FORECASTING GROWTH WITH TIME SERIES MODELS

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ABSTRACT

This paper compares the structure of three models for estimating future growth in a time series. It is shown that a regression model gives minimum weight to the last observed growth and maximum weight to the observed growth in the middle of the sample period. A first-order integrated ARIMA model, or I(1) model, gives uniform weights to all observed growths. Finally, a second-order integrated ARIMA model gives maximum weights to the last observed growth and minimum weights to the observed growths at the beginning of the sample period. The forecasting performance of these models is compared using annual output growth rates for seven countries.

KEYWORDS ARIMA models; integrated processes; regression; stationary processes

INTRODUCTION

An important problem in modeling economic time series is forecasting the future growth of a given time series. Assuming that a linear model is appropriate for the data, the procedures most often used are as follows:

(1) Detrend the observed data by regressing the observations on time, and use the residuals from this regression to build a stationary time series model. The series is forecasted by adding the values of the deterministic future trend and the forecast of the stationary residual.

(2) Differentiate the series, test for unit roots and if the series is assumed to be integrated of order one (I(1)) build a stationary ARMA model in the first difference of the series. Typically models built in this way include a constant for many economic time series.

(3) Differentiate twice the series and build the ARMA model on the second difference of the process that is assumed to be I(2). Then in most cases the I(2) model does not include a constant term.

The decision between these three procedures should be made by testing the number of unit roots in the time series model. However, the available tests are not very powerful, specially for short time series, and therefore it is important to understand the consequences of using these models.
Let \( Z_t \) be the time-series data and let us call \( b_t = Z_t - Z_{t-1} \) the observed growth at time \( t \). It is shown in this paper that the estimate of future growth by the three procedures can be written as

\[
\hat{\beta}_t = \sum \omega_i b_i
\]

where the coefficients \( \omega_i \) are a weighting function, that is, \( \omega_i > 0 \) and \( \sum \omega_j = 1 \). The next section of this paper proves that linear regression gives minimum weights to the last observed growth and maximum weights to the observed growth in the middle of the sample. The third section shows that an I(1) model with a constant term gives a uniform weight throughout the sample, that is, \( \omega_1 = n^{-1} \). The fourth section shows that an I(2) model gives maximum weight to the last observed growth and minimum to the oldest values. The fifth section compares these models in forecasting annual output growth for seven countries in the period 1960-91. The final section contains some conclusions.

**REGRESSION ON TIME**

Let us call \( Z_t \) the observed time series and let us assume for simplicity that the sample size is \( n = 2m + 1 \). Let \( t = \{-m, ..., 0, ..., +m\} \). Then the least squares estimator of the slope in the regression on time

\[
Z_t = \beta_0 + \beta_1 t + u
\]

is given by

\[
\beta_1 = \frac{\sum tZ_t}{\sum t^2} = \left( 2 \sum_{i=1}^{m} i^2 \right)^{-1} \sum_{t=1}^{m} t(Z_t - Z_{t-1})
\]

Calling \( b_t = Z_t - Z_{t-1} \), for \( t = -m+1, ..., m \), the observed growth at each period, we note that

\[
Z_t - Z_{t-1} = \sum_{j=-t+1}^{l=t} b_j
\]

and, after some straightforward manipulations that are shown in Appendix 1, the estimate of the slope can be written as

\[
\hat{\beta}_1 = \sum_{j=1}^{m} \omega_j (b_j + b_{1-j})
\]

where the weights are given by

\[
\omega_j = \frac{3(j+m)(m-j+1)}{2(2m+1)m(m+1)} \quad j = 1, ..., m
\]

and add up to one. Therefore the estimated growth \( \hat{\beta}_1 \) is a weighted mean of all the observed growths \( b_j \), such that the maximum weights are given to \( b_1 \) and \( b_0 \) that correspond to the observed growth in the middle of the sample period, and the minimum weights are given to \( b_m \) and \( b_{1-m} \), the first and last observed growth.

