

The Econometric Analysis of Economic Policy

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Abstract

The application of econometric analysis to the process of economic policy formulation is considered. A framework is provided by the theory of reduction, specifically reductions where key information losses would invalidate policy. Consequently, model evaluation; the role of econometric models; forecasting; exogeneity; causality; constancy and invariance; unobservables; seasonality; and data integrability are considered, together with specific policy issues where econometrics can clarify the problems.

1 Introduction

Although much has been written on the economics, politics, and technology of the economic policy process, and on the specification, estimation, and evaluation of the econometric systems often used for guiding policy, relatively little research has been undertaken on the econometric analysis of economic policy formulation using empirically-estimated macroeconomic models. One aim of this special issue, based on a conference financed by the UK Economic and Social Research Council, was to stimulate interest in that last topic, namely the formal analysis of econometric issues germane to basing economic policy on econometric models. The other aims were to help establish what was already known, and what major issues still needed to be addressed.

Our framework is provided by the theory of reduction (see e.g., Hendry and Richard, 1983, and Hendry, 1995a) specifically, those reductions where information losses could invalidate policy conclusions based on models. Reductions of information are essential to map from the billions of actions by agents in an economy to the econometric model of some subset of measurable variables. The success of an economic policy in achieving its ostensible objectives usually depends on the accurate and precise determination of a vector of parameters of interest. These may link policy instruments to intermediate or final targets, or may be the parameters of the system used to forecast the future values of variables integral to policy formulation. We have not managed to delineate necessary conditions for the validity of policy conclusions from econometric systems, and do not consider it reasonable to proceed on the sufficient condition that the model coincides with the economy. Instead, we focus on the requirements that the model is not seriously mis-specified, and can support the economic policy scenarios being considered, which in the absence of omniscience, or unfailing luck, will be needed to ensure reliable policy analysis.

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The former requires the evaluation of a model's congruence and encompassing ability; the latter requires the coherence of the model with the class of economic policies. Either or both could fail from invalid reductions. Those due to excessive aggregation, invalid marginalization, or a failure of sequential factorization affect the validity of the model (as against the validity of its use), and are open to direct empirical testing against specific alternatives (aggregation bias, omitted variables, and residual autocorrelation respectively), so will not be investigated in any detail here.

Instead, the volume focuses on reductions that affect the use of a model in the policy process, namely the mapping from integrated to $I(0)$ variables; conditional factorizations; constancy and invariance; and the treatment of unobservable variables. These respectively raise issues of cointegration and differencing; exogeneity (weak, strong, and super); changes in parameters, possibly due to the policy itself. The role of constructs such as 'excess demand', 'core inflation', etc., which are frequently used in policy analysis is also considered. Such constructs may in turn require adjustments for special factors like seasonality.

Since forecasting plays a crucial role in economic policy, we also consider its role for policy analysis when the model differs from the economic mechanism, and the latter changes over time, perhaps due to the very policy under analysis. In such a setting, one should not select policy models by forecast accuracy, even when that is assessed from the unadulterated *ex ante* forecasts: techniques exist for robustifying forecasts against unknown structural breaks (as a form of insurance) which need not reflect the usefulness of the model as a description of economic behaviour. A simple taxonomy of possible outcomes may clarify this surprising implication: (i) forecast accurate, policy coincides; (ii) forecast accurate (perhaps due to intercept corrections or differencing), but policy fails; (iii) forecast inaccurate (due to an unrelated structural break), but policy works; (iv) forecast inaccurate (as model is wrong) so policy fails. Cases (ii) and (iii) reveal the dangers of selecting or rejecting the model for policy on the basis of forecasts. Worse still, causal information need not enhance forecast accuracy, nor do there exist tests in-sample that can determine the constancy of models out of sample: see e.g., Hendry (1996). The problems in evaluating forecast accuracy due to the lack of invariance of mean square forecast error measures (MSFE) across isomorphic model representations are analysed in Clements and Hendry (1993) and will not be discussed here.

Consequently, while the main subjects discussed below span the range of formal econometric analyses (namely, exogeneity, causality, constancy, invariance, unobservables, non-stationarity, forecasting, and model evaluation), our concern is their impact on the valid use of models. Various requirements for the effectiveness of economic policy are discussed in section 2. For policy to be usefully based on an econometric system, its links must correspond to causality in the actual economy. Earlier research on the evaluation of large-scale macro models is noted in §3: for more general analyses, see *inter alia*, Britton (1989) (especially the chapter by Turner, Wallis and Whitley, 1989), and Bryant, Hooper and Mann (1993).

We next discuss unobservables in §4, since policy makes much use of concepts like 'excess demand', 'underlying inflation', 'volatility' etc. Then, to clarify the requisite conditions for models to deliver useful policy implications, we consider both exogeneity and causality. Since the role of weak exogeneity in economic policy analysis is analyzed in a separate paper (see Hendry and Mizon, 1992), it is only briefly noted here in §5. Then strong exogeneity is discussed in §6 in terms of the feedbacks between variables, followed by an evaluation of its role in conditional forecasting in §7. This section, therefore, also concerns one concept of causality (see Granger, 1969). The analysis then turns to a more formal consideration of multi-step forecasting in §7.1 in a multivariate system with unit roots, and compares computing the h -step ahead forecasts from powering up 1-step estimates as against direct minimization of an h -step criterion.

Issues of parameter constancy are the topic of §8, and the related concepts of super exogeneity and invariance lead to an alternative notion of causality for contemporaneous effects satisfying invariance under interventions in §8.3 (see Simon, 1953). A link is provided by the idea of co-breaking proposed in §8.4 to enable forecasting across structural breaks. This concept is applied to re-evaluate the Lucas (1976) critique in §9. The application of policy to macroeconomic models is the subject of §10. The paper concludes in §11.

2 Requirements for economic policy

Implementing policy to achieve target outcomes often requires shifting the means of the marginal distributions (and possibly those of the joint distributions) of target economic variables. Consider the sequential joint density $D_x(\cdot)$ at time t of the m variables \mathbf{x}_t conditional on $\mathbf{X}_{t-1} = (\mathbf{X}_0, \mathbf{x}_1, \dots, \mathbf{x}_{t-1})$ for $t = 1, \dots, T$, when \mathbf{X}_0 denotes the initial conditions:

$$D_x(\mathbf{y}_t, \mathbf{z}_t \mid \mathbf{X}_{t-1}, \boldsymbol{\theta}) \text{ where } \boldsymbol{\theta} = (\theta_1, \dots, \theta_n)' \in \boldsymbol{\Theta} \subseteq \mathbb{R}^n. \quad (1)$$

Partition $\mathbf{x}_t = (\mathbf{y}_t : \mathbf{z}_t)$ where \mathbf{y}_t and \mathbf{z}_t are $m_1 \times 1$ and $m_2 \times 1$ respectively. The former are endogenous and include all target variables; the latter include the policy instruments and will be the conditioning variables in the econometric analysis. Consequently, these variables must be dependent causally, not just conditionally. If there is no genuine causality from \mathbf{z}_t to \mathbf{y}_t , then shifts in \mathbf{z}_t will not affect current or future \mathbf{y}_t . The former will occur if there is contemporaneous causality as discussed in §8.3; the latter if there is Granger causality in the actual economy as discussed in §6.

Let:

$$\Psi_t = \frac{\partial \mathbf{y}_t}{\partial \mathbf{z}_t'},$$

denote the actual reaction of \mathbf{y}_t to changes in \mathbf{z}_t when the latter can be altered by the policy agency. Let the conditional model be:

$$E[\mathbf{y}_t \mid \mathbf{z}_t, \mathbf{X}_{t-1}] = \Pi_t \mathbf{z}_t + \sum_{i=1}^s \mathbf{A}_i \mathbf{x}_{t-i}.$$

Then:

$$\Pi_t = \Psi_t$$

is required for the policy implications of the model to match the outcome (similarly for lagged and long-run reactions). Such a requirement could fail for many reasons, including most forms of model mis-specification. Those considered below include invalid conditioning (so Π_t reflects features of the joint distribution other than just the causal dependence of \mathbf{y}_t on \mathbf{z}_t) in §5; non-constancy of either Π_t or Ψ_t when it is assumed constant in §8; and a lack of invariance of Π_t to changes in \mathbf{z}_t in §9.

Additionally, policy is often determined by forecasts of the future values of target variables, so §7 considers the conditions needed to make forecasts conditional on policy variables; and §8.4 discusses the possibility of forecasting across structural breaks.

3 Model evaluation techniques

One difficulty in judging the validity of policy implications from large-scale macro-econometric models is that because of their size and non-linearity, such systems have rarely been evaluated using formal econometric tests. Instead, *ad hoc* evaluation procedures have usually been tried, including:

- (a) within-sample dynamic simulation tracking performance;
- (b) *ex ante* forecasting accuracy;
- (c) economic plausibility of the model coefficients and multipliers;
- (d) mean square forecast error criteria;
- (e) small-block, or single equation, evaluation procedures.

All of these evaluation techniques seem sensible at first sight, but all are deficient, and some are invalid as we now show.

(a) Dynamic simulation has been shown to be an invalid model selection procedure in Hendry and Richard (1982), Chong and Hendry (1986) and Pagan (1989) *inter alia*: also see the discussion by Wallis (1993) of the attempted rebuttal by Mariano and Brown (1991). The ‘goodness’ of a simulation depends on treating variables as strongly exogenous, not on whether those variables really are in fact exogenous. Choosing models with ‘good’ simulation performance over-emphasizes external dynamics (attributing it to non-modelled factors) relative to internal dynamics (lagged values of modelled variables). Strong exogeneity is testable, so the validity of dynamic simulations can be evaluated, but this is insufficient to validate the model choice. §6 provides a formal analysis.

(b) *Ex ante* forecasts from large models reflect judgments and inputs of their proprietors, so that forecast track records do not reveal much about model quality. Even when pure forecast information is available, measures of forecast uncertainty are needed to test model validity, and these are rarely computed. As noted above, forecasts can be inaccurate for reasons unconnected with the invalidity of the model for policy, such as regime shifts; and conversely, methods that are robust to such shifts may outperform in terms of forecast accuracy, but need not have valid policy implications (see Hendry and Mizon, 1996). When forecasts reveal looming problems that induce policy changes to offset those problems, *ex post* evaluation using the actual values of policy variables is more reliable.

