

TECHNIQUES FOR SHORT-TERM ECONOMIC FORECASTING

GABRIEL FAGAN AND JOHN FELL
Central Bank of Ireland

(read before the Society, 21 February 1991)

1. INTRODUCTION

This paper presents a survey of the techniques which can be employed in producing short term economic forecasts such as those published in the Bulletins of the Central Bank of Ireland and by other organisations. The focus of the paper is on technique rather than on the past historical performance of forecasting agencies which has been examined elsewhere (Durkan and Kelleher, 1973; Skehan 1990). It should be noted that the paper does not cover all techniques. In particular, more recent developments such as non-linear methods and the use of neural networks, for example, are not considered, since these methods are in their infancy as far as economics is concerned and are, as yet, not widely used by practitioners. A flavour of these methods can be obtained from Frain (1990).

Broadly speaking, one or more of the following approaches can be employed in preparing forecasts for an economic variable:

- (i) formal techniques based on the past of the variable alone ;
- (ii) formal techniques based on the past of the variable and on the past of other variables;
- (iii) traditional structural econometric methods;
- (iv) judgmental and qualitative methods; and
- (v) Mysticism.

Given the difficulties involved in evaluating technique (v) this paper con-

centrates on the remaining techniques. This paper begins by presenting some key results from the theory of forecasting, as presented by Granger and Newbold (1977), which are of importance in choosing and evaluating forecasting techniques. The following section is devoted to the presentation of a common framework in which different methods can be embedded due to Zellner and Palm (1979). The objective of this section is to show the common basis which underlies many methods which is useful from the point of view of analysing and selecting forecasting techniques. In section four we survey the multivariate time series approach to generating economic forecasts. This is followed by a review of univariate time series methods and the use of structural econometric models. In section 7, the judgmental approach to forecasting - which appears to be the most popular method in the Irish case - is examined. This completes our review of techniques. The following two sections address the key issues of how to optimally combine forecasts from different techniques and how to measure and assess the accuracy of different techniques. In section 10 we examine the important issue of which techniques should be employed, taking into account both theoretical results and international empirical evidence. As an illustration of the previous discussion, some practical applications to Irish data are presented in section 11. This is followed by our conclusions.

2. THE THEORY OF FORECASTING

In general, the objective of short-term economic forecasting is to derive forecasts of a discrete time economic variable x_{t+i} or a group of variables Z_{t+i} given the information available at time t . For example x_{t+1} could be the rate of inflation in the next quarter; x_{t+2} the rate in the following quarter etc. Alternatively, one could be interested in forecasting a set of variables, for example, a forecast of the expenditure components of the national accounts (consumption, investment, etc.). Let I_t denote the information set available at time t . For example, in the case of a univariate forecasting technique, I_t consists of the present and past values of the series of interest. That is:

$$I_t = \{x_t, x_{t-1}, x_{t-2} \dots x_{t-n}\}$$

In multivariate forecasting techniques, I_t is taken to include the past and present of the series and of other series, e.g.

$$I_t = \{x_t, x_{t-1}, x_{t-2} \dots x_{t-n}, y_t, y_{t-1}, y_{t-2} \dots y_{t-n}\}$$

Everything that can be inferred about x_{t+i} given the information set I_t is contained in the conditional density of x_{t+i} given I_t , $D(x_{t+i}|I_t)$. From this function, one can, for example, obtain the conditional mean and variance of x_t . In practice, attempting to derive the conditional density of x_{t+i} is often a formidable task so one has to settle for a confidence band for x_{t+i} or a single value, known as a point forecast.

It is apparent the quality of any technique for producing point forecasts for x_{t+i} depends on the forecasting errors of the technique. If a technique can forecast a series without error, then clearly it can be considered a perfect. In practice, few series can be forecast without error, so one has to decide on a criterion for judging and comparing forecasting techniques. The concept of a cost function provides such a criterion.

Let $f_{t+i}(I_t)$ denote the forecast of x_{t+i} based on the information set I_t . The error of this forecast is given by:

$$e_{t+i} = x_{t+i} - f_{t+i}(I_t)$$

Obviously, in forecasting applications we want e to be as close to zero as possible. One of the more popular ways of formalising this requirement is the quadratic cost function which can be written:

$$C(e) = ae^2 \quad a > 0$$

The objective of optimal forecasting is to chose a forecasting technique based on the information set which minimises the expected value of this function.

$$E[C(e_{t+i})] = Q \int (x_{t+i} - f_{t+i}(I_t))^2 D(x_{t+i}|I_t) dx_{t+i}$$

Differentiation of this with respect to f yields:

$$f_{t+i} = E(x_{t+i}|I_t)$$

Thus if the cost function is taken to be quadratic, then the optimal forecast of x_{t+i} based on the information set I_t is the conditional expectation of x_{t+i} given I_t . For example suppose that $I_t = \{x_{t-1}, x_{t-2}, \dots\}$ and x_t follows an $AR(1)$ process:

$$x_t = 0.9x_{t-1} + e_t$$

where e_t is a mean zero white noise innovation, then the optimal forecast for x_{t+1} is simply

$$E(x_{t+1}|x_t) = 0.9x_t + E(e_{t+1}) = 0.9x_t$$

More general derivations of the optimal point forecast for different techniques, assuming a quadratic cost function, will be presented below.

A further result of relevance from the theory of forecasting relates to optimal forecasts based on different information sets. Consider two information sets I_1 and I_2 where the second information set contains all the information in the first set plus additional information. Now consider optimal forecasts based on I_1 and I_2 and their associated errors e_1 and e_2 . It can be shown that

$$\text{Var}(e_1) \geq \text{Var}(e_2)$$

This says that optimal forecasts based on the wider information set cannot be less accurate. The intuition behind this result is straightforward. Suppose the additional information in I_2 was of no value in forecasting x . In that case, this optimal forecast based on I_2 would discard this information

and would be identical to the optimal forecast based on I_1 . If, however, this additional information was of predictive value for x , then the second forecasting technique, which takes it into account, will produce better forecasts than the other technique which ignores it.

A related result is that, in general, an appropriately weighted combination of the forecasts of different techniques will produce more accurate forecasts than any individual forecasting technique. This issue of combining forecasts will be examined in one of the following sections.

To summarise this section, three relevant conclusions from the theory of forecasting emerge. First, assuming a quadratic loss function, the optimal forecast of a variable given an information set is the conditional expectation of the variable given the information set. Second, in general, forecasts which taken into account more information should be more accurate than forecasts based on narrower information sets. Finally, where a number of forecasts for a variable are available, it is generally the case that an appropriate combination of these forecasts will be more accurate than any of the individual forecasts.

3. A UNIFIED FRAMEWORK FOR FORECASTING TECHNIQUES

In economic forecasting, the objective is to derive predictions for a series x_t or a vector of series Z_t . A useful framework for embedding different approaches to forecasting is the data generating process concept employed by Hendry et al (1984):

$$D_t(Z_t, Z_{t-1}, Z_{t-2}, \dots, \Theta) \quad (3.1)$$

D_t is the joint density function for the sequence of data vectors parameterized by Θ . For example, $Z_t = [\text{Imports}, \text{Exports}]$ in a bivariate case. The data generating process describes the probabilistic laws which govern the evolution of Z_t . This can be factored as follows:

$$\prod_{t=1}^T D^*(Z_t | Z_{t-1}, Z_{t-2}, \dots, \Theta) \quad (3.2)$$

This is the density of Z conditional on past values of Z . Assuming a common functional form, n , for D^* , we have:

$$(Z_t|Z_{t-1}, Z_{t-2}, \dots, Z_{t-n} \sim n(\mu_t, l) \quad (3.3)$$

where

$$\begin{aligned} \mu_t &= E(Z_t|Z_{t-1}, Z_{t-2}, \dots) \\ Z_t &= \mu_t + v_t \end{aligned} \quad (3.4)$$

v_t is an innovation, i.e. a white noise process which cannot be forecast using its own past or past Z .

Further, assuming linearity and a finite lag length we may write:

$$Z_t = \sum_{i=1}^n B_i Z_{t-i} + v_t \quad (3.5)$$

or, more compactly,

$$B(L)Z_t = v_t$$

where L is the lag operator, i.e. $LX_t = X_{t-1}$.

This has the form of a vector autoregression model (VAR) for Z . In the case of a rational lag (i.e. if $B(L) = C(L)/D(L)$), a Vector autoregressive moving average representation (VARMA) representation is appropriate:

$$C(L)Z_t = D(L)v_t \quad (3.6)$$

Briefly stated, the multivariate time series approach to forecasting involves identifying the form of (3.6), for example the number of lags, estimating

the coefficient values and using the estimated model to generate forecasts. More details of this approach will be presented in below.

Traditional, econometric analysis has reflected the economists structural approach with the economy assumed to be governed by systems of simultaneous dynamic stochastic equations (assumed linear for convenience) e.g.

$$G(L)Y_t = F(L)X_t + U_t \quad (3.7)$$

where Y_t is a vector of endogenous variables (e.g. GNP, employment, inflation), X_t is a vector of exogenous variables (e.g. Government expenditure, the level of world trade etc.). $G(L)$ and $F(L)$ are matrix polynomials in the lag operator while U_t is a vector of stochastic 'noise' terms. As shown by Zellner and Palm (1979) and Wallis (1977), the structural econometric model (3.7) is a special case of the more general multivariate time series model (3.5). To see this, let

$$Z_t = \begin{bmatrix} Y_t \\ X_t \end{bmatrix}$$

Then (3.7) can be written:

$$\begin{bmatrix} G(L) & F(L) \\ 0 & P(L) \end{bmatrix} \begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} U_{1t} \\ U_{2t} \end{bmatrix} \quad (3.8)$$

Clearly reducing a general multivariate time series system such as (3.5) down to (3.7) involves the imposition of a number of restrictions on the data generation process. In this case, the zero restrictions in (3.8) are imposed because X is thought to be exogenous. Practitioners usually invoke a priori economic theory to justify such exclusion restrictions. The second line of (3.8) gives the data generation process for the 'exogenous' variables. Typically, in the structural approach to econometric modelling

this equation is ignored and some path for the exogenous variables is assumed or projected. This approach to econometric analysis has been subjected to severe criticism (Sims, 1980). The conditions under which a multivariate time series model such as (3.5) can be reduced to (3.8) and inferences on such models, e.g. forecasts and policy simulations, are valid is the main concern of the 'British' school of econometrics associated with Hendry and his co-workers.

Univariate time series models (such as Box Jenkins models) can also be derived from the general multivariate time series model such as (3.5) or (3.6). For example, by noting that $C^{-1}(L) = C^*(L)/|C(L)|$ (6) can be rewritten:

$$|C(L)|Z_t = C^*(L)D(L)e_t \quad (3.9)$$

where $C^*(L)$ is the adjoint of $C(L)$ and $|C(L)|$ is its determinant. This implies that each of the individual series in the Z vector has a univariate ARMA representation. Details of how this approach to forecasting is applied in practice will be presented below.

Judgmental forecasting can also be accommodated in the above framework. External information about a future event derives from either institutional or decision lags. For example, the level of Government expenditure is, in principle, determined at Budget time. By taking this information into account one can, as the section on the theory of forecasting above showed, improve ones' forecasts. Similarly investment or other activity may be preceded by the signing of contracts or decisions which are known before the event is recorded. Use of this foreknowledge can improve forecasts. In short, for such information to be of use, it must precede the event of interest. We may write:

$$Z_t = f(Y_{t-1}) + u_t \quad (3.11)$$

This tells us that Y today provides a good indicator of what will happen to Z in the future. Note, this does not necessarily imply that Z is determined by Y but merely that Y is an indicator of what will happen to

Z in the future. Much judgmental forecasting relies on informal use of leading information in this manner. It is clear that (3.10) can be seen either as an equation in the structural system (3.7) or as a special case of the multiple time series model (3.5). Other judgmental forecasting methods such as chartism, carry-over analysis or attempts to assess trends are clearly examples of an informal application of univariate time series methods. While impressionistic forecasts based on believed correlations between economic variables can be seen as examples, again informal, of either structural econometric models or multiple time series methods. For example, a forecaster who says that consumer expenditure should rise by 3 per cent. next year because real personal income has risen by 3 per cent this year, is, essentially, using a model of the form:

$$\dot{C}_t = \dot{Y}_{t-1}$$

Clearly, this can be interpreted as a structural equation within the system (3.7) above or a simple multiple time series model of the form (3.5) above.

3.1 A practical Example

Consider a second order multivariate AR representation for four variables - consumption (C_t), investment (I_t), GNP (Y_t) and Government Expenditure (G_t). The data vector is:

$$Z_t = [C_t I_t Y_t G_t]'$$

The AR representation of this data is:

$$Z_t = B_1 Z_{t-1} + B_2 Z_{t-2} + e_t \quad (3.11)$$

where

$$e_t = [r_t n_t v_t u_t]$$

The coefficients in the above system could be estimated by OLS and the estimated model could be used to generate forecasts out to any desired

horizon. However, suppose using a priori economic theory, a number of restrictions are imposed on the system. In particular:

$$B_1 = \begin{bmatrix} 0 & 0 & a & 0 \\ b & 0 & 0 & 0 \\ b & 0 & a & h \\ 0 & 0 & 0 & h \end{bmatrix}$$

$$B_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ -b & 0 & 0 & 0 \\ -b & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$v_t = r_t + n_t + u_t$$

u_t is distributed independently of n_t and r_t

These assumptions correspond to the specification and identification of a structural econometric model. Premultiplying (3.11) by

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ -1 & -1 & 1 & -1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

yields the following structural system:

$$C_t = aY_{t-1} + r_t \quad (3.12)$$

$$I_t = b(C_{t-1} - C_{t-2}) + n_t \quad (3.13)$$

$$Y_t = C_t + I_t + G_t \quad (3.14)$$

$$G_t = hG_{t-1} + u_t \quad (3.15)$$

This is a traditional multiplier-accelerator model with C , I and Y the endogenous variables and G an exogenous variable. In the traditional econometric approach to economic forecasts a model such as (3.12) to (3.15) would be specified using economic theory, the parameters would be estimated and, given an assumed path for G , forecasts for C , I and Y would be generated using the estimated model. Typically, the equations governing the evolution of the exogenous variables (G in this case) are ignored in traditional econometric models. As was indicated in the previous section, the structural model (3.12) to (3.15) is a special case of the more general multivariate time series model (3.11). Note that the imposition of the theoretical restrictions on the system (3.11) has enabled us to reduce the number of parameters from 32 to 3, which, if valid, should result in more efficient estimates and better forecasting performance. An approach for moving from general models such as (3.11) to more specific models has been developed by Hendry and Richard (1982).

