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ON UNIVARIATE FORECASTING COMPARISONS: THE CASE OF THE SPANISH AUTOMOBILE INSUSTRY

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ABSTRACT

This paper investigates the forecasting ability of a new univariate models family of unobservable components, when compared with other more standard univariate methodologies. A forecasting exercice is carried out with each method, in monthly time series of automobile sales.

The accuracy of the differents methods is assesed by comparing several measures of forecasting performance on the out of sample predictions for various horizons as well as differents assumptions on the models parameters.

RESUMEN

El artículo investiga la capacidad predictiva de un nuevo conjunto de modelos univariantes de componentes no observables, comparándolo con otras metodologías univariantes que usan parámettos fijos y variables en el tiempo. Para ello, se lleva a cabo un ejercicio predictivo, con cada uno de los métodos, en series mensuales de ventas de automóviles.

Finalmente, se analiza la eficiencia de estos métodos utilizando distintas medidas de comportamiento predictivo fuera de la muestra para diversos horizontes y con supuestos direrentes sobre ciertos parámetros de los modelós.

1. Introduction

Most of the forecasting literature in economics can be assigned to, bassically, two different frameworks. As Diebold (1989) has noted, on the one hand, there is a long tradition that places considerable emphasis on theoretical aspects (as opposed to empirical evidence) in guiding the evaluation of econometric models. Although some social scientists have clearly postulated that a good forecasting performance is a necessary condition for any theory to be given such status [Zellner (1988), Friedman and Schwartz (1991)], there is still a large number of academic economists and econometricians who tend to view the forecasting problem as one of a secondary importance. Within this framework, primary interest is concentrated in understanding the economy (by estimating the parameters of an equation suggested by a priori theory) resting secure in the belief that good forecasts will follow automatically from such understanding.

On the other hand, those involved in the *forecasting business* know (and can provide many practical examples) that understanding the structural relationships in an economic system may not be a sufficient condition to forecast it well. Even if we leave aside theoretical questions related to the constancy of the parameters in the models [Lucas (1976)], there are many practical situations where deadlines must be met and enlarging the information sets is either impossible or prohibitively costly [García-Ferrer and del Hoyo (1987)]. This pragmatic observation is one of the main reasons of the permanent interest on the univariate forecasting literature, in which forecasts rather than models are the basic object of analysis[1].

This paper describes a forecasting comparison between a variety of old and new statistical methodologies. Each method is used to forecast monthly automobile sales up to several horizons in the future. The accuracy of the different methods and models is assessed by comparing several measures of forecasting performanance of the out-of-sample predictions for various horizons as well as assumptions about certain parameters in the models. The plan of the paper is as follows. In section 2, we present the sources, definitions and characteristics of the data. Section 3 summarily describes the different univariate methodologies used, especially those with time varying parameters recently developed by Young (1984), Ng and Young (1990) and Young

(1994). In section 4, we present the empirical results and analyze the predictive performance of the models. Finally, in section 5, the conclusions are presented.

2. The Data

The automobile sector in Spain represent a very important area of economic activity both in terms of the financial flows involved, and its participation in the labor market. More than 10% of the Spanish working population are somehow involved with the auto industry and the total bill in 1980 U.S. dollars has increased from 5.6 billions in 1980 to 24 billions, nine years later. Also in terms of physical units sold, Spain ranks the fifth in Europe after West Germany, United Kingdom, France and Italy.

Monthly sales data provided by the National Association of Automobile Manufacturers (ANFAC) have been divided in five groups according to their characteristics:

1. The total number of cars sold in Spain (*CTM*).
2. The number of domestic (Spanish manufactured) cars sold in Spain (*CDOM*).
3. The number of imported cars sold in Spain (*CIMP*).
4. The number of luxury cars sold in Spain (*CLUX*).
5. Car sales of one of the leading import companies in Spain (*CSAL*).

[Insert Figs. 1-5]

Plots of these variables for the period 1981.1-1990.6 are shown in Figures 1-5, where both nonstationarity as well as strong seasonality are clearly evident. Also, in Table 1 the annual rates of growth of the different variables are shown, indicating very different behavior of the series through time. In particular, there are remarkable differences in the rates of growth between *CTM* and *CDOM* and the other three variables after 1986, when Spain became a full member of the EEC. Through a progressive reduction on import tariffs since that year, imported cars have become more and more affordable for the Spanish consumer.

[Insert Table 1]

3. Methodologies

Visual inspection of Figures 1 to 5 indicate that the statistical characteristics of such series change considerably over the sample interval, so that the series can be considered **nonstationary** in a statistical sense. All series exhibit a clear upward trend, together with pronounced annual periodicity. The trend behavior is a classic example of statistical **nonstationarity of the mean,** with the local mean value of the series changing markedly over time. The nature of the periodicity (or seasonality), on the other hand, varies over the five series but, in general, there are signs of steadily growing amplitude in most of them, indicating **nonstationarity in the seasonality** about the trend.

These kinds of nonstationarity are indicative of changes in the underlying statistical properties of the data. Therefore, any statistical model used to characterize these series should be able to model this nonstationarity feature if it is to represent them an acceptable way. Since Box and Jenkins (1970) proposed their influential ARIMA models, differencing (both the regular and the seasonal components) and using simple nonlinear transformations (such as the log of the data) prior to model identification and estimation, have been widely and successfully used as effective tools to deal with nonstationarity. None of them are without difficulties: in some cases, indiscriminate differentiation of the data will amplify high frequency components; in others, even after logarithmic transformation, the seasonality is still varying to some extent. What can we do in those situations? Are there other ways to account for the nonstationarity problems?

Some recursive methods recently developed for **Time Variable Parameter** (TVP) estimation can provide an interesting alternative to ARIMA modelling in which parameter variation is characterised by some form of stochastic state-space (SS) model. The SS model belongs to the class of unobserved component ARIMA (UC-ARIMA) models developed by Engle (1978) and Nerlove *et al.* (1979), and have been popular in the forecasting literature over the last years. However, it is only recently that papers which exemplify this TVP approach [Harvey (1984), Kitagawa and Gersch (1984), Engle *et al.* (1988) and Ng and Young (1990)] have been utilized

within the context of SS estimation. In particular, Young *et al.* (1990) and Young (1994) provide a novel spectral interpretation of the SS smoothing algorithms to decompose the series into various, **quasi-orthogonal components,** the models for which can be identified and estimated using recursive methods of TVP estimation [Young (1984)].
Following Young and Young (1990), we can write the *component* or *structural* model of a univariate time series Y_t as

$$Y_t = T_t + P_t + \epsilon_t \tag{3.1}$$

where, T_t is a low frequency or **trend** component; P_t is a **perturbational** component around the long run trend which may be either a zero mean **stochastic** component with fairly general statistical properties or a sustained **periodic** or **seasonal** component; and, finally, ϵ_t is a zero mean, serially uncorrelated **white noise** component with variance σ_ϵ^2.

