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Comment on “Economic Forecasting in a Changing World” (by Michael Clements and David Hendry)

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Abstract

Michael Clements and David Hendry make realistic assumptions about the nature of the economy and the models used to forecast it. Under those assumptions, Clements and Hendry clarify why forecasting models work when they do, and why they don't work when they don't. Their research also suggests how to improve the forecasting abilities of existing models.

A taxonomy of the sources of forecast error underpins Clements and Hendry's analysis. In my comments, I summarize their taxonomy; illustrate several implications, including for predictable and unpredictable forecast uncertainty; and re-examine forecast criteria, focusing on how mean square forecast errors can mislead.

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1 Introduction

Michael Clements and David Hendry have revolutionized the way we think about economic forecasting. Over the last two decades, they have developed a body of research that makes realistic assumptions about the nature of forecasting models and the economy itself. In that framework, Clements and Hendry have derived strong implications about those models, clarifying why forecasting models work when they do, and why they don't work when they don't. And, their research provides guidance on how to improve the forecasting abilities of existing models. In their current paper, Clements and Hendry (2008) summarize key results from their ongoing research on forecasting.

At the heart of Clements and Hendry's analysis is a classification of the sources of forecast error. Clements and Hendry (2008) utilize this taxonomy throughout their discussion but reference it only briefly, so Section 2 below provides an explicit exposition of the taxonomy and illustrates several implications, including for predictable and unpredictable forecast uncertainty. Section 3 turns to forecast criteria and, in particular, how mean square forecast errors can mislead. Section 4 summarizes what Clements and Hendry's research implies for forecasting in the future.

2 Sources of Forecast Uncertainty

Forecasts of economic variables play a prominent role in business decision-making, government policy analysis, and economic research. Forecasts often are model-based, with forecasts from an estimated model being constructed as the model's fitted values over a sample that was not used in estimation. Forecasts typically differ from the realized outcomes, with discrepancies between forecasts and outcomes reflecting forecast uncertainty.¹ Depending upon the degree and sources of forecast uncertainty, forecasts may range from being highly informative to being utterly useless for the tasks at hand.

In order to understand the sources of forecast uncertainty, Clements and Hendry (1998, 1999a) develop a formal theory of forecasting from mis-specified models when the economy is subject to structural change. Clements and Hendry's framework contrasts with traditional forecast theory, which assumes correctly specified models of ergodic data. The difference in assumptions between

¹Strictly speaking, "forecast uncertainty" should be called "forecast error uncertainty", as the forecast error is what is uncertain, not the forecast. However, following common usage in the literature, and for brevity's sake, the phrase "forecast uncertainty" is used throughout.

the two theories gives rise to Clements and Hendry's comprehensive taxonomy for the sources of forecast error. This section thus summarizes that taxonomy (Section 2.1), illustrates some consequences of that taxonomy for predictable and unpredictable forecast uncertainty (Section 2.2), and highlights several additional implications (Section 2.3).

Hendry and Ericsson (2001) focus on the implications of this forecast theory for forecast uncertainty, and Clements and Hendry (2002) compile a wealth of recent results on forecasting. See also Emerson and Hendry (1996), Clements and Hendry (1997, 1999b), Hendry and Mizon (1999, Section 9; 2005), Clements and Hendry (2001), Hendry and Clements (2004), and Clements and Hendry (2005a, 2005b, 2006).

2.1 A Taxonomy

This subsection examines the determinants of forecast uncertainty, drawing on a taxonomy for the sources of model-based forecast error in Clements and Hendry (1998, Chapter 7.3, especially Table 7.1).

The sources of forecast error depend on the forecast model itself and on the process generating the data. Forecast models typically have three components: the variables of the model (including deterministic terms such as intercepts and trends, and stochastic terms such as inflation and output), the coefficients of those variables, and unobserved errors or shocks. Each component can contribute both predictable and unpredictable uncertainty to the forecast although, in practice, the uncertainty in the measurement of the variables themselves is typically treated as being entirely unpredictable.

