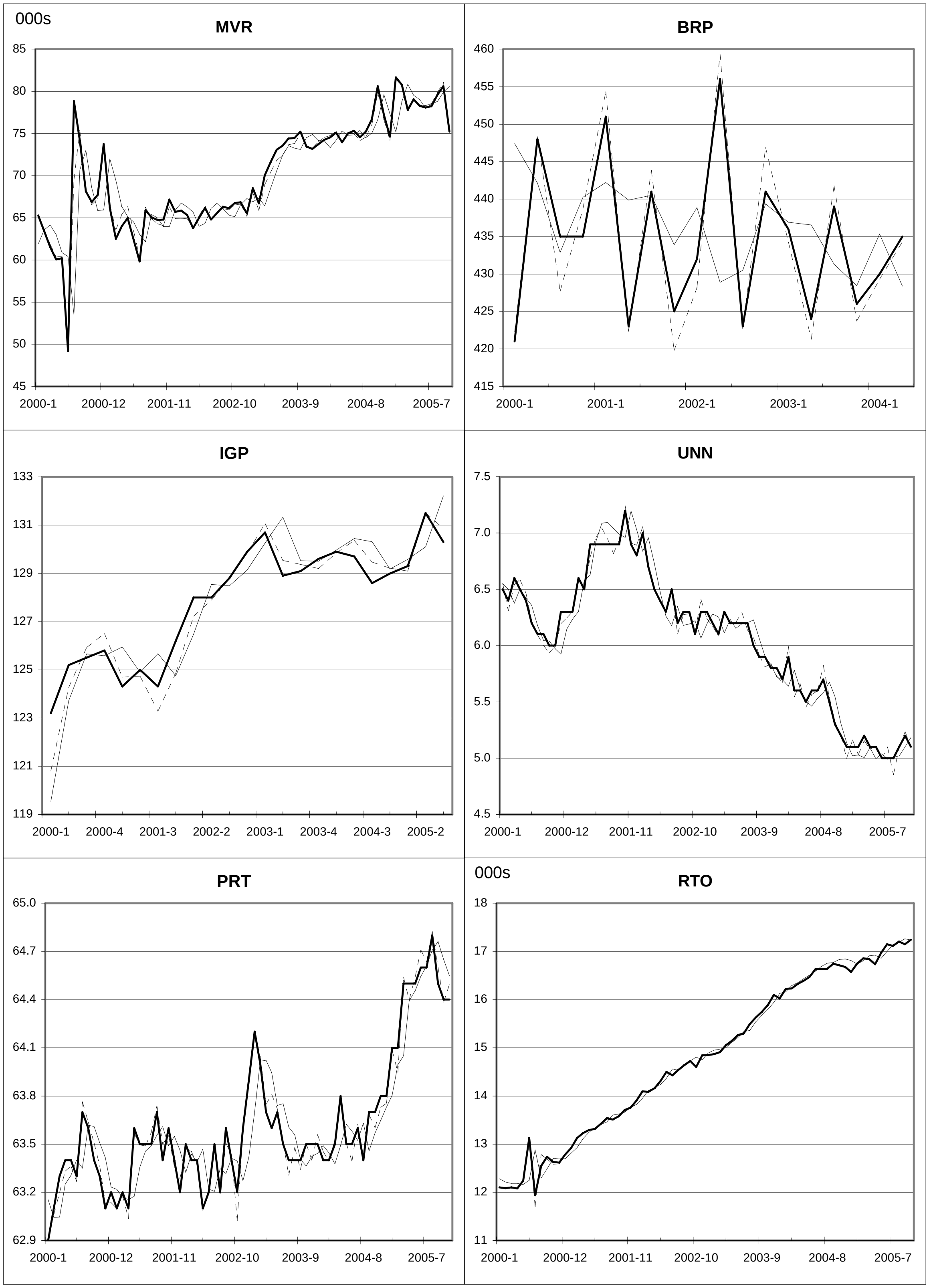

Figure 2 (Con't): One-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

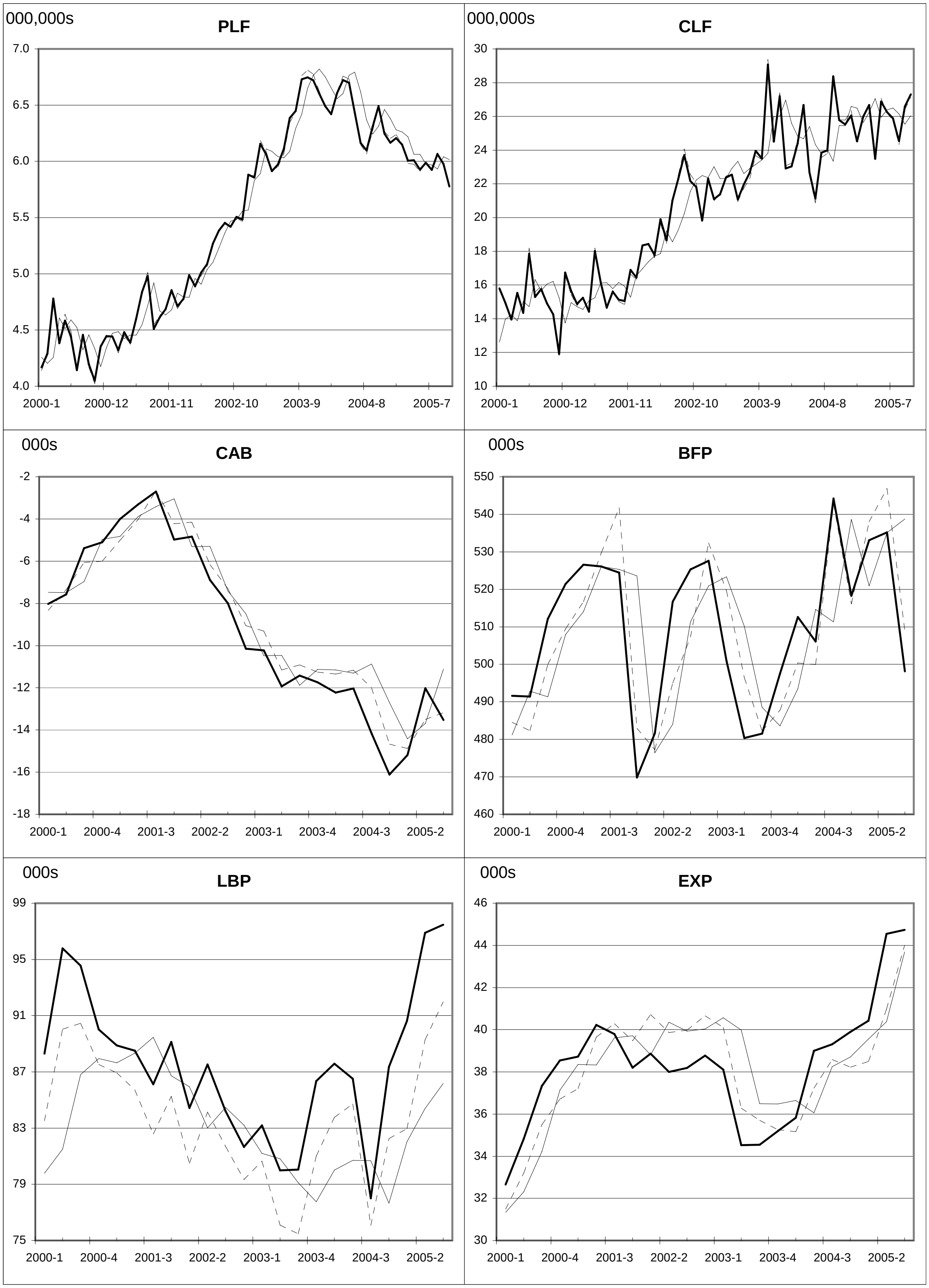