From (3.11) we can also derive the univariate representation for each series. For example, assuming the above restrictions are justified, repeated substitutions into (3.12) to (3.15) yields:

$$(1 - hL)(1 - aL - abL^2 + abL^3)C_t = m_t$$

where m_t is an MA(1) process

This univariate ARMA model could be estimated and used to generate forecasts for C . The other variables in the system also have similar representations.

Thus to forecast C or any of the other variables, the above suggests three approaches. First, the unrestricted multivariate system could be estimated and used for forecasting. Second, the structural model could be specified and estimated and, given a forecast path for G (or the prediction of equation (3.15)) the estimated model could be generated using the estimated model. Finally, each series could be modelled as a univariate process.

The use of judgmental techniques can also be illustrated in the above example. Suppose that we are interested in one step ahead forecasts of

investment and we know the parameters of one of the above models. Denote the optimal forecast of one of these models as I^f . Then

$$I_{t+1} = I^f + w_{t+1}$$

where w_{t+1} is the forecast error.

Now suppose, for illustration, that all investment expenditure is grant-aided at a rate of 50 per cent and that this aid must be approved in the period before the investment actually takes place. If the forecaster knows the amount of approvals in period t , this information can be used to improve the accuracy of the forecast. Indeed, in the extreme case, a perfect forecast can be obtained. In effect, the improvement results from the fact that the information on approvals provides information of the part of investment which, according to the above models, is 'unpredictable' (w_{t+1}). In forecasting with one of the above models w_{t+1} would be set to its expected value of zero. Thus the use of extraneous information, i.e. information external to the model in question, can be seen as an effort to estimate the value of the 'noise' terms in the above models. Clearly, if such information has predictive value for the noise term, then it can result in improved forecasts.

4. MULTIVARIATE TIME SERIES FORECASTING METHODS

Multivariate time series methods are concerned with the identification, estimation of models of the form (3.5) or (3.6) above and their use for forecasting. Broadly speaking these methods can be conveniently divided into two categories. The first concerns the use of models with an MA as well as an AR component (VARMA models):

$$Z_t = C_0 + C_1 Z_{t-1} + C_2 Z_{t-2} + \dots + C_p Z_{t-p} + V_t + D_1 V_{t-1} + D_2 V_{t-2} + \dots + D_q V_{t-q} \quad (4.1)$$

where Z is a $k \times 1$ vector of the variables of interest, V is a $k \times 1$ vector of noise terms and C and D are $k \times k$ coefficient matrices while p is the

number of AR lags and q the number of MA lags. This can be represented more compactly as a matrix polynomial in the lag operator L :

$$C(L)Z_t = D(L)V_t \quad (4.2)$$

Alternatively, a more popular approach in econometric analysis is the Vector Autoregression model (VAR) which has no MA part:

$$Z_t = B_0 + B_1Z_{t-1} + B_2Z_{t-2} + \cdots + B_pZ_{t-p} + V_t \quad (4.3)$$

which can be compactly represented as:

$$B(L)Z_t = V_t \quad (4.4)$$

By noting that, subject to suitable invertibility conditions, $B(L) = D^{-1}(L)C(L)$, the equivalence between (4.2) and (4.4) is apparent. However, this also shows that a representation of the form (4.2) is likely to be more parsimonious than (4.4). While, statisticians have tended to concentrate on the more parsimonious VARMA models, econometricians following Sims (1980) have tended to employ VAR models which are easier to deal with from the point of view of identification, estimation and forecasting.

4.1 VARMA Models

The development of a VARMA model for a vector of variables requires a number of steps. First, the model must be identified. This involves choosing the orders (i.e. the number of lags in) the $C(L)$ and $D(L)$ polynomials above, and deciding which elements of the matrices are non-zero. Given a chosen model, the parameters must be estimated after which the model can be used for forecasting.

The identification of VARMA models is similar to the Box-Jenkins procedures described below except that it is more complicated and differencing

variables on the right hand side of each equation are identical. The main issue which arises in the estimation of a VAR, given the choice of variables in the system, is the choice of the order of the $B(L)$ polynomial. How many lags of the dependent variable and of the other variables should be included in each equation?

The first approach employed is sequential likelihood ratio testing. In this approach VARs of different orders are estimated, and likelihood ratio tests of each order vis-a-vis lower order VARs are carried out. Alternatively, using information theory, an order can be chosen which minimizes some chosen criterion such as Akaike's Information Criterion (AIC) or Schwartz's criterion (SC). It is important to ensure that the residuals of the chosen VAR, V_t , are unautocorrelated. This can be done on an equation-by-equation basis using the Box-Pierce Q statistic or on a system-wide basis using Hosking's (1980) multivariate Q statistic.

Given an appropriate order, the coefficients of the VAR can be estimated using *OLS*. This is equivalent to SURE estimation in this case, since the right-hand side variables are identical in each equation. It is a well known result, that *OLS* applied to equations with lagged dependent variables, such as (4.4), will yield biased but consistent estimates.

An obvious problem with an unrestricted VAR such as (4.4) is that, even for small systems, it involves a large number of parameters, many of which may not be significant, which may result in inefficient parameter estimates and poor forecasts. A number of techniques for reducing the number of parameters have been put forward. One of the more popular of these is the Bayesian Vector Autogression (BVAR) procedure which attempts to incorporate prior information into the estimation of the system suggested by Litterman (1984). The form of the prior information employed, which has become known as the Minnesota Prior, is as follows:

- the prior mean for the coefficient on the lagged dependent variable in each equation is set to unity;
- the prior mean for the remaining coefficients is set to zero;
- the prior variances of the coefficients is reduced for higher lags.

This prior implies that each of the variables in the system follows a univariate random walk. Once the variances, or tightness, of the prior has been set, the parameters can be estimated using Theil-Goldberger mixed estimation procedures. Litterman shows that the use of this prior results in more accurate forecasts than an unrestricted VAR in the case of his US model.

Once the parameters of the VAR have been estimated, the model can be used to produce unconditional forecasts. Again, using the squared error loss criterion, optimal forecasts are derived by solving the vector difference equation (4.4) as far forward as required setting the error vector equal to its unconditional expectation, a null vector, outside the sample period.

5. UNIVARIATE TIME SERIES FORECASTING METHODS

A general forecasting methodology for univariate time series, known as ARIMA modelling, was introduced by Box and Jenkins (1970). This methodology has become widely used because of the ease with which it can be adapted to either stationary or non-stationary series. It involves the forecast of a time series from a knowledge of its past history alone. Other techniques which produce forecasts of a series on the basis of its past alone include, among others, exponential smoothing and, more recently, structural time series modelling developed by Harvey (1983).

The theoretical foundations of Box-Jenkins methodology are based on the properties of stationary series. In the case of weak or mean-variance stationarity this implies that the mean, variance and autocorrelation function are independent of time. In the more general case of strong stationarity the joint distribution of the series is constant through time. Box and Jenkins have shown, using the World Decomposition Theorem, that a stationary series can usually be well represented by finite autoregressive moving average models, as discussed in section 3 above, e.g. an ARMA(p, q) model of the form:

$$x_t = a_0 + a_1x_{t-1} + \dots + a_px_{t-p} + e_t + b_1e_{t-1} + \dots + b_qe_{t-q} \quad (5.1)$$

or, more compactly,

$$a(L)x_t = b(L)e_t$$

Stationarity of x implies that the roots of the polynomial, $a(L) = 0$, lie outside the unit circle.

The *ARMA* models described above cannot be readily applied to economic time series which usually exhibit some form of trend and seasonal pattern. However, Box and Jenkins show that such series can usually be reduced to stationary form by first differencing and seasonal differencing. It is important to note that in order to achieve the stationarity requirement of a constant variance it is also often necessary to transform the series by taking logs or raising the series to some suitable power. Given an appropriate differencing and transformation of the series, it is then possible to apply the Box-Jenkins methodology to the resulting series. For example, if it is decided to first difference the series d times and seasonally difference D times we can then work with the resulting series, $w_t = (1 - L)^d(1 - L^s)^D x_t$, which we can attempt to model as an *ARMA* process. Series which, when differenced appropriately, can be modelled as *ARMA* processes are known as Autoregressive Integrated Moving Average (*ARIMA*) models and are capable of encompassing a range of trend, seasonal, cyclical and irregular behaviour. Thus a model which involves second differencing, three AR lags and one MA lag is denoted *ARIMA*(3,2,1).

Box and Jenkins have developed a number of methods for identifying, fitting and checking *ARIMA* models. The identification procedure is very much an interactive process between the modeller and the data. Often, two different modellers can produce two different models for the same series, but this may not lead to markedly different forecasts. The identification stage involves a number of steps.

First, the modeller must decide whether the data should be transformed, by taking logs, for example, in order to ensure that the series has constant variance. This can be decided on the basis of graphical examination of the data to see if it is heteroskedastic or by means of mean-range plots.

Secondly, the degree of differencing must be determined. It is usually decided to difference the data if the autocorrelations do not die out quickly

enough as the lag increases, since this is an indicator of non-stationarity. In addition, unit root tests such as those of Dickey and Fuller (1981) can be applied.

Once the transformation and degree of differencing is decided, the next step is to choose an appropriate *ARMA* model. This involves selecting the appropriate number of lags in the autoregressive and in the moving average parts of the representation. This is done by comparing the autocorrelogram and partial autocorrelogram of the actual data, suitably transformed and differenced, with the theoretical correlograms produced by different ARMA models and selecting an appropriate form. This stage involves considerable skill on the part of the modeller and an art as well as a science.

The next stage is the estimation of the parameters of the chosen model which is usually carried out using maximum likelihood. Given estimates of the parameters, it is necessary to ensure that the fit of the model is adequate by testing the residuals for autocorrelation. If this is present, the iterative procedure outlined above is repeated until white noise residuals are achieved.

Once the parameters of the chosen model have been estimated it is possible to derive forecasts for the series x , h steps by using the estimated model. Under the mean square error criterion, discussed in section one, the optimal h step ahead forecast is obtained by solving the difference equation (5.1) above forward and setting e_i equal to its unconditional mean, zero, for $i > t$. i.e.

$$x_T(h) = a_1 x_{t+h-1} + \dots + a_p x_{t+h-p} + b_h e_T + \dots + b_{h+q} e_{T-q} \quad (5.2)$$

where $x_T = x_t$ for $t < T$
 $x_T(j)$ for $j = 1, 2, \dots, h-1$

It can be seen that just as in the VARMA case above the further one forecasts ahead, the MA component begins to drop out and for $h > q$ the forecast is generated by a pure AR model. In addition to point forecasts, it is also possible to derive confidence intervals for the forecast by assuming that e follows a particular distribution, usually the normal distribution.

in the Box-Jenkins approach, non stationarity due to trend and seasonal factors is handled by first and seasonal differencing. The resulting ARIMA models have the property that shocks to the variable have permanent effects on the level and the seasonality of the series. Whether this is appropriate for economic variables is the matter of continuing controversy within the econometrics profession (Nelson & Plosser, 1982).

An alternative approach to univariate modelling is to assume that the trend and seasonal components are deterministic functions of time and that the series fluctuates around this deterministic path. This leads to autoregressive deterministic models of the form:

$$a(L)x_t = b_0 + b_1 \text{ Trend} + \text{seasonals}$$

Such models can be easily estimated using *OLS* with appropriate techniques - e.g. Schwartz's criterion, residual autocorrelation - for selecting the order of autoregression. Forecasts can be readily derived from the fitted equation in the same way as in the case of ARIMA models. A range of tests to determine whether autoregressive deterministic models are more appropriate than ARIMA models have been developed and are easy to apply (Dickey & Fuller, 1981).

One disadvantage to the Box-Jenkins approach to forecasting is its apparent black box nature and it is difficult to analyse a forecast in terms of the components of the series such as trend, seasonal, cycle etc. Techniques for extracting these components with a Box-Jenkins model have been derived by Nerlove, Grether and Carvalho (1979) and by Hillmer and Tiao (1982) and these can be used in explaining both the past evolution of the series and the forecasts. An alternative approach is to model and estimate these components directly. This is the approach taken in exponential smoothing and in Harvey's structural time series modelling.

To illustrate these methods consider the following case:

$$x_t = T_t + S_t + u_t \quad (5.3)$$

$$T_t = T_{t-1} + G_{t-1} + e_{1t} \quad (5.4)$$

$$G_t = G_{t-1} + e_{2t} \quad (5.5)$$

$$S_t = S_{t-s} + e_{3t} \quad (5.6)$$

This says that the series equals trend plus seasonal plus noise. T is the level of the series which follows a random walk with drift G . G is the growth rate of the series, a random walk. S is the seasonal part of the series which follows a seasonal random walk and u, e_1, e_2 and e_3 are independent white noise terms. The example presented here is linear with additive seasonality. However, a wider range of assumptions is possible, with no seasonality, multiplicative seasonality, constant level etc. The range of possibilities is presented graphically in chart 1. A cycle could also be included in the system 5.3 to 5.6 but this is excluded for ease of exposition.

If we had estimates of T, G and S over the period of our data we could use equations 5.4 to 5.6 to derive forecasts of the future values of these components. These could then be plugged into equation 5.3 to generate a forecast for future x . Exponential smoothing and Harvey's structural time series modelling provide a methodology for doing this.

In exponential smoothing, the Holt-Winters approach to estimating and forecasting using 5.3 to 5.6 can be easily applied. Given suitable initial values for T, G and S and values for the smoothing parameters a, b and c , updated estimates and forecasts of these components can be obtained by solving the following equations recursively:

$$T_t = a(x_t - S_{t-s}) + (1 - a)(T_{t-1} + G_{t-1}) \quad (5.7)$$

$$G_t = b(T_t - T_{t-1}) + (1 - b)G_{t-1} \quad (5.8)$$

$$S_t = c(x_t - T_t) + (1 - c)S_{t-s} \quad (5.9)$$

One could then derive a one step ahead forecast for x_t , say f_t :

$$f_t = T_{t-1} + G_{t-1} + S_{t-s} = x_t + e_t \quad (5.10)$$

The intuition behind equations 5.7 to 5.9 is that when a forecast error is made this could indicate 1) the pure noise due to u in 5.3; or 2) a change

in the level of the series (T) due to e_1 in 5.4; 3) a change in the growth rate (G) due to e_2 or, finally, 4) a change in the seasonal pattern due to e_3 in 5.6. The smoothing parameters a, b, c determine how much of the forecast error is attributed to each of these sources. Hence, when an error occurs, the estimated level, growth and seasonal are revised by an amount determined by the smoothing parameters.