The Trend Model

The low-frequency or trend component can be represented by a second-order generalized random walk (GRW) model of the form:

$$\begin{aligned} T_t &= T_{t-1} + S_{t-1} + \eta_t \\ S_t &= S_{t-1} + \xi_t \end{aligned} \tag{3.2}$$

where S_t may be interpreted as the local slope or 'derivative' of the trend and η_t and ξ_t are zero mean, serially and mutually uncorrelated white noise inputs. It is further assumed that they are statistically independent of the white noise observational errors ϵ_t in equation (3.1), and therefore:

$$\mathrm{E}(\epsilon_t \eta_s) = \mathrm{E}(\epsilon_t \xi_s) = \mathrm{E}(\eta_t \xi_s) = 0 \quad \forall t, s \tag{3.3}$$

By introducing a trend model of this type, it is assumed that the time-series can be characterised by a varying mean value whose variability will depend upon the specific form of the GRW model chosen. It can be shown that η_t is mainly necessary to handle sharp discontinuities of level or slope [Young and Ng (1989)] and unless they exist, can be constrained to zero. If this is the case, then the variance of ξ_t is the only unknown in (3.2) and can be determined by the **Noise Variance Ratio** (NVR), that is the relation between σ_ξ^2 and the variance σ_ϵ^2 of the observational noise ϵ_t in equation (3.1)[2].

The Periodic or Seasonal Model

It is assumed that the periodic component in (3.1) can be either a **General Transfer Function** (GTF) or a **Dynamic Harmonic Regression** (DHR) model: the former is a more general representation of any stochastic time-series; the latter is restricted primarily to series with strong seasonality and is particularly useful in the context of adaptive seasonal adjustment.

The General Transfer Function Model

The GTF model is similar to the ARIMA model employed by Box and Jenkins (1970) although **no stationarity restrictions** are imposed here. It is assumed that the sum of the stochastic perturbation P_t and the white noise component ϵ_t follows an ARMA process of the form:

$$P_t + \epsilon_t = \frac{\gamma(L)}{\phi(L)} a_t \tag{3.4}$$

where

$$\phi(L) = \sum_{j=0}^{m} \phi_j L^j, \quad \phi_0 = 1$$

and

$$\gamma(L) \equiv \sum_{j=0}^{m} \gamma_j L^j, \quad \gamma_0 \equiv 1.$$

For convenience, the order m is assumed the same for both polynomials; however, different orders can be introduced without any further problem. In the empirical applications of the GTF model described in the next section, we will concentrate on the use of the purely Autoregressive (AR) form of (3.4). In that case, an AR or subset AR model is identified for the perturbations using some of the identification criteria described in [Young (1985)].

The Dynamic Harmonic Regression Model

In this case, the periodic component P_t is represented in the following form:

$$P_t = \sum_{i=1}^{F} \left[\theta_{1it} \cos(2\pi f_i t) + \theta_{2it} \sin(2\pi f_i t)\right] \tag{3.5}$$

where f_i, $i = 1,2,\ldots,F$, are the frequencies in cycles per unit of time, and the coefficients θ_{jit}, $j = 1,2$ and $i = 1,2,\ldots,F$ are assumed to be **time-variable,** so that the model is able to handle nonstationary seasonality. The parameter variations are modelled as GRW processes which then allows the time series to exhibit amplitude-modulated periodic behavior. Since there are two parameters associated with each frequency component, the changes in the amplitude A_t of each component, defined by,

$$A_{it} = \sqrt{\theta_{1it}^2 + \theta_{2it}^2} \tag{3.6}$$

provides a useful indication of the estimated amplitude modulation.

Two additional comments about the DHR model are worth mentioning. First, the DHR model is rather different to the GTF model in that its parameters are assumed to be **inherently time variable,** rather than normally constant, over the observation interval. Second, the DHR model can be contrasted with the Fourier model proposed by Harvey (1984), where the sine and cosine terms for each frequency appear in the state equations of the periodic model rather than, as here, in the observation equation.

Having defined SS model structures for all the components of the structural model, it is straightforward to assemble these into an aggregate SS form where the state vector is composed of all the states from the different submodels and the observation matrix is simply a vector chosen to extract from the state vector the structural components T_t and P_t [Ng and Young (1990)]. The problems of **structural identification** (similar to the ones that appear in standard econometric models) and subsequent **parameter estimation** for the complete SS model are clearly non-trivial. In general, the imposition of certain restrictions —that is, imposing a given structure— has been the way to achieve identification in the statistical literature on signal extraction and a standard set of such restrictions is the orthogonality of the components (trend, perturbation and noise in our case). A logical way to proceed is to verify these convenient identifying restrictions after an initial, unrestricted estimation of the component models[3]. Unfortunately, as noted by Grether and Nerlove (1970), the model for a component is different from the model obtained by its estimator, and so it is perfectly possible to find that, whereas the theoretical components are uncorrelated in general, the estimated components will be correlated. Nevertheless, for practical purposes, it is important to verify the actual degree of orthogonality among the estimated components in order to avoid spurious decompositions commonly found with these procedures [García-Ferrer and del Hoyo (1992)]. In such cases, it can be shown that, through an adequate choice of the NVR ratio (selecting a NVR value for the trend that does not contain higher frequency components associated with the perturbational behavior) the orthogonality problem is considerably reduced.

Finally, as regards estimation, the most obvious approach is to formulate the problem in maximum likelihood (ML) terms. If the disturbances in the SS model are normally distributed, the likelihood function for the observations may be obtained from the Kalman filter via the *prediction error decomposition* [Harvey and Peters (1990)]. However, some practice with this approach indicate that it can turn out to be rather complex even for particularly simple structural models[4]. An alternative, discussed in Young (1988) and based on an sequential spectral decomposition, applies the SS smoothing algorithms to the various component submodels, decomposing the solution to the overall estimation problem into a series of linear steps, each solved in fully recursive terms. Although the procedure is suboptimal (in a ML sense), it is robust in practical applications and well suited for adaptive forecasting.

4. Empirical Results and Forecasting Performance

All models are estimated for three different period intervals: 1981.01 to 1988.12, 1981.01 to 1989.06 and 1981.01 to 1989.12, in order to generate, respectively, 18, 12 and 6 step-ahead forecasting errors for each model[5].

The estimation results for the ARIMA models for the period 1981.01 to 1988.12 are shown in Table 2. Careful examination of the estimated residuals and their acf and pacf, as well as the Ljung-Box statistics (not shown), did not indicate either the presence of important outliers in any of the models or the existence of any type of stochastic structure in the residuals[6].