(c) Economic plausibility is insufficient to justify model choice, given the conflicting views reflected in extant UK macroeconomic models, and the significant changes which have occurred in theories and model specifications over time (see e.g., Wallis *et al.*, 1985, Wallis, Andrews, Fisher, Longbottom and Whitley, 1986, and Wallis, Fisher, Longbottom, Turner and Whitley, 1987).

(d) MSFE comparisons across models (within or post sample) are inadequate, since for a model to have the minimum MSFE in a class, it is neither necessary nor sufficient that the model have: valid exogeneity; constant parameters; or provide accurate forecasts. Encompassing ensures 1-step MSFE dominance (but not conversely), but this too is minimal for large systems used in multi-step forecasting. MSFEs of systems, or any multi-step forecasts, are not invariant to linear transforms of models that leave the models invariant: see Clements and Hendry (1993) and the ensuing discussion.

(e) Few models have been tested by system methods for mis-specifications, although there has been a rapid increase in diagnostic testing of individual equations or small blocks of equations (see, for example, the Warwick Macromodelling Bureau reports cited above). Tests for a structural system encompassing the associated vector autoregression are discussed in Hendry and Mizon (1993).

Some of these difficulties may stem from an incomplete analysis of the necessary econometric constructs, and the remainder of our overview therefore focuses on doing so. We begin by considering the problems associated with unobservable variables.

4 Unobservables

Two papers in this Special Issue deal with unobservables. The first, by Jean-François Richard and Wei Zhang considers stochastic and dynamic extensions of a model for UK house prices proposed by Hendry

(1984). Their analysis uses accelerated Monte Carlo procedures (based on Richard and Zhang, 1996b, 1996a) to compute likelihood functions for estimation and inference in dynamic models with latent variables.

From a purely numerical viewpoint, the paper demonstrates the important gains obtainable from using this new approach to numerical integration based on efficient samples. The authors are able to allow for processes which are not conditionally deterministic (compare ARCH, Engle, 1982) and the availability of efficient Monte Carlo importance sampling integration techniques enable them to accommodate routinely dynamic latent variable model specifications and to test alternative hypotheses relative to such variables.

The example of excess demand in the UK housing market, an important practical policy problem, demonstrates the advantages of allowing for a stochastic process, switching the errors away from the price adjustment equation and allowing for stochastic (instead of deterministic) excess demand. Richard and Zhang find that prices adjust perfectly to a stochastic latent variable (excess demand) whose distribution depends only on observable characteristics on the market and not on its own lagged values. Thus while the predicted values for price changes are very close to those obtained by Hendry, the predictive confidence intervals are not and, in particular, exhibit substantial heteroskedasticity with greater uncertainty in periods of price volatility. Let $\Delta p_{h,t}$ denote the change in the log of house prices, then their simplified Model 1 has the form:

$$\begin{aligned}\Delta p_{h,t} &= g(x_t + v_t) = g(w_t) \\ x_t &= \theta' \mathbf{z}_t \\ g(w_t) &= w_t + \phi_2^2 w_t^2 + \phi_3^2 w_t^3\end{aligned}\tag{2}$$

where $g(w_t)$ is a stochastic cubic excess-demand relation, which from the first line of (2), deterministically explains house-price inflation (due to very rapid clearing). The vector \mathbf{z}_t includes all the relevant causal variables (income, interest rates, mortgage lending etc.). Hence, assuming homoskedasticity and no skewness in the underlying error process, so $E[v_t^3] = 0$, taking account of the non-linearities, expected house-price inflation is:

$$\begin{aligned}E[\Delta p_{h,t}] &= E[g(w_t)] \\ &= E[x_t + v_t + \phi_2^2 x_t^2 + \phi_2^2 v_t^2 + 2\phi_2^2 x_t v_t] + E[\phi_3^2 x_t^3 + \phi_3^2 v_t^3 + 3\phi_3^2 x_t^2 v_t + 3\phi_3^2 x_t v_t^2] \\ &= x_t + \phi_2^2 x_t^2 + \phi_3^2 x_t^3 + \phi_2^2 \sigma_v^2 + 3\phi_3^2 x_t \sigma_v^2 \\ &= g(x_t) + \phi_2^2 \sigma_v^2 + 3\phi_3^2 x_t \sigma_v^2.\end{aligned}$$

Consequently, its variance is given by:

$$\begin{aligned}V[\Delta p_{h,t}] &= V[g(w_t)] = E[(g(w_t) - E[g(w_t)])^2] \\ &= E\left[(v_t + (\phi_2^2 + 3\phi_3^2 x_t)(v_t^2 - \sigma_v^2) + 2\phi_2^2 x_t v_t + \phi_3^2 v_t^3 + 3\phi_3^2 x_t^2 v_t)^2\right] \\ &= (1 + 4\phi_2^2 x_t + 2\phi_2^4 x_t^2 + 9\phi_3^4 x_t^4 + 6\phi_3^2 x_t^2 + 12\phi_2^2 \phi_3^2 x_t^3) \sigma_v^2 \\ &\quad + \left[2(\phi_2^2 + 3\phi_3^2 x_t)^2 + 3\phi_3^2 + 18\phi_3^4 x_t^2\right] \sigma_v^4 + \phi_3^4 E[v_t^6].\end{aligned}$$

There is a huge difference from the variance formula of the non-stochastic form, which underpins the better performance of their Model 1. Note, however, that it ‘exploits’ the contemporaneous information rather more. Since forecast evaluation requires use of this heteroskedastic variance, Hendry was too ‘hard’ on the performance of his model by requiring a constant forecast-error variance.

This paper thus resolves an issue of apparent forecast failure (i.e., the unmodelled heteroskedasticity) and represents an advance in technique so that the desired model can be handled instead of an approximation. Tests of the actual functioning of the housing market (or indeed of similar markets) should therefore inform correct policy choices.

The second paper, by Robert Engle and Svend Hylleberg, addresses the issue of seasonal patterns in economic time series in a multivariate context. Economic policy is often based on seasonally-adjusted data and hence entails a signal extraction problem to determine the underlying state.

The issue of extracting the common underlying seasonal factors in a multivariate context is considered within the familiar reduced-rank framework. Engle and Hylleberg start with the basic (uncontestable) premise that systems of economic variables can have trends, cycles and unit roots as well as various types of seasonality. If each of a collection of series has a certain type of seasonality but a linear combination of these series can be found without seasonality, the authors define this seasonality as being common. Their paper proposes new tests to determine if seasonal characteristics are common to a set of time series, tests which can be employed in the presence of various time-series structures.

The analysis is applied to OECD data on unemployment for the period 1975.1 to 1993.4 and it is found that four countries as diverse as Australia, Canada, Japan and the USA not only have common trends in their unemployment but also have common deterministic seasonal features and a common cycle/stochastic seasonal feature. In particular, the dominance of US unemployment as a common seasonal factor is demonstrated, shedding important light on this most intractable of policy problems confronting the OECD economies.

A basic assumption is that the relevant econometric model is conditional on the policy instruments which will be used to achieve the desired target values of the economic variables. This conditioning inherently raises issues of exogeneity and causality: the former are important to ensure that the parameters in the conditional distributions coincide with the derivatives that the policy analysis assumes; the latter matters such that the changes in the policy instruments do indeed alter the values of the economic variables. We now turn to these concerns.

5 Weak exogeneity

Let ψ denote the k parameters of interest in the model of \mathbf{y}_t given \mathbf{z}_t . The weak exogeneity of \mathbf{z}_t for ψ in the defines conditions on (1) whereby \mathbf{z}_t need not be analyzed to learn how \mathbf{y}_t is determined without loss of information about ψ . Weak exogeneity was proposed by Richard (1980) and analyzed in Engle, Hendry and Richard (1983), building on Koopmans (1950) and Barndorff-Nielsen (1978): Ericsson (1992) provides an excellent exposition. Transform $\theta \in \Theta$ to $\phi \in \Phi$ given by:

$$\phi = \mathbf{f}(\theta) \text{ where } \phi \in \Phi \text{ and } \theta \in \Theta, \quad (3)$$

such that $\mathbf{f}(\cdot)$ is one-one and $\phi' = (\phi'_1, \phi'_2)$, where ϕ_i has n_i elements ($n_1 + n_2 = n$), corresponding to the factorization of the joint density (1) into a conditional and a marginal density:

$$D_{\mathbf{x}}(\mathbf{y}_t, \mathbf{z}_t \mid \mathbf{X}_{t-1}, \theta) = D_{\mathbf{y}|\mathbf{z}}(\mathbf{y}_t \mid \mathbf{z}_t, \mathbf{X}_{t-1}, \phi_1) D_{\mathbf{z}}(\mathbf{z}_t \mid \mathbf{X}_{t-1}, \phi_2). \quad (4)$$

Then \mathbf{z}_t is weakly exogenous for ψ if:

- (i) $\psi = \mathbf{g}(\phi_1)$ alone; and
- (ii) ϕ_1 and ϕ_2 are variation free

Condition (i) ensures that ψ can be learnt from ϕ_1 , and (ii) precludes ψ depending on ϕ_2 , so no information about ψ can be derived from the marginal model. However, the weak exogeneity of \mathbf{z}_t for

ψ does not imply that \mathbf{z}_t causes \mathbf{y}_t . A failure of (ii) usually results in inefficiency, whereas forms of failure of (i) can induce inconsistency or non-constancy. Invalid conditioning was defined in Ericsson, Hendry and Mizon (1996) to entail that the parameters of interest cannot be obtained from the conditional model. Formulations of weak exogeneity conditions and tests for various parameters of interest in cointegrated systems are discussed in Boswijk (1995, 1992), Dolado (1992), Hendry (1995b), Hendry and Mizon (1992), Johansen (1992a, 1992b), Johansen and Juselius (1990) and Urbain (1992).

6 Strong exogeneity

If the marginal density $D_z(\cdot)$ in (4) does not depend on \mathbf{Y}_{t-1} , so that:

$$D_z(\mathbf{x}_t \mid \mathbf{Y}_{t-1}, \mathbf{Z}_{t-1}, \cdot) = D_z(\mathbf{z}_t \mid \mathbf{Z}_{t-1}, \cdot), \quad (5)$$

then \mathbf{Y}_{t-1} does not Granger cause \mathbf{z}_t : see Granger (1969). Such a condition sustains marginalizing $D_z(\mathbf{z}_t \mid \mathbf{X}_{t-1}, \cdot)$ with respect to \mathbf{Y}_{t-1}^1 , although when $D_{y|z}(\cdot)$ contains information about ψ , analyzing only $D_z(\cdot)$ would lose information.