Given a set of initial conditions and values for the smoothing parameters, exponential smoothing is easy to apply and is ideally suited as an automatic procedure which can be applied mechanically when a large number of series have to be forecast. A comprehensive survey of exponential smoothing methodology, including techniques for choosing the initial conditions and estimating the smoothing of the parameters is presented in Gardner (1985).

The structural time series method of Harvey (1983) is closely related to the Holt-Winters approach to exponential smoothing. Harvey's approach rests on the recognition that the system 5.3-5.6 is a state-space model with 5.3 as the observation equation and equations 5.4 to 5.6 the transition equation. As a result the results obtained by Kalman (1965) can be used to produce optimal estimates and forecasts of the components S, T, I and G . Given initial observation for these components, estimates/forecasts can be obtained by running the Kalman filter over the sample period and using 5.3 to 5.6 to derive forecasts. The theory underlying the Kalman filter can also be used to derive confidence intervals for the forecasts. The use of the Kalman filter requires estimates of the variances of the terms u, e_1, e_2, e_3 etc. and Harvey presents methods, in both the frequency and the time domain, with which these parameters can be derived. It can be shown, (Harvey 1984) that various forecasting techniques, such as Holt-Winters exponential smoothing, are special cases of structural time series modelling.

Exponential smoothing and structural time series modelling can be shown to be a special case of ARIMA modelling. For example, second differencing and seasonal differencing equation 4.3 and substituting from 5.4 to 5.6 yields:

$$\begin{aligned}
(1 - L)^2(1 - L^s)x_t &= (1 - L^s)e_{2t-1} + (1 - L)(1 - L^s)e_{1t} + (1 - L)^2e_{3t} \\
&\quad + (1 - L)^2(1 - L^s)u_t \\
&= (1 + c_1L + c_2L^2 + \dots + c_{s+2}L^{s+2})n_t
\end{aligned}$$

This implies that, after second and seasonal differencing, x is an $mA(s+2)$ process with coefficients which depend on the variances of the noise terms in 4.3 to 4.6. This ARIMA process is observationally equivalent to the Holt-Winters and Harvey models and should produce similar forecasts. Viewed in this light, it is apparent that exponential smoothing and structural modelling involve the imposition of strong restrictions on the process generating the data which may not be valid. However, against this, their advantage is that the forecasts produced can be analysed in terms of readily understood concepts, such as trend and seasonality.

6. FORECASTING WITH STRUCTURAL ECONOMETRIC MODELS

The development of structural econometric models for forecasting and policy analysis is the principal concern of most econometric textbooks such as Johnston. Indeed, according to some definitions econometrics is concerned with the estimation of the parameters of theoretical behavioural relationships.

The approach to forecasting using structural models differs from that of time series analysts largely because of the importance given to insights from economic theory in formulating models.

Structural econometric forecasting involves three stages. The first stage consists of the specification of the model. In contrast to time-series analysis, such as Box-Jenkins methods or VARs, where the form of the model is, for the most part, determined by the properties of the data, econometric modelling begins with the behavioural relationships implied by the relevant economic theory. Thus, in the case of a macromodel for example, theory will be used to determine the form of the equations which govern the behaviour of each variable of interest. On this basis, for example it may be postulated that consumer expenditure is determined by the level of personal disposable income. Investment will be determined by the level of activity, interest rates etc. Such equations are called behavioural

equations, because they supposedly reflect the behaviour of the agents in the relevant sector. In formulating such equations for econometric analysis, the key role of theory is to decide which variables appear in which equation, and, therefore, which variables are excluded on a priori grounds from each equation. Since there is no agreed corpus of econometric theory which enjoys universal support, it follows that different analysts may adopt different specifications.

In addition to behavioural equations, the other type of equation which arises are accounting identities. An obvious example is the equality between GNP and the sum of its expenditure components. These equations are used to complete the model into a coherent whole.

In time series analysis, all variables are considered to be endogenous in the sense that their evolution over time is determined by the equations of the system. In contrast, the traditional econometric approach divides the variables in the system into endogenous variables and exogenous variables whose values are determined outside the system and which form an input to the model in forecasting and simulation experiments.

The second stage of the econometric approach is the estimation of the parameters of the model. This issue receives considerable attention in econometrics textbooks. Because the behavioural equations of the econometric variables usually include dependent variables from other equations as explanatory variables, this implies that the assumption of an error term uncorrelated with the explanatory variables is invalid. In these circumstances, the application of *OLS* will yield both biased and inconsistent estimates. A number of techniques have been developed to overcome this problem. These include Full Information Maximum Likelihood and instrumental Variables estimation. In practice, however, most large macroeconomic models are estimated using *OLS* in spite of the problems attaching to this estimator (Waelbroeck, 1976).

Once a forecaster has specified and estimated the parameters of the models, the next stage is to derive forecasts. In theory, this is done by first solving for the dynamic reduced form of the model. For example, suppose the model is a multivariate dynamic model as in equation (3.7) above, i.e.

$$G(L)Y_t = F(L)X_t + U_t$$

where Y_t is the vector of endogenous variables at time t , X_t the exogenous variables and U_t a vector of error terms. This can be rearranged as:

$$Y_t = G^{-1}(L)F(L)X_t + G^{-1}(L)U_t \text{ or, less compactly}$$

$$Y_t = C_0X_t + C_1X_{t-1} + \dots + D(L)U_t \quad (6.1)$$

where $D(L) = G^{-1}(L)$

In order to generate forecasts for the endogenous variables for periods $i=t+1$ to $t+n$, one must assume or generate a path for the exogenous variables (x) up to $t+n$. These are then plugged into equation (6.1) from which forecasts from y can be derived. Of course, in practice it is not necessary for the forecaster to reduce the model to form (6.1). The usual procedure is to input the path of the exogenous variables and the solution of (6.1) for the forecast endogenous variables is carried out by computer software using an appropriate algorithm, for example the Gauss-Seidel method. A practical example of the use of this approach in the Irish case can be found in Bradley and Fitzgerald (1989).

Using this approach to forecasting, forecasts can be mechanically generated conditional on an assumed path of the exogenous variables. In practice, model based forecasters tend to take information from other sources into account and judgmentally adjust the mechanical forecasts. This process is quaintly known as 'tuning the model'. The usefulness of such adjustments will be discussed below.

In addition to point forecasts, it is also possible to derive confidence intervals for forecasts from structural models. Forecasts derived from models such as (6.1) contain three sources of error. First, the equations are stochastic and the error terms U_t contribute to the overall error in the forecasts. Secondly, in practical applications, the parameters are estimates rather than the 'true' parameters. This also contributes to the overall forecast error. Finally, the assumed values for the exogenous variables are forecasts from another source and usually differ from the actual

path taken by these variables. Detailed techniques for identifying the contribution of these different sources to the overall error variance, using stochastic simulation, have been developed by Fair (1980). These techniques can also be used to provide confidence intervals for the forecasts derived from structural methods. An alternative approach, which is widely used, for example, in comparing the performance of different forecasting, is to derive confidence intervals from the past forecasting performance of the model in question.

The above discussion has focused on the estimation and use of complete systems for forecasting. However, the structural approach to forecasting need not involve a complete system. In many forecasting situations, an eclectic approach is adopted and forecasts for different variables are derived using different techniques. In such an approach a single equation or a group of equations could be used to forecast some of the variables. In the Irish context, for example, one of the more widely known forecasting equations is the O'Malley-Scott (1987) equation which relates profit repatriations to lagged exports. Similarly, in forecasting imports, for example, the Central Bank uses an estimated import demand equation. In this case, the forecast values of consumption, investment etc. are plugged into the import equation to derive a conditional forecast of the growth in imports. This approach is clearly a special case of the more general systems approach outlined above.

7. QUALITATIVE AND JUDGMENTAL FORECASTING

The techniques of forecasting examined in previous sections involved the application of straightforward formal rules to derive forecasts based on the information set available. These processes can be succinctly described and the results can be easily replicated by other forecasters using the same techniques. Judgmental forecasting, which at present appears to be the dominant paradigm in macroeconomic forecasting in Ireland, does not generally facilitate easy and explicit explanation of the processes involved.

A general flavour of the use of judgmental methods in macro forecasting in the Irish context can be obtained from the surveys by Menton (1965) and Cavanagh and Mooney (1973) which appeared in this journal. Briefly stated, judgmental forecasting involves a subjective assessment by the forecaster of how the economy is likely to evolve given the disparate

pieces of information available. These include the recent behaviour of various indicators - retail sales, trade data etc. - institutional information such as budgetary developments derived both from publicly available sources as well as from private contacts and, finally, a range of information from publicly available and private sources which affect the judgement of the forecaster. Examples of the latter include newspaper reports of national and international developments and information gained from contacts working in the 'real world'. This information, combined with the forecaster's subjective assessment, derived from experience, of how the economy works - the 'implicit model' - and intuitive feeling as to the evolution of the economy is used to arrive at point forecasts for the various economic variables of interest.

It follows that the results of judgmental forecasting are, in contrast to the methods outlined in earlier sections, strongly dependent on the personality of the forecaster involved and it is often difficult, if not impossible, for another forecaster with the same information to replicate the forecasts. Indeed, it is often difficult for a judgmental forecaster himself to explain precisely how some particular forecast number was derived. These considerations make it extremely difficult both to learn and to analyse judgmental forecasting methods. Nonetheless, it is possible to accommodate the judgmental approach to forecasting into the general forecasting framework outlined in section 3, and many of the 'tricks of the trade' employed by judgmental forecasters can be shown to be applications, albeit informal and subjective, of the techniques described in earlier sections.

(i) Judgmental and Univariate Time Series Analysis

In judgmental forecasting, a considerable emphasis is placed on assessing movements in variables for which published data is available with a view to projecting the full-year outturn. Obvious examples of this include the retail sales index, various price data and monthly trade data. Thus as new data becomes available the forecaster seeks to determine how this will affect the full year position and if the previous forecast needs to be revised. In practice, this involves a number of methods of various degrees of sophistication. The first of these is 'carry-over' analysis. This shows what the outturn for the full-year position would be if the series stays at the level of the last available data (seasonally adjusted) over the remainder of the forecast period. Alternatively, various ad hoc moving averages can

be applied to the data to assess what is happening to the trend in the series and what will happen if this trend is projected forward. These methods can often be supplemented by graphical analysis - 'eyeballing the data'.

It is immediately apparent, that such methods are, in fact, special cases of the univariate time series forecasting techniques. For example, the carry-over forecast is simply equivalent to the forecast generated from a specific AR process, the random walk process. According to this model,

$$Y_{t+i} = Y_t$$

This says that our forecasts for Y in future periods is simply equal to the latest available value of the series - identical to the carry-over forecast. Similarly, a forecast based on a moving average of the data is equivalent to using a more general AR model to derive forecasts.

While this equivalence provides some justification for these 'back of the envelope' methods, it also points to their limitations. In time series analysis, the form and parameters of the process which is used to generate forecasts is derived from the past behaviour of the data in a rigorous manner. In contrast, the judgmental approach imposes both the form and the parameters on the data. It follows that, except in special cases, the time series methods should produce forecasts which are consistent with past performance and are more accurate.

(ii) Judgmental Forecasting, Multivariate Time Series Analysis and Econometrics

Like all forecasters, judgmental forecasters place particular emphasis on the relationships between variables. This may be a casual relation, such as the relationship between import growth and growth in final demand, or an indicative relation such as the link between retail sales and the national accounts measure of consumption. These are used by judgmental forecasters in the form of implicit 'rules of thumb' or 'ready reckoners'. For example, a forecaster might believe that every one per cent increase in retail sales implies a one per cent rise in consumer expenditure, for example. The derivation of these rules is often unclear. Sometimes they

are based on past empirical work and sometimes on the a priori judgement of the forecaster.

Briefly stated, the rules of thumb employed by forecasters take the form:

$$Y = f(X)$$

where Y is the variable being forecast and X is another variable. Clearly, multivariate analysis and econometric techniques can be used to derive versions of these rules. In this approach, historical data can be analysed using regression or time series techniques to determine, from the historical experience, how closely the variables are related, what form the relationship takes (for example, the lag structures) and, finally, to provide quantification of the relationship. Once again, use of such soundly-based methods will improve our understanding of these relationships and provide more accurate forecasts.

(iii) Extraneous Information and Judgmental Forecasting

Often the type of information taken into account in judgmental forecasting does not readily lend itself either to time series analysis or econometric investigation. This may arise because of insufficient observations, or because the information is of a qualitative rather than a quantitative nature. As an example of the former, consider the case of information of specific large scale transactions on certain companies. Since such transactions may occur infrequently, there will be insufficient information to conduct statistical analyses. For example, fleet replacement by Aer Lingus and investment by other semi-state companies had a significant effect on investment in 1989/90. A mechanical forecasting method which did not take such developments would be expected to give rise to large forecast errors. This is particularly important in the case of a small country like Ireland where the actions of a few large agents can have a major effect on aggregate economic data. The judgmental approach to forecasting provides scope to incorporate information of this kind into the forecast and this is one of its major advantages over formal forecasting methods.

Qualitative information, which is not readily amenable to statistical analysis, can also be incorporated into judgmental forecasts. For example,

discussions with representatives of companies or the public sector may bring to light trends which, due to lags or simple unavailability of data, may not yet have appeared in official data. Similarly, general news and newspaper reports on developments relevant to the economy, can give a general indication of direction in which the economy is heading. In judgmental forecasting, this sort of information is likely to play a significant role in the formation of a broad view of the path of the economy and to provide a range or 'ball-park' in which more precise forecasts will fall.

It is clear from the above discussion that the judgmental approach to economic forecasting is an eclectic approach which employs different techniques and disparate information sets. As shown above, some of the methods used can be seen as informal applications of more mechanical techniques. The results of these techniques, combined with the both qualitative and quantitative information as well as the subjective views of the forecaster are used in deriving final forecasts. Indeed, judgmental forecasting as a whole can be seen as a method, again informal, of combining forecasts from different sources such as described in the previous section.