In Table 3, the estimated GTF (IRW trend plus subset AR) for the detrended (perturbation) data are shown. To obtain this model, the low-frequency trend which is so obvious in Figures 1 to 5 was first estimated and removed by the IRWSMOOTH algorithm (included in microCAPTAIN) with different NVR values which were selected interactively so that the trend derivative contains only a very slight leakage of the higher frequency components associated with the annual, 12 month cycle. The chosen NVR parameter for the trend should: (1) reflect the long term, low frequency behavior of the series and (2) not contain (on the basis of the estimated derivative, or slope of the trend) any higher frequency components associated with the perturbational behavior around this trend. Also, an interesting byproduct of the estimated slope is the possibility of verifying the existence of underlying quasi-periodic long term behavior so common in socio-economic and business data.

[Insert Tables 2 and 3]

As indicated in the previous section, for models of the type given by equations (3.1) and (3.2), the *chosen* NVR uniquely defines the performance of the algorithm. However, the question of how to choose it remains an open one, since there are several ways in which the NVR can be chosen. They all can be interpreted as defining the bandwidth of the filter in spectral terms. It has been shown [Young, T.J. (1987)] for example, that the *cut-off* frequency F_{50} (i.e. the frequency at which the filter attenuates the signal by 50%) is related to the NVR by the empirical equation,

$$F_{50} = 0.158\,(NVR)^{0.25}$$

so that the NVR that will extract a given band of low frequencies could be computed from this expression. Suppose, for instance, that we require that the trend reflects a typical economic cycle of, say, five years but contains the minimum of any higher frequency components such as annual cycles. For our monthly data, F_{50} can then be chosen to just pass the frequency components of 0.0167 $\left[= \frac{1}{5 \times 12} \right]$ cycles per sample. Substituting this value for F_{50} yields an NVR $= 10^{-4}$ which is a very useful **default** value for this type of periodicity.

In any case, the estimated derivative can provide additional useful information in deciding an appropriate set of values for the NVR. To see how changing the NVR values affects the trend estimation, let us try a number of different parameter values for one of the series, i.e. the *CSAL* data set. Figures 6a to 6c show the results obtained in each of the three cases (NVR values of 10^{-1}, 10^{-2} and 10^{-4}, respectively). Apparently, the three trends track the long period behavior very well. However, the results for NVR $= 10^{-1}$ and NVR $= 10^{-2}$ are not as good as it looks at first sight: we see from the associated trend derivative plots (Figures 7a and 7b) that the estimated trends actually contain some higher frequency components related to the shorten period annual cycle; *components which are amplified by the derivative operation inherent in the trend derivative estimation* and show up very well on the derivative plot.

[Insert Figures 6 and 7]

An additional piece of confirmation of this fact is provided by the periodograms of the three derivatives shown in Figures 8a to 8c. While in the two former cases there is a strong evidence of higher frequencies, the periodogram for the default value (NVR = 10^{-4}) shows the typical low frequency concentration with no leakage of higher frecuencies.

[Insert Figure 8]

Once the perturbational series are obtained, the procedures for AR model identification used in microCAPTAIN are based on the identification criteria proposed by Akaike (1974). After the unrestricted AR model is chosen and estimated, further examination may indicate that different subset AR models with certain parameters constrained to zero provide superior *AIC* and *YIC* values, although with only marginal decreases in the R^2. These restricted subset AR models shown in Table 3[7].

The complete estimation results for the DHR models with *default* NVR value (*DHRD*) are based on a fundamental frequency (the 12 months annual cycle) and its principal harmonics at periods 6, 4, 3, 2.4, and 2 months, respectively, using the F suboption in microCAPTAIN (where the parameters are modelled as *RW* processes), with the automatic mode (NVR = 10^{-4} for the trend component and NVR = 10^{-2} for all the other components). The complete results of the estimation process include information about the trend, the seasonal components, the nonseasonal component, the seasonal amplitudes, and the fitted (forecasted) data. Exhaustive analysis of these results are outside the scope of this paper, but as might expected from a TVP estimation method, the statistical fitting to the historical data in all series is quite remarkably accurate.

Comparisons among the **statistical fittings** of the estimated ARIMA, GTF and DHRD models for this particular data set must be carried out cautiously since the different measures of statistical fitting are not always strictly comparable. However, there are two cases in which such comparison is possible: the residual variances (s_a^2 and s_e^2) of estimated ARIMA and GTF models in Tables 2 and 3, and the R^2 for the original series in the case of the ARIMA and the DHRD models. The results are shown in Table 4, where, except for the CTM series, the GTF shows better statistical fitting than its correspondent ARIMA alternative under the residual variance criterion. When using the R^2 criterion, the DHRD clearly outperforms the ARIMA model as expected, given the characteristics of the DHRD algorithms and the strong periodic behavior of our series. As a matter of fact, we have observed that the DHRD model beats almost any other univariate (and many multivariate) alternative models for this type of data in terms of statistical fitting, as might be expected because its parameters are allowed to vary over the observation interval.

[Insert Table 4]

Forecasting Performance

Leaving aside the statistical fitting characteristics of the different alternatives, our main interest in this paper is to analyze the predictive performance of the models for several time horizons. The forecast period (1989.01 to 1990.06) was chosen because it is not particularly easy to predict since 1989 anticipated a reduction in the rate of growth of sales (after four consecutive years of booming sales) that lead to a negative growth rate in 1990 of 10.4%[8]. Since our information set only includes historical data, without any leading indicator variables or any device to predict turning points as it is the case in Zellner *et al.* (1991), we expect considerable overprediction in the most important series (*CTM*, *CDOM* and *CIMP*), while the biases in the other series may have different signs. In any case, it is very important to see how the models **adapt** their predictions as soon as new information becomes available.

Forecasts have been evaluated according to different (individual and aggregate) forecasting measures [Meese and Geweke (1984)]:

1. ***The One Step-Ahead Percentage Forecasting Error (OSFE)*** computed after each estimation period. Since we have 3 estimation periods and 5 variables, we will have 15 observations to compare for each model.

2. ***The Percentage Prediction Error (%PE)*** defined as

$$\%PE \equiv \frac{F(t+j) - A(t+j)}{A(t+j)} \times 100$$

where $A(t)$ is the actual value, $F(t)$ denotes the forecast value, and $j = 1,2,\ldots$ is the total number of forecasts.

3. ***The Aggregate Percentage Prediction Error (APE)*** defined as

$$APE \equiv \frac{\sum_{j=1}^{h} F(t+j) - \sum_{j=1}^{h} A(t+j)}{\sum_{j=1}^{h} A(t+j)} \times 100$$

$h = 6$, 12 and 18. This is not commonly used since it allows for the cancellation of large errors of different signs, but it becomes relevant when the target is the total number of units in the long run rather than its monthly distribution.

4. ***The Percentage Root Mean Squared error (%RMSE)*** defined as

$$\%RMSE \equiv \left[\frac{1}{h} \sum_{j=1}^{h} \left(\frac{F(t+j) - A(t+j)}{A(t+j)} \right)^2 \times 100 \right]^{1/2}$$

$h = 6$, 12 and 18.