Figure 2 (Con't): One-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

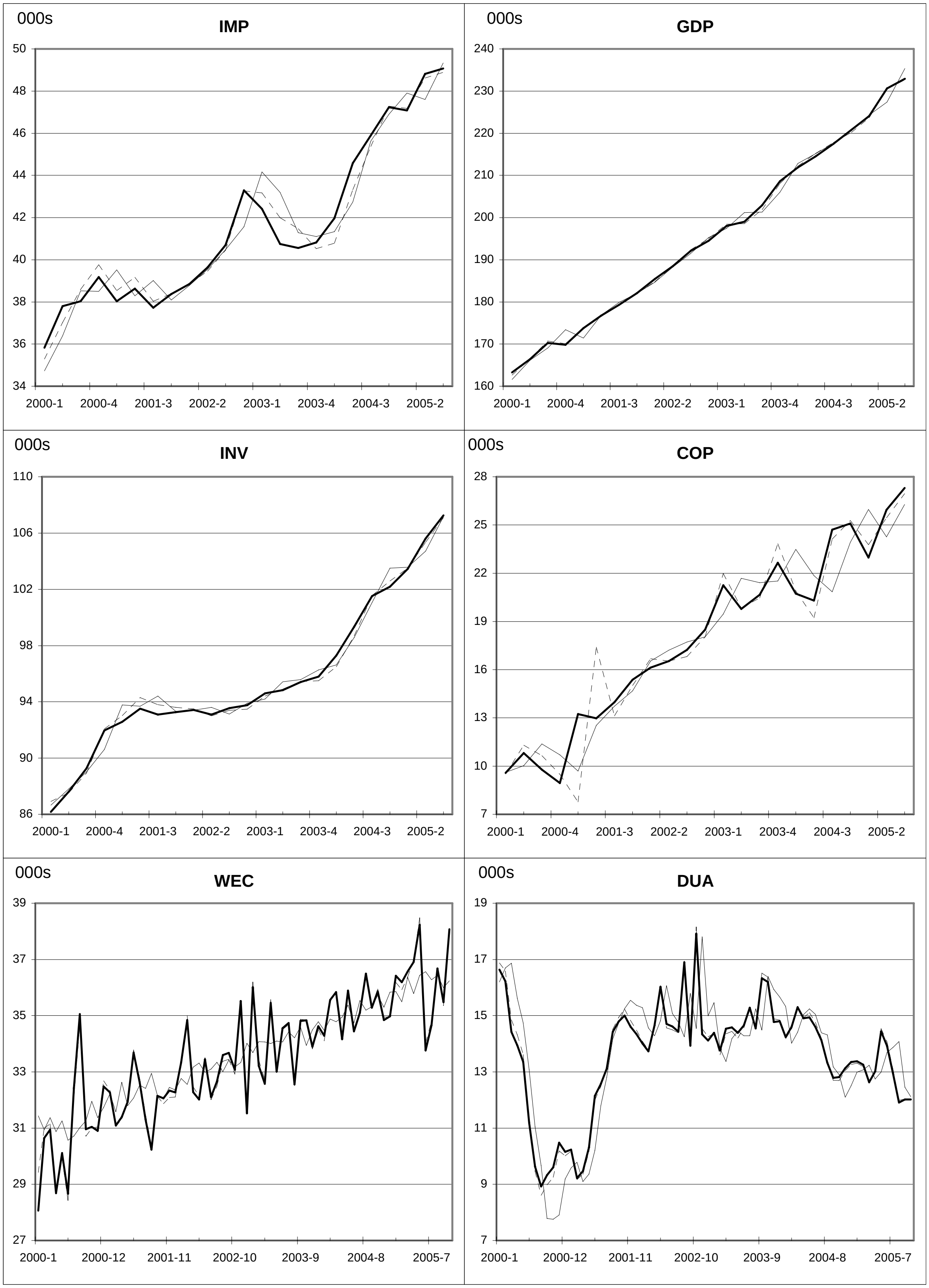

Figure 3: Multi-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