Next, a subvector \mathbf{z}_t of \mathbf{x}_t is strongly exogenous for ψ if \mathbf{z}_t is weakly exogenous for ψ , and:

$$(iii) D_z(\mathbf{z}_t \mid \mathbf{X}_{t-1}, \phi_2) = D_z(\mathbf{z}_t \mid \mathbf{Z}_{t-1}^1, \mathbf{X}_0, \phi_2).$$

When (iii) is satisfied, \mathbf{z}_t does not depend upon \mathbf{Y}_{t-1} , so if ϕ is constant:

$$D_z(\mathbf{z}_t \mid \mathbf{X}_{t-1}, \phi_2) = D_z(\mathbf{Z}_T^1 \mid \mathbf{X}_0, \phi_2) \quad (6)$$

and hence:

$$D_X(\mathbf{X}_T^1 \mid \mathbf{X}_0, \theta) = D_{Y|Z}(\mathbf{Y}_T^1 \mid \mathbf{Z}_T^1, \mathbf{X}_0, \phi_1) D_z(\mathbf{Z}_T^1 \mid \mathbf{X}_0, \phi_2). \quad (7)$$

Thus, the full-sample joint density factorizes into the product of full-sample density functions for $\mathbf{Y}_T^1 \mid \mathbf{Z}_T^1$ and \mathbf{Z}_T^1 , which thereby sustains full-sample conditioning and hence valid conditional multi-step forecasting. However, it is not necessary: $D_X(\mathbf{x}_t \mid \mathbf{X}_{t-1}, \theta)$ could be modelled and (7) derived therefrom, even if (i) and/or (ii) were violated. When \mathbf{z}_t is weakly but not strongly exogenous for ψ , from (4) under constant parameters, the full-sample joint density can be factorized validly as:

$$D_X(\mathbf{X}_T^1 \mid \mathbf{X}_0, \theta) = \prod_{t=1}^T D_{Y|Z}(\mathbf{y}_t \mid \mathbf{z}_t, \mathbf{X}_{t-1}, \phi_1) \prod_{t=1}^T D_z(\mathbf{z}_t \mid \mathbf{X}_{t-1}, \phi_2). \quad (8)$$

$D_X(\cdot)$ can also be factorized into conditional and marginal full-sample densities as:

$$D_X(\mathbf{Y}_T^1, \mathbf{Z}_T^1 \mid \mathbf{X}_0, \theta) = D_{Y|Z}^*(\mathbf{Y}_T^1 \mid \mathbf{Z}_T^1, \mathbf{Y}_0, \kappa_1) D_Z^*(\mathbf{Z}_T^1 \mid \mathbf{Z}_0, \kappa_2). \quad (9)$$

However, inference will be efficient using the full-sample conditional density $D_{Y|Z}^*(\mathbf{Y}_T^1 \mid \mathbf{Z}_T^1, \mathbf{X}_0, \kappa_1)$ only if it coincides with $D_{Y|Z}(\mathbf{Y}_T^1 \mid \mathbf{Z}_T^1, \mathbf{X}_0, \phi_1)$, which requires strong exogeneity (see e.g., Florens, Mouchart and Rolin, 1990). This implication is important for conditional multi-step forecasting, and its extreme of dynamic simulation, since the policy implications of these methods may be misleading when strong exogeneity is absent. Since most policy rules relate to past information about the economy, strong exogeneity seems unlikely.

A first step in economic policy analysis is usually forecasting the path of \mathbf{y} , prior to policy intervention and after any changes. Both directions of Granger causality between \mathbf{y} and \mathbf{z} have implications for forecasting. In particular, Granger causality from \mathbf{z} to \mathbf{y} is essential for forecasting \mathbf{y} conditional on \mathbf{z} (see Granger and Deutsch, 1992), or if \mathbf{z}_t is to be used for implementing economic policies aimed at achieving targets for \mathbf{y}_t . Conversely, Granger causality from \mathbf{y} to \mathbf{z} precludes conditional multi-step

forecasting of y . Though these statements are obvious consequences of the definition of Granger causality, the absence of parameters in the definition is an important drawback, particularly when conditional policy analysis is being considered. For example, even if y does not Granger cause z , when the conditional distribution of y_t contains information about the parameters ϕ_2 of the marginal distribution in (4), and the latter helps determine the parameters of interest, then conditioning on z_t could lead to a loss of information. Similarly, even if z alone Granger causes y , it would be inappropriate solely to analyze the conditional distribution in (4) when z_t is not weakly exogenous for the parameters of interest ψ .

As Noud van Giersbergen and Jan Kiviet show in their paper in this Special Issue, the absence of strong exogeneity may have important implications for estimation and inference. Their paper investigates the finite-sample behaviour of ordinary and bootstrap inference procedures in stable first- and second-order autoregressive distributed-lag conditional models with non-stationary weakly exogenous regressors. The case of ordinary asymptotic inference with strongly exogenous regressors was analysed by Kiviet and Phillips (1992), Banerjee and Hendry (1992), Banerjee, Dolado, Galbraith and Hendry (1993) and Banerjee, Dolado and Mestre (1996).

Within the framework of the Special Issue, their set-up can be interpreted in the following way. Suppose that the conditional and marginal models represent agents' and policy makers' decision rules respectively. Since policy makers often set targets for the endogenous variables which characterize the behaviour of the economic agents, policy rules are likely to involve feedbacks from past economic outcomes onto current decisions; as noted, policy variables are unlikely to be strongly exogenous. However, if the feedback is not related to deviations from long-run equilibria, policy variables can be weakly exogenous, and then asymptotically efficient inference on the parameters of the agents' model can be obtained without the need to analyze the policy makers' decision rules simultaneously.

In an empirically relevant class of such models, van Giersbergen and Kiviet investigate by Monte Carlo methods the accuracy of standard first-order inference procedures in finite samples, and what gains in accuracy are achievable when particular implementations of the bootstrap are used for inference purposes. The simulations are designed to mimic situations that are relevant when a weakly exogenous policy variable affects (and is affected by) the outcome of agents' behaviour. In some of these implementations, it is examined whether or not modelling of the marginal model (the policy makers' behaviour), may improve finite-sample inference. van Giersbergen and Kiviet find that, irrespective of the intensity of the feedback, bootstrap inference out-performs standard inference, while the latter is vulnerable to small-sample problems. It is also found that incorporating the policy rule model in bootstrap resampling sometimes adds little to the already quite impressive performance of a naive bootstrap implementation which treats the weakly exogenous regressors as fixed. For a range of other cases, better results are obtained if the bootstrap also resamples the marginal model for the policy makers' behaviour.

We now consider forecasting y conditional on z , and jointly with z . Since forecasting procedures also could be preceded by joint or conditional estimation, and may assume strong, or only weak, exogeneity, the next section considers the issues that arise.

7 Forecasting

In this section, we assume that θ is constant, and first consider conditional forecasting, drawing on the analysis in section 6 above. We consider forecasting by the policy agency itself, and assume it knows the control rules it will implement.

From (7), forecasting y_{T+h} ($h > 0$) conditional on past, current and predicted future $\{z_t\}$ can be done efficiently when z_t is strongly exogenous for ψ . More precisely, full-sample conditional esti-

mation (i.e., estimation of ϕ_1 from $D_{Y|Z}(Y_T^1|Z_T^1, X_0, \phi_1)$ to yield $\hat{\phi}_1$, and separate estimation of ϕ_2 from $D_Z(Z_T^1|X_0, \phi_2)$ to yield $\hat{\phi}_2$ and hence \hat{z}_{T+h}), followed by conditional forecasting (generating the forecasts of y_{T+h} using $\hat{\phi}_1$ and \hat{z}_{T+h}) requires strong exogeneity. For the outcomes to match the forecasts, θ must remain constant. Hence conditional forecasting of y_{T+h} using an estimate of ϕ_1 from the conditional model, requires z_t to be super-strongly exogenous for ϕ_1 . That is a demanding condition in a policy setting where elements of z_t are set in the light of recent past economic behavior, and the objective of policy may be to alter entities that were previously constant.

Provided the system is estimated efficiently (i.e., jointly) within sample to yield $\hat{\theta}$, Granger non-causality from y_t to z_t is sufficient to sustain valid conditional forecasting using the implied estimates of ϕ_1 and ϕ_2 – weak exogeneity is only required for efficient conditional estimation of ϕ_1 . Consequently, the conditions for efficient parameter estimation and those for valid conditional forecasting are different and unrelated. The unconditional approach requires modelling the complete joint density $D_X(X_T^1|X_0, \theta)$, then deriving the conditional representation for forecasting. However, difficulty in modelling the past behavior of policy variables in $D_Z(\cdot)$ often results in conditional models being used in practice: an outside agency (such as a forecasting bureau) may perforce have to forecast y_{T+h} conditional on values for policy variables.

When policy rules depend on X_{t-1}^1 , Granger non-causality from y_t to z_t will not be valid, and conditional forecasts may be misleading, howsoever the parameters are estimated. Such an outcome could occur when fixing values of a policy variable to study the effects using an econometric model, but feedback from y to z occurs when the policy is implemented. This analysis suggests testing for weak and strong exogeneity to sustain estimation conditional on the policy variables, then forecasting jointly using the policy rule that will be implemented in reality, rather than conditionally on preassigned values for the policy variables. When the rule depends on correcting deviations from long-run equilibria determined by the private sector, long-run weak exogeneity will be violated so joint estimation is required.

The papers by Michael Clements and David Hendry, James Stock and John Muellbauer in the Special Issue deal with separate, but related, aspects of forecasting and economic policy, and highlight important difficulties with existing forecasting techniques (to the extent of sometimes vitiating their potential use for policy analysis). In all three papers, the issue of integrated time series also forms a key aspect of the analytical and empirical results. In Muellbauer, for example, the predictability of income, and hence the persistence of shocks – namely, is there a unit root in the income process? – is of great importance both for policy and for forecasting. The ability to pre-test accurately for unit or near-unit roots is of vital significance in the forecasting results presented by Stock, while Clements and Hendry's conditions for favouring multi-step, or dynamic, estimation for multi-step forecasting also depend on the existence of a unit root with possibly unmodelled moving average errors.

