

Macro-Economic Forecasting and Modelling

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1 Introduction

Confidence in macro-economic forecasting has periodically been punctured by episodes of economic turbulence and concomitant predictive failure. The poor performance in predicting the consumer boom in the late 1980's, and the depth and duration of the recession in the 1990's, can be viewed as merely the latest examples in a catalogue of failures, with noteworthy antecedents including the under-prediction of post-war consumption, and the 1974-5 and 1979-81 recessions.¹ Periods of economic turbulence may be informative in highlighting model inadequacy, but they also bring into question the usefulness of economic forecasting.²

Should we be surprised that such failures have occurred? Econometric theory comprises a body of tools and techniques for analyzing the properties of prospective methods under hypothetical states of nature. In the forecasting context, the methods are forecasting models and procedures, and the states of nature relate to the properties of the variables to be forecast. For an econometric theory of forecasting to be useful in terms of delivering relevant conclusions about empirical forecasting, those states must adequately capture the appropriate aspects of the real world to be forecast. However, the traditional, text-book theory of economic forecasting fails to allow for a number of vital features of the economy. In particular, analyses of forecasting have usually been based on assumptions that implicitly rule out structural change, or regime shifts, in the economy, namely:

- [1] a constant, time-invariant, data generating process (DGP);
- [2] a stationary (non-integrated) DGP;
- [3] a unique forecasting model of the economy, which coincides with the DGP.

Under these assumptions (particularly [1] and [3]), forecasts calculated as the conditional expectation given the model are optimal in the sense that they are unbiased and efficient – any other forecast will

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¹Spanos (1989) considers the contemporary predictive failure of aggregate consumption functions over 1945-51, arguing that model mis-specification played a role. Wallis (1989) discusses the forecasting record of the major UK model-based forecasting teams for the 1974-5 and 1979-81 recessions.

²Such concerns are not new. Morgenstern (1928) seems to be the first comprehensive treatise on the methodology of economic forecasting, and argues against the possibility of economic and business forecasting in principle. See Marget (1929) and Hendry and Morgan (1995).

have a larger forecast error variance. By definition, if the model is the DGP, then the expected future value of the variable, given all information available at the present time, is the conditional expectation with respect to the model. In general, forecasts are not the same as the future realizations of the process because the process is stochastic with a component which is unpredictable from past information (an innovation). This is a characteristic of the DGP, and by [3], also of the model. But forecasts are unbiased (correct on average), since this component has a zero mean (otherwise the model is incorrect, which is excluded by assumption). It is well known that any other predictor has a larger mean-square forecast error than the conditional expectation with respect to the DGP (see Granger and Newbold, 1977).

In a number of recent papers, we have argued that [1]–[3] are an inappropriate view of the world, and hence of the forecasting process (see Clements and Hendry, 1994b, 1995b, and Hendry and Clements, 1994a, 1994b). As a consequence, the predictive failures we have witnessed are less surprising. On the positive side, a theory of economic forecasting can be developed under more realistic assumptions, entailing a taxonomy of sources of forecast errors, and pointing towards ways in which forecasting performance can be improved.

In this review, we focus primarily on the consequences of allowing the DGP to be non-constant, so that its evolution is characterized by structural change and regime shifts. As presaged by our opening paragraph, this introduces an important facet of the actual economy, which may be responsible for some of the more dramatic predictive failures. We shall also discuss the interplay between [1] and [3]. For completeness, we note that in place of [2] it may be better to model the economy as consisting of integrated variables between which there exist a number of cointegrating relationships. The relevance in the forecasting context is that the properties of forecast error variances for integrated series differ from those for stationary variables, so that the behaviour of forecast error variances in this framework will depend on the choice of data transform examined, namely integrated levels, non-integrated differences or cointegrating combinations. The consequences for forecasting of economic data being integrated, and the implications for assessing forecast accuracy, are analyzed in Clements and Hendry (1993, 1995a).

The plan of the paper is as follows. In section 2, we discuss methods of forecasting, and explain why the focus of the paper is on an assessment of, and ways of improving, forecasting based on econometric systems. The role of leading indicators in forecasting has recently undergone a resurgence of interest, and is considered in subsection 2.2 based on Emerson and Hendry (1994). Sections 3 and 4 establish a framework for analyzing forecasts, and derive a taxonomy of sources of forecast error. In section 5, we discuss a research program into how econometrics might help. A number of factors are emphasized: the parameterization; two aspects of parsimony in forecasting; and strategies for robustifying forecasts against structural change. All have in common the aim of mitigating the impact on forecasts of non-constancy. Section 6 considers the implications of our arguments for policy analysis, and for the role of macro-economic forecasting in policy analysis. Section 7 concludes.