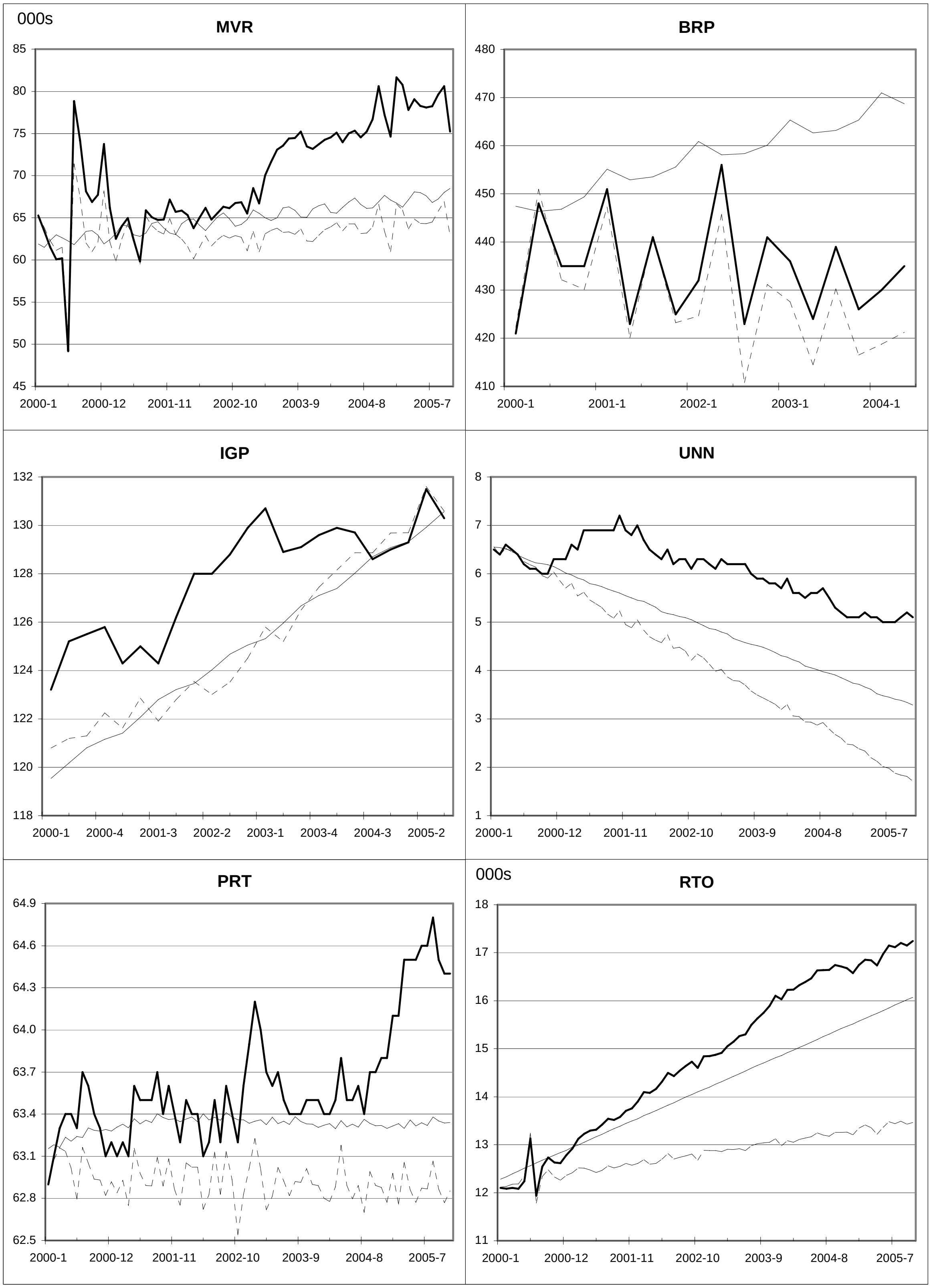

Figure 3 (Con't): Multi-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