Drawing on these two ways of viewing forecasts and their associated errors, Table 1 summarizes Clements and Hendry's taxonomy, partitioning the sources of forecast error into "what we know that we don't know" (predictable uncertainty: Items 1(a)–1(b)) and "what we *don't* know that we don't know" (unpredictable uncertainty: Items 2(a)–2(c)), paraphrasing Singer (1997, p. 38). In practice, all of the listed sources are important when analyzing forecast uncertainty.²

Items 1(a) and 1(b) are predictable in the sense that the degree of uncertainty arising from them can be anticipated and even calculated. Item 1(a)—the cumulation of future shocks to the economy—captures the uncertainty inherent to future events. It contains shocks that are expected to occur, given the model used in forecasting. Item 1(b) results in "estimation uncertainty",

²For expositional convenience, Table 1 aggregates the *nine* sources of forecast error mentioned by Clements and Hendry (2008, Section 3) into five sources.

Table 1: A taxonomy of the sources of model-based forecast error.

1. Sources of predictable uncertainty
“what we know that we don’t know”
(a) cumulation of future errors (“shocks”) to the economy
(b) inaccuracies in estimates of the forecast model’s parameters
2. Sources of unpredictable uncertainty
“what we <i>don’t</i> know that we don’t know”
(a) currently unknown future changes in the economy’s structure
(b) mis-specification of the forecast model
(c) mis-measurement of the base-period data

which is due to using coefficient estimates in forecasting, rather than the underlying parameter values.

By contrast, Items 2(a), 2(b), and 2(c) are unpredictable and unanticipated. If their extent and nature were known, they could be incorporated into the model and they—or at least the uncertainty that they create—would be predictable and predicted. Interactions between the three sources of unpredictable uncertainty can be particularly important, as Clements and Hendry (2008) discuss. The two sources of *predictable* uncertainty in Item 1 are central to evaluating the forecasts from empirical models, as summarized below.

Each of the five sources of forecast uncertainty could induce substantial forecast errors. However, detailed theoretical analyses, Monte Carlo simulations, and empirical evidence all suggest that the most pernicious source is Item 2(a)—currently unknown future changes in the economy’s structure—in particular, future shifts in the coefficients on deterministic terms. These shifts are equivalent to shifts in the equilibrium mean, which is how Clements and Hendry (2008) interpret that source. Such shifts typically induce large and systematic forecast failure, whereas the other sources of forecast error have less damaging effects. For example, quite large shifts in a model’s coefficients on stochastic variables—such as the feedback coefficients in a cointegrated system—have little effect on the forecast errors, provided that the equilibrium mean remains unchanged; see Clements and Hendry (1999a) and Hendry (2000). As Burns (2001) notes, data inaccuracy at the forecast’s origin (Item 2(c)) can deleteriously affect forecasts because the measurement error acts like a deterministic shift. Likewise, any sufficiently large stochastic

perturbation will reduce forecast accuracy. In general, however, Item 2(a) is the culprit when forecast failure occurs, and it is the focus of Clements and Hendry (2008).

2.2 Predictable and Unpredictable Forecast Uncertainty

Measures of *predictable* forecast uncertainty can be constructed from Item 1; see Ericsson (2001, 2002). These measures have two primary uses in economic practice—one *ex ante*, and the other *ex post*.

Prior to the realization of outcomes, measures of predictable forecast uncertainty convey the “expected” or anticipated uncertainty of the forecast errors, thus helping to qualify the forecasts themselves and to give a picture of the expected range of likely outcomes. That is, a measure of forecast uncertainty helps distinguish between a forecast’s numerical accuracy and its statistical accuracy. Information about forecast uncertainty is important in addition to the forecast itself.