Clements and Hendry show, by means of an analytical example, how dynamic estimation (DE) may accommodate incorrectly-specified models as the forecast lead alters, improving forecast performance for some mis-specifications. However, in correctly specified models, reducing finite-sample biases does not justify DE. In a Monte Carlo forecasting study for integrated processes, estimating a unit root in the presence of a neglected moving-average may favour DE, although other sensible solutions such as instrumental variables estimation exist in that scenario. A second Monte Carlo study obtains the estimator biases and explains these using asymptotic approximations.

Their analytical results and Monte Carlo simulations show that the comparisons are not unambiguously in favour of either estimator. Issues which affect the comparison include whether or not the series are integrated, the nature of the error processes, and the degree of model mis-specification. Clements and Hendry's results apply to h -period ahead forecasts from univariate models. We next show that similar results follow in the multivariate case, and thereby illustrate a setting where the use of Wiener

integrals allows a direct derivation of what is a complicated limiting distribution in the stationary case (see, inter alia, Schmidt, 1974, Baillie, 1979b, 1979a, Calzolari, 1981, and Chong and Hendry, 1986).

7.1 Multi-step forecasting

Consider the following vector unit-root process (this analysis draws on results in Phillips and Durlauf, 1986, Phillips, 1986, 1987, 1988, 1991, and Park and Phillips, 1988, 1989: see Banerjee and Hendry, 1992, Banerjee *et al.*, 1993, and Hendry, 1995a for expositions):

$$\begin{aligned} \mathbf{x}_t &= \mathbf{\Upsilon} \mathbf{x}_{t-1} + \mathbf{v}_t \text{ with} \\ \mathbf{v}_t &= \boldsymbol{\epsilon}_t + \mathbf{\Gamma} \boldsymbol{\epsilon}_{t-1} \text{ when } \boldsymbol{\epsilon}_t \sim \text{IN}(\mathbf{0}, \mathbf{\Sigma}) \end{aligned} \quad (10)$$

where $\mathbf{\Upsilon} = \mathbf{I}_n$, and all the eigenroots of $\mathbf{\Gamma}$ lie inside the unit circle. In (10), \mathbf{v}_t has an unconditional covariance:

$$\text{E}[\mathbf{v}_t \mathbf{v}_t'] = \mathbf{\Phi}_v = \mathbf{\Sigma} + \mathbf{\Gamma} \mathbf{\Sigma} \mathbf{\Gamma}',$$

with non-singular long-run covariance $\mathbf{\Omega}_v$:

$$\mathbf{\Omega}_v = \lim_{T \rightarrow \infty} \text{E} \left[T^{-1} \left(\sum_{t=1}^T \mathbf{v}_t \right) \left(\sum_{s=1}^T \mathbf{v}_s' \right) \right] = (\mathbf{\Sigma} + \mathbf{\Gamma} \mathbf{\Sigma} \mathbf{\Gamma}') + \mathbf{\Sigma} \mathbf{\Gamma}' + \mathbf{\Gamma} \mathbf{\Sigma} = \mathbf{\Phi}_v + \mathbf{\Lambda}_v + \mathbf{\Lambda}_v'.$$

The \mathbf{v}_t process can be standardized using $\mathbf{\Omega}_v^{-1} = \mathbf{K}_v \mathbf{K}_v'$ so that $\mathbf{K}_v' \mathbf{\Omega}_v \mathbf{K}_v = \mathbf{I}_n$. Since $\mathbf{\Omega}_v = (\mathbf{I}_n + \mathbf{\Gamma}) \mathbf{\Sigma} (\mathbf{I}_n + \mathbf{\Gamma})'$, and $(\mathbf{I}_n + \mathbf{\Gamma})$ is non-singular, $\mathbf{K}_v' = \mathbf{H}' (\mathbf{I}_n + \mathbf{\Gamma})^{-1}$ where $\mathbf{\Sigma}^{-1} = \mathbf{H} \mathbf{H}'$. We first derive the 1-step results, where DE and ‘powered-up’ approaches coincide.

From (10):

$$T^{-\frac{1}{2}} \sum_{t=1}^{[Tr]} \mathbf{v}_t \Rightarrow \mathbf{V}(r) \text{ for } r \in [0, 1] \text{ as } T \rightarrow \infty. \quad (11)$$

Correspondingly, the vector Brownian motion $\mathbf{V}(r) \sim BM(\mathbf{\Omega}_v)$ can be standardized to $\mathbf{W}(r) = \mathbf{K}_v' \mathbf{V}(r) \sim BM(\mathbf{I}_n)$.

Let $\hat{\mathbf{\Upsilon}}$ in (10) be estimated by least squares:

$$\hat{\mathbf{\Upsilon}} = \mathbf{\Upsilon} + \left(\sum_{t=1}^T \mathbf{v}_t \mathbf{x}_{t-1}' \right) \left(\sum_{t=1}^T \mathbf{x}_{t-1} \mathbf{x}_{t-1}' \right)^{-1}. \quad (12)$$

Since $\mathbf{\Upsilon} = \mathbf{I}_n$:

$$T^{-2} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}_t' \Rightarrow \int_0^1 \mathbf{V}(r) \mathbf{V}(r)' dr \quad (13)$$

and:

$$T^{-1} \sum_{t=1}^T \mathbf{x}_{t-1} \mathbf{v}_t' \Rightarrow \int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \mathbf{\Lambda}_v. \quad (14)$$

From the transpose of (12), therefore:

$$T \left(\hat{\mathbf{\Upsilon}}' - \mathbf{I}_n \right) \Rightarrow \left(\int_0^1 \mathbf{V}(r) \mathbf{V}(r)' dr \right)^{-1} \left(\int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \mathbf{\Lambda}_v \right) = \mathbf{B}' \quad (15)$$

(say). Standardizing the Brownian motions:

$$T \left(\hat{\mathbf{\Upsilon}}' - \mathbf{I}_n \right) \Rightarrow \mathbf{K}_v \left(\int_0^1 \mathbf{W}(r) \mathbf{W}(r)' dr \right)^{-1} \left(\int_0^1 \mathbf{W}(r) d\mathbf{W}(r)' + \mathbf{\Lambda}_v^* \right) (\mathbf{K}_v)^{-1} \quad (16)$$

where:

$$\Lambda_v^* = \mathbf{K}_v' \Lambda_v \mathbf{K}_v = \mathbf{H}' (\mathbf{I}_n + \Gamma)^{-1} \Sigma \Gamma' (\mathbf{I}_n + \Gamma')^{-1} \mathbf{H}; \quad (17)$$

the second expression in (17) is for a first-order moving average. The non-centrality Λ_v^* could be large if there is a substantial ‘negative’ vector moving-average error. The implication is that spurious cointegration vectors may appear (i.e., the null of n unit roots may be rejected in favour of $(n - p)$ roots). Unlike retaining irrelevant spurious regressions – as when estimating a VAR unrestrictedly (see e.g. Clements and Hendry, 1995) – these are important as they can bias the forecasts badly. This is not an inconsistency, but nevertheless persists in the normalized limiting distribution.

A useful special case, which highlights the main effect, is when scaling and between-error independence ensure that $\Sigma = \sigma^2 \mathbf{I}_n$ with $\Gamma = \gamma \mathbf{I}_n$, so that:

$$\Lambda_v^* = \frac{\gamma}{(1 + \gamma)^2} \mathbf{I}_n.$$

Then $\mathbf{K}_v' = \sigma (1 + \gamma)^{-1} \mathbf{I}_n$ so that:

$$T \left(\hat{\mathbf{Y}}' - \mathbf{I}_n \right) \Rightarrow \left(\int_0^1 \mathbf{W}(r) \mathbf{W}(r)' dr \right)^{-1} \left(\int_0^1 \mathbf{W}(r) d\mathbf{W}(r)' + \frac{\gamma}{(1 + \gamma)^2} \mathbf{I}_n \right) \quad (18)$$

Generalizations of this analysis hold if there already some stationary variables, or if deterministic terms are included. We now derive the distribution of powered-up estimates, to see how these effects are magnified.

7.1.1 h -step estimates

First rewrite (12) as:

$$\hat{\mathbf{Y}}' = \mathbf{I}_n + \left(T^{-2} \sum_{t=1}^T \mathbf{x}_{t-1} \mathbf{x}_{t-1}' \right)^{-1} \left(T^{-2} \sum_{t=1}^T \mathbf{x}_{t-1} \mathbf{v}_t' \right) = \mathbf{I}_n + T^{-1} \mathbf{D}'.$$

In finite samples, $\hat{\mathbf{Y}}$ is biased for \mathbf{I}_n to $O(T^{-1})$, since:

$$\mathbf{D}' \Rightarrow \left(\int_0^1 \mathbf{V}(r) \mathbf{V}(r)' dr \right)^{-1} \left(\int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \Lambda_v \right) = \mathbf{B}'$$

Consider h -step ahead joint forecasts from an end-of-sample point T . Since:

$$\mathbf{x}_{T+h} = \mathbf{\Upsilon}^h \mathbf{x}_T + \sum_{i=0}^{h-1} \mathbf{\Upsilon}^i \boldsymbol{\epsilon}_{T+h-i} = \mathbf{\Upsilon}_h \mathbf{x}_T + \mathbf{u}_{T+h}, \quad (19)$$

given an estimate of $\mathbf{\Upsilon}$, and forecasting under the assumption that $E[\boldsymbol{\epsilon}_t] = \mathbf{0} \forall t$:

$$\hat{\mathbf{x}}_{T+h} = \hat{\mathbf{\Upsilon}}^h \mathbf{x}_T \quad (20)$$

which this has average conditional error:

$$E[\mathbf{x}_{T+h} - \hat{\mathbf{x}}_{T+h} | \mathbf{x}_T] = \left(\mathbf{\Upsilon}^h - E[\hat{\mathbf{\Upsilon}}^h] \right) \mathbf{x}_T.$$

Alternatively, directly estimating $\mathbf{\Upsilon}_h$ in (19):

$$\tilde{\mathbf{x}}_{T+h} = \widetilde{\mathbf{\Upsilon}}_h \mathbf{x}_T \quad (21)$$

has average conditional error:

$$\mathbb{E}[\mathbf{x}_{T+h} - \tilde{\mathbf{x}}_{T+h} \mid \mathbf{x}_T] = \left(\mathbf{\Upsilon}^h - \mathbb{E}[\tilde{\mathbf{\Upsilon}}_h] \right) \mathbf{x}_T.$$

Thus, the relative accuracy of the multi-step forecast procedure (21) compared to (20) is determined by the relative accuracy of the powered estimate versus the estimated power.