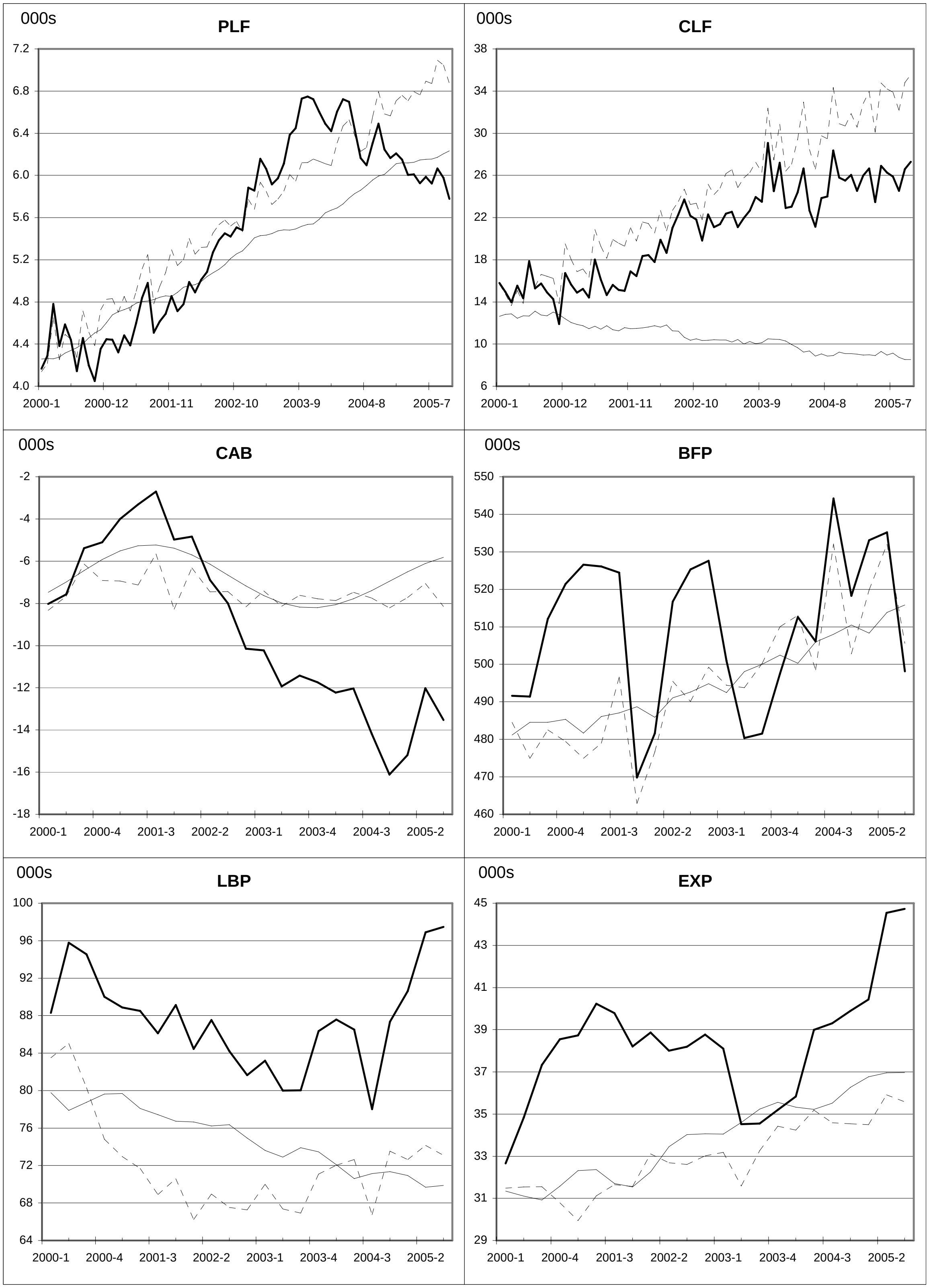

Figure 3 (Con't): Multi-Step Ahead Forecasts Using Seasonally Adjusted (Solid Line) and Trended (Dashed Line) Data Versus Actual (Bold Line)