5. ***The Percentage Mean Absolute Error (%MAE)*** defined as

$$\%MAE \equiv \frac{1}{h} \sum_{j=1}^{h} \left| \frac{F(t+j) - A(t+j)}{A(t+j)} \right| \times 100$$

$h = 6$, 12 and 18.

6. ***The Percentage Mean Error (%ME)*** defined as

$$\%ME \equiv \frac{1}{h} \sum_{j=1}^{h} \frac{F(t+j) - A(t+j)}{A(t+j)} \times 100$$

$h = 6$, 12 and 18.

Regardless of the model used to construct the forecast, all forecast values are for the original series in levels. For the component models, the estimated trend and/or seasonals were reinserted, and for the case of the ARIMA models the differences were converted to levels if preliminary differences had been employed.
Results for the *OSFE*, *APE*, *%RMSE*, *%ME*, and *%MAE* criteria for the three models considered so far are shown in the first three columns of Tables 5 to 9. The meaning of the fourth column will be explained later. As might be expected, **no model dominates the others under all the forecasting criteria.** However, some tentative conclusions can be drawn from such tables:

[Insert Tables 5-9]

1. In terms of the one-step ahead percentage forecasting error (OSFE) criteria, the ARIMA model seems to perform better than the other two alternatives. However, the dominance is not uniform among all series at all forecasting intervals. The ARIMA seems to work better for *CTM* and *CIMP*, the GTF model seems to be better for *CDOM* and *CLUX*, and the DHRD model for the case of *CSAL*.

2. The long-run forecasting behavior (as measured by the APE criteria) 18 months ahead is reasonably good, given that our three alternatives are univariate models. Within this criteria, the GTF model outperforms the other two alternatives by a considerable margin. Only in *CDOM* for the ARIMA and in *CSAL* for the DHRD, do the alternatives perform better for some time horizons.
3. In the case of the %RMSE criteria, the ARIMA model seems to perform better than the other two models. Again, the ARIMA advantage is concentrated on *CTM*, *CDOM* and *CIMP*. For the *CLUX* and *CSAL*, the DHRD model ouperforms the other alternatives. The GTF model does not seem to be working well under this criteria.
4. When using the remaining forecasting performance criteria (%MAE and %ME), the GTF model again outperforms the other two models. In the case of the %ME, the DHRD does not performs well, while in the case of the %MAE criteria, all models perform in similar terms.

The interpretation of the results in Tables 5 to 9 must be exercised with care. The main intention of this forecasting exercise was not to provide a kind of forecasting competition *a la* Makridakis *et al.* (1982), but to explore the potential forecasting ability for economic time series of a new set of univariate procedures recently developed in other areas of control engineering and systems theory. In this respect, the results obtained for the GTF model are very promising and compete very favorably with a well established univariate modelling strategy as it is the ARIMA methodology. The results for the DHRD model are somehow surprising, having in mind the excellent statistical fitting shown by this TVP estimation method.

One explanation of this finding is related to the difficulties in forecasting the parameters variation. Given our present assumptions, the DHRD model will only work if the RW or IRW forecasts are good.

Another explanation has to do with the way in which the models were estimated. While in the case of the GTF model the choice of the NVR value was decided by the authors by looking at the trend derivative in each data set, this was not the case for the DHRD model, where all the estimation and forecasting exercises were carried out under the **automatic mode** (using default values for the NVR). This was not a very sensible decision since forecasts using this SS

approach can be very sensitive to the estimation of the trend NVR, probably because the assumed RW or IRW models, which reflect only the characteristics of the local trend, do not adequately model any long term variations in the trend derivative. The implications of the previous results suggest that a different NVR value may improve the forecasting behavior over different parts of the data and, consequently, that **the trend NVR should be adaptively updated during estimation**; an option which has not been available in microCAPTAIN until very recently.

The Choice of the NVR Value Revisited

The following example provides a good illustration of the potential gain if the NVR is used as a *tuning* parameter in a forecasting exercise. Let us take the cases of the *CTM* and *CLUX* variables, where the DHRD model has not performed too well over the prediction interval. In particular, and to maintain brief the exposition, let us look at the *CTM* variable where systematic overprediction has taken place along the predictive horizon. It is obvious that, as soon as we observe the trend changes, the default NVR value is not a very realistic assumption. As an alternative, if an arbitrary higher value is selected (i.e. NVR = 10^{-3}), the forecasting algorithm weights more heavily the recent changes in the trend and produces better multi-step forecasts as shown in Table 10.

[Insert Table 10]

If we compare the results from Table 10 with those of the first three columns of Tables 5 to 9, we can see that, except for the case of the OSFE criterion, the DHR could rank first in forecasting performance for the *CTM* variable at the 18 steps-ahead forecasting horizon. We think that this result is very promising and demonstrates the potential advantage of using the NVR as a tuning device. Nevertheless, this last point deserves further analysis since it is also desirable to have in practice general guidelines for the actual choice of the NVR value.

So far, somehow, our approach in dealing with the DHR model can be considered half the way between the *objective optimisation* approach and the *subjective bayesian* one: parameters need to be chosen, but those selected are reduced to a minimum, and values are provided to aid in their choice. Note, however, that manual tuning can be dangerous and some more objective adaptive adjustment would be preferably.

Recently, Tych and Young (1993) have developed a method of optimising the NVR values based upon the spectral properties of the random walk family of models used to describe the nonstationary parameters, so that the logarithm of the pseudo-spectrum (*pseudo* because the IRW model is nonstationary) matches the logarithm of either the AR spectrum or the periodogram of the data, in a least squares sense. A measure of goodness of fit is introduced, closely related to the Fisher metric, and the method also allows **the estimation of the NVR values associated with the main seasonal frequency (and its harmonic) of the DHR models**.

With this alternative, we estimated the corresponding new DHR models for the whole set of variables using the same sample intervals as before in order to produce 18, 12, and 6 forecast errors for each variable. After the last iteration, the estimated (optimised) NVR values for the trends, ranging between 8×10^{-3} and 10^{-3}, show both large differences among the different variables as well as big discrepancies with the 10^{-4} defalult value used in the DHRD model. Also, there are some discrepancies in the NVR values corresponding to the fundamental seasonal frequency and its harmonic. The forecasting results for the different measures are shown in the fourth column of Tables 5 to 9 under de DHRO (for *optimised*) heading. The first thing we notice is the considerable improvement in forecasting accuracy over the previous *default* DHRD model for almost all time forecasting horizons and different citeria. As a matter of fact, out of the 75 possible outcomes, the DHRO model beats the DHRD one in 52 cases (70% approximately), confirming the potencial advantage of updating the NVR over the sample interval in terms of forecasting accuracy.

[Insert Tables 11, 12a and 12b]

As regards overall comparisons among the different methods, we have summarized the results of Table 5 to 9 in Table 11, where we show the number of times that each method ranks first

and last under the different criteria. The same exercise is carried out on Tables 12a and 12b where the results have been splitted according to the different forecast horizons. Again, the interpretation of the results in these tables must be exercised with care. The reader should be aware that although it is useful to report forecast performance based on various measures, **it might be misleading to synthesize the performance of different methods by aggregating results of various measures**.