Predictable forecast uncertainty now takes a prominent role in the economic policy arena, as exemplified by the Bank of England’s “fan charts”. For the last several years, the Bank of England—followed by several other central banks—has published its assessment of (predictable) forecast uncertainty through fan charts for its forecasts of both inflation and GDP growth; see the Bank of England (2008). Figure 1 reproduces the Bank’s fan chart (their Chart A, on p. 46) for its February 2007 forecast of inflation. The Bank describes their fan charts of inflation as follows.

The fan chart depicts the probability of various outcomes for CPI inflation in the future. If economic circumstances identical to today’s were to prevail on 100 occasions, the [Monetary Policy Committee’s] best collective judgement is that inflation over the subsequent three years would lie within the darkest central band on only 10 of those occasions. The fan chart is constructed so that outturns [i.e., outcomes] of inflation are also expected to lie within each pair of the lighter red areas on 10 occasions. Consequently, inflation is expected to lie somewhere within the entire fan chart on 90 out of 100 occasions. The bands widen as the time horizon is extended, indicating the increasing uncertainty about outcomes. Bank of England (2008, p. 8)

This fan chart summarizes the Bank’s predicted or anticipated probability distribution of inflation outcomes. Outcomes for inflation could occur outside

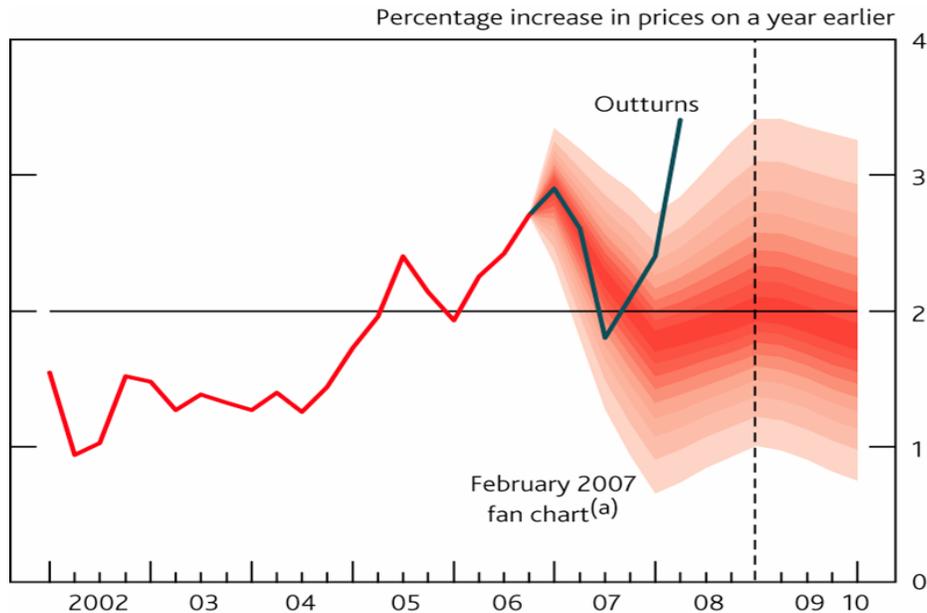


Figure 1: Actual U.K. CPI inflation, the February 2007 forecasts by the Bank of England, and the corresponding fan chart for predictable forecast uncertainty. Source: Bank of England (2008, p. 46, Chart A).

that range, but the probability of those outcomes is believed to be relatively small.

In fact, the outcome for the most recent quarter (2008Q2) lies well above the 90% band, reflecting "... three key unanticipated developments: the sharp rise in energy and food prices; the tightening in credit conditions; and the marked depreciation of sterling." (p. 46) As the Bank's *Inflation Report* notes, these reasons for the higher rate of inflation were unanticipated; and they appear to be persistent—precisely the circumstances in which forecasts benefit from adjustments such as intercept correction. And, the Bank did markedly increase its inflation projections in light of these factors. Such an analysis of forecasts thus can benefit the construction of monetary policy, intertwining the statistical and economic aspects of predictable uncertainty.