For the process in (10):

$$\begin{aligned} \hat{\mathbf{\Upsilon}}^h &= \left[\left(T^{-2} \sum_{t=1}^T \mathbf{x}_t \mathbf{x}'_{t-1} \right) \left(T^{-2} \sum_{t=1}^T \mathbf{x}_{t-1} \mathbf{x}'_{t-1} \right)^{-1} \right]^h \\ &= [\mathbf{I}_n + T^{-1} \mathbf{D}] \hat{\mathbf{\Upsilon}}^{h-1} = \hat{\mathbf{\Upsilon}}^{h-1} + T^{-1} \mathbf{D} \hat{\mathbf{\Upsilon}}^{h-1}. \end{aligned}$$

Solving recursively after transposing:

$$\begin{aligned} \left(\hat{\mathbf{\Upsilon}}^h \right)' &= \mathbf{I}_n + \left[\sum_{i=0}^{h-1} \hat{\mathbf{\Upsilon}}^i \right]' T^{-1} \mathbf{D}' \\ &= \mathbf{I}_n + \left[\sum_{i=0}^{h-1} [\mathbf{I}_n + T^{-1} \mathbf{D}']^i \right] T^{-1} \mathbf{D}' \end{aligned}$$

and since higher powers of $T^{-i} \mathbf{D}^i$ are asymptotically negligible:

$$T \left(\left(\hat{\mathbf{\Upsilon}}^h \right)' - \mathbf{I}_n \right) \Rightarrow \left(\sum_{i=0}^{h-1} \mathbf{I}_n^i \right) \mathbf{B}' = h \mathbf{B}'.$$

Thus, the h -step limiting distribution is simply h times the 1-step. Since there is a lower bound of $-T$ to the bias in finite samples, we correct for lower-order biases using the better approximation:

$$T \left(\left(\hat{\mathbf{\Upsilon}}^h \right)' - \mathbf{I}_n \right) \Rightarrow \left[\sum_{i=0}^{h-1} (\mathbf{I}_n + T^{-1} \mathbf{B}')^i \right] \mathbf{B}'.$$

The asymptotic distribution for the h -step DE follows in a similar way:

$$T \left(\tilde{\mathbf{\Upsilon}}_h' - \mathbf{I}_n \right) = \left(T^{-2} \sum_{t=1}^T \mathbf{x}_{t-h} \mathbf{x}'_{t-h} \right)^{-1} T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h} \mathbf{u}'_t, \quad (22)$$

where:

$$\mathbf{u}_t = \sum_{j=0}^{h-1} \mathbf{v}_{t-j} = \sum_{i=1}^h \mathbf{v}_{t-h+i}$$

since $\mathbf{\Upsilon} = \mathbf{I}_n$. The denominator is again (13). For the numerator, the various terms are (for $i = 1$):

$$T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h} \mathbf{v}'_{t-h+1} \Rightarrow \int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \mathbf{\Lambda}_v,$$

whereas for $i = 2, \dots, h$:

$$\begin{aligned} T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h} \mathbf{v}'_{t-h+i} &= T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h+1} \mathbf{v}'_{t-h+i} - T^{-1} \sum_{t=1}^T \mathbf{v}_{t-h+1} \mathbf{v}'_{t-h+i} \\ &= T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h+i-1} \mathbf{v}'_{t-h+i} - T^{-1} \sum_{t=1}^T \left(\sum_{j=1}^{i-1} \mathbf{v}_{t-h+j} \right) \mathbf{v}'_{t-h+i} \\ &\Rightarrow \int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \mathbf{\Lambda}_v - \mathbf{\Gamma} \mathbf{\Sigma} = \int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' \end{aligned}$$

so that:

$$T^{-1} \sum_{t=1}^T \mathbf{x}_{t-h} \sum_{i=0}^{h-1} \mathbf{v}_{t-i} \Rightarrow h \int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' + \mathbf{\Lambda}_v \quad (23)$$

and hence we obtain equation (24):

$$T \left(\widetilde{\mathbf{Y}}_h - \mathbf{I}_n \right) \Rightarrow h \left(\int_0^1 \mathbf{V}(r) \mathbf{V}(r)' dr \right)^{-1} \left(\int_0^1 \mathbf{V}(r) d\mathbf{V}(r)' dr + h^{-1} \mathbf{\Lambda}_v \right). \quad (24)$$

As can be seen, there is only a small reduction in the relative bias compared to powering up. Equally, despite the presence of unit roots, analytically useful expressions can be obtained.

Stock's paper focuses on an important aspect of economic forecasting, the construction of forecasts over long horizons. He investigates the properties of long-horizon (h) forecasts when the estimation sample is perhaps under half that of the forecast (h/T is 'large'). Under this condition, the distributions are altered by the existence of processes with roots that are local to unity, so that estimation biases accumulate.

A theme of his paper is that the presence of persistence in the form of large, possibly autoregressive, unit roots, presents particular difficulties for long horizon forecasting. These largest roots, on which both the true long horizon conditional mean and the formula for a valid prediction interval depend, cannot be measured with sufficient precision to obtain asymptotically unbiased forecasts or prediction intervals with asymptotically correct coverage rates. Interval forecasts at long horizon face an additional difficulty beyond those confronted by long horizon point forecasting. While model-selection based forecasts (pre-testing for unit roots/cointegration) can work well when there is truly a unit root, pre-test forecasts work poorly for deviations from an exact unit root which are sufficiently small that they will often not be detected even by efficient pre-tests. Long-horizon forecasting even with a consistent pre-test produces point forecasts which have large MSFEs and prediction intervals which are far wider than desirable.

In the most applied of this set of three papers on forecasting, Muellbauer analyses and forecasts annual time series of aggregate real income per-capita in the US. It is shown that aggregate real per capita income is subject to significant trend reversion. Second, evidence is found in favour of the Lucas critique from shifts in the macro-policy reactions functions causing shifts in the reduced form income forecasting equation. Finally, allowing for deterministic breaks in means to account for phenomena such as the 1973 oil shock, the multivariate framework adopted in this paper is used to provide useful three-year ahead forecasts using, what in the Clements and Hendry terminology adopted above would amount to dynamic estimators.

8 Parameter constancy

Parameters of economic systems may, but need not, be constant over time, and changes in them may, but again need not, be connected with the policy being implemented. Nevertheless, both incorrect forecasts and/or policy advice may ensue when parameters change. For example, when the degree of integration d of a variable alters (e.g., during a hyperinflation), unless a valid equilibrium-correction formulation has been adopted which preserves cointegration despite changes in d , model failure will result. Conversely, if the mean of any equilibrium relation alters, equilibrium-correction formulations may perform badly but models in differences (or with intercept corrections) could continue to forecast as expected, yet not have useful policy implications. A much-debated topic is whether the parameters of models will remain constant when policy changes, so we now develop the relevant framework to analyze this issue.

8.1 Super exogeneity and invariance

First, we define ϕ_1 as invariant to a class of interventions if it is constant over those interventions. Then super exogeneity augments weak exogeneity with parameter invariance:

\mathbf{z}_t is super exogenous for ψ if \mathbf{z}_t is weakly exogenous for ψ and:

(iv) ϕ_1 is invariant to interventions affecting ϕ_2 .

Under super exogeneity, ϕ_2 can change without affecting ϕ_1 . Importantly, this requires weak, but not strong, exogeneity which is a vital weakening of the conditions for empirical models to be useful for economic policy. As noted above, governments monitor what happens in the economy, and usually base their policies on the past outcomes of the variables they wish to influence, so strong exogeneity is an unlikely condition for policy variables. Thus, valid economic policy statements would be rare if super-strong exogeneity was needed (namely, their joint occurrence). Conversely, when super exogeneity holds, although the parameters $\{\theta_t\}$ of the joint density change over time so that $\phi_t = \mathbf{h}(\theta_t)$:

$$\prod_{t=1}^T D_{y|z}(\mathbf{y}_t | \mathbf{z}_t, \mathbf{X}_{t-1}, \phi_1) \prod_{t=1}^T D_z(\mathbf{z}_t | \mathbf{X}_{t-1}, \phi_{2t}) \text{ where } \phi_t = (\phi'_1 : \phi'_{2t})'. \quad (25)$$

Thus, the conditional model isolates the invariants.

Eilev Jansen and Timo Teräsvirta's paper in this Issue is concerned with testing super exogeneity in a linear or partially non-linear single equation. A joint test for testing both weak exogeneity and a form of invariance, together amounting to super exogeneity, is presented and its properties discussed. The considerations also include testing parameter constancy and modelling parameter constancy prior to testing for super exogeneity..

Their paper also looks at the theory and empirics of the smooth transition regression (STR) approach to testing super exogeneity. If policy change implies that the parameters of the model also change, then the policy outcome will deviate from its anticipated effects. The theory involves allowing the parameters of the interest to be functions of the marginal variables, evolving at data-determined points. The identification issue is addressed and relevant distributions are derived.

An STR model is shown to have two main roles. First, it offers a flexible constant-parameter alternative to linear models with stable parameters. Secondly, it forms a convenient alternative against which to test invariance. It is shown that combining testing invariance and testing weak exogeneity in the STR framework is fairly easily accomplished: because the asymptotic statistical theory is simple, leading to standard null distributions, applying the testing procedure is straightforward.

The practical application of the tests is demonstrated by an example in which super exogeneity is re-tested in a previously published paper on a consumption function for Norway (see Brodin and Nymoen, 1992, and the accompanying discussion in Banerjee and Hendry, 1992). Only slight evidence is found against the earlier specification, attributable mainly to shifts in seasonal factors. Nevertheless, since the STR models of the marginal process reveal considerable non-constancy, the procedures described in Jansen and Teräsvirta should have high power to detect super exogeneity failures if such occur.