With this caveat in mind, we will try to summarize the main results that emerge from the previous tables. Firstly, again **no model dominates the others under all the forecasting criteria** for all series and forecasting intervals. This is not surprising, given the different trend behaviour of the different series during the forecasting period. Secondly, Table 11 confirms this finding showing the superiority of the GTF model in the case of the APE and %ME criteria, while the DHRO model performs the best for the %RMSE and %MAE measures. For the OSFE criterion, both the ARIMA and the DHRO share the lead. Thirdly, if we pay attention to the *worst* performers, the DHRO appears to be clearly superior to its competitors for all measures except for the APE one. Somehow, if we use a *minimax* criterion, the DHRO might emerge as the best alternative for this particular data set and forecasting period. Fourthly, with regard to the performance for different forecast horizons, Table 12a indicates that both the GTF and the DHRO outperform the other methods for the 18 and 12 months forecasting horizons. Only for the short 6 months period, the ARIMA works as well as the GTF does. Again, Table 12b indicates how the DHRO model appears very few times as the worst alternative, confirming its good minimax properties.

5. Conclusions

This paper has explored the forecasting abilities of a new set of univariate unobserved components models with fixed and time varying parameters and compares its performance with a well established methodology like the ARIMA Box-Jenkins approach. The time series data, belonging to the Spanish automobile sector, were chosen because they showed a non-homogeneous break in the trend during the forecasting period in some of the series, making the prediction exercise more complicated. In order to assess the forecasting abilities of the different alternatives, five measures of the forecasting accuracy are proposed.

According to the empirical results of the previous sections, several conclusions can be advanced, though it must be recognized that these are inferences from a particular data set and forecast period and that further evidence is necessary before any generalization is made. Neither the scope nor the number of series analyzed allow very strong statements about the superiority of one particular method over the others. Nevertheless, some tentative conclusions can be suggested:

1. In terms of the statistical fitting to the historical data, the DHR models outperform the fixed parameter models by considerable margin. Although it is well known that gains in residual variance are not a sufficient condition for gains in forecasting accuracy, improvements in residual variance always imply shorter forecasting intervals.
2. In our forecasting exercise, there has been no intention to rank the different forecasting performance criteria. On the contrary, we believe that this is something that has to be decided by the user in terms of his/her needs. Conflicts among them (although not desirable) are only an indication of different goals of alternative prediction exercises. However, our results contend that many forecasting comparisons in the literature may be misleading if they are based solely in a single criterion. A thorough discussion on the nature and the relationships among the forecasting criteria should be provided before any *general* conclusions are drawn.
3. For the set of forecasting performance criteria used in this paper, there is no uniform dominance of one method over the others (for all criteria and at all forecasting intervals). Being unknown, the statistical distribution of these criteria cannot be used to pose the empirical evidence in a formal statistical testing framework. Therefore, some of the discrepancies found among the models may not be statistically significant. However, if we use an aggregate *minimax* criterion across measures and forecast horizons (given the warnings mentioned in the previous section), the DHRO model can be considered as the best candidate for this particular data set and forecasting period. Other forecasting exercises with a larger data set, as in García-Ferrer *et al.* (1994), confirm its potential as an interesting methodology in the field of univariate forecasting.

Notes

1. An interesting attempt to reconcile these two divergent lines of literature may be seen in Diebold (1989).
2. This NVR ratio uniquely defines the performance of the algorithm since all the other parameters in the model are constrained to unity. There are various ways in which the NVR can be chosen, some of which are discussed in Young and Benner (1988). The choice of the NVR value is a very important step in the identification process, among other things, to ensure the orthogonality condition among the different components in (3.1).
3. Unconstrained ML estimation could have problems with a poorly defined ML hypersurface. Indeed, there is some evidence that the likelihood surface in this class of models is generally rather flat. Unfortunately, this evidence is inconclusive since no one, as far as we are aware, has studied the problem in depth.
4. Additionally, it is not easy to solve the ML problem with the parameters, as well as the states, being estimated recursively.
5. Two different types of software were used. For the component models, both the GTF and the DHR options are estimated using the microCAPTAIN software recently developped by Young and Benner (1988). The ARIMA models were estimated by exact ML methods using the SCA computer program.
6. The interpretation of the R^2 criterion is somehow misleading here since it refers to the fitting of the original series not the transformed (stationary) ones.
7. YIC represents the *Young Information Criterion* and provides a good compromise between model fitting parameter efficiency. As with the AIC, the best model will normally be the one with the greatest negative YIC. The exact definition of the YIC can be found in Young (1985).
8. Again this behavior is not uniform during the forecast period among the different subgroups in the automobile industry.