The estimator (3) has an interesting interpretation. On the assumption that the linear model (1) holds, the \( 2m \) values \( b_t \) (\( t = -m+1, ..., m \)) are unbiased estimates for \( \beta \). These estimates are
correlated and have covariances
\[
\text{Cov}(b, b_{t+j}) = E[(b_t - \beta)(b_{t+j} - \beta)] = E[(u_t - u_{t-1})(u_{t+j} - u_t)] = -\sigma^2 \\
\text{Cov}(b, b_{t+j}) = 0 \quad j > 1
\]

Therefore, the covariance matrix of these \(2m\) estimates is the Toeplitz matrix:
\[
V = \begin{bmatrix}
2\sigma^2 & -\sigma^2 & 0 & \ldots & 0 \\
-\sigma^2 & 2\sigma^2 & & \ldots & \\
& \ddots & \ddots & \ddots & \ddots \\
0 & \ldots & \ldots & -\sigma^2 & 2\sigma^2
\end{bmatrix}
\]

It is easy to show (Newbold and Granger, 1974) that given a vector \(\hat{\theta}\) of unbiased estimators of a parameter \(\theta\) with covariance matrix \(V\), the best (in the mean squared sense) linear unbiased estimator of \(\theta\) given by
\[
\hat{\theta}_r = (1'V^{-1}1)^{-1}(1'V^{-1}\hat{\theta})
\]

where \(1' = (1 \ 1 \ \ldots \ 1)\). Now, the inverse of the Toeplitz matrix (5) has been studied by Shaman (1969), who obtained the exact inverse of a first-order moving average process. As \(V\) can be interpreted as the covariance matrix of a non-invertible \((\theta = 1)\) first-order moving average process, then \(V^{-1}\) will be given by
\[
v_{ij} = \frac{i(2m-j+1)}{2m+1} \quad j \geq i, \quad i = 1, \ldots, 2m
\]

and \(v_{ij} = v_{ji}\). Therefore
\[
V^{-1} = \frac{1}{(2m+1)} \begin{bmatrix}
2m & 2m - 1 & 2m - 2 & \ldots & 1 \\
2m - 1 & 2(2m - 1) & 2(2m - 2) & \ldots & 2 \\
2m - 2 & 2(2m - 2) & 3(2m - 2) & \ldots & 3 \\
& \ddots & \ddots & \ddots & \ddots \\
2 & 4 & 6 & \ldots & 2m - 1 \\
1 & 2 & 3 & \ldots & 2m
\end{bmatrix}
\]

It is proved in Appendix 1 that the estimator (3) can also be obtained by applying (6) to the unbiased but correlated estimates \(b_i\).

Suppose now that an ARMA model is fitted to the residuals of the regression model (1). Then the equation for the \(h\)-steps-ahead forecast is
\[
\hat{Z}_t(h) = \hat{\beta}_0 + \hat{\beta}_1 h + \hat{r}_t(h)
\]

where \(\hat{r}_t(h)\) is the forecast of the zero mean stationary process fitted to the residuals. As for a stationary process the long-run forecast converges to the mean, \(\hat{r}_t(h) \to 0\), and the parameter \(\hat{\beta}_1\) is the long-run estimated growth of the time series.

**FORECASTING GROWTH WITH AN I(1) MODEL**

The ARIMA approach in modelling time series with trend is to differentiate the data and then fit a stationary ARMA process. Assuming that a difference is enough to obtain a stationary series,
that is, the series is integrated of order one or \( I(1) \), the fitted model is

\[ \nabla Z_t = \beta + n_t \]  
(8)

where \( n_t \) follows an ARMA model

\[ n_t = \sum \psi_i a_{t-i} \]  
(9)

The process \( \{ a_t \} \) is a Gaussian white-noise process and the series \( \{ \psi_i \} \) converge, so that \( n_t \) is a zero mean stationary process. Calling \( \mathbf{V} \) to the covariance matrix of \( n_t \), the estimate of \( \beta \) in model (8) is given by the generalized least squares estimator

\[ \hat{\beta} = (\mathbf{V}^{-1})^{-1}(\mathbf{V}^{-1}b) \]  
(10)

where the vector \( b \) has components \( b_i = \nabla Z_t \). Assuming that \( n_t \) is stationary and invertible it is well known (see Fuller, 1976) that \( \hat{\beta} = 1/n \sum b_i \) is asymptotically unbiased for \( \beta \) with variance \( \sigma^2/n \).