8.2 Changing exogeneity

Pre-existing exogeneity conditions can be altered by policy (fixed to floating exchange rates provides one example), and models in which this happens are not reliable guides to the outcomes that will result. As an illustration, under weak exogeneity, conditional models are not invariant to renormalization. This can be especially pernicious when the parameters are non-constant. Reconsider (25) but factorized in

the reverse direction:

$$\prod_{t=1}^T D_{z|y}(\mathbf{z}_t | \mathbf{y}_t, \mathbf{Y}_{t-1}, \mathbf{Z}_{t-1}, \boldsymbol{\rho}_{1,t}) \prod_{t=1}^T D_y(\mathbf{y} | \mathbf{Y}_{t-1}, \mathbf{Z}_{t-1}, \boldsymbol{\rho}_{2,t}) \quad (26)$$

where $\boldsymbol{\rho}_t = (\boldsymbol{\rho}'_{1,t} : \boldsymbol{\rho}'_{2,t})' = \mathbf{g}(\boldsymbol{\phi}_1, \boldsymbol{\phi}'_{2,t})$. Because both $\boldsymbol{\rho}_{1,t}$ and $\boldsymbol{\rho}_{2,t}$ depend on all elements of $\boldsymbol{\phi}_t$, neither model in (26) can have constant parameters; nor can both marginal models. Such an effect can be implicit in subsamples.

8.3 Invariance under interventions

Simon (1953) proposed using the invariance of a relationship under interventions to an input variable as an operational notion of cause (also see Hoover, 1990, and Cartwright, 1989). Thus, if in the conditional model (27):

$$D_{y|z}(\mathbf{y}_t | \mathbf{z}_t, \mathbf{X}_{t-1}, \boldsymbol{\phi}_1), \quad (27)$$

there is a non-zero dependence of \mathbf{y}_t on \mathbf{z}_t , where \mathbf{z}_t is super exogenous for $\boldsymbol{\phi}_1$, and $\boldsymbol{\phi}_2$ has changed without affecting (27), then changes in \mathbf{z}_t cause changes in \mathbf{y}_t . This is a testable claim, although the power of any test to detect the invariance of $\boldsymbol{\phi}_1$ to changes in $\boldsymbol{\phi}_2$ will depend on the magnitude of the change in the latter. Given invariance under intervention of this form, the response of \mathbf{y}_t to \mathbf{z}_t is the same for different sequences $\{\mathbf{z}_t\}$, so could sustain policy when \mathbf{z}_t was under government control. Conversely, an absence of invariance could vitiate the proposed policy, a potential example of which is discussed in section 9.

8.4 Structural breaks and co-breaking

Structural breaks (permanent, large shifts occurring intermittently) which affect several variables may be related. Just as cointegration denotes eliminating non-stationarity due to unit roots in integrated systems by taking linear combinations of variables (see Engle and Granger, 1987), co-breaking denotes the removal of regime shifts in the same way. In the simplest case, when $\mathbf{E}[\mathbf{x}_t]$ is non-constant, but $\mathbf{E}[\boldsymbol{\Phi}'\mathbf{x}_t]$ is constant where $\text{rank}(\boldsymbol{\Phi}) = r < n$, then there is co-breaking of order r . A general theory is developed in Hendry (1995c); here we consider its application to conditional models, and develop its implications for the Lucas critique below.

As an example, constant conditional models with changing marginal processes generate co-breaking in the solved form. Consider a linear integrated system with p cointegration vectors $\boldsymbol{\beta}'\mathbf{x}_{t-1}$, where the marginal process is subject to shifts affecting the growth rates γ_t and equilibrium means $\boldsymbol{\mu}_t$:

$$\Delta \mathbf{x}_t = \gamma_t + \boldsymbol{\alpha} (\boldsymbol{\beta}'\mathbf{x}_{t-1} - \boldsymbol{\mu}_t) + \boldsymbol{\nu}_t \quad \text{where } \mathbf{v}_t \sim \text{IN}_m[\mathbf{0}, \boldsymbol{\Omega}]. \quad (28)$$

Let p_1 cointegration vectors $\boldsymbol{\beta}'_1\mathbf{x}_{t-1}$ appear in the first m_1 block and p_2 in the second, so $\boldsymbol{\beta} = (\boldsymbol{\beta}_1 : \boldsymbol{\beta}_2)$. The conditional/marginal model is:

$$\begin{pmatrix} \Delta \mathbf{y}_t \\ \Delta \mathbf{z}_t \end{pmatrix} = \begin{pmatrix} \boldsymbol{\Gamma} \Delta \mathbf{z}_t \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \gamma_{1t} + \boldsymbol{\Gamma} \gamma_{2t} \\ \gamma_{2,t} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\alpha}_{11} + \boldsymbol{\Gamma} \boldsymbol{\alpha}_{21} & \boldsymbol{\alpha}_{12} + \boldsymbol{\Gamma} \boldsymbol{\alpha}_{22} \\ \boldsymbol{\alpha}_{21} & \boldsymbol{\alpha}_{22} \end{pmatrix} \begin{pmatrix} \boldsymbol{\beta}'_1\mathbf{x}_{t-1} - \boldsymbol{\mu}_{1,t} \\ \boldsymbol{\beta}'_2\mathbf{x}_{t-1} - \boldsymbol{\mu}_{2,t} \end{pmatrix} + \begin{pmatrix} \mathbf{e}_{1,t} \\ \boldsymbol{\nu}_{2,t} \end{pmatrix}$$

where $\boldsymbol{\Gamma} = \boldsymbol{\Omega}_{12}\boldsymbol{\Omega}_{22}^{-1}$ and $\mathbf{v}_{1t} = \mathbf{e}_{1t} + \boldsymbol{\Gamma}\mathbf{v}_{2t}$ with $\mathbf{E}[\mathbf{e}_{1,t}\mathbf{v}'_{2,t}] = \mathbf{0}$. Weak exogeneity for any parameterization that includes the cointegrating vectors requires that $\boldsymbol{\alpha}_{12} + \boldsymbol{\Gamma}\boldsymbol{\alpha}_{22} = \mathbf{0}$ and $\boldsymbol{\alpha}_{21} = \mathbf{0}$. When the

non-constancy is due to changes in the marginal process alone, $\gamma_1 = \gamma_{1,t} + \Gamma\gamma_{2,t}$ and $\mu_t = (\mu_1, \mu_{2,t})$, so the conditional model becomes:

$$\begin{pmatrix} \Delta y_t \\ \Delta z_t \end{pmatrix} = \begin{pmatrix} \Gamma \Delta z_t \\ \mathbf{0} \end{pmatrix} + \begin{pmatrix} \gamma_1 \\ \gamma_{2,t} \end{pmatrix} + \begin{pmatrix} \alpha_{11} & \mathbf{0} \\ \mathbf{0} & \alpha_{22} \end{pmatrix} \begin{pmatrix} \beta'_1 \mathbf{x}_{t-1} - \mu_1 \\ \beta'_2 \mathbf{x}_{t-1} - \mu_{2,t} \end{pmatrix} + \begin{pmatrix} \mathbf{e}_{1,t} \\ \nu_{2,t} \end{pmatrix} \quad (29)$$

Then $\Phi = (\mathbf{I}_{m_1} : -\Gamma)$ is co-breaking of order m_1 for both growth-rate and equilibrium-mean shifts, since premultiplying (28) by Φ and using (29) delivers:

$$(\mathbf{I}_{m_1} : -\Gamma) \Delta \mathbf{x}_t = \Delta \mathbf{y}_t - \Gamma \Delta \mathbf{z}_t = \gamma_1 + \alpha_{11} (\beta'_1 \mathbf{x}_{t-1} - \mu_1) + \mathbf{e}_{1,t}$$

which does not depend on the structural changes.

Co-breaking is a valuable property for econometric models, especially in a policy context, since aspects remain constant (and hence invariant) despite policy changes. Similarly, when forecasting subject to structural breaks, r relations will not suffer predictive failure when $\text{rank}(\Phi) = r$. When co-breaking occurs, it confers immunity of a subset of equations to the Lucas (1976) critique. In turn, this has implications for its testability, so we now consider these issues.

9 Lucas critique

Behavioural parameters in econometric models may be invariant to some interventions, but not others. The Lucas (1976) critique of conflating expectations held by agents with their plans, when the former vary with policy, is well known to vitiate the implications of policy analyses based on econometric models (also see Frisch, 1938, Haavelmo, 1944, and Marschak, 1953). Certainly, if implementing a policy would change the implications from the model, that model cannot be used for policy. However, the force of the critique seems less in practice than theory; its empirical relevance is in doubt; tests potentially allow its rejection; and solutions exist (such as separately modelling expectations). For example, Favero and Hendry (1992) find tests for mis-specification in conditional models for changes in expectations processes to have low power, even though the same tests have high power to detect the omission of relevant variables subject to interventions. Next, the literature search in Ericsson and Irons (1995) reveals almost no cases showing the empirical relevance of the critique. Thirdly, direct tests of the Lucas critique are proposed in Hendry (1988), building on ideas later published in Engle and Hendry (1993) who develop a class of single-equation tests for parameter invariance: Hendry and Ericsson (1991) is one example demonstrating their practical value (in modelling UK money demand). Since all sensible forms of expectations must be cointegrated with outcomes, aspects of the Lucas (1976) critique are testable when expectations variables are subject to regime shifts. However, formal system procedures need further development and practical assessment. Finally, many macro-models embody model-consistent expectations, and solve appropriately for their forecasts and policy analyses accordingly.

As mentioned above, Muellbauer finds significant evidence in favour of the Lucas critique. The interpretation of the productivity slowdown as being due to a government debt shift (or change in the government's stance on debt, evinced by the passage of the Gramm-Rudman Acts) suggests an important role for structural change.

As noted in the previous subsection, co-breaking would entail the constancy of a subset of equations despite structural breaks, so offers a further solution when it can be established. Conversely, Hendry (1988) provides conditions for parametric relations in conditional models derived from expectational processes, and obtains a contradiction between constant conditional models and non-constant marginal processes when such dependence is claimed. However, since the expectations-based model entails at

least one co-breaking relation between the marginal variables subject to the policy shifts, this casts doubt on his proof of the power of the Lucas critique tests, so we now reconsider that.

9.1 Implications of co-breaking for the Lucas critique

Consider a postulated $l(0)$ single conditional equation:

$$E[y_t | \mathbf{z}_t] = \beta' \mathbf{z}_t \quad (30)$$

where $\epsilon_t = y_t - E[y_t | \mathbf{z}_t]$, facing the non-constant marginal process:

$$\mathbf{z}_t = \boldsymbol{\rho}_t + \boldsymbol{\Pi} \mathbf{z}_{t-1} + \mathbf{e}_t \text{ where } \mathbf{e}_t \sim \text{IN}_k[\mathbf{0}, \boldsymbol{\Omega}]. \quad (31)$$

As shown in Hendry (1996), a shifting intercept is the important non-constancy case to consider. Since they did not consider it, that point reduces the impact of the power findings in Favero and Hendry (1992).