After outcomes are known, measures of predictable forecast uncertainty can help evaluate the forecasts, as in Figure 1. Evaluation may also include a formal statistical analysis with tests of parameter constancy, and such tests have been central to assessing and improving empirical economic models. Fisher (1922) and Chow (1960) provide the initial development of these evaluation

techniques, with Hansen (1992a, 1992b) and Andrews (1993) constructing constancy tests with an unknown breakpoint. Goldfeld (1973, 1976), Judd and Scadding (1982), and Baba, Hendry, and Starr (1992) examine constancy tests in their central role in modeling the demand for money. At a more general level, constancy tests are key to evaluating the Lucas (1976) critique, with constancy tests providing the primary empirical basis for refuting the Lucas critique; see Hendry (1988), Engle and Hendry (1993), Ericsson and Irons (1995), and Hendry (2002). Predictable forecast uncertainty is also central to calculating forecast encompassing test statistics; see Chong and Hendry (1986), Granger (1989), Ericsson (1992), Ericsson and Marquez (1993), and West (1996).

Measures of predictable forecast uncertainty have immediate economic implications. For instance, if the forecast uncertainty for a certain variable is viewed as being considerable, insurance might be desirable as a mechanism for protecting against untoward outcomes; and different types of insurance might be available. Also, forecast uncertainty is inherent to many economic activities, such as business investment, with the possibility of large successes often being an attraction of such investment. Forecast uncertainty is ubiquitous in economics, and many consequences follow from the presence and extent of that uncertainty.

2.3 Additional Implications

Several additional implications follow from the taxonomy of forecast errors.

First, models that inherently preclude deterministic terms can never suffer from deterministic shifts, so those models are unlikely to experience systematic forecast failure. As Clements and Hendry (2008) discuss, this implication is consistent with the empirical findings by Eitrheim, Husebø, and Nymoen (1999) *inter alia*.

Second, reformulating econometric models to make them more robust to such shifts becomes a priority. Cointegration removes a specific form of non-stationarity: that due to stochastic trends or unit roots. Unfortunately, cointegration makes the resulting models sensitive to deterministic shifts, such as shifts in the equilibrium mean.

Third, a potential solution is intercept correction, which adjusts an equation's constant term when forecasting. Historically, intercept correction has been heavily criticized, in fair part because it had no role in the formal theory of forecasting, even although it had long been known to improve forecast performance in practice; see McNees (1990) *inter alia*. In light of the forecast taxonomy in Table 1 and its underlying analytics, intercept correction regains

a prominent role in forecasting. Intercept correction places the model back on track at the forecast origin, setting the most recent *ex post* forecast error to zero. That procedure offsets deterministic shifts after they have occurred. Intercept correction thus can mitigate a model's sensitivity to shifts, where that sensitivity was induced by incorporating equilibrium relations through cointegration analysis. Intercept correction should typically be implemented if shifts are suspected, as when forecast failure has recently occurred. The benefits of intercept correction place a value on early detection of structural change in the economy; see Groen, Kapetanios, and Price (2008).

Fourth, models with no causal variables may outperform those with some correctly included causal variables; see Clements and Hendry (1998, pp. 47ff). Intercept correction, however, can reflect and so offset the deterministic shifts that can swamp useful information from causal factors.

Fifth, and at a more prosaic level, forecast uncertainty depends upon the variable being forecast, the economic process determining the variable being forecast, the information available for constructing forecasts, and the type of model used for forecasting; see Ericsson and Marquez (1998). Specifically, some variables may be inherently more difficult to forecast than others. For instance, imports and exports each might be highly predictable, and good models might exist for forecasting them. The trade balance—that is, the value of exports minus imports—might be quite difficult to forecast. In particular, by being the difference between two relatively large and similar quantities (exports and imports), the trade balance is itself a relatively small quantity, whereas its forecast error reflects the forecast errors of both imports and exports. As another example, forecasting the level of the exchange rate might be relatively easy, in that the exchange rate in (say) a month's time is likely to be close to today's exchange rate. That said, forecasting the change in the exchange rate over the next month could be quite difficult. So, the particular variables being forecast and the transformations applied to those variables can affect the degree of forecast uncertainty present.