8. EVALUATING THE ACCURACY OF FORECASTING TECHNIQUES

A number of traditional measures of forecasting accuracy have been developed and are widely used in examining the forecasting performance of different techniques for different series. To facilitate the discussion, we employ notation used earlier. Let y_t denote the actual value taken on by a variable at time $t + h$, F_{t+h} the forecast based on some technique. Then $e_{t+h} = y_{t+h} - F_{t+h}$ is the error of the forecast.

Clearly if $e > 0$ the forecaster has underpredicted the series, for $e < 0$ an overprediction has occurred, $e = 0$ implies a perfect forecast. The traditional measures of forecast accuracy are concerned with key properties of the forecast errors.

The first measure is the mean forecast error (\bar{e}), defined as:

$$\frac{1}{n} \sum_{t=1}^n e_t$$

This provides an estimate of the expected value of the forecast error. If \bar{e} is not significantly different from zero, this implies that there is no systematic tendency either to overpredict or underpredict. However, a non-zero \bar{e} indicates a systematic bias in the forecast.

Although, as noted in a previous section, unbiasedness may be a desirable property of a forecasting technique, it is not, on its own, an adequate measure of the accuracy of the forecast. In particular, an average value of e could be accomplished by having massive negative errors offsetting massive positive errors. To guard against this possibility some measures of the dispersion of the forecast errors are required. The most popular measures are in this context:

The Mean Absolute Error MAE:

$$\frac{\sum_{t=1}^n |e_t|}{n}$$

The Mean Square Error MSE:

$$\frac{\sum_{t=1}^n e_t^2}{n} \quad \text{and}$$

The Mean Square Percentage Error (MSPE):

$$\frac{\sum_{t=1}^n (e_t/y_{t+h})^2}{n}$$

Note that when $e = 0$, the MSE is equivalent to the variance of the forecast error. With a perfect forecasting system, all of the above measures would be equal to zero. A high value for any of these measures indicates a poor forecasting technique. The MSE, being quadratic, penalises high values of e , e.g. outliers, to a much greater extent than the MAE, which, as a result, may be more robust with respect to outliers. Both the MAE and MSE are sensitive to units of measurement (e.g. just multiplying the variable and its forecast by 10 results in a tenfold rise in the MAE). Therefore, these

statistics can be unreliable when comparing the forecasting accuracy for different series. The MSPE overcomes this difficulty, in that the errors are scaled by the value of the series for each time period. However, the MAPE should not be used in the case of series which alternate in sign, e.g. the trade balance.

All of the above statistics are of limited use, however, when comparing the performance of a technique on different series which have different degrees of forecastability or volatility. A simple statistic developed by Theil (1966) can be employed in an attempt to overcome this problem and compare the performance of techniques across different series. Consider a 'naive' random walk forecast for an arbitrary series, i.e.

$$F_{t+1} = y_t$$

As noted above, this is also the carry-over forecast. Now the MSE of this technique - which is approximately equal to the variance of the change in the series - can be considered as a measure of the inherent volatility/forecastability of the series. For example, if this MSE is zero, the series is constant and can easily be forecast. By comparing the MSE of any forecasting technique with the MSE of the random walk forecast, we can derive a unit free measure of the performance of the technique with this series which takes into account, to some extent, the underlying volatility of the series. This statistic is Theil's U statistic which is defined, for a technique a , as:

$$U(\text{technique } a) = \text{MSE}(\text{technique } a) / \text{MSE}(\text{Random Walk Forecast})$$

This statistic ranges from zero to positive infinity. A zero value indicates a perfect forecast. A value less than one indicates a better forecasting performance than the naive random walk forecast. A value greater than one indicates that the technique is outperformed by the random walk forecast and, therefore, is not up to much. This unit-free volatility-adjusted measure can be used to compare different techniques for the same and for different series. An obvious objection, however, relates to the choice of the naive benchmark technique, the random walk forecast. Whilst this

may be appropriate for many series, it will not be suitable, for example, for series which exhibit trend or seasonal behaviour. Therefore, in the case of these series, the fact that any technique is better than a random walk forecast tells us little about its usefulness.

The rational expectations revolution has had a significant effect on the development of macroeconomic theory and econometric practice. Insights from this approach can also be used in the evaluation of the quality of economic forecasts. In most applications, the expectations of agents are not observed directly and, therefore, these have to be either substituted or instrumented out in econometric applications. Published forecasts, which are the expectations of the forecaster regarding behaviour of economic variables, are observable and therefore present an opportunity of testing the rational expectations hypothesis. Are economic forecasts rational in the Muth sense? In addition to being a test of an economic theory, this question provides an opportunity to evaluate the quality of economic forecasts in the light of rational expectations theory. This approach to analysing published forecasts has been developed by Turnovsky (1970), Carlson (1977) and Brown and Maital (1981).

In modern macroeconomic theory, an agent's expectation of an economic variable x_{t+i} is considered rational if it is equal to the conditional expectation of the variable given the information set I_t .

$$F_{t+i} = E(x_{t+i}|I_t)$$

and the forecast error is

$$e_{t+i} = x_{t+i} - F_{t+i}$$

Recall from our discussion of the theory of forecasting that such an expectation is an optimal forecast under the squared error loss criterion. The approach adopted by Brown and Maital is to derive testable implications from this assumption for the forecasts, and in particular the forecast errors. Given a set of forecasts or agents, these can be tested for their consistency with rational expectations.

The first test, called a weak test of partial rationality, is to examine whether the forecasts are biased, i.e. whether the mean of the forecast errors is zero. This can be performed by simply calculating the forecast errors from published forecasts and actual data and performing a standard test for the equality of the mean with zero. An alternative approach, which appears to have been much favoured in the literature, is to run the regression

$$x_{t+i} = a + bF_{t+i}$$

and carry out a standard test for $(a, b) = (0, 1)$. However, Holden and Peel (1989) show that there are circumstances when this restriction will be rejected when the forecasts are unbiased. Therefore, the regression approach seems unreliable and it is better to use direct tests on the forecast errors.

The second weak test for partial rationality relates to the autocorrelation structures of the forecast errors. For example, in the case of a one-step ahead forecast these errors should be innovations i.e. uncorrelated with their own lags and with the other elements of the information set. If this condition did not hold then one could take into account the relationship between successive error terms and between the error and other elements in the information set to derive more accurate forecasts. If this could be done, the original forecast could not be rational. This leads to a test of forecast errors for autocorrelation. It also implies that the variance of the forecasts should be less than the variance of the series being forecast (Shiller 1979) - a variance bounds test which is particularly popular in financial economics.

The above tests are weak tests in the sense that unbiasedness and errors which are unautocorrelated - as well as the variance bounds conditions - are necessary but not sufficient conditions for full rationality. To perform an adequate test of full rationality one would need to know the information set used by the agent/forecaster to test whether the forecast errors are independent of variables in the information set. Clearly, this is impossible. In practice, however, one can regress the forecast error on some variables which are known to the forecaster at the time of the forecast. If there is a significant relationship, then this provides evidence against full rationality.

9. COMBINATION OF ECONOMIC FORECASTS

Most of this paper so far has dealt with the use of particular techniques for forecasting. However, even for one series, there is no reason for a forecaster to stick rigidly to the forecasts derived from just one technique. Indeed, it can be shown (Granger & Newbold) that, under certain conditions, a combination of forecasts will produce greater forecast accuracy than any of the individual forecasts.

For example if F_1 and F_2 are unbiased forecasts with errors which are independent and have variances V_1 and V_2 . Consider a third forecast which consists of a weighted average of these forecasts.

$$F^* = w_1 F_1 + (1 - w_1) F_2$$

Minimisation of the variance of F^* requires that

$$w_1 = \frac{V_2}{V_1 + V_2}$$

which leads to a combined forecast with an error variance which is less than the minimum of V_1 and V_2 for $V_1, V_2 > 0$. Note that the weight on each forecast is inversely related to the variance of its forecast error. This intuitive results says that good techniques, techniques which have a low error variance, should be given a higher weight.

These results can be extended to the more general case where the forecasts are no longer independent. If $F = (f_1, f_2, f_3...)$ is a set of unbiased forecasts with error covariance matrix C . The optimal weights for the combined forecasts $w'F$ where the $w'i = 1, i = (1, 1, 1, ...)$, is:

$$w = \frac{C^{-1}i}{i'C^{-1}i}$$

In practical terms, one would not know the C matrix above. However, this could be estimated from past forecasting errors and used in the above formula to derive the optimal weights.

Granger and Ramanathan (1984) developed a more general procedure which allows for bias in the forecasts. In this approach, the actual values of the series is regressed on a set of past forecasts. The estimated regression coefficients can then be used to weight forecasts of the future.

In theory, use of the above methods should result in improved forecast accuracy. However, in practical situations, if the correlation structure between forecasts changes over time, then use of past data to estimate weighted combination is not guaranteed to produce forecasts which are better than all of the individual components.

The discussion so far has concentrated on the combination of forecasts of the same periodicity. Techniques have been developed which allow comparison, monitoring and combination of forecasts for different periods. For example, consider the following situation which often arises in practice. Suppose a forecaster has produced a forecast for the average (or sum) value of a variable for a full year, e.g. the annual trade balance or the annual rate of inflation. Suppose monthly data is available during the year. Can the information contained in the monthly data be used to derive an improved forecast? What does the annual forecast imply for the monthly series? When monthly data becomes available, how should this be used to change the annual forecast?

Techniques for addressing these questions have been developed by Choulette (1982) and extended by Guerrero (1989). In this approach an ARIMA model for the monthly series is identified and estimated. Using the model, forecasts are derived for each month in the year. Usually the ARIMA forecast for the full year will differ from the forecaster's forecast. However, the methods presented enable the forecaster to optimally adjust the ARIMA forecast to derive a monthly path which is consistent with the annual forecast. Alternatively, the two may be combined to form a new forecast. As the year progresses, the monthly data which becomes available can be compared with the forecast monthly path to see if the data is consistent with expectations and if the forecast needs to be revised.

10. CHOICE OF FORECASTING TECHNIQUE

The previous sections have been devoted to an examination of different techniques which can be employed in macroeconomic forecasting. The obvious question is which technique should be chosen. In deciding between techniques, a number of criteria will be taken into account. These include:

- 1, the nature of the data;
- 2, the costs of alternative techniques;
- 3, their user-friendliness; and, finally
- 4, the accuracy of different techniques.

The impact of these criteria on the choice of technique will be discussed in turn. From the outset, it should be noted that the main focus in this section will be on the accuracy of the different techniques which appears to be the principal concern of the forecasting literature.

10.1 Data

The nature of the available data is likely to exert a significant effect on which method can be employed. If the number of observations is limited so that statistical/econometric analysis cannot be conducted then simple extrapolation techniques such as exponential smoothing and carry-over analysis may be the only available options. This may be supplemented by various judgmental forecasts. If sufficient observations are available but the series appears to have a life of its own in the sense that one is not able to detect a significant relationship with other variables, then multivariate techniques and structural models are likely to be of little use. In this case, the use of univariate techniques such as Box-Jenkins methods is unavoidable. If, on the other hand, there is no shortage of observations and significant relationships with other variables appears to exist, then multivariate time series methods and structural econometric methods may be employed.

10.2 Costs

In general the more complex the technique, the more resources will be required to generate the forecasts. The cost depends not just on the

required levels of skill of the operators and hardware/software requirements but also on the data requirements. Obviously, a method which requires a large database to be maintained will prove more costly than a simple univariate method. This criterion, therefore, tends to favour time series methods, particularly univariate methods, rather than large scale structural models which involve significant resource requirements. Depending on the degree of sophistication involved, judgmental forecasting may also prove a cheap method of generating forecasts. Rough and ready back of the envelope calculations, for example, should be relatively inexpensive.

10.3 User Friendliness

Obviously, the more user-friendly the forecasting system the better, *ceteris paribus*. This depends on the extent of the knowledge of the user. Users may find, for example, the results of time-series methods and structural models difficult to comprehend. In macroeconomic forecasting, however, the user-friendliness is not a particularly important criteria in choosing between techniques, since the ability of users to understand the results ultimately depends on the manner in which the forecasts are presented rather than techniques used to derive them.

10.4 Accuracy of Different Forecasting Techniques

The accuracy of different methods is a crucial criterion in choosing between different techniques. Clearly, one should choose the most accurate forecasting technique, all other things being equal. Can one make any general rules about the relative accuracy of the different approaches to forecasting? Which techniques are better? Is any one technique better than all the others in all circumstances? This section addresses these issues.

Recall from our discussion of the theory of forecasting that, in principle, forecasting techniques which take into account more information should be better, or at least should not be worse, than techniques which use a more limited information set. On this basis, we can on a priori grounds, derive a hierarchy of techniques on the criterion of accuracy. Assuming correct specification and exogenous variable assumptions, structural econometric models should produce more accurate forecasts than multivariate time series methods. This arises because the former take into

account the restrictions implied by theory and therefore, should give rise to more efficient parameter estimates than the less parsimonious time-series methods. Similarly, in general, multivariate time series methods should result in forecasts at least as accurate as univariate time series methods. This arises because multivariate techniques take into account information on the evolution of other series other than the variable being forecast and hence, according to the theory of forecasting, should give rise to more accurate forecasts. An exception is in the case of absence of Granger Causality (Granger 1969) which implies that information about the behaviour of other variables is of no predictive value for a series. In this case multivariate techniques cannot improve on the forecasts of univariate techniques.

These conclusions may not, however, apply in practical situations. For example, actual structural models may be seriously misspecified by virtue of 'incredible identification' - the imposition of invalid zero restrictions (Sims 1980) - or by virtue of failing to adequately account for the dynamic properties of the data resulting in dynamic misspecification. In these situations, there is no guarantee that structural based model forecasts will outperform even simple univariate time series models. Early empirical work on the relative forecasting performance of large-scale macromodels concluded that these models did not produce better forecasts than Box-Jenkins methods (Nelson 1972; Cooper 1972; Naylor 1972; and Armstrong 1978). These results represented a damning verdict on the large-scale models of the time and contributed to the success of the rational expectations revolution and the resulting disillusionment with large scale models. The use of improved econometric methods and taking account more fully the dynamic properties of the data, however, appears to have resulted in some improvements in the accuracy of structural model forecasts. More recent studies (McNees 1988 and 1990) showed that structural models produce more accurate forecasts than Box-Jenkins techniques. However, in many cases the improvement in accuracy is relatively small and, when account is taken of the substantial resource requirements in building and maintaining large scale models, Box-Jenkins techniques are a useful alternative to large scale modelling.