The DGP for y_t is in fact the expectational model:

$$E[y_t | \mathcal{I}_{t-1}] = \boldsymbol{\tau}' E[\mathbf{z}_t | \mathcal{I}_{t-1}], \quad (32)$$

where \mathcal{I}_{t-1} denote the information available at time $t-1$, and $\mathbf{z}_{t-1} \in \mathcal{I}_{t-1}$. From (31), when all the eigenvalues of $\boldsymbol{\Pi}$ lie inside the unit circle:

$$E[\mathbf{z}_t] = \boldsymbol{\rho}_t + \boldsymbol{\Pi} E[\mathbf{z}_{t-1}] = \sum_{i=0}^{\infty} \boldsymbol{\Pi}^i \boldsymbol{\rho}_{t-i} = \boldsymbol{\eta}_t \quad (33)$$

so that:

$$\mathbf{z}_t - \boldsymbol{\eta}_t = \boldsymbol{\Pi} (\mathbf{z}_{t-1} - \boldsymbol{\eta}_{t-1}) + \mathbf{e}_t. \quad (34)$$

By assumption, therefore, $\boldsymbol{\tau}$ in (32) is a co-breaking vector, linking the conditional expectations in a constant way howsoever the marginal process alters. We now consider the implications of its existence for the non-constancy of the mis-specified conditional model, first recording the derived (reduced form) equation for later reference:

$$y_t = \boldsymbol{\tau}' E[\mathbf{z}_t | \mathcal{I}_{t-1}] + u_t = \boldsymbol{\tau}' \boldsymbol{\rho}_t + \boldsymbol{\tau}' \boldsymbol{\Pi} \mathbf{z}_{t-1} + u_t \quad (35)$$

where $u_t = y_t - E[y_t | \mathcal{I}_{t-1}]$.

From (31)–(32):

$$y_t = \boldsymbol{\tau}' (\mathbf{z}_t - \mathbf{e}_t) + u_t = \beta'_t \mathbf{z}_t + \omega_t \quad (36)$$

where β'_t is determined by imposing $E[\mathbf{z}_t \omega'_t] = \mathbf{0}$. Letting $\mathbf{M}_t = E[\mathbf{z}_t \mathbf{z}'_t]$ (assumed non-singular for simplicity):

$$\beta_t = (E[\mathbf{z}_t \mathbf{z}'_t])^{-1} E[\mathbf{z}_t y_t] = (\mathbf{I}_k - \mathbf{M}_t^{-1} \boldsymbol{\Omega}) \boldsymbol{\tau},$$

as, from (36) and (31):

$$E[\mathbf{z}_t y_t] = E[\mathbf{z}_t \mathbf{z}'_t] \boldsymbol{\tau} - E[\mathbf{z}_t \mathbf{v}'_t] \boldsymbol{\tau} = \mathbf{M}_t \boldsymbol{\tau} - \boldsymbol{\Omega} \boldsymbol{\tau}.$$

From (34) $\forall t$:

$$\mathbf{P} = E[(\mathbf{z}_t - \boldsymbol{\eta}_t)(\mathbf{z}_t - \boldsymbol{\eta}_t)'] = \boldsymbol{\Pi} \mathbf{P} \boldsymbol{\Pi}' + \boldsymbol{\Omega} = \mathbf{M}_t - \boldsymbol{\eta}_t \boldsymbol{\eta}'_t,$$

so that:

$$\mathbf{M}_t^{-1} \boldsymbol{\Omega} = (\boldsymbol{\Omega}^{-1} \mathbf{M}_t)^{-1} = (\mathbf{I}_k + \boldsymbol{\Omega}^{-1} \boldsymbol{\eta}_t \boldsymbol{\eta}'_t + \boldsymbol{\Omega}^{-1} \boldsymbol{\Pi} \mathbf{P} \boldsymbol{\Pi}')^{-1}.$$

Let $\Omega^{-1} = \mathbf{H}\mathbf{H}'$, then β_t will be constant under the assumed conditions if \mathbf{H}' is co-breaking for η_t : $\mathbf{H}'\eta_t = \mathbf{0}$. But \mathbf{H} is $k \times k$ and non-singular, so the only possible constant solution is $\eta_t = \mathbf{0}$, which precludes non-constancy. Thus, co-breaking due to τ in (32) does not offer an escape from the contradiction between a constant conditional model with non-constant marginals and the claim inherent in the Lucas critique, leaving the latter potentially refutable.

Conversely, co-breaking in the joint distribution of $(y_t : \mathbf{z}_t)$ is essential if the conditional model is to be constant. Such could occur when agents acted in a contingent manner. Consider a joint normal, allowing linear conditional models (ignoring lagged y_t for simplicity of notation):

$$\begin{pmatrix} y_t \\ \mathbf{z}_t \end{pmatrix} | \mathcal{I}_{t-1} \sim \mathbf{N}_{k+1} \left[\begin{pmatrix} \delta_t + \kappa' \mathbf{z}_{t-1} \\ \rho_t + \Pi \mathbf{z}_{t-1} \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma'_{21} \\ \sigma_{21} & \Sigma_{22} \end{pmatrix} \right]$$

so that:

$$\mathbb{E}[y_t | \mathbf{z}_t] = \delta_t + \kappa' \mathbf{z}_{t-1} + \sigma'_{21} \Sigma_{22}^{-1} (\mathbf{z}_t - \rho_t - \Pi \mathbf{z}_{t-1}).$$

If (30) is to be valid, we require:

$$\beta = \Sigma_{22}^{-1} \sigma_{21} \quad \text{and} \quad \delta_t = \beta' \rho_t \quad \text{with} \quad \kappa = \Pi' \beta.$$

The first and second conditions ensure $(1 : -\beta')$ is co-breaking for $(\delta_t : \rho_t)$, and the third entails the weak exogeneity of \mathbf{z}_t for β . Referring back to (35), when (30) is valid, it is seen that $\tau = \beta$ and hence $\tau' \rho_t = \mathbf{0}$ only if $\delta_t = 0$. Thus, the constancy of (35) is neither entailed nor denied by the constancy of either (30) or (32).

10 Macro-models

Kari Eika, Neil Ericsson and Ragnar Nymoen argue in favour of the use of congruent macro-econometric models when deriving an index of monetary conditions to inform economic policy. They contrast this with using, as some recent studies have suggested, a Monetary Conditions Index (MCI) as an indicator of monetary policy stance. The central banks of Canada, Sweden, and Norway have all constructed MCIs, and (to varying degrees) use them in conducting monetary policy.

Empirically, an MCI is calculated as the weighted sum of a short-term interest rate and the exchange rate: the weights aim to reflect these variables' effects on the longer-term foci of economic activity and inflation. Their paper derives analytical and empirical properties of MCIs in an attempt to ascertain their role in monetary policy. It is shown that strong untested assumptions are, in general, needed, including exogeneity, constancy and invariance, as well as cointegration, omitted variables and an absence of dynamic reactions (see the discussion of van Giersbergen and Kiviet above). None of these requirements is likely to be satisfied in the underlying model relating activity and inflation to the variables in the MCI. Empirical analyses of Canadian, Swedish, and Norwegian MCIs confirm such difficulties in their use.

Katarina Juselius constructs a cointegrated VAR model for the German economy, estimated on sample data split before and after 1983. Her small macroeconomic system consists of money, income, prices and interest rates. The monetary mechanisms are found to be significantly different in two samples. Before 1983, the money supply seemed controllable and expansion or contraction of money supply had the expected effect on prices, income and interest rates. After 1983 the conventional mechanisms no longer seemed to work. The empirical analysis points to the crucial role of the bond rate in the system particularly for the more recent period.

The paper emphasizes the role of econometric concepts in model specification, showing the need for consistency between equation specifications and assumed statistical properties, and deals with the issue of structural breaks empirically.

11 Conclusion

The conference on which this Special Issue is based sought to stimulate interest in the econometric issues associated with using macro-econometric systems to guide economic policy. Undoubtedly, it raised many more issues than it resolved. Nevertheless, the papers that follow break new ground in investigating many of the central concerns, including: explicitly modelling important dynamic latent variables; conditioning on policy variables; the constancy and invariance of parameters under regime shifts; forecasting in a policy context; and developing policy-relevant indexes and models.

References

- Baillie, R. T. (1979a). The asymptotic mean squared error of multistep prediction from the regression model with autoregressive errors. *Journal of the American Statistical Association*, **74**, 175–184.
- Baillie, R. T. (1979b). Asymptotic prediction mean squared error for vector autoregressive models. *Biometrika*, **66**, 675–678.
- Banerjee, A., Dolado, J. J., Galbraith, J. W., and Hendry, D. F. (1993). *Co-integration, Error Correction and the Econometric Analysis of Non-Stationary Data*. Oxford: Oxford University Press.
- Banerjee, A., Dolado, J. J., and Mestre, R. (1996). An ECM test for cointegration in a single equation framework. Mimeo, Institute of Economics and Statistics, University of Oxford.
- Banerjee, A., and Hendry, D. F. (1992). Testing integration and cointegration: An overview. *Oxford Bulletin of Economics and Statistics*, **54**, 225–255.
- Barndorff-Nielsen, O. E. (1978). *Information and Exponential Families in Statistical Theory*. Chichester: John Wiley.
- Boswijk, H. P. (1992). *Cointegration, Identification and Exogeneity*, Vol. 37 of *Tinbergen Institute Research Series*. Amsterdam: Thesis Publishers.
- Boswijk, H. P. (1995). Efficient inference on cointegration parameters in structural error correction models. *Journal of Econometrics*, **69**, ??–??
- Britton, A. (ed.) (1989). *Policy Making with Macroeconomic Models*. Aldershot, UK: Gower.
- Brodin, A., and Nymoen, R. (1992). Wealth effects and exogeneity: The Norwegian consumption function 1966(1)–1984(4). *Oxford Bulletin of Economics and Statistics*, **54**, 431–454.
- Bryant, R., Hooper, P., and Mann, C. L. (eds.) (1993). *Evaluating Policy Regimes: New Research in Empirical Macroeconomics*. Washington, DC: Brookings Institution.
- Calzolari, G. (1981). A note on the variance of ex post forecasts in econometric models. *Econometrica*, **49**, 1593–1596.
- Cartwright, N. (1989). *Nature's Capacities and their Measurement*. Oxford: Clarendon Press.
- Chong, Y. Y., and Hendry, D. F. (1986). Econometric evaluation of linear macro-economic models. *Review of Economic Studies*, **53**, 671–690. Reprinted in Granger C. W. J. (ed.) (1990), *Modelling Economic Series*. Oxford: Clarendon Press.
- Clements, M. P., and Hendry, D. F. (1993). On the limitations of comparing mean squared forecast errors. *Journal of Forecasting*, **12**, 617–637. With discussion.
- Clements, M. P., and Hendry, D. F. (1995). Forecasting in cointegrated systems. *Journal of Applied Econometrics*, 127–146.