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FIGURES

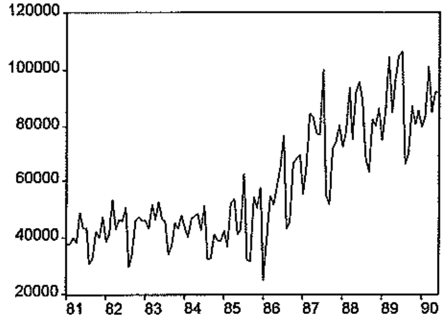


Figure 1: Total Car Sales in Spain

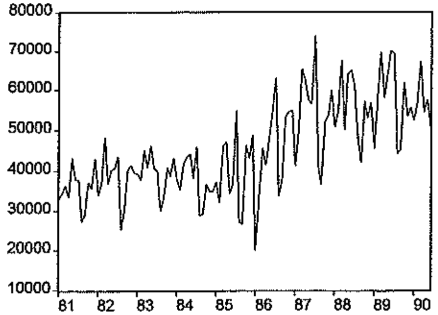


Figure 2. Domestic Car Sales in Spain

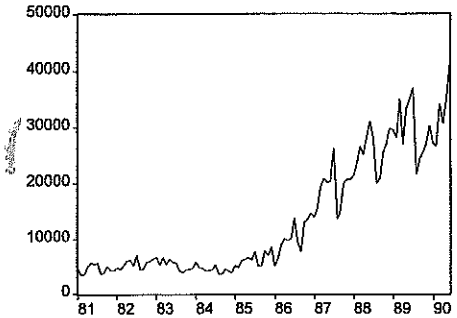


Figure 3. Imported Car Sales in Spain

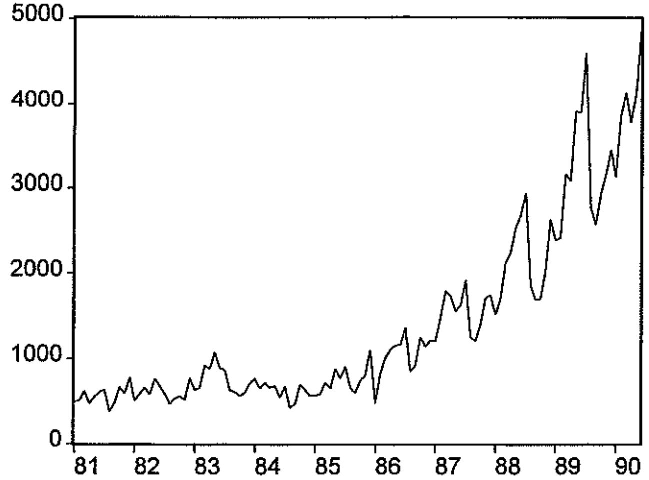


Figure 4. Luxury Car Sales in Spain

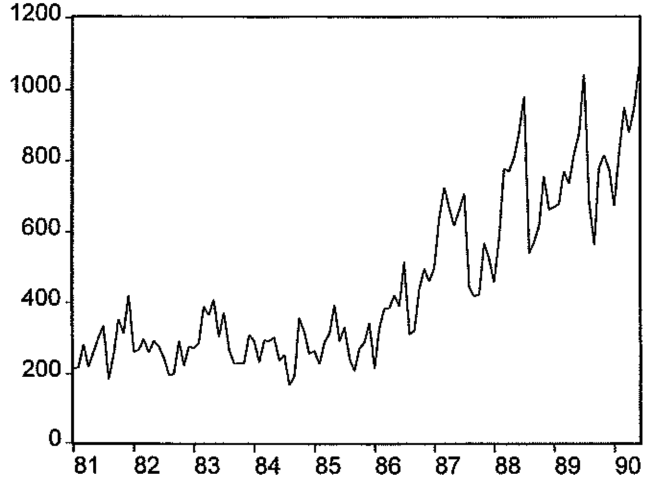


Figure 5. Company X Car Sales in Spain

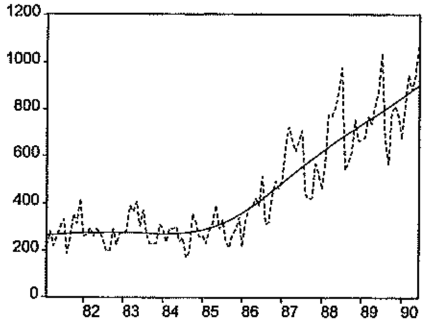


Figure 6.a: Original data and estimated trend of CSAL (NVR=0.0001)

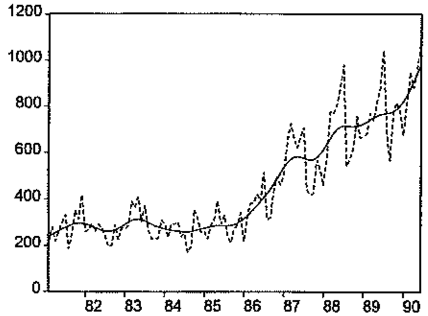


Figure 6.b: Original data and estimated trend of CSAL (NVR=0.01)

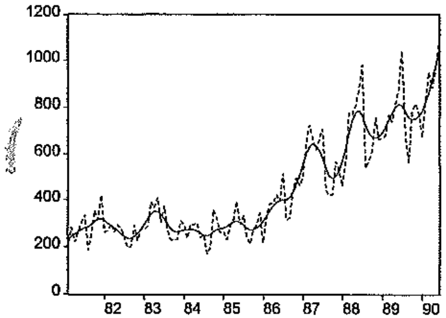


Figure 6.c: Original data and estimated trend of CSAL (NVR=0.1)

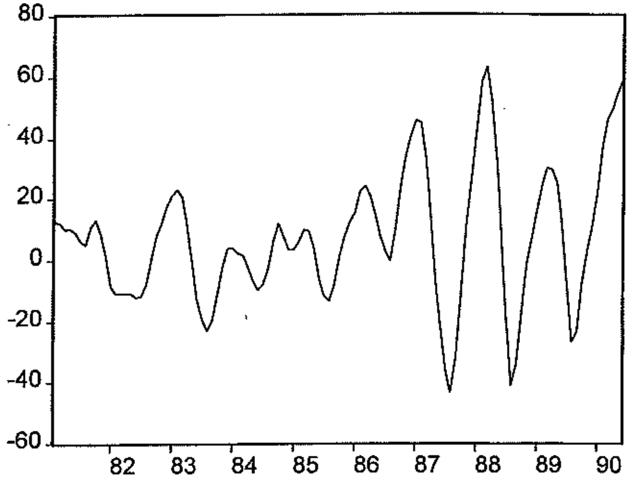


Figure 7.a: Estimated Trend Derivative for CSAL (NVR=0.1)

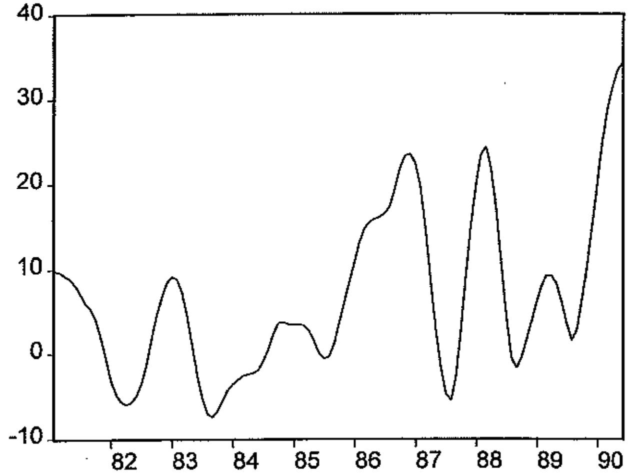


Figure 7.b: Estimated Trend Derivative for CSAL (NVR=0.01)

Figure 8.a: Periodogram of the Derivative NVR = 10^{-1}.

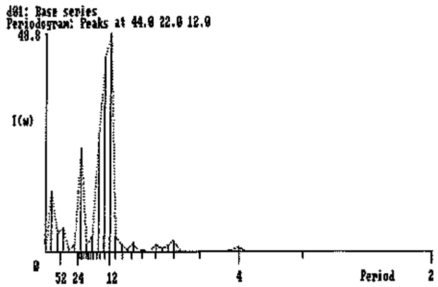


Figure 8.b: Periodogram of the Derivative NVR = 10^{-2}.

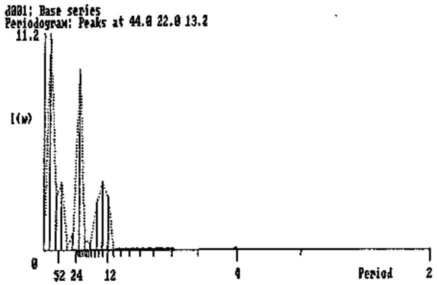
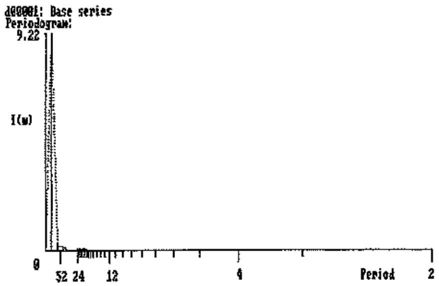


Figure 8.c: Periodogram of the Derivative NVR = 10^{-4}.