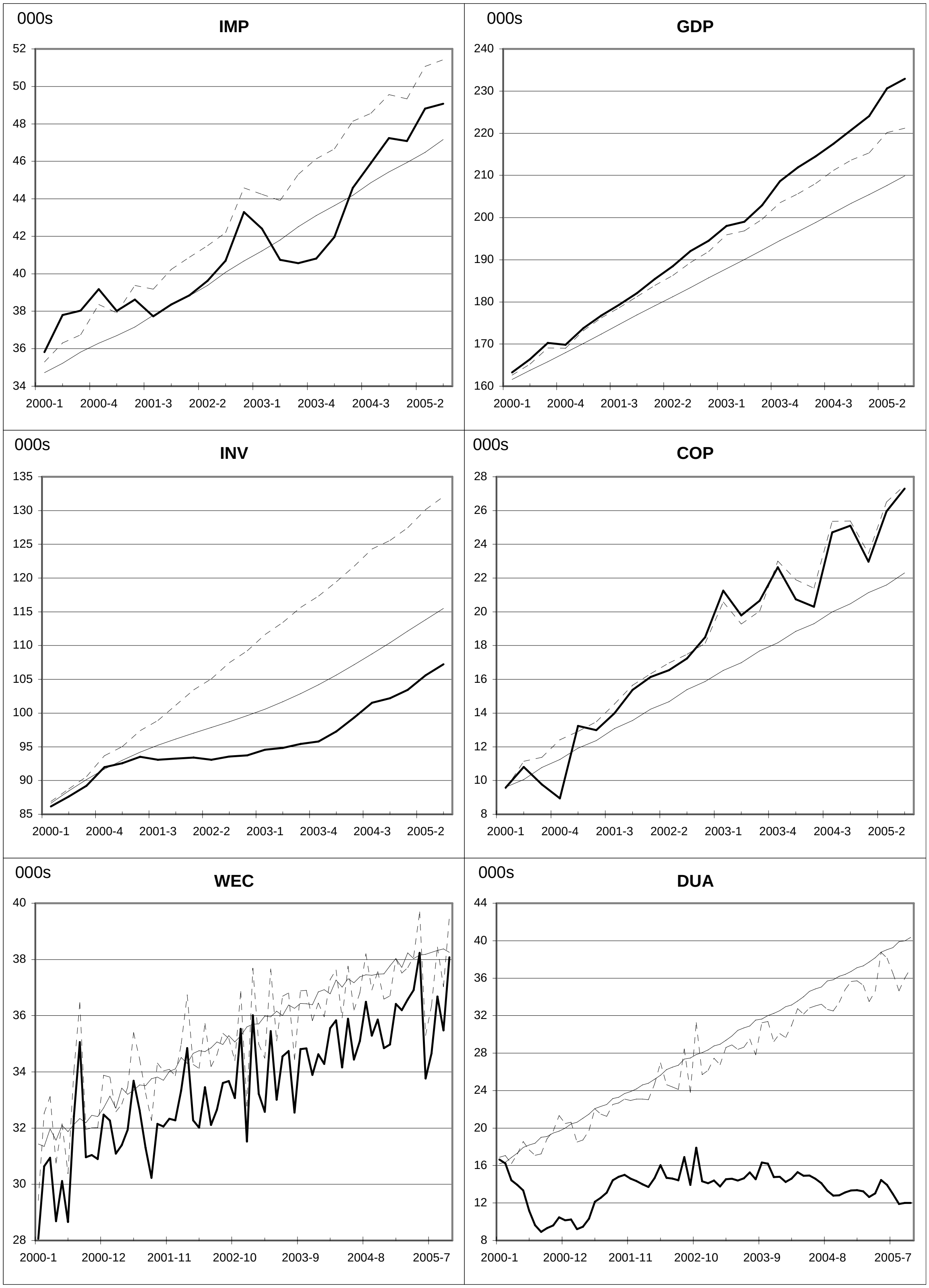

Table 4: Measures of Forecasting Accuracy of Various Models Based on Both the Seasonally Unadjusted versus Seasonally Adjusted Series

(a) One-Period Ahead Forecasts

	SAE	*MAE*	*SSE*	*MSE*	*RMSE*	*MAPE*	*TIC*	*TPE*
MVR(U)	165,683	2,367	1.22×10^{9}	1.74×10^{7}	4,165	3.4265	0.92	33
MVR(T)	41,108	587.26	1.12×10^{8}	1.60×10^{6}	1,263	0.8424	0.28	6
BRP(U)	153.32	8.5178	2,341	130.03	11.40	1.9481	0.64	3
BRP(T)	48.96	2.7201	201.10	11.17	3.3425	0.6249	0.19	0
IGP(U)	22.93	0.9970	41.23	1.7925	1.3389	0.7889	0.98	3
IGP(T)	12.73	0.5534	13.41	0.5832	0.7637	0.4414	0.56	0
UNN(U)	8.4926	0.1196	1.6076	0.0226	0.1505	1.9405	1.01	16
UNN(T)	3.4173	0.0481	0.2714	0.0038	0.0618	0.8032	0.41	0
PRT(U)	11.70	0.1648	3.0241	0.0426	0.2064	0.2590	1.02	22
PRT(T)	3.6117	0.0509	0.3122	0.0044	0.0663	0.0799	0.33	1
RTO(U)	7,544	107.78	2.40×10^{6}	34,259	185.09	0.7727	0.83	16
RTO(T)	1,236	17.65	129,008	1,843	42.93	0.1294	0.19	0
PLF(U)	1.10×10^{7}	156,639	2.61×10^{12}	3.72×10^{10}	192,961	2.9424	1.04	34
PLF(T)	1.40×10^{6}	20,056	4.28×10^{10}	6.11×10^{8}	24,717	0.3714	0.13	3
CLF(U)	9.69×10^{7}	1.38×10^{6}	2.45×10^{14}	3.50×10^{12}	1.87×10^{6}	6.9025	0.91	23
CLF(T)	1.03×10^{7}	147,217	2.26×10^{12}	3.22×10^{10}	179,484	0.7181	0.09	1