2 Economic forecasting

There are undoubtedly many ways of making economic forecasts, but any model-based method appears to require four ingredients, namely that:

- (i) there are regularities on which to base models;
- (ii) such regularities are informative about the future;
- (iii) they are encapsulated in the selected forecasting model; and

(iv) non-regularities are excluded.

In section 4, we consider an example where some regularities persist over the period to be forecast, and consider how parsimony in forecasting may affect the chances of precisely these regularities being encapsulated in the forecasting model.

2.1 Forecasting methods

Clements and Hendry (1994b) enumerate a number of distinct forecasting methods, including:

guessing (which relies on luck);

extrapolation (which relies on persistence);

leading indicators (which rely on the indicators continuing to lead systematically);

surveys (which rely on plans being implemented);

analysis ‘in the context of an implicit, perhaps informal model’ (see Wallis, 1989), (which relies on the adequacy of the postulated framework);

time-series models such as the ARIMA class (see Box and Jenkins, 1970), structured models (see Harvey, 1981), and vector autoregressions (VARs, see Doan, Litterman and Sims, 1984), (which rely on the ‘continuity’ of the time series representation); and

econometric systems (which rely on the model capturing the invariants of the economic structure).

Econometric systems would appear to have a number of advantages. Formal econometric systems of national economies fulfill many useful roles other than just being devices for generating forecasts; for example, such models consolidate existing empirical and theoretical knowledge of how economies function, provide a framework for a progressive research strategy, and help explain their own failures. They are open to adversarial scrutiny, are replicable, and hence offer a scientific basis for research: compare, in particular, guessing and the use of informal models. Perhaps at least as importantly, time-series and econometric methods are based on statistical models, and therefore allow derivations of measures of forecast uncertainty, and associated tests of forecast adequacy. It is not clear how to interpret point forecasts in the absence of any guidance as to their accuracy.³

Nevertheless, in practice the other forecasting methods may have a useful contributory role to play. Although conceptually distinct, the various methods draw on each other to a greater extent than is often acknowledged. Most macro-econometric model-based forecasts make use of several methods, according them complementary rather than adversarial roles. In making adjustments to model equations, and setting the paths for exogenous variables, for example, the forecaster is engaged in many of these methods of forecasting.

2.2 Leading indicators

Partly as a reaction to forecasting failures using econometric systems, research on forecasting using composite leading indicators (CLIs) has gained pace in recent years (see, *inter alia*, the papers in Lahiri and Moore, 1991). Emerson and Hendry (1994) consider the usefulness of CLIs as forecasting devices from a theoretical perspective, both in isolation and in conjunction with VAR models. Their analysis

³See the review article on calculating interval forecasts by Chatfield (1993).

builds on the ‘real-time’ evaluation of CLIs in Diebold and Rudebusch (1991) and Stock and Watson (1992) who find disappointing post-sample performance relative to in-sample performance.

There are a number of problems with using CLIs for forecasting. Frequent alterations in the composition of CLIs suggest that they do not systematically lead for long. Sometimes it is unclear what the CLIs are meant to track: ‘the business cycle’, GDP growth, turning points, etc. Sidestepping this last issue, some insight can be gleaned by likening the construction of CLIs from component series to a standard econometric modelling exercise, but one in which the time-series properties of the data, such as its autoregressive, dynamic character, and the integration-cointegration attributes, are largely ignored: only simple correlations are used, and a formal statistical framework is eschewed, pre-empting the possibility of calculating confidence intervals. In standard modelling parlance, the strong restrictions that are imposed may lead to the models for the CLIs being mis-specified. Moreover, when CLIs are used in macro-economic models, further (usually untested) restrictions are imposed by the index on how the components would enter the model.

3 A framework for economic forecasting

For tractability, the following analysis assumes a linear, closed system, where all non-deterministic variables are forecast within the system.^{4,5} The vector of n variables of interest is denoted by \mathbf{x}_t , and its DGP is the first-order VAR:⁶

$$\mathbf{x}_t = \boldsymbol{\delta} + \boldsymbol{\Gamma}\mathbf{x}_{t-1} + \boldsymbol{\epsilon}_t, \quad (1)$$