TABLES

Table 1: Annual Growth Rates for Different Subgroups in the Spanish Automobile Sector: 1981-1989

Year	*CTM*	*CDOM*	*CIMP*	*CLUX*	*CSAL*
1982	8.3	6.7	21.7	6.2	-8.0
1983	3.2	4.2	-3.7	25.5	18.7
1984	-6.6	-5.3	-16.6	-17.2	-12.6
1985	10.4	6.5	43.9	19.9	8.1
1986	18.9	12.1	61.7	39.1	34.8
1987	32.5	20.6	85.0	49.2	47.9
1988	11.5	3.1	35.8	37.9	21.8
1989	7.3	3.7	15.3	49.4	11.7

Source: ANFAC.

Table 2: Estimated ARIMA Models for the Different Series: 1981.1-1988.12

Series	*Model*	R^2	s_a^2
CTM (4.1)	$(1 + \underset{(.116)}{.246} L^2)(1 - L)(1 - L^{12})CTM_t = (1 - \underset{(.098)}{.577} L)(1 - \underset{(.094)}{.601} L^{12}) a_t$	.846	4.62×10^7
CDOM (4.2)	$(1 - \underset{(.084)}{.707} L^{12})(1 - L)CDOM_t = (1 - \underset{(.108)}{.683} L - \underset{(.110)}{.121} L^2) a_t$	.643	3.98×10^7
CIMP (4.3)	$(1 + \underset{(.106)}{.589} L + \underset{(.106)}{.356} L^2)(1 - L)(1 - L^{12})CIMP_t = a_t$	.952	2.82×10^6
CLUX (4.4)	$(1 + \underset{(.121)}{.167} L^2 + \underset{(.117)}{.187} L^3)(1 - L)(1 - L^{12})CLUX_t = (1 - \underset{(.116)}{.286} L) a_t$	.891	3.54×10^4
CSAL (4.5)	$(1 + \underset{(.154)}{.607} L)(1 - L)(1 - L^{12})CSAL_t = (1 - \underset{(.098)}{.865} L)(1 - \underset{(.112)}{.315} L^{12}) a_t$	.864	4.18×10^3

Table 3: Estimated GTF Models for the Perturbations of the Series: 1981.1-1988.12

NVR	*Model*	*AIC*	*YIC*	R^2	s_a^2
10^{-5} (4.6)	$(1 - \underset{(.067)}{.149} L - \underset{(.084)}{.181} L^3 - \underset{(.069)}{.618} L^{12} - \underset{(.086)}{.201} L^{15})\, PCTM_t = a_t$	17.7	-2.41	.426	4.93×10^7
10^{-3} (4.7)	$(1 + \underset{(.082)}{.156} L^2 + \underset{(.089)}{.196} L^4 + \underset{(.084)}{.203} L^6 - \underset{(.114)}{.339} L^{12} - \underset{(.123)}{.403} L^{24})\, PCDOM_t = a_t$	17.2	-2.17	.534	2.56×10^7
10^{-5} (4.8)	$(1 - \underset{(.105)}{.376} L + \underset{(.084)}{.163} L^4 + \underset{(.101)}{.189} L^{10} - \underset{(.101)}{.288} L^{11} - \underset{(.102)}{.636} L^{12} + \underset{(.124)}{.392} L^{13})\, PCIMP_t = a_t$	14.7	-2.51	.450	2.27×10^6
10^{-4} (4.9)	$(1 - \underset{(.096)}{.521} L - \underset{(.118)}{.788} L^{12} + \underset{(.142)}{.294} L^{13})\, PCLUX_t = a_t$	10.3	-2.89	.428	2.80×10^4
10^{-4} (4.10)	$(1 - \underset{(.085)}{.609} L - \underset{(.082)}{.162} L^4 + \underset{(.086)}{.268} L^5 - \underset{(.102)}{.699} L^{12} + \underset{(.119)}{.475} L^{13})\, PCSAL_t = a_t$	8.25	-3.15	.545	3.45×10^3

Table 4: Measures of Statistical Fitting of the Estimated Models

Series	*Residual Variance*		R^2	
	ARIMA	*GTF*	*ARIMA*	*DHRD*
CTM	4.62×10^7	4.93×10^7	.846	.961
CDOM	3.98×10^7	2.56×10^7	.643	.928
CIMP	2.82×10^6	2.27×10^6	.952	.991
CLUX	3.54×10^4	2.80×10^4	.891	.992
CSAL	4.18×10^3	3.45×10^3	.864	.970

Table 5: One-Step Ahead Percentage Forecasting error

%OSFE	*ARIMA*	*GTF*	*DHRD*	*DHRO*
CTM (18)	**.76**	7.57	*9.68*	.81
CTM (12)	**.23**	*-10.08*	1.74	-2.61
CTM (6)	**-1.80**	*6.01*	5.97	-1.88
CDOM (18)	15.97	12.62	*18.86*	**6.43**
CDOM (12)	*-8.81*	-4.24	3.12	**2.12**
CDOM (6)	-6.26	**.03**	-1.45	*-7.08*
CIMP (18)	**-3.25**	*-9.35*	-4.45	-8.21
CIMP (12)	-14.27	*-23.07*	**-.81**	-6.65
CIMP (6)	9.23	17.37	*20.35*	**6.37**
CLUX (18)	-3.75	**2.50**	*-8.50*	-6.73
CLUX (12)	**-10.65**	-15.17	*-20.64*	-17.79
CLUX (6)	*11.91*	**1.95**	4.69	3.22
CSAL (18)	-7.01	*-20.15*	-2.98	**.12**
CSAL (12)	-6.61	*-14.38*	**-3.26**	-7.96
CSAL (6)	7.27	*21.22*	18.10	**3.94**

Note: Bold typescript means the method ranks first, while italic typescript means the method ranks last.

Table 6: Aggregate Percentage PE Criterion

APE	*ARIMA*	*GTF*	*DHRD*	*DHRO*
CTM (18)	2.98	**2.12**	*8.42*	2.28
CTM (12)	12.44	**9.25**	*16.94*	9.93
CTM (6)	**4.82**	*10.81*	8.80	6.09
CDOM (18)	**-0.63**	-.85	*6.35*	-2.86
CDOM (12)	**6.87**	11.40	*14.45*	6.99
CDOM (6)	7.80	**1.11**	9.32	*9.44*
CIMP (18)	*17.58*	**.98**	12.35	6.21
CIMP (12)	7.70	**2.26**	*21.61*	14.65
CIMP (6)	-2.58	**-.61**	*7.90*	-3.03
CLUX (18)	-12.16	**-1.81**	*-19.97*	-12.87
CLUX (12)	*5.04*	**.12**	-1.54	-2.89
CLUX (6)	*7.33*	**-2.06**	-3.42	3.90
CSAL (18)	7.32	**-2.24**	3.19	*17.21*
CSAL (12)	-5.53	-3.06	**1.96**	*-7.99*
CSAL (6)	*-5.22*	**.33**	1.10	-4.89

Note: Bold typescript means the method ranks first, while italic typescript means the method ranks last.