CAB(U)	26,854	1,168	5.01×10^{7}	2.18×10^{6}	1,476	15.44	1.03	7
CAB(T)	17,942	780.08	1.87×10^{7}	812,244	901.25	9.6528	0.63	6
BFP(U)	378,710	16,466	1.05×10^{10}	4.55×10^{8}	21,335	3.2274	1.00	10
BFP(T)	227,473	9,890	3.02×10^{9}	1.31×10^{8}	11,455	1.9499	0.54	5
LBP(U)	118,101	5,135	1.02×10^{9}	4.41×10^{7}	6,642	5.9016	1.50	11
LBP(T)	91,247	3,967	4.23×10^{8}	1.84×10^{7}	4,286	4.5696	0.97	8
EXP(U)	40,963	1,781	1.08×10^{8}	4.71×10^{6}	2,170	4.7827	1.30	13
EXP(T)	33,758	1,467	6.13×10^{7}	2.66×10^{6}	1,632	3.9079	0.98	10
IMP(U)	19,785	860.22	2.69×10^{7}	1.17×10^{6}	1,082	2.1168	0.84	6
IMP(T)	10,983	477.52	8.70×10^{6}	378,164	614.95	1.1877	0.48	3
GDP(U)	26,797	1,165	5.67×10^{7}	4.63×10^{6}	1,570	0.6099	0.45	1
GDP(T)	8,459	367.79	2.47×10^{6}	201,103	448.45	0.1900	0.13	0
INV(U)	12,034	523.22	1.04×10^{7}	451,126	671.66	0.5534	0.52	2
INV(T)	7,045	306.30	3.62×10^{6}	157,531	396.90	0.3276	0.31	2
COP(U)	31,864	1,385	6.88×10^{7}	2.99×10^{7}	1,730	8.6411	0.92	7
COP(T)	18,832	818.79	3.12×10^{7}	1.36×10^{7}	1,164	5.5966	0.62	2
WEC(U)	67,784	968.34	1.18×10^{8}	1.68×10^{6}	1,295	2.9254	0.72	14
WEC(T)	10,156	145.08	3.54×10^{6}	50,507	224.74	0.4459	0.12	1
DUA(U)	66,249	946.41	1.04×10^{8}	1.48×10^{6}	1,216	7.1829	1.11	39
DUA(T)	9,253	132.18	1.88×10^{6}	26,900	164.01	1.0250	0.15	6