where $\boldsymbol{\Gamma}$ is an $n \times n$ matrix of coefficients, and $\boldsymbol{\delta}$ is an n dimensional vector of constant terms. The error $\boldsymbol{\epsilon}_t \sim \text{IN}_n(\mathbf{0}, \boldsymbol{\Sigma})$, with expectation $\text{E}[\boldsymbol{\epsilon}_t] = \mathbf{0}$ and variance matrix $\text{V}[\boldsymbol{\epsilon}_t] = \boldsymbol{\Sigma}$. Although the *form* of the model coincides with (1), its specification could differ in every important regard from that of the DGP, due to imposing invalid restrictions on the parameters. We write the model as:

$$\mathbf{x}_t = \boldsymbol{\delta}_p + \boldsymbol{\Gamma}_p\mathbf{x}_{t-1} + \mathbf{u}_t, \quad (2)$$

where the parameter estimates $(\hat{\boldsymbol{\delta}} : \hat{\boldsymbol{\Gamma}} : \hat{\boldsymbol{\Sigma}})$ are possibly inconsistent, with $\boldsymbol{\delta}_p \neq \boldsymbol{\delta}$ and $\boldsymbol{\Gamma}_p \neq \boldsymbol{\Gamma}$, because of the model mis-specification.

When the system is integrated of order one (denoted $I(1)$), it satisfies $r < n$ cointegration relations such that:

$$\boldsymbol{\Gamma} = \mathbf{I}_n + \boldsymbol{\alpha}\boldsymbol{\beta}', \quad (3)$$

where $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $n \times r$ matrices of rank r (see Johansen, 1988). Then (1) can be reparameterized as a vector equilibrium-correction model (VECM):

$$\Delta\mathbf{x}_t = \boldsymbol{\delta} + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{x}_{t-1} + \boldsymbol{\epsilon}_t. \quad (4)$$

⁴The assumption of linearity is made for analytical convenience, and is clearly unrealistic. Salmon and Wallis (1982), Brown and Mariano (1984), Brown and Mariano (1989), Mariano and Brown (1991) and Granger and Teräsvirta (1993) provide references to the forecasting literature for non-linear models. However, we believe the implications of our analysis are not greatly altered by non-linearity.

⁵The analysis could be extended to open systems, where a subset of variables is treated as strongly exogenous, and predicted ‘off-line’. However, non-modelled variables may not be ‘exogenous’ in any of the senses in Engle, Hendry and Richard (1983).

⁶The first-order VAR can be interpreted as the companion form to a p^{th} order VAR.

Both $\Delta \mathbf{x}_t$ and $\beta' \mathbf{x}_t$ are $I(0)$ but may have non-zero means. Let $\delta = \gamma - \alpha \mu$. Then we can write (4) as:

$$(\Delta \mathbf{x}_t - \gamma) = \alpha (\beta' \mathbf{x}_{t-1} - \mu) + \epsilon_t \quad (5)$$

so that the system grows at the rate $E[\Delta \mathbf{x}_t] = \gamma$ and the long-run solution is:

$$\alpha E[\beta' \mathbf{x}_t] = \alpha \mu \quad (6)$$

so that both $\Delta \mathbf{x}_t$ and $\beta' \mathbf{x}_t$ are expressed as deviations about their means. Further, by suitable non-singular linear transformations, this $I(0)$ system can be represented as a VAR in the variables $\mathbf{w}'_t = [\mathbf{w}'_{at} : \mathbf{w}'_{bt}]' = [\mathbf{x}'_t \beta - \mu' : \Delta \mathbf{x}'_t - \gamma_{bt}]$, yielding:

$$\mathbf{w}_t = \boldsymbol{\tau} + \boldsymbol{\Upsilon} \mathbf{w}_{t-1} + \boldsymbol{\nu}_t \quad (7)$$

where $\boldsymbol{\tau} = \mathbf{0}$. The relevance of this particular parameterization is discussed in sub-section 5.1, so we switch to the \mathbf{w}_t notation below.⁷

4 A taxonomy of forecast errors

Consider forecasts from a system parameterized in the \mathbf{w}_t notation as in (7), when there is a structural change in the forecast period. The forecast commences from initial conditions denoted by $\hat{\mathbf{w}}_T$, which may differ from the ‘true’ value \mathbf{w}_T due to poor provisional statistics (which are subject to revision), as well as the terms noted in the previous footnote. Then, j -step ahead forecasts are given by:

$$\hat{\mathbf{w}}_{T+j} = \hat{\boldsymbol{\tau}} + \hat{\boldsymbol{\Upsilon}} \hat{\mathbf{w}}_{T+j-1} = \sum_{i=0}^{j-1} \hat{\boldsymbol{\Upsilon}}^i \hat{\boldsymbol{\tau}} + \hat{\boldsymbol{\Upsilon}}^j \hat{\mathbf{w}}_T, \quad j = 1, \dots, h. \quad (8)$$

under the (possibly mistaken) assumption of parameter constancy. The forecast errors are $\hat{\boldsymbol{\nu}}_{T+j} = \mathbf{w}_{T+j} - \hat{\mathbf{w}}_{T+j}$.