When \( n \) is large, the expected growth \( h \) periods ahead is given by

\[ \beta_r(h) = E[Z_{t+h} - Z_{t+h-1}] \]

and it will be estimated by

\[ \hat{\beta}_r(h) = \hat{\beta} + \hat{n}_r(h) \]

where \( \hat{n}_r(h) \) is the \( h \)-steps-ahead forecast of the stationary process \( n_t \). As for \( h \) large the \( \hat{n}_r(h) \) will go to zero, the mean value forecast, the long-run growth will be estimated by \( \hat{\beta} \). As

\[ \hat{\beta} = \frac{1}{n} \sum b_i = \frac{1}{n} (Z_n - Z_t) \]  
(11)

the long-run growth will be estimated simply by using the first and last observed values. Also, this estimate can be interpreted as a weighted average with uniform weighting of the observed growths \( b_i \).

FORECASTING GROWTH WITH AN I(2) MODEL

Some economic time series require differencing twice to obtain a stationary model. Then the series is called integrated of order two or \( I(2) \), and the model used is

\[ \nabla^2 Z_t = n_t \]  
(12)

where

\[ n_t = \sum \psi_i a_{t-i} \]  
(13)

and the process \( \{ a_t \} \) is a Gaussian white-noise process. The series \( \{ \psi_i \} \) converge so that \( n_t \) is a zero mean stationary and invertible process. The \( h \)-steps-ahead forecast from model (12) can be written

\[ \hat{Z}_t(h) = \hat{\beta}_0^{(t)} + \hat{\beta}_1^{(t)} h + \hat{n}_r(h) \]  
(14)

where \( \hat{\beta}_0^{(t)} \) and \( \hat{\beta}_1^{(t)} \) depend on the origin of the forecast and \( \hat{n}_r(h) \) is the \( h \)-steps-ahead forecast of the zero mean stationary process. Again, as the forecast \( \hat{n}_r(h) \) will go to zero, the long-run growth will be estimated by \( \hat{\beta}^{(t)} \). To understand the structure of \( \hat{\beta}^{(t)} \) let us consider first the simplest case in which \( n_t \) follows an MA(1) process, \( n_t = (1-\theta B) a_t \). Then the forecast for any lag \( h \) is given by

\[ \hat{Z}_t(h) = \hat{\beta}_0^{(t)} + \hat{\beta}_1^{(t)} h \]  
(15)
because \( n_t(1) \) is a constant. Let us obtain the form of \( \hat{\beta}_t^{(1)} \) as a function of the observed growths \( \nabla Z_t \). Assuming that the origin is \( t = T - 1 \), then we can obtain \( \hat{\beta}_0^{(T-1)} \) in model (15) using the two forecasts \( \hat{Z}_{T-1} \) and \( \hat{Z}_{T-2} \) as follows:

\[
\begin{align*}
\hat{Z}_{T-1} &= Z_{T-1} + \nabla Z_{T-1} - \theta a_{T-1} = \hat{\beta}_0^{(T-1)} + \hat{\beta}_1^{(T-1)} \\
\hat{Z}_{T-2} &= 2Z_{T-1} - Z_{T-1} = \hat{\beta}_0^{(T-1)} + 2\hat{\beta}_1^{(T-1)}
\end{align*}
\]

and substracting the first equation from the second,

\[
\hat{\beta}_1^{(T-1)} = \nabla Z_{T-1} - \theta a_{T-1} = b_{T-1} - \theta(1 - \theta B)^{-1}\nabla b_{T-1}
\]

which leads to

\[
\hat{\beta}_1^{(T-1)} = (1 - \theta)[b_{T-1} + \theta b_{T-2} + \theta^2 b_{T-3} + \ldots] \quad (16)
\]

that is, the forecasted future growth is an exponentially weighted average of past observed growths.