Table 4 (Con't): Measures of Forecasting Accuracy of Various Models Based on Both the Seasonally Unadjusted versus Seasonally Adjusted Series

(b) Multiple-Period Ahead Forecasts

	SAE	*MAE*	*SSE*	*MSE*	*RMSE*	*MAPE*	*TIC*	*TPE*
MVR(U)	418,110	5,973	3.91×10^{9}	5.58×10^{7}	7,472	8.1568	0.76	32
MVR(T)	498,843	7,126	5.21×10^{9}	7.44×10^{7}	8,627	9.3910	0.87	32
BRP(U)	423.22	23.51	12,814	711.90	26.68	5.3878	1.85	6
BRP(T)	121.36	6.7425	1,116	62.02	7.8751	1.5520	0.55	3
IGP(U)	65.32	2.8401	248.79	10.82	3.2889	2.2426	0.37	10
IGP(T)	62.58	2.7210	236.64	10.29	3.2076	2.1457	0.36	10
UNN(U)	81.19	1.1435	112.36	1.5825	1.2580	19.48	1.42	17
UNN(T)	134.08	1.8884	320.68	4.5166	2.1252	32.62	2.40	14
PRT(U)	24.99	0.3520	18.46	0.2600	0.5099	0.5496	0.85	20
PRT(T)	49.62	0.6989	47.82	0.6736	0.8207	1.0944	1.37	24
RTO(U)	50,599	722.84	5.03×10^{7}	719,173	848.04	4.6273	0.27	48
RTO(T)	140,173	2,003	3.88×10^{8}	5.55×10^{6}	2,355	12.73	0.76	50
PLF(U)	2.56×10^{7}	365,794	1.65×10^{13}	2.36×10^{11}	485,552	6.2990	0.32	30
PLF(T)	2.48×10^{7}	354,475	2.36×10^{13}	1.90×10^{11}	435,443	6.4115	0.29	25
CLF(U)	7.02×10^{8}	1.00×10^{7}	9.29×10^{15}	1.33×10^{14}	1.15×10^{7}	44.44	1.31	34
CLF(T)	2.54×10^{8}	3.63×10^{6}	1.26×10^{15}	1.80×10^{13}	4.25×10^{6}	16.79	0.48	25
CAB(U)	75,320	3,275	4.08×10^{8}	1.77×10^{7}	4,209	33.63	1.02	14
CAB(T)	75,965	3,303	3.59×10^{8}	1.56×10^{7}	3,949	38.60	0.95	12
BFP(U)	487,325	21,188	1.41×10^{10}	6.11×10^{8}	24,728	4.1347	0.80	7
BFP(T)	429,013	18,653	1.26×10^{10}	5.48×10^{8}	23,406	3.6492	0.76	6
LBP(U)	291,388	12,669	4.50×10^{9}	1.96×10^{8}	13,986	14.48	1.81	11
LBP(T)	355,112	15,440	5.84×10^{9}	2.54×10^{8}	15,929	17.70	2.07	11
EXP(U)	103,371	4,494	6.12×10^{8}	2.66×10^{7}	5,159	11.69	0.65	14
EXP(T)	122,169	5,312	7.98×10^{8}	3.47×10^{7}	5,891	13.85	0.75	17
IMP(U)	31,953	1,389	6.14×10^{7}	2.67×10^{6}	1,634	3.4041	0.20	9
IMP(T)	50,157	2,181	1.50×10^{8}	6.51×10^{6}	2,551	5.2614	0.31	6
GDP(U)	232,680	10,117	3.31×10^{9}	1.44×10^{8}	11,993	4.9664	0.29	19
GDP(T)	85,374	3,712	5.69×10^{8}	2.47×10^{7}	4,973	1.7842	0.12	9
INV(U)	113,590	4,939	7.83×10^{8}	3.40×10^{7}	5,835	5.0881	0.48	2
INV(T)	317,894	13,822	6.17×10^{9}	2.68×10^{8}	16,372	14.21	1.35	2
COP(U)	55,143	2,398	1.83×10^{6}	7.98×10^{6}	2,825	13.28	0.28	13
COP(T)	52,772	2,294	2.26×10^{6}	9.81×10^{6}	3,132	11.22	0.31	4
WEC(U)	130,690	1,867	3.14×10^{8}	4.49×10^{6}	2,118	5.6574	0.75	25
WEC(T)	120,025	1,715	2.12×10^{8}	3.03×10^{6}	1,741	5.1600	0.61	21
DUA(U)	1.03×10^{6}	14,759	1.85×10^{10}	2.64×10^{8}	16,254	111.08	5.30	35
DUA(T)	933,915	13,342	1.50×10^{10}	2.14×10^{8}	14,626	101.13	4.77	35