Sixth, the underlying process generating the data plays a role in determining forecast uncertainty, such as by placing limits on the minimum forecast uncertainty obtainable from a model. That distinguishes between the predictable forecast uncertainty—that is, the forecast uncertainty anticipated, given the model—and the actual forecast uncertainty, which is the uncertainty arising from the combination of the model with the actual behavior of the economic data.

Seventh, forecast uncertainty depends upon the information available for constructing the forecasts. This aspect is closely tied to the design of the forecast model. More information would seem to be beneficial for forecasting,

and it is so in some situations. That said, when the model is mis-specified and there are structural breaks in the data, use of additional information can actually increase forecast uncertainty; see Clements and Hendry (1999a, Chapter 2).

Eighth, forecast uncertainty depends upon the model that is being used for forecasting. Some models may simply be better for forecasting than others. Also, the particular form of the model determines what the predictable forecast uncertainty is, as distinct from the *actual* forecast uncertainty that arises. That distinction exists because a model is a simplified characterization of the economy, not a reproduction of the economy.

To illustrate the dependence of predictable forecast uncertainty on the choice of model, consider forecasting monthly oil prices from two (albeit simple) models: a deterministic linear trend model, and a random walk with drift. For each model, estimation is over January 2002–June 2006, and forecasting is for July 2006–December 2009. The data are the nominal spot price (P) on West Texas Intermediate (Cushing, Oklahoma) crude oil FOB (US\$/barrel), available online from the U.S. Department of Energy ([tonto.eia.doe.gov/dnav/pet/pri_spt_s1_m.htm](http://tonto.eia.doe.gov/dnav/pet/pet_pri_spt_s1_m.htm)).

Figure 2a shows the results from estimating the linear trend model and forecasting from it. The left half of Figure 2a plots the actual oil price and its fitted values; the right half plots the model's forecasts. The vertical bars around those forecasts represent the predictable forecast uncertainty, as measured by the 95% confidence intervals, which are roughly $\pm 2\hat{\sigma}$ (i.e., plus-or-minus twice the estimated equation standard error). While this model for the oil price does include a trend, that trend is deterministic, implying that its future values are known, as well as its current and past values. So, in essence, this model is static, and the anticipated forecast uncertainty is constant across different forecast horizons.

Figure 2b plots the actual, fitted, and forecast values from the random walk model of the oil price, using the same sample periods for estimation and forecasting as with the trend model. The confidence intervals for the random walk forecasts in Figure 2b increase very substantially as the forecast horizon itself increases, contrasting with confidence intervals of (approximately) fixed width in Figure 2a.

Figures 2a and 2b portray two very different patterns for the anticipated (or predicted) forecast uncertainty, and their comparison illustrates how model choice can affect those patterns. Exactly the same series is being modeled and forecast in Figures 2a and 2b: only the models themselves differ. Static models often imply predicted forecast uncertainty that is time invariant or nearly so, whereas dynamic models often imply time-dependent predicted forecast