Table 7: Percentage RMSE Criterion

%RMSE	*ARIMA*	*GTF*	*DHRD*	*DHRO*
CTM (18)	.78	1.12	*1.19*	**.61**
CTM (12)	1.38	1.39	*1.87*	**1.16**
CTM (6)	**.64**	*1.20*	.95	.74
CDOM (18)	.92	.93	*1.22*	**.77**
CDOM (12)	1.36	1.63	*1.90*	**1.27**
CDOM (6)	**1.50**	*1.73*	1.55	1.59
CIMP (18)	*2.29*	**1.25**	1.92	1.46
CIMP (12)	**1.38**	1.49	*2.62*	1.96
CIMP (6)	**.90**	1.31	*1.36*	.91
CLUX (18)	1.31	**.97**	*2.01*	1.37
CLUX (12)	*1.05*	.96	.85	**.83**
CLUX (6)	*1.21*	.82	**.81**	.83
CSAL (18)	1.26	1.18	**1.02**	*1.99*
CSAL (12)	.98	*1.41*	1.10	**.96**
CSAL (6)	6.94	*7.14*	5.26	**.57**

Note: Bold typescript means the method ranks first, while italic typescript means the method ranks last.

Table 8: Percentage ME Criterion

%ME	*ARIMA*	*GTF*	*DHRD*	*DHRO*
CTM (18)	3.46	3.39	*8.95*	**2.62**
CTM (12)	12.60	10.28	*17.36*	**10.02**
CTM (6)	**4.70**	*10.98*	8.79	5.93
CDOM (18)	.42	**.21**	*7.10*	-2.43
CDOM (12)	7.75	12.37	*15.07*	**7.22**
CDOM (6)	**8.29**	*11.72*	9.82	9.81
CIMP (18)	*18.70*	**2.46**	13.77	7.71
CIMP (12)	8.90	**3.78**	*23.44*	16.34
CIMP (6)	-1.59	**1.01**	*9.36*	-1.66
CLUX (18)	-11.43	**-1.01**	*-18.76*	-11.87
CLUX (12)	*5.36*	**.32**	-.65	-2.89
CLUX (6)	*7.52*	**-1.85**	-2.96	3.90
CSAL (18)	7.82	**-1.16**	3.93	*17.63*
CSAL (12)	-4.68	**-.95**	3.38	*-7.10*
CSAL (6)	*-4.52*	**1.28**	2.08	-4.39

Note: Bold typescript means the method ranks first, while italic typescript means the method ranks last.

Table 9: Percentage MAE Criterion

%MAE	*ARIMA*	*GTF*	*DHRD*	*DHRO*
CTM (18)	6.77	9.90	*10.11*	**5.15**
CTM (12)	12.60	12.17	*17.36*	**10.43**
CTM (6)	**5.30**	*10.98*	8.79	6.47
CDOM (18)	7.26	**7.25**	*8.55*	6.17
CDOM (12)	10.20	13.08	*15.07*	**9.07**
CDOM (6)	10.37	11.72	**10.30**	*11.84*
CIMP (18)	*19.65*	**10.70**	15.75	12.35
CIMP (12)	12.07	**11.24**	*23.58*	17.67
CIMP (6)	8.12	*11.76*	11.70	**7.21**
CLUX (18)	11.43	**7.82**	*18.76*	12.26
CLUX (12)	*8.75*	8.13	**6.54**	6.71
CLUX (6)	*10.19*	7.11	7.20	**6.43**
CSAL (18)	10.86	9.12	**8.52**	*17.63*
CSAL (12)	8.08	*10.29*	**8.07**	8.79
CSAL (6)	6.94	*7.14*	**5.26**	5.52

Note: Bold typescript means the method ranks first, while italic typescript means the method ranks last.

Table 10: Forecasting Performance of the DHR model for *CTM*.

NVR Values for the Trend	*Forecasting Performance Criteria (18 steps ahead)*				
	OSFE	APE	%RMSE	%MAE	%ME
10^{-4}	9.68	8.42	1.19	10.11	8.95
10^{-3}	3.97	-1.23	0.55	4.78	-0.81

Table 11: Number of Times that Each Method Ranks First (Lowest) and Last (Highest) under Different Criteria.

Forecasting Performance Criteria	*Ranks First*				*Ranks Last*			
	Models				*Models*			
	ARIMA	GTF	DHRD	DHRO	ARIMA	GTF	DHRD	DHRO
OSFE	5	3	2	5	2	8	4	1
APE	3	11	1	0	4	1	7	3
%RMSE	4	2	2	7	2	4	8	1
%MAE	1	3	5	6	3	4	6	2
%ME	2	10	0	3	4	2	7	2
Total	15	29	10	21	15	19	32	9

Source: Tables 5 to 9.

Table 12a: Number of Times that Each Method Ranks First (Lowest) under Different Criteria for Different Forecast Horizons.

Forecasting Performance Criteria	*18 Months Ahead*				*12 Months Ahead*				*6 Months Ahead*			
	Models				*Models*				*Models*			
	ARIMA	GTF	DHRD	DHRO	ARIMA	GTF	DHRD	DHRO	ARIMA	GTF	DHRD	DHRO
OSFE	2	1	0	2	2	0	2	1	1	2	0	2
APE	1	4	0	0	1	3	1	0	1	4	0	0
%RMSE	0	2	1	2	1	0	0	4	3	0	1	1
%MAE	0	2	1	2	0	1	2	2	1	0	2	2
%ME	0	4	0	1	0	3	0	2	2	3	0	0
Total	3	13	2	7	4	7	5	9	8	9	3	5

Table 12b: Number of Times that Each Method Ranks Last (Highest) under Different Criteria for Different Forecast Horizons.

Forecasting Performance Criteria	*18 Months Ahead*				*12 Months Ahead*				*6 Months Ahead*			
	Models				*Models*				*Models*			
	ARIMA	GTF	DHRD	DHRO	ARIMA	GTF	DHRD	DHRO	ARIMA	GTF	DHRD	DHRO
OSFE	1	2	2	0	1	3	1	0	1	3	0	1
APE	1	0	3	1	1	1	3	0	2	1	1	1
%RMSE	0	0	4	1	1	1	3	0	1	3	1	0
%MAE	1	0	3	1	1	1	3	0	1	3	0	1
%ME	1	0	3	1	1	0	3	0	2	2	1	0
Total	4	2	15	4	5	6	13	1	7	12	3	3

Source: Tables 5 to 9.

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