Suppose the system experiences a step change between the estimation and forecast periods, such that $(\boldsymbol{\tau} : \boldsymbol{\Upsilon})$ changes to $(\boldsymbol{\tau}^* : \boldsymbol{\Upsilon}^*)$ over $j = 1, \dots, h$, and the variance, autocorrelation and distribution of the error change to $\boldsymbol{\nu}_{T+j} \sim D_n(\mathbf{0}, \boldsymbol{\Omega}^*)$. Imposing $E[\boldsymbol{\nu}_{T+j}] = \mathbf{0}$ is without loss of generality when $\boldsymbol{\tau}^* \neq \boldsymbol{\tau}$. Thus, the data actually generated by the process for the next h periods is given by:

$$\begin{aligned} \mathbf{w}_{T+j} &= \boldsymbol{\tau}^* + \boldsymbol{\Upsilon}^* \mathbf{w}_{T+j-1} + \boldsymbol{\nu}_{T+j} \\ &= \sum_{i=0}^{j-1} (\boldsymbol{\Upsilon}^*)^i \boldsymbol{\tau}^* + \sum_{i=0}^{j-1} (\boldsymbol{\Upsilon}^*)^i \boldsymbol{\nu}_{T+j-i} + (\boldsymbol{\Upsilon}^*)^j \mathbf{w}_T. \end{aligned} \quad (9)$$

From (8) and (9), the j -step ahead forecast error is:

$$\hat{\boldsymbol{\nu}}_{T+j} = \sum_{i=0}^{j-1} (\boldsymbol{\Upsilon}^*)^i \boldsymbol{\tau}^* - \sum_{i=0}^{j-1} \hat{\boldsymbol{\Upsilon}}^i \hat{\boldsymbol{\tau}} + (\boldsymbol{\Upsilon}^*)^j \mathbf{w}_T - \hat{\boldsymbol{\Upsilon}}^j \hat{\mathbf{w}}_T + \sum_{i=0}^{j-1} (\boldsymbol{\Upsilon}^*)^i \boldsymbol{\nu}_{T+j-i}. \quad (10)$$

We denote deviations between sample estimates and population parameters by $\delta \boldsymbol{\tau} = \hat{\boldsymbol{\tau}} - \boldsymbol{\tau}_p$ and $\delta \boldsymbol{\Upsilon} = \hat{\boldsymbol{\Upsilon}} - \boldsymbol{\Upsilon}_p$.

⁷In practice, β , μ and γ have to be estimated to implement the transformation to mean-zero $I(0)$ variables, so terms reflecting their estimation uncertainty are being omitted here.

The terms in (10) can be decomposed in many ways; that adopted here explicitly allows for the model being mis-specified, but ignores powers and cross-products in the δ s. To this order of approximation, our taxonomy is:

$$\begin{aligned}
\hat{\nu}_{T+j} \simeq & \sum_{i=1}^{j-1} \left((\Upsilon^*)^i - \Upsilon^i \right) \tau_p + \left((\Upsilon^*)^j - \Upsilon^j \right) \mathbf{w}_T & (i) \text{ slope change} \\
& + \sum_{i=0}^{j-1} (\Upsilon^*)^i (\tau^* - \tau) & (ii) \text{ intercept change} \\
& + \sum_{i=1}^{j-1} (\Upsilon^i - \Upsilon_p^i) \tau_p + \left(\Upsilon^j - \Upsilon_p^j \right) \mathbf{w}_T & (iii a) \text{ slope mis-specification} \\
& + \sum_{i=0}^{j-1} (\Upsilon^*)^i (\tau - \tau_p) & (iii b) \text{ intercept mis-specification} \\
& - \sum_{i=1}^{j-1} i \Upsilon_p^{i-1} \delta_{\Upsilon} \tau_p + j \Upsilon_p^{j-1} \delta_{\Upsilon} \mathbf{w}_T & (iv a) \text{ slope estimation} \\
& - \sum_{i=0}^{j-1} \Upsilon_p^i \delta_{\tau} & (iv b) \text{ intercept estimation} \\
& + \hat{\Upsilon}^j (\mathbf{w}_T - \hat{\mathbf{w}}_T) & (v) \text{ initial condition} \\
& + \sum_{i=0}^{j-1} (\Upsilon^*)^i \nu_{T+j-i} & (vi) \text{ error accumulation.}
\end{aligned} \tag{11}$$