If one response to the problems of the poor forecasting performance of macroeconomic models was to attempt to improve the models, an alternative approach spearheaded by Sims (1980) was to abandon structural

models in favour of 'atheoretical' multivariate time series methods. In this regard the main model employed was the vector autoregression. At first, these were estimated by straightforward OLS but later procedures were developed by Litterman (1984) which took into account some prior information about the parameters which resulted in improved forecast accuracy. In the early 1980s, Litterman showed that these procedures tended to produce better forecasts than structural models in most cases, although there were exceptions. More recent evidence, however, is somewhat more mixed (McNees 1986 and 1990). This later evidence suggests that BVARS are as successful at forecasting real variables such as GNP growth and Unemployment but less so in the case of inflation and nominal variables. In the UK, where the work of Hendry and his co-workers on the selection of appropriately specified dynamic models has exercised a strong influence on econometric practice, Wallis (1989) reports that VAR methods have not outperformed structural model based forecasts.

In relation to the performance of judgmental forecasts compared to more formal quantitative methods, the evidence is again mixed. Makridakis et al (1983) surveyed over two dozen case studies and found that simple quantitative techniques often outperform detailed judgmental forecasts. They attributed this relatively poor performance to the biases which psychological research has shown to be present in judgement based information processing. McNees (1990) on the other hand, investigated whether judgmental adjustment of mechanically generated model forecasts results in improved forecast accuracy. He found that such adjustments did improve accuracy in around two-thirds of cases.

The conclusion which follows from an examination of the evidence of the accuracy of different forecasting techniques is that there is no one technique which dominates the performance of the others. The relative accuracy of the different methods will differ for different series in different circumstances. This suggests that an eclectic approach to forecasting can be justified in which different techniques can be used for different series. It also suggests that there may be some gain in combining the forecasts of the different approaches as discussed in an earlier section. Some evidence on the performance of different forecasting methods will be presented in the following section which presents some practical examples with Irish data.

11. SOME PRACTICAL APPLICATIONS OF FORECASTING TECHNIQUES

The previous part of this paper has outlined, largely from a theoretical point of view, a range of different forecasting techniques. In this section we present some applications applied to Irish data. The examples are confined to a limited set of methods, since the presentation of a comprehensive set of examples would require a voluminous paper of its own. In this section we present evidence on the forecasting performance of two time series techniques - a VAR and a Box-Jenkins model - for forecasting Irish inflation. In addition, a range of univariate techniques are applied to the forecasting of industrial export volume growth. In both cases, the results are compared with the judgmental forecasts published in the Central Bank Bulletin. Finally, some evidence on the relative merits of time series compared to large scale macromodels is presented.

11.1 Forecasting Irish Inflation

Within the Bank a bivariate model for forecasting Irish consumer price inflation has been developed and has been used in the preparation of the Bank's published forecasts since 1990. The two variables in the system are quarterly observations of the consumer price index and the wholesale price index, both variables expressed in logs. The VAR has four lags and includes seasonal dummy variables. In short, the VAR has the form:

$$CPI_t = a_0 + \sum_{i=1}^4 a_i CPI_{t-i} + \sum_{i=1}^4 a_i WPI_{t-i} + \text{seasonals}$$

$$WPI_t = c_0 + \sum_{i=1}^4 c_i CPI_{t-i} + \sum_{i=1}^4 d_i WPI_{t-i} + \text{seasonals}$$

Clearly, given estimates of the parameters, which were obtained by *OLS*, dynamic forecasts can be readily derived for the *CPI* and *WPI* out to any desired horizon.

In addition, a univariate ARIMA model has also been developed. This takes the form:

$$(1 - L)(1 - L^4)CPI_t = (1 + aL)(1 - bL^4)e_t$$

The forecasting performance for both of these models for the period 1981-1989 is presented in Table 1. These are compared with the judgmentally derived forecasts published in the Annual Report of the Central Bank in each of these years. For both of the time series methods, data up to the first quarter of the year in question was used to generate forecasts for the remaining three quarters. From these forecasts for the year as a whole were derived. The information used corresponds to the amount of data which was available at the time when the Bank forecasts were being prepared.

The results for the VAR model in table 1 are quite impressive with all the indicators of forecast accuracy showing a more accurate forecasting performance than the Bank's forecasts which were based on complicated judgmental analysis. Indeed, it is worth noting that this comparison is somewhat unfair to the VAR in that certain information which would have been known to the Bank forecasters at the time - such as movements in mortgage rate or oil prices - is not incorporated into the VAR forecasts. The performance of the ARIMA model is worse than either the Bank or the VAR forecasts, indicating that a considerable improvement in the accuracy of inflation forecasts can be obtained by taking into account movements in the Wholesale price index and other indicators rather than relying on the past of the series alone. Overall, the results suggests that the use of multivariate time series methods can result in improved forecast accuracy in Irish circumstances.

11.2 Univariate Models for Forecasting Industrial Exports

Research carried out in the Bank indicated that it was difficult to find variables, other than the past of the series, which were useful or 'Granger Caused' industrial export volumes. As a result, attention was confined to univariate forecasting techniques. Since 1989, these methods have been used in preparing the forecasts for publication in the Bank's bulletin. Three techniques were considered:

(i) An ARIMA model of the form:

$$(1 - L)(1 - L^{12})(1 - aL - bL^2)IXV = (1 + cL^{12})e_t$$

(ii) A third order autoregressive model with trend and seasonals:

$$IXV_t = a_0 + a_1IXV_{t-1} + a_2IXV_{t-2} + a_3IXV_{t-3} + a_4 \text{ Trend + seasonals: and}$$

(iii) Holt-Winters exponential smoothing of the log of industrial export volume with linear trend and additive seasonality.

With each of these models data up to February in the forecast year was used to generate forecasts for the following ten months to yield an annual forecast. Once again, the use of the first two months' data corresponds to the information which was available to the forecaster at the time when the Bulletin forecasts were prepared. The results of this exercise from the period 1981-1988 are presented in Table 2 along with the Bank's Annual Report forecasts which were based on judgmental assessment of trends in the data and in export markets.

The statistics on forecast accuracy presented in Table 2 clearly show that all of the univariate time series methods employed resulted in more accurate forecasts than those published in the Annual Report. In terms of both RMSE and MAE the best of the univariate techniques - the third-order AR model - was almost twice as accurate. Within the time series methods, the AR model appears best followed by the forecasts derived from exponential smoothing. The ARIMA model comes in a close third. These results are again impressive and suggest that the use of appropriate univariate techniques can lead to an improvement in forecasting accuracy in the Irish case.

11.3 Time Series and Structural Econometric Models

The above examples suggest that for some series, time series are a useful alternative, or at least a useful supplement, to the judgmental methods hitherto employed in Irish forecasting. But what of structural econometric

models and, in particular, large scale macro models? Can these improve on both judgmental and time series methods? The theoretical and empirical results presented earlier suggests that such models can result in greater accuracy. How true is this for Ireland?

In order to compare different methods in practice, it would be desirable to have a reasonably long, consistent series for the forecasts generated by the different techniques. Unfortunately, such data is not available in the case of macromodels for Ireland. However, Bradley and Fitzgerald (1989) have presented data on the within-sample performance of the HERMES model of the Irish economy for a number of key macroeconomic variables covering the period 1967-1984. We can compare these results with the corresponding results for some time-series models.

In table 3 we present the RMSPE (or, where appropriate, the RMSE) for the HERMES model as reported by Bradley and Fitzgerald and the results for simple univariate autoregressive models estimated from annual data over the same time period. The results are somewhat mixed. In the case of 5 of the 12 variables (GNP, GDP, Exports, the Consumption Deflator and Numbers Unemployed) the model is outperformed by simple autoregressive models. In the other cases, the model is superior, sometimes, as in the case of investment, markedly superior to the univariate AR model. It must be stressed that the comparison is somewhat unfair to time series methods since the extremely simple univariate models, which only uses information of the lagged values of the series in question in generating forecasts, has been employed as against a large - over 400 equation - model which assumes knowledge of all the exogenous variables. This larger information set gives the model an advantage over time series methods, in theory, but, in practice, forecasters using the model would not know the values of the exogenous variables in forecasting situations.

Adherents of Hendry's variance dominance criterion - that any model should, at a minimum, outperform naive autoregressions - might be tempted to suggest that the results presented in table 3 cast some doubt on the reliability of the HERMES model for forecasting and policy simulation. From our point of view, however, the results obtained suggest that time series methods are not dominated by large scale structural models in the Irish case and that the results of more recent empirical studies, which appear to favour large scale models, does not apply with respect to existing

Irish large-scale models. However, this is not to deny that, in the case of some series, further gains in accuracy may be obtained from the use of structural models, probably on a single equation basis.

12. CONCLUDING REMARKS

The preceding sections have covered a wide area, including a discussion of different techniques and other relevant aspects of economic forecasting and the presentation of some practical examples applied to Irish data. The main conclusion which follows from this paper is that, in general, no one technique dominates the others in the sense that it will always and everywhere produce accurate forecasts. This suggests that an eclectic approach, in which different methods are applied to different series, offers the best prospect of producing the most accurate forecasts. Further gains may be obtained by using techniques for combining forecasts from different sources.

The paper also has considerable relevance to the practice of short-term forecasting in Ireland. At present, the judgmental approach appears to be the most popular, if not the only, method of short-term forecasting used in this country. While the use of judgmental forecasting is, as shown above, very useful in certain circumstances, sole reliance on this technique is not likely to result in the most accurate forecasts. This view is strongly confirmed by the theoretical discussions above and by international empirical evidence.

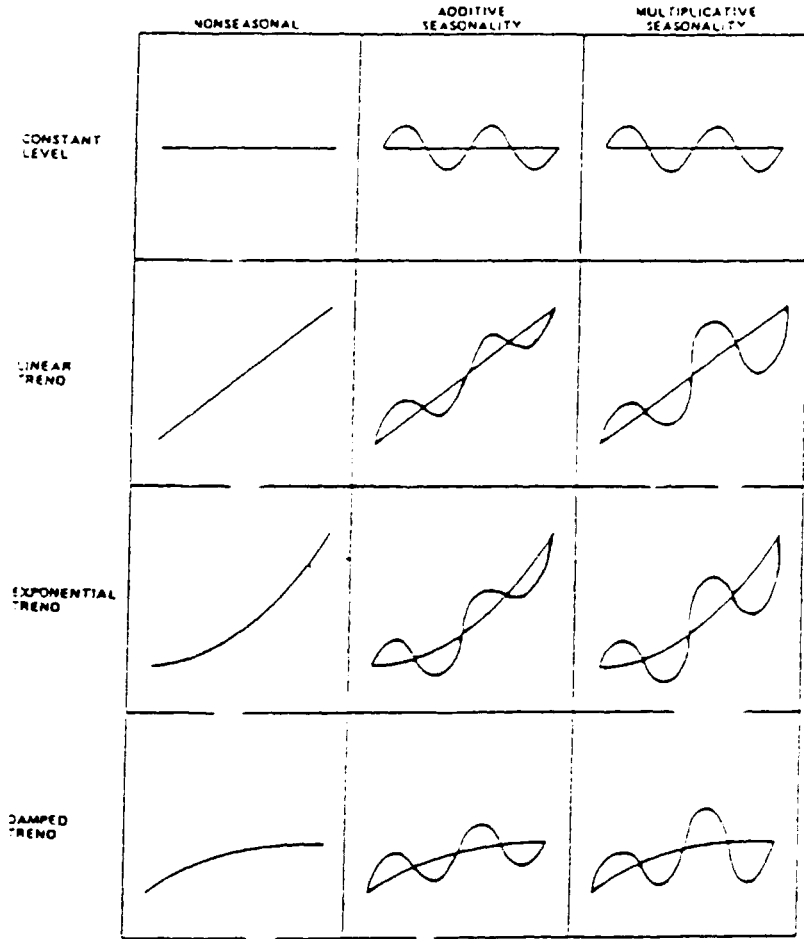
Moreover, it is strongly reinforced by the practical examples presented which show that for some series, simple time series methods perform better than the judgmental projections of skilled economists. On this basis, it is evident that formal techniques, such as time series analysis, should be used to a much greater extent than is currently the case.

In relation to large-scale macromodels, recent international evidence suggests that these can produce more accurate forecasts than time series methods. The evidence for Ireland above, however, casts some doubt on this judgement. This is not to say that the structural approach to forecasting cannot yield more accurate forecasts for some variables. Once again, the choice between time series methods and structural modelling must ultimately rest on pragmatic criteria such as the relative forecasting

performance for the series in question.

Overall, the conclusion of this paper is that an eclectic approach based on pragmatic consideration such as relative forecasting performance is the best route to a more accurate system for short-term economic forecasting. In this system, different techniques will be employed for different variables. It seems likely that the adoption of this approach will result in significant improvements on the performance of the current methods, which appear to be unduly dominated by the judgmental paradigm.

Chart 1. Patterns of Trend and Seasonality for Exponential Smoothing



Source: Gardner (1984)

Table 1: Comparison of Inflation Forecasts 1981-1989

	Actual	Forecasts by:		
		Bank ¹	VAR	BJ
1981	20.4	17.5	19.6	19.5
1982	17.1	17.8	18.1	17.2
1983	10.5	10.0	9.1	12.7
1984	8.6	8.5	9.1	11.5
1985	5.4	5.5	5.9	7.7
1986	3.8	3.0	3.9	5.8
1987	3.2	3.0	3.1	4.6
1988	2.1	2.0	1.2	2.6
1989	4.0	3.8	3.8	3.7
Av Error		.44	.14	-1.10
Av Abs Error		.62	.61	1.40
RMSE		1.05	.74	1.69
Theil U		.35	.25	.56

¹ Forecasts published in the Central Bank's Annual Report in each year.