- Dolado, J. J. (1992). A note on weak exogeneity in VAR cointegrated systems. *Economic Letters*, **38**, 139–143.
- Engle, R. F. (1982). Autoregressive conditional heteroscedasticity, with estimates of the variance of United Kingdom inflations. *Econometrica*, **50**, 987–1007.
- Engle, R. F., and Granger, C. W. J. (1987). Cointegration and error correction: Representation, estimation and testing. *Econometrica*, **55**, 251–276.
- Engle, R. F., and Hendry, D. F. (1993). Testing super exogeneity and invariance in regression models. *Journal of Econometrics*, **56**, 119–139.
- Engle, R. F., Hendry, D. F., and Richard, J.-F. (1983). Exogeneity. *Econometrica*, **51**, 277–304. Reprinted in Hendry D. F. (1993), *Econometrics: Alchemy or Science?* Oxford: Blackwell Publishers.
- Ericsson, N. R. (1992). Cointegration, exogeneity and policy analysis: An overview. *Journal of Policy Modeling*, **14**, 251–280.
- Ericsson, N. R., Hendry, D. F., and Mizon, G. E. (1996). Econometric issues in economic policy analysis.. Forthcoming, *Journal of Business and Economic Statistics*.
- Ericsson, N. R., and Irons, J. S. (1995). The Lucas critique in practice: Theory without measurement. In Hoover, K. D. (ed.), *Macroeconometrics: Developments, Tensions and Prospects*. Dordrecht: Kluwer Academic Press.
- Favero, C., and Hendry, D. F. (1992). Testing the Lucas critique: A review. *Econometric Reviews*, **11**, 265–306.
- Florens, J.-P., Mouchart, M., and Rolin, J.-M. (1990). *Elements of Bayesian Statistics*. New York: Marcel Dekker.
- Frisch, R. (1938). Statistical versus theoretical relations in economic macrodynamics. Mimeograph dated 17 July 1938, League of Nations Memorandum. Reproduced by University of Oslo in 1948 with Tinbergen's comments. Contained in Memorandum 'Autonomy of Economic Relations', 6 November 1948, Oslo, Universitets Økonomiske Institutt. Reprinted in Hendry D. F. and Morgan M. S. (1995), *The Foundations of Econometric Analysis*. Cambridge: Cambridge University Press.
- Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, **37**, 424–438.
- Granger, C. W. J., and Deutsch, M. (1992). Comments on the evaluation of policy models. *Journal of Policy Modeling*, **14**, 497–516.
- Haavelmo, T. (1944). The probability approach in econometrics. *Econometrica*, **12**, 1–118. Supplement.
- Hendry, D. F. (1984). Econometric modelling of house prices in the United Kingdom. In Hendry, D. F., and Wallis, K. F. (eds.), *Econometrics and Quantitative Economics*, pp. 135–172. Oxford: Basil Blackwell.
- Hendry, D. F. (1988). The encompassing implications of feedback versus feedforward mechanisms in econometrics. *Oxford Economic Papers*, **40**, 132–149.
- Hendry, D. F. (1995a). *Dynamic Econometrics*. Oxford: Oxford University Press.
- Hendry, D. F. (1995b). On the interactions of unit roots and exogeneity. *Econometric Reviews*, 383–419.
- Hendry, D. F. (1995c). A theory of co-breaking. Mimeo, Nuffield College, University of Oxford.
- Hendry, D. F. (1996). The econometrics of macro-economic forecasting. Presidential Address, Royal Economic Society. Forthcoming, *Economic Journal*.

- Hendry, D. F., and Ericsson, N. R. (1991). Modeling the demand for narrow money in the United Kingdom and the United States. *European Economic Review*, **35**, 833–886.
- Hendry, D. F., and Mizon, G. E. (1992). The role of weak exogeneity in econometric model policy analyses. Working paper, Institute of Economics and Statistics, Oxford.
- Hendry, D. F., and Mizon, G. E. (1993). Evaluating dynamic econometric models by encompassing the VAR. In Phillips, P. C. B. (ed.), *Models, Methods and Applications of Econometrics*, pp. 272–300. Oxford: Basil Blackwell.
- Hendry, D. F., and Mizon, G. E. (1996). Selecting econometric models for policy analysis by forecast accuracy. Mimeo, Nuffield College, University of Oxford.
- Hendry, D. F., and Richard, J.-F. (1982). On the formulation of empirical models in dynamic econometrics. *Journal of Econometrics*, **20**, 3–33. Reprinted in Granger C. W. J. (ed.) (1990), *Modelling Economic Series*. Oxford: Clarendon Press and in Hendry D. F. (1993), *Econometrics: Alchemy or Science?* Oxford: Blackwell Publishers.
- Hendry, D. F., and Richard, J.-F. (1983). The econometric analysis of economic time series (with discussion). *International Statistical Review*, **51**, 111–163. Reprinted in Hendry D. F. (1993), *Econometrics: Alchemy or Science?* Oxford: Blackwell Publishers.
- Hood, W. C., and Koopmans, T. C. (eds.) (1953). *Studies in Econometric Method*. No. 14 in Cowles Commission Monograph. New York: John Wiley & Sons.
- Hoover, K. D. (1990). The logic of causal inference: Econometrics and the conditional analysis of causation. *Economics and Philosophy*, **6**, 207–234.
- Johansen, S. (1992a). Cointegration in partial systems and the efficiency of single-equation analysis. *Journal of Econometrics*, **52**, 389–402.
- Johansen, S. (1992b). Testing weak exogeneity and the order of cointegration in UK money demand. *Journal of Policy Modeling*, **14**, 313–334.
- Johansen, S., and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration – With application to the demand for money. *Oxford Bulletin of Economics and Statistics*, **52**, 169–210.
- Kiviet, J. F., and Phillips, G. D. A. (1992). Exact similar tests for unit roots and cointegration. *Oxford Bulletin of Economics and Statistics*, **54**, 349–367.
- Koopmans, T. C. (1950). When is an equation system complete for statistical purposes?. In Koopmans, T. C. (ed.), *Statistical Inference in Dynamic Economic Models*, No. 10 in Cowles Commission Monograph, Ch. 17. New York: John Wiley & Sons.
- Lucas, R. E. (1976). Econometric policy evaluation: A critique. In Brunner, K., and Meltzer, A. (eds.), *The Phillips Curve and Labor Markets*, Vol. 1 of *Carnegie-Rochester Conferences on Public Policy*, pp. 19–46. Amsterdam: North-Holland Publishing Company.
- Mariano, R. S., and Brown, B. W. (1991). Stochastic-simulation tests of nonlinear econometric models. In Klein, L. R. (ed.), *Comparative Performance of U.S. Econometric Models*, pp. 250–259: Oxford University Press.
- Marschak, J. (1953). Economic measurements for policy and prediction. in Hood, and Koopmans (1953).
- Pagan, A. R. (1989). On the role of simulation in the statistical evaluation of econometric models. *Journal of Econometrics*, **40**, 125–139.
- Park, J. Y., and Phillips, P. C. B. (1988). Statistical inference in regressions with integrated processes.

- part 1. *Econometric Theory*, **4**, 468–497.
- Park, J. Y., and Phillips, P. C. B. (1989). Statistical inference in regressions with integrated processes. part 2. *Econometric Theory*, **5**, 95–131.
- Phillips, P. C. B. (1986). Understanding spurious regressions in econometrics. *Journal of Econometrics*, **33**, 311–340.
- Phillips, P. C. B. (1987). Time series regression with a unit root. *Econometrica*, **55**, 277–301.
- Phillips, P. C. B. (1988). Regression theory for near-integrated time series. *Econometrica*, **56**, 1021–1043.
- Phillips, P. C. B. (1991). Optimal inference in cointegrated systems. *Econometrica*, **59**, 283–306.
- Phillips, P. C. B., and Durlauf, S. N. (1986). Multiple time series regression with integrated processes. *Review of Economic Studies*, **53**, 473–495.
- Richard, J.-F. (1980). Models with several regimes and changes in exogeneity. *Review of Economic Studies*, **47**, 1–20.
- Richard, J.-F., and Zhang, W. (1996a). Accelerated importance sampling. Mimeo, University Of Pittsburgh, USA.
- Richard, J.-F., and Zhang, W. (1996b). Accelerated Monte Carlo integration: An application to dynamic latent variable models. In Mariano, R., Weeks, M., and Schuermann, T. (eds.), *Simulation Based Inference in Econometrics: Methods and Applications*. Forthcoming.
- Schmidt, P. (1974). The asymptotic distribution of forecasts in the dynamic simulation of an econometric model. *Econometrica*, **42**, 303–309.
- Simon, H. A. (1953). Causal ordering and identifiability. in Hood, and Koopmans (1953), Ch. 3.
- Turner, D. S., Wallis, K. F., and Whitley, J. D. (1989). Using macroeconomic models to evaluate policy proposals. in Britton (1989).
- Urbain, J.-P. (1992). On weak exogeneity in error correction models. *Oxford Bulletin of Economics and Statistics*, **54**, 187–207.
- Wallis, K. F. (1993). Comparing macroeconomic models: A review article. *Economica*, **60**, 225–237.
- Wallis, K. F., Andrews, M. J., Fisher, P. G., Longbottom, J., and Whitley, J. D. (1986). *Models of the UK Economy: A Third Review by the ESRC Macroeconomic Modelling Bureau*. Oxford: Oxford University Press.
- Wallis, K. F., Fisher, P. G., Longbottom, J., Turner, D. S., and Whitley, J. D. (1987). *Models of the UK Economy: A Fourth Review by the ESRC Macroeconomic Modelling Bureau*. Oxford: Oxford University Press.
- Wallis, K. F., et al. (1984, 1985). *Models of the UK Economy, I and II*. Oxford: Oxford University Press.