At first sight, this expression is both somewhat daunting and not suggestive of positive implications. However, our decomposition supports a meaningful interpretation of the forecast error in (11). For example, an aggregated six-fold partition of sources of forecast error can be expressed as:

- (i) regression-parameter change: $\Upsilon^* \neq \Upsilon$;
- (ii) intercept change: $\tau^* \neq \tau$;
- (iii) model mis-specification: $\Upsilon_p \neq \Upsilon$, $\tau_p \neq \tau$;
- (iv) estimation uncertainty: $V[\hat{\Upsilon} - \Upsilon_p] \neq \mathbf{0}$, $V[\hat{\tau} - \tau_p] \neq \mathbf{0}$;
- (v) initial condition mis-measurement: $(\mathbf{w}_T - \hat{\mathbf{w}}_T) \neq \mathbf{0}$;
- (vi) error accumulation: $V[\sum_{i=0}^{j-1} (\Upsilon^*)^i \nu_{T+j-i}] \neq \mathbf{0}$.

Equation (11) simplifies in various states of nature. For example, (iii a)–(iii b) vanish if the model is ‘correctly specified’, but otherwise the formula remains intact on replacing (Υ_p, τ_p) by (Υ, τ) . Similarly, if parameters remain constant, (i)–(ii) disappear, and the formula applies with $(\Upsilon^*, \tau^*) = (\Upsilon_p, \tau_p)$.

The main setting we want to examine uses the approximations that $E[\hat{\Upsilon}^j] \simeq \Upsilon_p^j$ and $E[\hat{\tau}] \simeq \tau_p$; conditions on \mathbf{w}_T assuming the actual initial condition is unbiased ($E[\hat{\mathbf{w}}_T | \mathbf{w}_T] = \mathbf{w}_T$); and takes the model to be correctly specified in-sample ($\tau_p = \tau$ and $\Upsilon_p = \Upsilon$). Imposing this state, we obtain:

$$E[\hat{\nu}_{T+j} | \mathbf{w}_T] = \left\{ \sum_{i=1}^{j-1} \left((\Upsilon^*)^i - \Upsilon^i \right) \tau^* + \left((\Upsilon^*)^j - \Upsilon^j \right) \mathbf{w}_T \right\} + \sum_{i=0}^{j-1} (\Upsilon^*)^i (\tau^* - \tau). \tag{12}$$

Consequently, forecasts are biased when the DGP is non-constant, unless considerable cancellation occurs, contrasting with the outcome when the forecast is the conditional expectation. In particular, when

only the intercept τ changes, the expected forecast error is:

$$\mathbb{E} [\hat{\nu}_{T+j} \mid \mathbf{w}_T] \simeq \sum_{i=0}^{j-1} \Upsilon^i (\tau^* - \tau). \quad (13)$$

This more tractable expression highlights a major effect due to parameter change, namely a persistent, and usually increasing, bias (when $(\tau^* - \tau) > 0$ say). Conditional forecast error variances can be derived from (11), but we will not consider the algebraic details here.

5 Reducing forecasting errors

All of the sources of error in (11) can be reduced to some extent by appropriate techniques. Here we review three possibilities, namely parameterization, parsimony, and intercept corrections: Clements and Hendry (1994b, 1995b) provide more comprehensive treatments.

5.1 Parameterization

Three of the error terms identified in (11) are scaled by \mathbf{w}_T , the realized value of the process on which forecasts are conditioned. Therefore, these errors will be small for parameterizations of the model for which \mathbf{w}_T is close to zero. This is analogous to the result for regression-model forecasts that the minimum forecast error variance occurs for predictions at the mean. Model formulations that entail stochastic initial conditions close to zero may have advantages here: two examples are VARs in first (or even second) differences (with the acronym DVARs), and VECMs as in the parameterization in (7), where $\mathbb{E}[\mathbf{w}_{at}] = \mathbf{0}$ and $\mathbb{E}[\mathbf{w}_{bt}] = \mathbf{0}$.

5.2 Parsimony

The desire for parsimonious specifications has several motivations. First, economy-wide econometric models involving large numbers of parameters inevitably suffer from the ‘curse of dimensionality’. One consequence is that the need to select the specification from the sample could lead to ‘over-fitting’. Equally, by including too many variables, accidental or irrelevant data features may become embodied in the model and reduce forecast performance when their behaviour changes later. Thus, the ‘curse of dimensionality’ may contribute to poor forecast performance by increasing the chances of the model including features that are non-constant over the future, and we discuss this aspect below. Secondly, parameter estimates may be poorly determined in-sample due to the sheer number of variables, perhaps exacerbated by the high degree of collinearity manifest in the levels of integrated data. It is convenient to consider this issue next.