Table 2: Central Bank vs. Univariate Time Series Forecasts of Industrial Export Volume Growth

	Actual	Bank ¹	AR	Box Jenkins	Exponential Smoothing
1981	8.5	6.0	9.1	7.9	6.9
1982	10.8	11.0	10.9	9.6	8.9
1983	14.7	9.0	11.3	11.2	9.7
1984	19.7	15.0	15.0	21.4	17.3
1985	7.3	13.0	10.7	16.7	13.3
1986	3.7	7.0	6.7	3.3	5.4
1987	15.4	6.0	11.5	7.1	8.8
1988	7.5	12.0	9.2	8.3	9.1
AE		1.0	0.4	0.3	1.0
AAE		4.5	2.6	3.2	3.4
RMSE		5.2	3.0	4.7	3.9

¹Forecasts published in the Central Bank's Annual Report in each year

Table 3: RMSPE of Hermes and Univariate AR Models 1967-1984

Variable	Hermes	AR
GNP Volume	1.85	1.54
GDP Volume	1.83	1.33
Import Value	4.00	7.50
Exports Value	3.78	3.70
Private Consumer Expenditure	2.45	3.37
Investment	3.81	7.38
Private Consumption Deflator	2.71	2.62
Total Employment	0.96	1.07
Unemployment Rate*	0.89	1.00
Unemployment Numbers	15.80	12.70
EBR (% GNP)*	0.79	1.49
BOP (% GNP)*	1.60	3.27

* RMSE

References

- Armstrong, J.S., 1978.** "Forecasting with Econometric Methods: Folklore vs. Fact", *Journal of Business*, S1, pp. 549-600.
- Box, G.E.P. & Jenkins, G.M., 1970.** *Time Series Analysis, Forecasting and Control*, Holden Day, San Francisco.
- Box, G.E.P. & Tino, G.C., 1981.** "Modelling Multiple Time Series with Applications", *Journal of the American Statistical Association*, Vol. 76, pp. 802-816.
- Bradley, J. & Fitzgerald, J., 1989.** *Medium Term Review: 1989-1994*, Economic and Social Research Institute, Dublin.
- Bradley, J. & Fitzgerald, J., 1989.** *Hermes-Ireland A Model of the Irish Economy; Structure and Performance*, Economic and Social Research Institute, Dublin.
- Brown, B. & Matal, S., 1981.** "What do Economists Know: An Empirical Study of Experts' Expectations", *Econometrica*, Vol. 49 pp. 491-504.
- Carlson, J., 1977.** "A Study of Price Forecasts", *Annals of Economic and Social Measurement*, Vol. 6, pp. 27-56.
- Cavanagh & Mooney, 1973.** "Trends in Short-term Macroeconomic Forecasting for Demand Management", *Journal of the Statistical and Social Enquiry Society of Ireland*, Vol. 22(5), pp. 133-161.
- Chollette, P.A., 1982.** "Prior Information and ARIMA Forecasting", *Journal of Forecasting*, Vol. 1, pp. 3750-83.
- Cooper, R.L., 1972.** "The Predictive Performance of Quarterly Econometric Models of the US", in B.C. Hickman (ed.), *Econometric Models of Cyclical Behaviour*, NBER, New York.
- Dickey, D.A. & Fuller, W.A., 1981.** "Likelihood Ration Test Statistics for Autoregressive Time Series with a Unit Root", *Econometrica*, Vol. 49,

pp. 1957-72.

Durkan, J. & Kelleher, R., 1975. "Short-term Forecasting A Review of Recent Experience", *Economic & Social Review*, Vol. 6, pp. 167-185.

Engle, R.F. & Granger, C.W.J., 1987. "Cointegration and Error Correction: Representation, Estimation and Testing", *Econometrica*, Vol. 55, pp. 251-276.

Fair, R.C. "Estimating the Expected Predictive Accuracy of Econometric Models", *International Economic Review*, Vol. 21, pp. 355-378.

Frain, J., 1991. "Dynamic Methods for Economists", *Technical Paper 1/RT/91*, Central Bank of Ireland.

Gardner, E.S., 1985. "Exponential Smoothing: The State of the Art", *Journal of Forecasting*, Vol. 4, pp. 1-37.

Granger, C.W.J., 1969. "Investigating Causal Relations by Econometric Models and Cross Spectral Methods", *Econometrica*, Vol. 37, pp. 424-438.

Granger, C.W.J. & Newbold, P., 1977. *Forecasting Economic Time Series*, Academic Press, New York.

Granger, C.W.J. & Ramanathan, 1984. "Improved Methods for Combining Forecasts", *Journal of Forecasting*, Vol. 3, pp. 197-204.

Guerrero, V.M., 1989. "Optimal Conditional ARIMA Forecasts", *Journal of Forecasting*, Vol. 8, pp. 215-230.

Harvey, A.C., 1983. "Forecasting Economic Time Series with Structural and Box-Jenkins Models: A Case Study", *Journal of Business and Economic Statistics*, pp. 299-315.

Hendry, D.F., Pagan, A.R. & Sargan, D.J., 1984. "Dynamic Specification", *Handbook of Econometrics*, North Holland, Chapter 18.

Hendry, D.F. & Richard, J.F., 1982. "On the Formulation of Empirical Models in Dynamic Econometrics", *Journal of Econometrics*, Vol. 20, pp. 3-34.

Hillmer, S.C. and Tiao, G.C., 1982. "An ARIMA Model Based Approach to Seasonal Adjustment", *Journal of the American Statistical Association*, Vol. 77, pp. 63-70.

Holden, D.A. & Peel, K.A. "Unbiasedness, Efficiency and the Combination of Economic Forecasts", *Journal of Forecasting*, Vol. 8, pp. 175-188.

Hoskins, J.R.M., 1980. "The Multivariate Portmanteau Statistic", *Journal of the American Statistical Association*, Vol. 15, pp. 602-608.

Johnston, J., 1984. *Econometric Methods*, McGraw Hill, London.

Kalman, R.E., 1960. "A New Approach to Linear Filtering and Prediction Problems", *Journal of Basic Engineering*, Vol. 82, pp. 95-108.

Litterman, R.B., 1984. "Specifying Vector Autoregressions for Macroeconomic Forecasting", *Staff Report 92*, Federal Reserve Bank of Minneapolis.

Makridakis, S., Wheelwright, S.C. & McGee, V.E., 1983. *Forecasting: Methods and Applications*, Wiley, New York.

McNees, S.K., 1986. "The Accuracy of Two Forecasting Techniques: Some Evidence and an Interpretation", *New England Economic Review*, March/April, pp. 20-31.

McNees, S.K., 1988. "How Accurate are Macroeconomic Forecasts", *New England Economic Review*, July/August, pp. 15-36.

McNees, S.K., 1990. "Man vs. Model? The Role of Judgement in Forecasting", *New England Economic Review*, July/August, pp. 41-52.

Menton, B.P., 1965. "Short-Term Economic Forecasting", *Journal of the Statistical and Social Enquiry Society of Ireland*, Vol. 21(3) pp. 15-35.

Naylor, T.H., 1972. "Box-Jenkins Methods: An Alternative to Econometric Forecasting" *International Statistical Review*, Vol. 40, pp. 123-137.

Nelson, C., 1972. "The Prediction Performance of the FRB-MIT-PENN Model of the US Economy", *American Economic Review*, Vol. 62, pp. 902-917.

Nelson, C.R. & Plosser, C.I. 1982. "Trends and Random Walks in Macroeconomic Time Series", *Econometrica*, Vol. 49, pp. 741-51.

Nerlove, M., Grether, D.M., and Carvalho, J.L., 1979. *Analysis of Economic Time Series*, Academic Press, New York.

O'Reilly, L., 1982. *The Analysis of Irish Economic Time Series*, Unpublished Phd Thesis, Department of Statistics, Trinity College, Dublin.

O'Malley, E. & Scott, S., 1987. "Determinants of Profit Outflows from Ireland", *Medium Term Review 1987-1992*, Economic and Social Research Institute, Dublin, pp. 55-64.

Shiller, R.S., 1979. "The Volatility of Long-Term Interest Rates and Expectations Models of the Term Structure", *Journal of Political Economy*, Vol. 88, pp. 1159-1176.

Sims, C., 1980. "Macroeconomics and Reality", *Econometrica*, Vol. 48, pp. 1-48.

Skehan, D., 1990. "A Comparison of the Central Bank and ESRI Economic Forecasts 1984-1988", Unpublished BPA Thesis, Institute of Public Administration.

Theil, H., 1966. *Applied Economic Forecasting*, North-Holland, Amsterdam.

Tiao, G.C. & Tsay, R.S., 1982. "Consistent Estimates of Autoregressive Parameters and Extended Sample Autocorrelation Function for Stationary and Non-Stationary ARMA Models", *Technical Report 683*, Department of Statistics, University of Wisconsin.

Turnovsky, S., 1970. "Empirical Evidence on the Formation of Price Expectations", *Journal of American Statistical Association*, Vol. 65, pp. 1441-1454.

Waelbroeck, J., 1976. *The models of Project Link*, North Holland, Amsterdam.

Wallis, K.F., 1977. "Multiple Time Series Analysis and the Final Form of Econometric Models", *Econometrica*, Vol. 45, pp. 1481-1497.

Wallis, K.F., 1989. "Macroeconomic Forecasting: A Survey", *Economic Journal*, Vol. 99, pp. 29-61.

Zeller, A. & Palm, F., 1979. "Time Series and Simultaneous Equation Econometric Models", *Journal of Econometrics*, Vol. 2, pp. 17-54.

DISCUSSION

J. Durkan: It gives me great pleasure to propose this vote of thanks to Gabriel Fagan and John Fell for their paper, "Techniques for Short Term Economic Forecasting".

The paper is, as the authors indicate, a survey of techniques which can be used to produce short term economic forecasts. The orientation of the paper lies within a particular tradition viz the statistical, and is very different to the orientation that forecasters in Ireland or indeed other countries would take. In some respects, it is very similar to the survey by Chatfield¹, which covers much the same ground, though the present paper is much more technique oriented. I have little to say on the question of technique, beyond noting that section 3, "A Unified Framework for Forecasting techniques" is the most valuable, providing a general framework within which the formal techniques can be seen to fit neatly.

My comments relate to the nature of judgmental forecasts in Irish circumstances, the reason for carrying out forecasts, and the comparisons of judgmental to more formal techniques carried out in the Central bank.

Judgmental Forecasts in the Irish Context

The ESRI has been involved in forecasting almost from its inception (Paper 2, 15, 21, 27, 33, 39 and the series of Quarterly Economic Commentaries since 1988). An analysis of these papers reveals a movement from informal to formal methods initially, and the development of partial models, used in generating elements of the forecasts (Industrial Exports, Imports, Consumer Prices). The models were very simple, reflecting the lack of, computational facilities, data and a well thought out theoretical framework for the economy.

Throughout the 1960s it is clear that the ESRI was moving towards more formal techniques. However, three factors arrested this:

1. In a paper published in September 1970 by the QEC "The Updating of certain Econometric Models"², we attempted an updating of the simple models used previously. The general conclusion I came to was

that these models were of limited value; they had little economics, poor forecasting and parameter instability.

2. It was clear that we lacked a theoretical framework suitable for explaining the performance of the economy. Thus it was difficult to see how we could generate model based forecasts. During my sojourn in Nigeria, I experimented with techniques developed by ICI³, but was generally unhappy about forecasts of a variable I could only explain by reference to its past history.
3. The oil crisis of 1973/74 rendered impotent existing models. Models of other economies generally lacked a supply side. These models were unable to handle the supply side effect of the rise in oil prices. (Actually as a result of (ii) the official position in Ireland was that there were no demand effects either).

Since I had primary responsibility for the forecasts, I regarded it as essential that the macro-forecasts we produced be based on a view as to how the economy functioned. The QECs from 1974-77 were an attempt to work this out. The forecasts produced in that period were based on this view as it developed. While not based on an estimated model, the greater realism of the view of the world, produced "better" forecasts than the application of previous formal if rudiments techniques. I will refer to the term "better" later.

These were the principal reasons why the initiatives of the 1960s were not carried into the 1970s. Judgmental forecasting was forced upon us by events. I regarded this as a period when more formal techniques were interrupted while we cleared our minds. However, the experience with simple models convinced me that a model (econometric) forecast was not what was needed. The short term forecaster is mostly trying to predict deviations of parameters from estimated values, i.e. the judgmental element remains important. The claim in the paper that both the form and the parameter are imposed by judgmental forecast is incorrect. The most serious forecasting error I made (excluding cases where I was deliberately misled or the single case after I left the ESRI when I was obliged to change forecasts) was model based and this was against my own judgement.

The estimated model is just one input into what makes a forecast. When

model 80 was available, we used it. The constraint on the development of a forecasting model, in the sense I mean it, was resources, not a belief that it would be of little value. Our experience with model 80 was disappointing. It was difficult to set up and although it had too many variables that took too long to input, it was actually more limiting than the procedures adopted in the proportion of QEC forecasts where the range of variables considered were much wider. The underlying model of the QEC was that Ireland was a small open economy. I still find that to be a better description of the economy than model 80. Of course, the issue post 1977 was not that of forecasting but of policy - hence the emphasis on the latter.

Why carry out forecasts?

The reason we carry out forecasts is not to produce a single figure for one variable - whether that is GNP, consumer prices or whatever. The purpose of forecasting is to tell a story about likely future events, to highlight potential future stresses, and, where the economy in general is concerned, to indicate policy options or the failure of existing policy options. The key element is however the story presented. The importance of this is not that your forecasts will be believed, but that you are presenting those who need forecasts with a set of reasoned propositions and it is up to them to make their own judgements. The future is essentially unknowable and the claim that we can foretell it lays us open to the "absurd pretensions" charge. It is in this sense that I use the term "better". Now the point is that model based forecasts tell no story, and pure time series forecasts are even poorer at this. Of course, it is possible to have non-formal forecasting techniques which tell no story - most official forecasts fall into this category, though I did find a behavioural relationship (which I disagreed with) in a 1970's issue of the Review and Outlook. This issue of the objective of forecasts is important. If the forecast matters to anybody, then it is not enough to simply produce figures. The National Institute fell into this trap for a period where their model generated results which were then described in a series of tables. The forecasts were of little value as they stood. The present emphasis is more towards understanding the economy, but not in a readily comprehensible form. There is still a tendency to produce results. At the recent IESG annual conference the NIESR produced results of the effects of fiscal policy and exchange rate changes which were very familiar to anyone coming from here, but failed to see that if one believed

them this was effectively saying the UK was a SOE. This latter insight is more important and once grasped will improve models. In telling this story however the forecaster will make use of every tool available. He uses a univariate time series model for GNP - not to generate it, but to test its realism against past performance. A 7% growth rate produced by judgmental methods alone needs to be confronted with the past. Note that forecasters in Ireland operate within narrow margins - the surest indication of implicit time series bias.