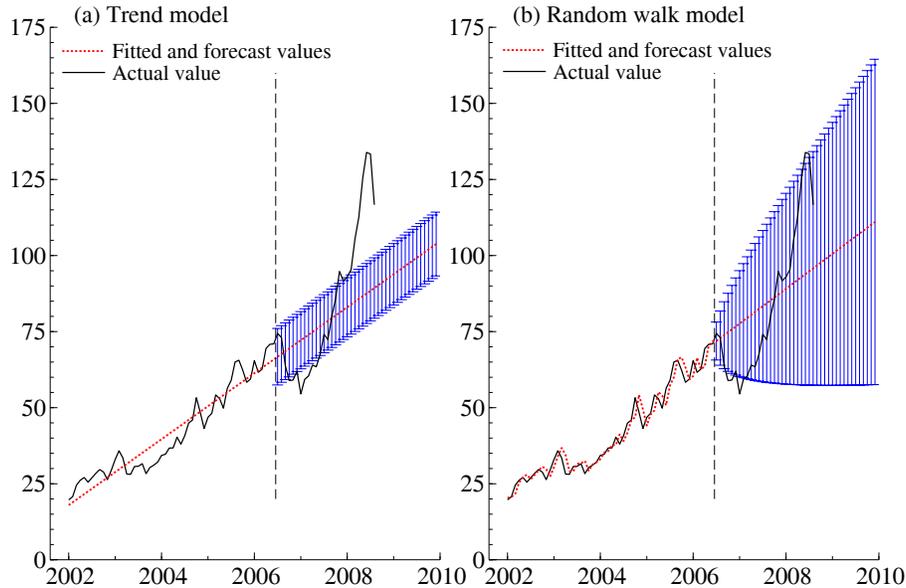


Figure 2: Actual, fitted, and forecast values from the trend and random walk models of the oil price, with 95% confidence intervals for the forecasts.

uncertainty that increases in the forecast horizon. While the models underlying Figures 2a and 2b present static and dynamic relationships as black and white, a whole spectrum of models exists with both static and dynamic aspects, and with consequent effects on the models' predictable forecast uncertainty.

3 Forecast Criteria

Many criteria exist for evaluating forecasts. Test statistics of parameter constancy form one class of criteria, with a given model's in-sample performance being compared with the same model's out-of-sample record. Mean square forecast errors (MSFEs) provide another common criterion, in which a given model's forecasts are compared with the forecasts of other models. While MSFEs are ubiquitous in economic analysis, comparisons of MSFEs are hazardous; see Clements and Hendry (1993). This section shows how comparison of MSFEs can be misleading and, in so doing, shows how the MSFE itself lacks robustness as a measure of forecast performance.

To illustrate, consider the forecasts for the crude oil spot price P over January 2007–June 2008 from two new models—Model A and Model B—as

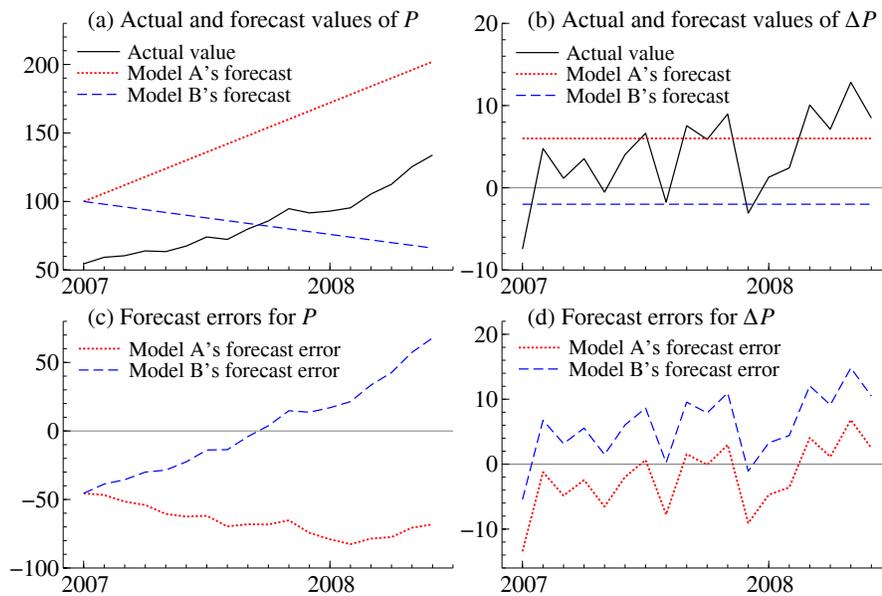


Figure 3: Actual values of P and ΔP , forecast values from Models A and B, and the corresponding forecast errors.

given in Figure 3a. The models' forecasts are both simple linear trends, but with different slopes. Model A systematically over-forecasts the price of oil, but the change in its forecast from one period to the next is roughly the same as the increase in the price of oil. The forecasts from Model B are numerically closer to the price of oil, but the path of the forecasts and the path of actual oil prices head in opposite directions.