5.2.1 Multicollinearity

It may be thought that a ‘shaky’ forecast performance must result when parameter estimates are poorly determined because of collinearity. In fact, this is a non sequitur. Linear models are invariant under linear (and hence orthogonal) transforms, so their forecasts are not affected by a constant degree of ‘collinearity’. Multicollinearity cannot of itself cause forecast failure, where the latter is defined in terms of how well the model forecasts relative to its fit in-sample. Large models may forecast better or worse

than simple models, but under unchanged structure will forecast in accordance with their in-sample error variances.⁸

When models are not congruent specifications of the economic mechanism, changes in one part of a system can induce apparent parameter change in other equations (see Hendry, 1979). Simulation evidence in Favero and Hendry (1992) suggests that this can produce important predictive failures. Thus, predictive failure may result from model mis-specification coupled with changes in relevant variables, and does not necessarily imply that a structural break has occurred in the underlying behavioural equations. Nor does the absence of predictive failure imply that models are not mis-specified: under unchanged structure, incorrect models will perform as expected.

5.2.2 Excluding non-constant features

The general issues of ‘over-fitting’ and capturing accidental data features in empirical models are discussed in Hendry (1994), as is the related problem of the Lucas (1976) critique noted below. Here we consider the consequences of a shift in the equilibrium mean.

Suppose the DGP is (5), and there are two forecasting models. The first is the VECM. Ignoring the need to estimate the parameters $(\alpha, \beta, \mu, \gamma)$ of the model, the VECM here coincides with the DGP.⁹ The second model is a VAR in the differences of the variables. In keeping with the Box and Jenkins (1970) time-series modelling methodology, the data are reduced to $I(0)$ by differencing prior to modelling. The first-order DVAR is then:

$$\Delta \mathbf{x}_t = \gamma + \boldsymbol{\eta}_t \quad (14)$$

This model coincides with (5) when $\alpha = \mathbf{0}$ (in which case $\boldsymbol{\eta}_t = \boldsymbol{\epsilon}_t$).

Clements and Hendry (1994a) show that forecasts from the DVAR will be unconditionally unbiased under parameter constancy, as will those from the VECM.¹⁰ Surprisingly, forecasts from the DVAR remain unconditionally unbiased when the parameter μ in (5) changes (to μ^* , say) prior to the period when the forecast is made, provided $\alpha'_{\perp} \mu^* = \mathbf{0}$ (where $\alpha'_{\perp} \alpha = \mathbf{0}$). That is, forecasts from the DVAR remain unbiased when the long-run equilibrium mean has changed prior to forecasting, and the underlying growth rate of the system is unchanged. The VECM, however, will produce biased forecasts: the equilibrium-correction terms tend to pull the forecasts towards the now inappropriate ‘equilibrium’.¹¹ This does not mean that DVARs should be used in preference to VECMs. Clements and Hendry (1995a) show that DVARs will have larger forecast error variances, although this is dependent on the linear transformation of the data being forecast. However, for a sufficiently large structural change, the bias component will dominate the forecast error-variance component, so the DVAR will have the smaller mean-square forecast error (MSFE) in the face of a shift in the equilibrium mean.¹²

⁸Classical tests for predictive failure, such as Chow (1960), compare the forecast error variance to the estimation period error variance, under the null that the model parameters and error variance are unchanged.

⁹Clements and Hendry (1995a) assess the impact of parameter estimation uncertainty on forecasting in cointegrated systems.

¹⁰This result holds more generally, such as when the DGP contains a linear trend which lies in the column space of α .

¹¹Following Davidson, Hendry, Srba and Yeo (1978), these terms have been known as ‘error -corrections’. The recognition that they may play the opposite role when the equilibrium changes accounts for the change in terminology to ‘equilibrium-correction’. Fortunately the acronym is unchanged!

¹²Recall that:

$$\text{MSFE} = (\text{bias})^2 + \text{variance}.$$

We have discussed the merits of squared-error loss in Clements and Hendry (1993).

Many macro-econometric systems are in VECM form. The historical coincidence of serious forecast errors and apparent regime shifts may be due in part to the adverse effects of equilibrium-correction mechanisms in such states of nature (for example, the OPEC oil-price hike and the 1974-5 recession; OPEC II, the Thatcher government's policies, and the 1979-81 recession; financial deregulation and the consumer boom in the late 1980s; etc.).