The forecaster will use econometric models where available, either the full blown macro model or the partial models produced by others. In the early 1980s I had a repository of "bits and pieces" most of which forecast poorly, or fell apart on re-estimation with better data. The most robust single equation I found was that by B.M. Walsh, linking emigration, employment and unemployment. It might be interesting to see if it stood the test of time.

The forecaster will not use these models exclusively. The exercise of judgement comes in the values attached to exogenous variables and in the changes he is willing to make to parameters. Ultimately, the forecaster is making assumptions rather than predicting, but it is rare for him to proceed by assumption alone and when he does, the tendency will be to minimise this. Note that official forecasts appear to be assumption based. I generally can find no analysis, only results - one reason why official forecasts are so dull.

It is reassuring to know that using all available techniques is better than reliance on a single approach, though I find it unconvincing to say that the judgmental element can be fitted into the framework outlined.

Comparison of Techniques

1. The Inflation Forecast

The first point that we see from the table is that it all hinges on the 1981 forecast. The 1981 forecast was heavily conditioned by the circumstances of the time. I would be reasonably certain that the published figure was not that of the forecaster. There was also a regime change. Since this year is so important to the conclusion,

either run the series back, say to 1975, or drop this year. The result is overrated. The benefit of formal techniques in this case would only be realised if the time series results were not subject to discussion and change.

2. The Industrial Exports Forecast

The comparison is, in my judgement, not likely to be valid. In February of each year the Bank would not have information on the volume of industrial exports in the previous year because of the unit value problem. In carrying out the test, did the modellers use actual export volumes in the estimation of the equation? If so, this would automatically bias the model results. What you need to do is estimate the equation using the volume figures "available" to the forecasters. In general, people were much better at "forecasting" the value of industrial exports than the volume because the volume was really unknown often until mid year. The claim in this case is also overstated. The comparison between actual and forecast is however damning enough. There is something seriously wrong with these forecasts.

The Issue of Carryover

The authors misunderstand the nature of carryover. Carryover was really a device to get away from annual forecasts. The rationale is this: many variables are available monthly and quarterly while others were available only annually. Furthermore, the forecasts were prepared in an annual context. If annual figures are used for all variables, this conceals information currently available. If the carryover was used as the forecast this is really a statement that on average over the next 12 months there will be no change. This is very like a 4th Q to 4th Q forecast and was intended to give extra information. It would be astonishing if a forecaster took the carryover as the forecast. Perhaps I am being too hard on the authors and this is what is done in the Bank. Carryover has a useful side-effect. There was a time when annual forecasts were prepared independently of available information. Carryover highlighted the implication of this.

The logic of carryover however is that we should move away from annual forecasting. It is of little value to say that the economy will grow by 2%

this year if all the action took place last year and if output is declining during this year. This has been the obvious direction for forecasts for some time.

Concluding Remarks

I would like to look at the issue of formal v informal techniques in a slightly different light. The formal technique is in the nature of an export system. Really what the formal technique is trying to do is model the forecaster. What is frustrating for the formal technique is that the goal posts are constantly shifting. The forecaster attaches different weights at different times to seemingly similar circumstances. The forecaster is constantly looking forward whereas (until recently) the formal technique was attempting to explain the future in terms of the past. The forecaster can replicate, but sees no virtue in it, since he knows that the world has changed. The forecaster wonders why modellers cannot produce useful models, why models are always so simple and why these always fall apart.

Having said this, the paper is extremely worthwhile, forces us to think again and provides a very good survey which will be useful. The authors are to be congratulated and I propose the vote of thanks on the paper.

References

1. Chatfield, C., 1987 (mimeo). *What is the "Best" Method of Forecasting.*
2. Baker, T.J. & Durkan, J, 1970. "The updating of Certain Econometric Models" *Quarterly Economic Commentary*, ESRI.
3. ICI Monographs, Nos. 1, 2, 3, 1964. *Mathematical Trend Curves, Short Term Forecasting, Cumulative Sum Techniques,*.

Patrick Honohan: Let me begin by addressing myself to the part of the paper which the authors evidently regard as most controversial, namely the comparison they made between the success of their own forecasts and those of Central Bank's own judgmental forecasters and those of the ESRI model HERMES. I have a serious worry about the comparison with the judgmental forecasts, additional to that mentioned by Mr. Durkan; specifically, it appears that the authors used the whole of the period up to date to estimate their forecasting models, even though, in producing forecasts for specific years they used only past data in the model. If so, this gives their model an unfair advantage over the judgmental forecasters who, of course, did not have the benefit of hindsight in forming their impressions about how the economy works.

As to the model HERMES, which began as the Central Bank's own model, and evolved into the Central Bank-Department of Finance model before migrating to the ESRI, I can truthfully say that I hold no particular brief for the model as, although I have successively worked in the Central Bank, a Government Department and now the ESRI, I have never worked directly on the model. It is certainly true that the model has rather wide confidence intervals as indicated by the root-mean-square percentage errors reproduced in tonight's paper. For instance, that for GNP implies a 95 per cent confidence interval of over 7 percentage points - not much narrower than the actual range of GNP growth rates in the sample period. It would be very surprising if a simple autoregression could not improve on that, and what is noteworthy to me about the results shown by the authors is not the fact that their autoregressions outperform some of the HERMES simulations, but that HERMES does relatively so well. Of the dozen series selected by the authors, their autoregressions lose seven times: so in fact HERMES wins this particular contest.

More to the point, however, is the fact that any macroeconometric model like HERMES is not set up to make short-term forecasts. To compare it with a time series forecasting framework is like comparing a greyhound with an elephant, each is very good in some respects, but they are good at different things. The authors imply that, because of its modest forecasting performance, HERMES must make an inefficient use of the data available to it, but this is not so. Bear in mind that it is not a single equation that is being simulated in HERMES to fit, say, GNP, but, at the limit, the whole 500-equation model (with some sixty stochastic equations). Errors

in different equations can and do accumulate with the result that the fit for a single variable like GNP is almost bound to be worse than that for a single equation dedicated simply to forecasting as are the authors' autoregressions.

The main purpose of a macroeconometric model is for use in policy simulations, and possibly for long-term predictions. The authors' autoregressions would be of no use in trying to work out the consequences of a specific tax change for example. That being so, I would disagree with the authors' view that the development costs of a macro-model are excessive considering its short-term forecasting performance. The costs are wholly justified by its main purpose - policy simulations - and whatever forecasting is done with such a model comes at almost zero marginal cost.

I would like to turn now to the methodological approach adopted by the authors. The authors have effectively taken us inside the black box of forecasting tools rather than asking, what do we put into this black box, and what sorts of things come out of it. Specifically, they assume a stable data generating process, which is then amenable to modelling with the use of standard time series methods. This would be wholly acceptable for some types of data set, such as daily exchange rates, for example. But I believe that for a small set of macroeconomic aggregates over a period as long as two or three decades, the assumption of a stable data generating process is "incredible". To an arguably greater extent than is the case with the exclusion restrictions of the macro-modeller, the exclusion restrictions implied by the use of a small set of aggregates is likely to cause serious forecasting problems as soon as the time horizon of the forecasts is extended for some quarters. The sample period correlations between the chosen aggregates are unlikely to be stable much into the future.

To illustrate this point I generated an autoregressive forecasting equation for the CPI from quarterly data 1969Q4-1981Q4. Although the estimated equation had a very good fit ($RSQ=0.999$), and satisfied structural stability tests (CUSUM, CUSUMSQ), the equation failed miserably to forecast inflation from 1982Q1. By 1990Q4, the equation had forecast average annual inflation of 27 per cent instead of an actual of 5 per cent.

Another example comes from unemployment statistics. By September 1986, forecast of the twelve-month change in unemployment based on

autoregressive methods would have predicted negative values for each month in the coming year. However, informed observers knew of several administrative actions (tougher screening of school leavers; end of the start-up phase of the large Social Employment job-creation scheme) which would undoubtedly result in an increase in unemployment in the immediate future. It is not clear how easy it would be to build in such information into the simple quasi-automatic forecasting procedures advocated by the authors.

The authors' methodological approach does not take enough account of such deficiencies engendered by the nature of macroeconomic data series. Macroeconomic forecasting is very unreliable, and I fear that the authors have not made sufficient allowance for this.

Finally, I would comment that, although the authors have presented a lot of technical material, readers should be aware that these formal statistical results used do depend on assumptions about the nature of the processes being established. While I would not expect such details to be included in the present paper, it is as well to be aware of the fact that the satisfaction of such assumptions may often need to be tested. As an example, I would refer to the large literature in recent years on the econometric analysis of non-stationary series, a topic that was neglected until about fifteen years ago, but which has led to a sweeping revision in the way econometricians deal with such variables. Econometric methods which were quite inappropriate to the analysis of non-stationary series were in general use, largely because users had not troubled to verify that the assumptions underlying estimators and test statistics were satisfied. Now new tests and estimators have been derived for use with non-stationary series and have resulted in significant new inferences. Many, if not most, macro-variables are non-stationary, and I believe that these methods - including cointegration analysis and error-correction models - are most useful in macro-modelling. In the context of our present discussion of macro-forecasting, I think that they can help researchers identify long-term correlations between macro-variables in a way that should aid long-term forecasting and policy analysis.

John FitzGerald: In developing the HERMES model, as in most model development, there were three main considerations: the purpose for which the model was required, i.e. its relevance; the consistency of the model's results with economic theory; the adequacy with which the model represents the available data.

HERMES has been developed over many years to meet a perceived need for a tool to simulate the effects of policy changes and external shocks on the Irish economy and to help in the task of preparing medium-term forecasts (over a time horizon of five to seven years). For these purposes it is essential that the model can handle the wide range of policy issues and shocks which may be of interest to users. To date HERMES has evolved to meet the changing requirements of its users in the ESRI and the Department of Finance. No single equation or reduced form model can meet this particular need, given the variety of questions and problems to be tackled. However, as the authors indicate, for other purposes, such as short-term forecasting, other considerations apply and other models, along the lines they describe, meet the *relevance* criterion.

The *consistency* criterion can be tested in a number of ways. In the case of HERMES this was done by applying a wide range of shocks to the model and checking that the results were consistent with economic theory. These tests are described in Bradley et al., 1989. For short-term forecasting the consistency requirement is much more limited.

When it comes to *adequacy* there are a wide range of criteria which can be used to judge the model. As the authors indicate, HERMES within sample tracking performance for certain variables was not satisfactory. However, there is a trade-off between the relevance and consistency criteria and the adequacy criterion. The imposition of many restrictions on the model, needed to ensure consistency, greatly disimproves the fit, even within sample. This need to improve the model's consistency has resulted in the imposition of additional restrictions. When the tracking performance of the MODEL-80 model, the precursor of HERMES, is compared with that of HERMES itself, it can be seen that the fit has disimproved, while the consistency has improved. (See FitzGerald & Keegan, 1981 and Bradley, et al., 1989).

It is interesting to note that one of the areas where HERMES outperformed

the authors' simple model was in investment. As it is the pattern of growth in this variable which will determine the productive performance of the economy in the medium to long-term, the improved performance obtained from the HERMES model amply justifies the increase complexity which is imposed on it. It was precisely the need to model the supply side of the economy which has added to the model's complexity, and its usefulness. Without it, as in MODEL-80, we could produce a much better tracking performance in the short-term for variables such as GNP and a much less useful model for policy simulation and medium-term forecasting.

The authors make great play of the need to let the data speak for themselves and to minimise the number of restrictions imposed on a model a priori. I would fully agree with them. However, where I disagree with them is how this can be implemented in practise. When one is interested in the supply side of the economy, involving long cycles in investment and other key variables, very many observations are required to allow the data to *speak for themselves*. However, the number of observations available to a model such as HERMES is only 15 to 20. Without the additional restrictions derivable from economic theory the data, speaking on their own, present a *tower of Babel* to the listener. To ignore economic theory is to waste information.

While the authors are correct in saying that HERMES is not suitable for short-term forecasting they suggest that it is also unsuitable for policy simulation. They adduce no evidence to support this conclusion. The paper does not address this issue at all and, as suggested above, I believe that HERMES has over time evolved specifically to meet such a need.

I also feel that a macro-economic model such as HERMES is an essential tool in preparing medium-term forecasts. It can give guidance on the underlying productive potential of the economy and it can often point to future turning points, if not to their exact timing. Given the limited amount of data available, the atheoretic approach, advocated by the authors, has problems in forecasting variables such as investment and productive potential many years out of sample.

I would generally agree with the authors when they speak of the need to use more sophisticated methods for short-term forecasting. However, the two concrete examples which they give show an unfamiliarity with

the practises of short-term forecasting. J. Durkan and P. Honohan have already adverted to this issue. In the case of their example on forecasting exports, they do not take account of the fact that the unit value series always undergo major revision three to nine months after the beginning of the following year. Thus the Central Bank Forecasters being criticised in the paper did not have access to reasonable or accurate data on the volume of exports in the recent past when they were preparing their forecast early each year. The univariate model might perform much worse if it were applied to the data actually available to the forecaster when preparing his or her forecast.

This criticism is not meant to imply that the methodology suggested by the authors is not appropriate to economic forecasting. I feel that many of their arguments are valid. However, their approach should not be adopted as a theology for forecasters but should be viewed in the balanced light of the authors' own concluding section.

References:

Bradley, J., FitzGerald, J., Hurley, D., O'Sullivan, L. and Storey, A. 1989. *HERMES-IRELAND A Model of the Irish Economy: Structure and Performance*, The Economic and Social Research Institute.

Fitzgerald, J. and Keegan, O. 1981. "The Behavioural Characteristics of the MODEL-80 model of the Irish Economy", *Journal of the Statistical and Social Inquiry Society of Ireland*, Vol. XXIV Part IV, 1981-2.

Denis Conniffe: Before making a few points, I'd like to say how much I enjoyed the paper. A paper of this nature, with both a high technical content and practical relevance to an area of widespread interest, is an infrequent enough occurrence at SSISI meetings. The size of audience is also unusually large, which I'm glad to see. I have three main points to make.

The first relates to combining forecasts: a topic the authors discussed in section 9. Forecasts will rarely be independent, so that the weighting for adding a new forecast to a 'previously best combined estimate' (PBCE) will be:

$$\frac{V - C}{V + V_n - 2C}$$

where V is the variance of the PBCE, V_n the variance of the new forecast and C the covariance of the PBCE with the new forecast. Since forecasters, or different forecasting methods, will be using the same evidence, at least to a large degree, V may quickly fall to C , once a few forecasts have been combined. I've heard it said that, in practice, Irish economic forecasters pay great attention to each other's predictions and adjust their own towards the mean.