Table 5: Results for Selected Models in Selected Countries of the AGS Test for Statistical Significance of the Difference between *RMSE*s of Alternative Forecasting Procedures

(a) One-Period Ahead Forecasts

	κ_0	κ_1	*CR*
	(standard error)		
MVR	24.62	0.5882*	378.04*
	(156.53)	(0.0303)	
BRP	1.7191	0.7165*	43.43*
	(1.4053)	(0.1106)	
IGP	-0.1032	1.3852*	16.56*
	(0.3206)	(0.3415)	
UNN	0.0021	0.6512*	71.86*
	(0.0131)	(0.0768)	
PRT	0.0147	0.6965*	146.33*
	(0.0135)	(0.0578)	
RTO	0.1211	1.1202*	355.15*
	(10.11)	(0.0594)	
PLF	13,833*	0.9690*	None
	(5,944)	(0.0307)	
CLF	74,134	0.9587*	None
	(42,475)	(0.0224)	
CAB	261.40	0.2640*	15.55*
	(153.14)	(0.0743)	
BFP	-651.51	0.3530*	17.88*
	(2,538)	(0.0836)	
LBP	285.70	0.5778*	86.22*
	(397.17)	(0.0624)	
EXP	-93.43	0.1575*	6.7252*
	(223.74)	(0.0615)	
IMP	16.67	1.3613*	15.77*
	(261.53)	(0.3429)	
GDP	86.54	0.7402*	60.58*
	(165.97)	(0.0953)	
INV	41.73	0.3166*	9.8083*
	(97.68)	(0.1021)	
COP	-402.20	0.4498*	6.5301*
	(391.52)	(0.1923)	
WEC	85.23	0.8397*	610.98*
	(47.31)	(0.0341)	
DUA	51.84	0.8728*	1,075*
	(34.36)	(0.0267)	

Table 5 (Con't): Results for Selected Models in Selected Countries of the AGS Test for Statistical Significance of the Difference between *RMSE*s of Alternative Forecasting Procedures

(b) Multi-Period Ahead Forecasts

	κ_0	κ_1	*CR*
	(*t*-stats)		
MVR	1,712*	-0.0238	26.50*
	(335.70)	(0.0336)	
BRP	17.08*	0.5667*	136.09*
	(1.6570)	(0.1037)	
IGP	0.2278	-0.0543	3.6500
	(0.1567)	(0.0438)	
UNN	0.7667*	0.2630*	1,254*
	(0.0245)	(0.0158)	
PRT	0.4049*	0.0169	508.41*
	(0.0180)	(0.0215)	
RTO	1,343*	0.4000*	3,260*
	(26.67)	(0.0149)	
PLF	37,834	0.5226	None
	(96,227)	(0.3895)	
CLF	6.43×10^{6}*	0.4768	None
	(279,908)	(0.0370)	
CAB	741.74*	-0.0211	3,260*
	(188.03)	(0.0273)	
BFP	-25.17	0.0456	0.5521
	(2,305)	(0.0613)	
LBP	2,771*	-0.2590*	13.71*
	(965.97)	(0.1106)	
EXP	915.98*	-0.0303	19.67*
	(209.50)	(0.0406)	
IMP	-1,034	0.9026	5.3790
	(626.87)	(0.5538)	
GDP	6,405*	0.3249*	1,084*
	(216.74)	(0.0224)	
INV	8,909*	0.4739*	5,360*
	(144.02)	(0.0121)	
COP	-174.77	0.1725	2.3608
	(444.86)	(0.1161)	
WEC	23.04	0.8218*	252.29*
	(67.01)	(0.0518)	
DUA	1,404*	0.0698*	148.69*
	(139.26)	(0.0102)	

*Significant at the 5 per cent level. The critical value is approximately: $CR \sim \chi^2(2) \approx 5.99$.

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