The next sub-section considers the advantages of 'intercept correcting' forecasts from VECMs when the DGP is non-constant.

5.3 Robustifying forecasts

Intercept corrections refer to the practice of specifying non-zero values for a model's error terms over the forecast period. They are perhaps the prime way in which a forecaster's judgement shapes the model-generated forecast, at least if we abstract from setting values of the non-modelled variables.

The importance of the role of judgement in model-based forecasting has long been recognized. For example, Marris (1954) warned against the 'mechanistic' adherence to models in the generation of forecasts when the economic system changes:

'the danger of its operators becoming wedded to belief in the stability of relationships (parameters) which are not in fact stable.' (Marris, 1954, p.772).

The recognition of the scope for, and importance of, adjusting purely model-based forecasts has a long lineage (see, *inter alia*, Theil, 1961, p.57; Klein, 1971; Klein, Howrey and MacCarthy, 1974; the sequence of reviews by the UK ESRC Macroeconomic Modelling Bureau in Wallis, Andrews, Bell, Fisher and Whitley, 1984, 1985, Wallis, Andrews, Fisher, Longbottom and Whitley, 1986, Wallis, Fisher, Longbottom, Turner and Whitley, 1987; Turner, 1990; and Wallis and Whitley, 1991). Forecasters' adjustments appear to improve forecast accuracy empirically, as documented by Wallis *et al.* (1986), Table 4.8, Wallis *et al.* (1987), Figs. 4.3 and 4.4, and Wallis and Whitley (1991). Clements (1995) assesses the impact of such adjustments on the rationality of forecasts from large-scale macroeconomic models. One possibility is that adjustments are used to bring forecasts more in line with the consensus view, or to prevent large changes in forecasts in response to news. Thus, as a result of the forecaster's interventions, revisions to fixed-event forecasts (forecasts of the same 'event', for example, the rate of inflation at the end of the year) may be 'too smooth' to accurately reflect the flow of new information. The notion of smoothness is based on Nordhaus (1987), and the testing procedures are discussed and refined in Clements (1994).

Whatever the forecaster's own motivation for making the adjustments, whether in response to perceived model inadequacy over the past, or to incorporate new information, it is possible to establish a general framework for the analysis of adjustments to model-based forecasts. This is the aim of Hendry and Clements (1994b), who analyze intercept corrections in terms of the relationship between the DGP and the estimated econometric model, the mechanics of the forecasting technique, data accuracy, and any information about future events held at the beginning of the forecast period. Clements and Hendry (1994a) show that intercept corrections can largely eliminate the bias of VECM forecasts when a break occurs prior to forecasting, although at the cost of (a possibly considerable) increase in forecast error variance. Testing for the importance of the break prior to using intercept corrections merits consideration.

6 Macro-economic forecasting and policy analysis

In the context of forecasting, parsimony may help in capturing only those regularities that persist while excluding those that do not, yet render models barren in terms of policy advice. For example, excluding the causal channels by which policy variables affect the behavioural variables in a macro-econometric model entails that the policy changes cannot be implemented in that model. In the example in sub-section 5.2, forecasting considerations suggest omitting the long-run information, although it may be crucial to the outcome of the policy change. Manifestly, do not select models for policy by their *ex ante* forecasting ability, irrespective of their use of such explicit devices as intercept corrections.

One possible resolution to this conundrum is to use separate models for forecasting and policy. The *ex ante* desirability of any policy depend on the its effects and on the baseline forecasts prior to its implementation. Given the governments' ideological concerns, whether Lawson's income tax cuts in the late 1980s were advisable depended on whether the economy was overheating or required boosting. Suppose the effects of his policy were estimated (as percentage changes on the base) by simulation of the policy model. Their timing could then be assessed given the economic outlook indicated by the forecasting model. Ignoring the problems of baseline dependence in the policy model is hardly satisfactory. A better solution might be to attempt to robustify forecasts from the policy model, as in sub-section 5.3.

Stringent conditions must be satisfied to support econometric-model based policy analysis, including the proposed policy measure being identified in the model (see Hendry and Mizon, 1992). The super exogeneity of the policy instruments for the parameters of the forecasting system is also required, and not just their weak exogeneity: this issue is analyzed in Engle and Hendry (1993) and Favero and Hendry (1992). A failure of super exogeneity may arise if agents alter the way they form expectations (the Lucas, 1976, 'critique'), or if regime shifts occur out of sample. The Lucas critique does not of itself condemn the forecasting enterprise to failure: in any specific instance, the critique is testable, and seems to lack force (see Ericsson and Irons, 1994, on its empirical (ir)relevance). In other cases, potential effects from regime shifts can be determined *ex ante*: see Hendry and Ericsson (1991) for a model of financial innovation which could have been partially implemented prior to the change having its effect. In general, if anticipated future changes in policy are reasonably correlated with past episodes, then previous *ex post* errors may suggest a pattern of adjustments to the model-based forecasts. Nevertheless, if it is desired to use a model across policy regimes, either the relevant parameters must be invariant, or the effect of the policy change must be incorporated.