My second point is that the topic of cointegration; or error correction models, possibly deserves a little more space than the authors give it when they remark that differencing can lead to the loss of the predictive power of cointegrated relationships, that is, stable relationships holding between non-stationary variables. I do not disagree with the comment and indeed I think one of the funniest episodes in modern econometrics is the progression of analysts such as Granger from believing in the seventies that relationships between non-stationary variables were 'spurious' (for example, Granger and Newbold, 1974), to the discovery in the eighties (for example, Engle and Granger, 1987) that the same relationships were highly significant. However, one could have differenced data and added back error correction variables to the model rather than work with undifferenced data. Which procedure should be preferred depends, I think, on how much faith the forecaster has in economic theory. Does he believe economic theory can specify, or at least suggest, plausible cointegrated relationships, or

would he prefer to let the data do the identifying? I do not want to take up more time with cointegration, because it may not be the most relevant issue in the context of *short-term* forecasting, but it does lead me to my third point.

The large macro-models that were easily outperformed by time series methods, as described by the authors in section 10.4, were built at a time when an international near-consensus on a more-or-less Keynesian macro-economics existed. That macro-economic framework is gone and, as far as I know, no large scale macro-model has yet been based on the 'new' macro-economics built on rational expectations and micro-economic foundations. The later large macro-models mentioned by the authors, which proved were competitive with time series methods, are not, I suspect, models based solidly on theory at all, but just 'fudged' models that permit better fits by allowing the data more freedom to mould the model via lots more unknown parameters embodied in 'dynamics' etc. A recent paper (Mankiw, 1990) draws an analogy between the current situation in macro-economics and that of astronomy for a time after Copernicus. No academically respectable scientist any longer believed in the sun circling the earth, in spite of the fact that Ptolomaic theory could be stretched and squeezed into explaining all observed facts. The problem was that Copernican theory, with the earth and other planets circling the sun, could not match the facts nearly as well. All came right later, when it was realised orbits were elliptical and not circular. So perhaps macro-model forecasting will become clearly superior when a new macro-economic consensus matures.

Reference

Engle, R.F. and Granger, C.W.J., 1987. "Co-integration and Error Correction: Representation, Estimation and Testing", *Econometrica*, Vol. 55, pp. 251-276.

Granger, C.W.J. and Newbold, P., 1974. "Spurious regressions in econometrics", *Journal of Econometrics*, Vol. 2, pp. 111-120.

Mankiw, N.G. 1990. "A Quick Refresher Course in Macroeconomics", *Journal of Economic Literature*, Vol. 28, pp. 1645-1660.

Dr. Antony Unwin: I should like to discuss two issues related to judgmental forecasting: graphics and structuring qualitative information.

Graphical forecasting was more frequent in the past because analysis was onerous. Computers have made analysis easier and better and can now do the same for graphics. Two pieces of software are known to me: Edmundson's PC package which allows the user to forecast trend, seasonality and any remaining component separately, but which has only been developed so far for research purposes and for limited data sets; and, Diamond Fast, an interactive graphics package on the Macintosh for exploratory analysis of multiple time series developed by Graham Wills and myself at Trinity College. Given the emphasis on short-term forecasting in Fagan and Fell's paper, Edmundson's work should be of great interest to them. Certainly, graphical tools should be included as part of the eclectic approach recommended. Graphical methods complement analytic approaches. Graphics are useful for highlighting outliers, for identifying possible change points in series (and hence for deciding which data should be included in an analysis), for studying several series together (where up till now analytic methods have been weak), for assessing trends and stationarity and for inspecting short and irregular series where analytic methods offer no help at all.

Several comments on the paper have emphasised the importance of using knowledge not held in the data. Experts may adjust forecasts because they have additional information, often of a qualitative nature. In these cases, as in pure judgmental forecasting, it is difficult in retrospect to check why that particular adjustment or judgement was made and it is difficult to compare the forecasts of different experts. Current research at Trinity by myself in collaboration with Professor Denis Conniffe of the ESRI is looking at ways of formalising the process through the provision of software tools which aid subjective forecasting.

I congratulate the authors on a stimulating review of an important topic.

Reply: We would like to thank all of the speakers for their contributions. Given the wide range of comments, we would like to address our reply to what we regard as some of the more important issues discussed. We must first thank Joe Durkan for providing us with some very interesting and valuable anecdotes about his experiences with short-term macroeconomic forecasting. His comments are concentrated on judgmental forecasting which he concludes to be superior to more formal techniques particularly because of the latter's impotence in the wake of the oil crisis. The formal models are condemned for being poor at forecasting during this period. In our view this is not a sufficient justification for their abandonment, particularly when the models themselves say not have been very good in the first place (which is intimated in his comment) and little attempt appears to have been made to improve them. Also, there does not appear to be strong evidence that judgmental forecasts would have been any better during this period. In this context, Durkan says that the most serious forecasting error he made was with a formal model. However, a poor forecast for a single observation is hardly an adequate basis for making generalisations about the relative merits of different techniques. The solution should have been to produce better formal models which could then be more validly compared with judgmental methods. Of course, it is not disputed that judgmental methods which make use of a larger information set may out perform a well constructed formal model that uses a smaller information set. Indeed, this point is made forcefully in our paper.

Durkan remains unconvinced that judgmental methods fit into the unified forecasting framework, claiming that the form and parameters of the forecasting model are not imposed by judgmental forecasters. However, it is a fact that the form and the parameter will be imposed by judgmental forecasts *ex post*. This can be illustrated with a simple example of a situation which typically arises in practice. Suppose that a judgmental forecaster who is concerned with this years level of consumer expenditure, C , believes consumption depends only on past disposable income, Y . If he observes that disposable income rose by 5 per cent, last year, and on this basis he produces a forecast of 4 per cent, growth in consumption, then quite clearly he has imposed a form on his forecast according to the following 'model'

$$\Delta C_t = \beta \Delta y_{t-1}$$

He has also imposed a value on the parameter, β of 0.8. Quite clearly this 'model' could be extended to incorporate a number of dependent variables and the parameter restriction (0.8) may not be valid. Use of formal techniques to test for these issues should improve forecast accuracy. We find Durkan's claim that the job of the judgmental forecaster is to update the coefficients of formal models particularly puzzling, given the rest of his paper. Taken together this amounts to saying that although we do not have and do not need formal models we are above to update their parameters - a truly remarkable econometric feat.

Durkan believes that the key element of macroeconomic forecasting is to tell a story. The HERMES Model, for example, can tell a story. It can also highlight areas of potential dangers of deviating from a central forecast by producing different scenarios based on different assumptions about key exogenous variables. Pure time series models are not as good at telling stories but with, for example, multi-variate models it is possible to produce confidence intervals surrounding forecasts or to perform conditional forecasts to answer "what if" questions. Also, any story that takes the forecaster's fancy can be used to explain the forecast. On the theme of telling stories it should be recognised that Business Managers who may base future production decisions or consumers who may base future consumption decisions on expected future economic activity and hence on economic forecasts will be less appreciative of a good story and a poor forecast than a poor story and a good forecast. It has become well known, much to the embarrassment of many practising economists, that economies behave in much more complicated ways than had been thought during the Keynesian revolution. This has left many 'stories' redundant and helps to explain the increasing popularity of a theoretical multi-variate time series models. We would take the view that it is far more preferable to construct accurate forecasting models that may be subject to rigorous statistical testing than judgmental forecasting models which tell stories but do not lend themselves to statistical testing. However, as discussed in the paper, the use of a combination of judgmental methods with more formal methods should lead to more accurate forecasts than if a single approach is relied on.

On the comparison of forecasting techniques, Durkan argues that for the inflation forecasts, the 1981 forecast is important as it may not have been that of the forecaster. However, a similar point could have been made about the 1982 forecast which was also conditioned by the circumstances of the time. In any event, the exclusion of 1981 from this exercise still demonstrates the merits of the VAR as a method of producing quick, efficient and accurate forecasts of inflation. For the industrial exports forecasts, which was not made clear in the paper, for the purposes of fair comparison 'real-time' forecasts were produced, i.e., the time-series forecasts were prepared on the basis of data that would have been available to a forecaster at the time. On the question of carryover, we do not believe that the nature of carryover is misunderstood. The carryover forecast is essentially a random walk forecast and would never be used as an actual forecast unless it was believed that the series to be forecast is well described by random walk behaviour. The carryover forecast may serve as a useful first 'stab' or benchmark in many forecasting situations. For annual forecasts it can also serve as a decompositional tool, at mid-year for example, to illustrate whether a series is expected to increase or decrease in future remaining months of the year in question.

Our final remark on Durkan's comments is that it is incorrect to say that a forecaster using formal techniques will react to similar circumstances in different ways. Indeed, a formal model will always react in the same way to similar circumstances by definition, while a judgmental forecaster who may use more ad hoc methods would be far more likely to react to the same circumstances in different ways. While judgmental forecasting will always have an important role to play in macroeconomic forecasting, the rigour involved in constructing formal forecasting models should undoubtedly improve forecasting accuracy.

Turning to Patrick Honohan's comments, as pointed out above in the comparisons between judgmental and time series models, the forecasts produced by the models were 'real-time'. Contrary to what was suggested, the forecasts produced by the models were not fitted values but rather, they were forecasts that could have been produced with only the information available at the time.

On a more substantive issue, we find it surprising that Honohan is not surprised that a naive autoregressive model could outperform the fore-

casting performance of a large 500 equation econometric model for 5 out of 12 variables. We found this surprising given that the only information available to an autoregressive model is the past behaviour of the variable while a model can take into account sophisticated relationships between dozens of economic variables to produce a forecast, i.e., it is better informed. Efficient use of this larger amount of information should, in principle, lead to better forecasts. In this regard it is easy to show why our findings should be surprising as the following example illustrates. Consider a simple structural model where Y depends on lagged Z , i.e.,

$$Y_t = \beta Z_{t-1} + e_t, \quad e \sim N(0, \sigma_e^2) \quad (1)$$

The forecast produced by this model (βZ_{t-1}) will have error e_t with variance:

$$\text{Var}(\hat{Y} - Y) = \sigma_e^2 \quad (2)$$

Now, we can develop an ARIMA model for Y_t by differencing (1) i.e.,

$$\Delta Y_t = \beta \Delta Z_{t-1} + e_t \quad (3)$$

Now, for simplicity, we assume that Z is well described by a random walk, i.e.,

$$\Delta Z_t = V_t, \quad V \sim N(0, \sigma_V^2) \quad (4)$$

we substitute into (3) to give

$$\Delta Y_t = \beta V_{t-1} + e_t - e_{t-1} \quad (5)$$

Clearly Y_t has an MA(1) model. This allows us to simplify notation in (4) to give

$$\Delta Y_t = U_t + \phi U_{t-1}, \quad |\phi| \leq 1 \quad U \sim N(0, \sigma_u^2) \quad (6)$$

Forecasts using (6) will have an error (U_t). The variance of U_t can be found by equating (5) and (6)

$$\text{Var}(\Delta Y_t) = \beta^2 \sigma_v^2 + 2\sigma_e^2 = (1 + \phi^2) \sigma_u^2$$

Therefore,

$$\sigma_u^2 = \frac{\beta^2 \sigma_v^2}{(1 + \phi^2)} + \frac{2\sigma_e^2}{(1 + \phi^2)}$$

which demonstrates unambiguously that

$$\sigma_u^2 \geq \sigma_e^2$$

since $(1 + \phi^2)$ must be less than 2. Therefore, clearly an ARIMA model cannot explain any more of the variation in a series to be forecast than a correctly specified structural model. This example illustrates the general result (which is actually shown in Section 2 of our paper) that a correctly specified structural model which makes efficient use of the available information should produce better forecasts than 'naive' time series methods based on a narrower information set. If this result does not hold in practice, it suggests that the structural model is seriously misspecified. (This is the rationale for Hendry's 'variance-domination' criteria of model selection). To borrow Honohan's analogy, if your greyhound eats more than your elephant, then there's something amiss with your elephant.

Honohan presents two examples of how poorly autoregressive forecasting equations can perform in certain circumstances. First, they are of little use for long-term forecasting, which is not disputed, but our paper

addressed 'Techniques for Short-Term Economic Forecasting' not long-term forecasting. Second, additional information over and above that in an autoregressive model will improve forecasts if the information is used efficiently. Again this is not disputed. Indeed it is covered in the paper.

Both Patrick Honohan and Denis Conniffe mention the identification of a cointegrating relationship as a useful input to long-term forecasting. This is referred to in the multi-variate section of our paper. While the identification of cointegrating relationships would probably have limited use in short-term forecasting situations, they would have undoubted use in long-term forecasting situations. An interesting issue here is that if a model which is poor at short-term forecasting incorporates cointegrating relationships, its long-term performance could be substantially better. Therefore, it is possible that the HERMES model would outperform autoregressive models over a longer forecasting horizon than was evaluated in our paper.

Conniffe raised the very important issue that economic forecasts are rarely independent. This is undoubtedly true which possibly reflects the high penalties for being an outlier and getting it wrong relative to the benefits of being an outlier and getting it correct. This is essentially a definition of rational risk averse behaviour on the part of economic forecasters. This, of course, implies that the benefits to be gained from combining forecasts will be less than would be the case if they were independent.

John Fitzgerald also raised the issue of whether the data used to construct the industrial exports forecasts were those that would have been available to the forecaster at the time. Again, as already mentioned, the analysis was 'real-time'. To have done otherwise, as he correctly suggests, would have given an unfair advantage to the univariate models.

Fitzgerald also raises the issue of letting the data speak for itself which is seen to be a difficult task when only a small number of annual observations are being used. While unconstrained multi-variate models would leave few degrees of freedom and possible overfitting of the data, new time series techniques such as Bayesian Vector Autoregressions have been developed to get around this problem. BVAR's have the advantage of letting the data speak for themselves while at the same time they leave considerable degrees of freedom and impose little or no a priori theoretical constraints

on the data.

Antony Unwin mentioned the use of graphical methods as an aid to short-term forecasting. We agree that graphical inspection of data is a fundamental component of time series analysis and is an important complement to rigorous statistical examination of data series.

Last, but not least, Brendan Ryan identified an important issue that was not raised in our paper. This is that for many economic variables, different forecasting techniques should be used at different stages of the year as more information becomes available. This is in keeping with the principle that the more information that is available, and the more efficiently it is used, the more accurate forecasts should be.