In general, it is easy to show that

\[
\hat{\beta}_1^{(T-1)} = \sum a_j b_{T-j}
\]

where the \( a_j \) coefficients depend on the moving-average structure of the process and behave like the \( \pi(B) = \psi(B)^{-1} \) structure of weights.

**FORECASTING INTERNATIONAL GROWTH RATES**

In order to illustrate the performance of the three models compared in this paper we have applied them to forecast gross national product for seven countries in the period 1960–91. Many sophisticated models have been used to forecast international growth rates and turning points. See, for instance, Garcia-Ferrer et al. (1987), Zellner and Hong (1989), Min and Zellner (1993), and the references in these papers. Our objective here is not to build the ‘best’ model to forecast annual output growth, but to illustrate the forecast accuracy for different forecast horizons of the three models analysed in the paper.

The data we use are given in Appendix 2 and represent gross national product in the period 1960–91 for the United States, Japan, and the five largest countries of the European Union (France, Germany, Italy, Spain, and the United Kingdom).

Four models are used for the logarithm of the gross national product. The first (M1) is the linear regression on time given by equation (1). The second (M2) is a random walk with drift, that is model (8) with \( n_t = a_t \). The third is an IMA (2, 1) model, that is, model (12) with \( n_t = (1 - \theta B) a_t \). The fourth is a random walk without drift on the rate of growth \( \ln Y_t \), where \( Y_t \) is gross national product, and it is equivalent to the third model with \( \theta = 0 \). Note that the forecast from any of these four models is a linear trend. In the first the slope is obtained by a given maximum weight to the observed growth in the middle of the sample; in the second the slope gives equal weight to all observed growths; in the third the weights decrease exponentially; and in the fourth only the last observed growth is taken into account to build the forecast. Therefore, M1 gives, relatively, minimum weight to the more recent data whereas M4 gives them the maximum weight.

We have used the period 1960–79 to fit the models and 1980–91 to check their forecasting performance. M1 has been fitted by least squares to the 20 points, the parameter \( \beta \) in M2 (see equation (8)) has been estimated with equation (11), and the parameter \( \theta \) in M3 has been
estimated by maximum likelihood for the seven countries with the results given in Table I. M4 does not require any parameter estimation.

Table II presents the forecasting accuracy of the four models for three forecast horizons: one, two, and three steps ahead. The procedure used to build this table is as follows:

1. The fitted models were employed to generate twelve one-step-ahead forecasts, eleven two-step-ahead forecasts, and ten three-step-ahead forecasts for the years 1980–91. Models M1 and M2 were re-estimated to include all past data prior to the forecast origin. The parameter $\theta$ in M3 was always kept fixed to 0.7, the mean value for the seven countries (see Table I). We have checked that re-estimating the parameter $\theta$ with each new data improves very few results, but makes model M3 more expensive in computing time. In this way the updating of the forecast equation is very simple in all the models used. Finally, M4 does not need any parameter estimation.

2. The error of the three types of forecasts were computed for each of the seven countries. As an overall measure of accuracy we have used the mean squared error of the forecast. This measure has been computed for the three forecast horizons: one (S1), two (S2) and three (S3) steps-ahead.

It can be seen that for the one-step-ahead forecast I(2) models are the best in six of the seven countries. Only for the United States are the I(1) forecasts slightly better than those generated by the I(2) models. The I(2) models are also the best for two and three-steps-ahead forecasts for

<table>
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Table II. Mean squared error of the one, (S1), two, (S2), and three, (S3), steps-ahead forecasts for the four models

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<tbody>
<tr>
<td>S1 M1</td>
<td>0.0120</td>
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<td>S1 M1</td>
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<td>S2 M2</td>
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<td>0.0011</td>
<td>S3 M3</td>
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<td>S3 M3</td>
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<td>0.0007</td>
<td>S1 M1</td>
<td>0.0024</td>
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five of the seven countries. However, for the United States and the UK the I(1) model provides better forecasts than the best I(2) model. As can be expected, the forecasting performance of the deterministic linear trend is very poor for all horizons.