Figure 3c (directly below Figure 3a) plots the corresponding forecast errors, i.e., the actual oil price minus the forecast price. Model A has forecast errors that are always larger in magnitude than those from Model B, and that relationship is reflected in the MSFEs for the models. The MSFE for Model A is more than four times the MSFE for Model B: see the first column of numbers in Table 2.

Now consider the *change* in the oil price (denoted ΔP), and the forecasts for ΔP that are implied by the two models. Figure 3b plots the actual changes in the oil price and the forecasts of those changes by the models. Both models are linear trends, so their forecasts of ΔP are constants—the slopes of their trends. Figure 3d (directly below Figure 3b) plots the corresponding forecast errors, i.e., the change in the actual oil price minus the forecast of that change.

Table 2: Mean square forecast errors for the oil price (P) and the change in the oil price (ΔP) for Models A and B.

Forecast Model	Variable Being Forecast	
	P	ΔP
Model A	4444.7	28.8
Model B	1080.6	60.7

Model A has forecast errors that are usually smaller in magnitude than those for Model B, and the MSFE for Model A is less than half the MSFE for Model B; see the final column of Table 2.

Thus, a simple transformation of the variable being forecast can alter the ranking of MSFEs across models, *with no change to any of the forecasts or to the underlying data*. Furthermore, the MSFE is not invariant to this transformation for a *given* model: see the values of the MSFE for each row in Table 2. The MSFE thus lacks robustness to simple data transformations. As Clements and Hendry (1993) show, the MSFE also lacks robustness when forecasts are multivariate or multi-step ahead. Both situations are common in economics. Intuitively, the problem with the MSFE is that it is a measure designed for a single variable being forecast one period ahead: data transformations, multivariate forecasts, and multi-step ahead forecasts are all outside that limited structure. Robust alternatives do exist, such as the predictive likelihood; again, see Clements and Hendry (1993).

Other issues also come into play when evaluating economic forecasts. As Granger (2001) discusses, the user of the forecasts—such as a policy agency or a firm—may treat positive and negative forecast errors differently, contrary to the standard symmetric assumption embodied in (e.g.) quadratic loss functions. Furthermore, in designing a model, the objectives for forecasting typically differ from those for policy analysis or for economic inference. While this statement may be surprising at first sight, it parallels the different types of exogeneity discussed in Engle, Hendry, and Richard (1983), and it follows from Clements and Hendry (1998, 1999a). One possible implication is to design different models for forecasting, policy, and economic inference. An alternative possible implication—suggested by Clements and Hendry (2008, Sections 3 and 4.2)—is to use a single model differently in those different contexts—for

instance, by modeling the data with an equilibrium correction model (EqCM) but forecasting from a differenced EqCM.

4 Forecasting in the Future

The implications of Clements and Hendry's analysis raise the following puzzle: why should economists develop econometric models that aim to elucidate the causal connections in an economy if such models cannot be shown to be of value in forecasting? The answer comes in two parts.

First, models are needed to address policy issues, and no theorems exist to justify non-causal models in that domain. Recent advances in computer-automated model selection have vastly improved the abilities of empirical modelers to develop congruent, economically interpretable models; see Hoover and Perez (1999), Hendry and Krolzig (2001), Campos, Ericsson, and Hendry (2005), and Doornik (2008) *inter alia*.

Second, forecasting competitions tend to be won by models that are robust to or rapidly adapt to structural change. Those characteristics of robustness and rapid adaptability can be transferred to econometric models, albeit in modified ways, without impugning their value in a policy context; see Hendry and Mizon (2000). These developments in forecasting and modeling lead to a sustainable framework for interpreting forecasts, although much analysis remains to be undertaken in order to establish the most appropriate forecasting procedures.

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