The inherent uncertainty in the DGP place a limit on our ability to forecast even with parameter constancy.¹³ It may be that only a few periods ahead are necessary for economic stabilization policy (e.g. 4–8 quarters), and that forecasts are informative over this horizon, but policy debate would surely be better served if forecasters were to move away from reporting only point forecasts, to provide a reasonable idea of the uncertainties inherent in their predictions. This would appear to be a necessary precursor to a more informed judgement on what models can and cannot contribute to debates over government economic policy.

¹³Forecasts become uninformative when the forecast error variance (on which forecast confidence intervals are based) is within a small fraction of the unconditional variance of the process (when it exists). See Hendry and Clements (1994a).

7 Conclusions

Our research findings to date are mainly for simple models, but strongly suggest that econometric analysis can help improve macro-economic forecasting procedures. We have discussed how good practice can partially mitigate errors in forecasting that are generated by the evolving nature of the economy, interacting with the impossibility of building models that are exact facsimiles of it.

In such a world, intercept corrections can improve forecast accuracy against certain classes of structural breaks, even though the model proprietor does not know the timing, the magnitude, the size, nor the form of the break. In effect, ‘add-factors’ can robustify forecasts against some forms of structural change. Many other aspects await investigation in the task of developing an adequate theory of economic forecasting.

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$$\begin{aligned}
\hat{\nu}_{T+j} \simeq & \left((\mathbf{I}_n - \Upsilon^*)^{-1} \left(\mathbf{I}_n - (\Upsilon^*)^j \right) - (\mathbf{I}_n - \Upsilon)^{-1} \left(\mathbf{I}_n - \Upsilon^j \right) \right) \tau_p + \left((\Upsilon^*)^j - \Upsilon^j \right) \mathbf{w}_T \\
& + (\mathbf{I}_n - \Upsilon^*)^{-1} \left(\mathbf{I}_n - (\Upsilon^*)^j \right) (\tau^* - \tau) \\
& + \left((\mathbf{I}_n - \Upsilon)^{-1} \left(\mathbf{I}_n - \Upsilon^j \right) - (\mathbf{I}_n - \Upsilon_p)^{-1} \left(\mathbf{I}_n - \Upsilon_p^j \right) \right) \tau_p + \left(\Upsilon^j - \Upsilon_p^j \right) \mathbf{w}_T \\
& + (\mathbf{I}_n - \Upsilon^*)^{-1} \left(\mathbf{I}_n - (\Upsilon^*)^j \right) (\tau - \tau_p) \\
& - \sum_{i=1}^{j-1} i \Upsilon_p^{i-1} \delta \Upsilon \tau_p + j \Upsilon_p^{j-1} \delta \Upsilon \mathbf{w}_T \\
& - (\mathbf{I}_n - \Upsilon_p)^{-1} \left(\mathbf{I}_n - \Upsilon_p^j \right) \delta \tau \\
& + \hat{\Upsilon}^j (\mathbf{w}_T - \hat{\mathbf{w}}_T) \\
& + (\mathbf{I}_n - \Upsilon^*)^{-1} \left(\mathbf{I}_n - (\Upsilon^*)^j \right) \nu_{T+j-i}
\end{aligned} \tag{15}$$

$$\mathbb{E} [\mathbf{w}_T] = \boldsymbol{\mu} = \tau_0 + \Upsilon_0 \boldsymbol{\mu} = (\mathbf{I}_n - \Upsilon_0)^{-1} \tau_0$$

where τ_0, Υ_0 may equal τ, Υ or τ^*, Υ^* .

$$\mathbb{E} \left[\mathbf{w}_T - (\mathbf{I}_n - \Upsilon_0)^{-1} \tau_0 \right] = \mathbf{0}.$$

and:

$$\sum_{i=0}^{j-1} \Upsilon^i = \mathbf{I}_n + \Upsilon + \Upsilon^2 + \dots + \Upsilon^{j-1} = (\mathbf{I}_n - \Upsilon)^{-1} (\mathbf{I}_n - \Upsilon^j)$$

so could add/subtract the mean of \mathbf{w}_T .