The main conclusion from this exercise is that, on average, I(2) models, even the simplest ones that do not require any estimation, seem to be best for forecasting international growth in the countries considered in this example.

CONCLUSION

We have compared three time-series models in this paper. The three models forecast future growth by using a weighted average of the observed growths in the sample. Linear regression gives minimum weight to the last observed growth and maximum weight to the centre of the sample period. This implies that, for instance, if we use this method to forecast next year’s gross national product (GNP) with a sample of 40 data, we are saying that the most informative item to forecast 1994 growth is the growth in 1974, whereas the last observed growth in 1993 receives a weight equal to the one in 1954. If we use an I(1) model, the growth is forecast by using a uniform weighting in all the years in the sample. In the GNP example the observed 1993 growth is as relevant as the one observed in 1960 or 1965 for forecasting 1994 growth. The logical requirement that the most relevant year to forecast GNP growth are the last observed growth is only accomplished by using an I(2) model. In particular, an ARIMA (0, 2, 1) model leads to an exponentially weighting of last observed growths.

Many econometric papers and some well-known books on time series (see, for instance, Brockwell and Davis, 1987, p. 25) use least squares regression on time as an alternative to differencing for removing a trend in a time series. However, the logical implications of both procedures are seldom analysed. It is important to stress that if a series follows an I(2) model but we detrend it by least squares regression on time, the residuals from this fit do not provide, in general, a sound basis for fitting an ARMA model, and the forecast performance of the procedure may be poor.

ACKNOWLEDGEMENTS

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REFERENCES

APPENDIX 1

Using
\[ \sum_{j=1}^{m} i^2 = \frac{(2m+1)m(m+1)}{6} \]
(A1)

and
\[ \sum_{j=1}^{m} \sum_{i=1}^{m} t_{-t+1} b_j = (b_1 + b_0) \sum_{i=1}^{m} t_{i=1}^{m} i + (b_2 + b_{-1}) \sum_{i=2}^{m} i + \cdots + (b_m + b_{1-m})m = \sum_{j=1}^{m} \sum_{j=1}^{m} (b_j + b_{1-j}) \]

we have
\[ \hat{\beta} = \sum_{j=1}^{m} \omega_j (b_j + b_{1-j}) \]
(A2)

where
\[ \omega_j = \frac{3(j+m)(m-j+1)}{(2m+1)m(m+1)} \]

and the sum of all the weights \( \omega_j \) adds up to one:
\[ 2 \sum_{j=1}^{m} \omega_j = \left( \sum_{i=1}^{m} i^2 \right)^{-1} \sum_{i=1}^{m} \sum_{i=1}^{m} i = 1 \]

On the other hand, let \( l' = (1, ..., 1) \) be a vector of \( 2m \) ones. Then using equation (7)
\[ l'V^{-1} = (m, (2m-1), \frac{3}{2} (2m-2), ..., \frac{i}{2} (2m-i+1), ..., m) \]

and
\[ l'V^{-1} \cdot 1 = \sum_{i=1}^{2m} \frac{i}{2} (2m-i+1) = \frac{m(2m+1)(m+1)}{3} \]

Therefore the estimate is given by
\[ \hat{\beta} = \sum_{i=1}^{2m} \frac{3i(2m-i+1)}{m(2m+1)(m+1)} b_{1-m} \]
However,

\[
\beta = \sum_{i=1}^{2m} \frac{3i(2m-i+1)}{m(2m+1)(m+1)} b_{-m} + \sum_{j=1}^{m} \frac{3(m+j)(m-j+1)}{2m(2m+1)(m+1)} b_j = \sum_{j=1}^{m} \frac{3(m-j+1)(m+j)}{2m(2m+1)(m+1)} b_{-j}
\]

\[+ \sum_{j=1}^{m} \frac{3(m+j)(m-j+1)}{2m(2m+1)(m+1)} b_j\]

\[= \sum_{j=1}^{m} \omega_j (b_j + b_{-j})\]

in agreement with equation (A.2).

### APPENDIX 2

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<td>63 530</td>
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