Discussion
Comments on 'Time-series Analysis, Forecasting and Econometric Modelling: The Structural Econometric Modelling, Time-series Analysis (SEMTSA) Approach', by A. Zellner.

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Professor Zellner has greatly contributed to econometrics in many aspects. This paper compiles a line of research developed by him and associates that goes back to the early 1970s, in which time-series techniques and Bayesian analysis are used in the construction of econometric models.

The starting point in this strategy is that the economic analysis must be based on statistical models which have been tested against data. Therefore the aim is to produce good models in order to forecast and explain reality and to serve policy makers.

Trying to obtain all these objectives at once is risky. On the other hand, before using a model the analyst must have evidence that the model is worth while. This can be obtained by submitting the model to the proof of forecasting. Therefore a first aim in modelling could be to obtain models that forecast well.

In this respect another principle of this strategy is to start from simple models, which means modelling specific variables and then trying to put them together. From a general multi-equational econometric model (SEM) the single transfer function corresponding to a particular variable can be derived. This transfer function constitutes the starting point of the SEMTSA methodology.

The variable chosen in Zellner's paper is the growth on real GDP (y) and a dynamic leading indicator model is constructed. The final model is

$$\alpha_3(L)y_t = c + \omega_1(L)SR_{t-1} + \beta GM_{t-1} + \gamma WSR_{t-1} + u_t, \tag{1}$$

where $\alpha_3(L)$ and $\omega_1(L)$ are polynomials on the lag operator L of order three and one, respectively. This is an extension of the univariate model:

$$\phi_3(L)y_t = a_t. \tag{2}$$

In passing from model (2) to model (1) some care must be taken in computing the dynamics of the endogenous variable. In order to clarify the discussion it is convenient to reformulate model (1) as

$$y_t = c^* + \frac{\omega_1(L)}{\alpha_3(L)} SR_{t-1} + \frac{\beta}{\alpha_3(L)} GM_{t-1} + \frac{\gamma}{\alpha_3(L)} SR_{t-1} + \frac{u_t}{\alpha_3(L)}. \tag{3}$$

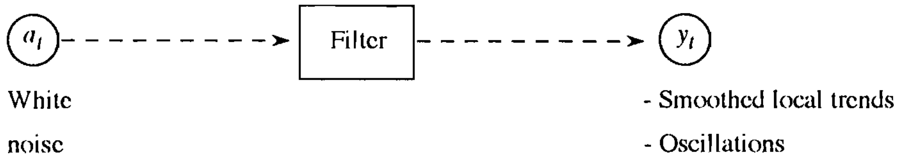

Figure 1

Model (2) can be explained by the use of Figure 1. In this figure, by passing a white-noise process through a filter—the polynomial $\phi_3(L)^{-1}$—we obtain a process that generates the y_t series, which can contain smoothed local trends and periodic oscillations. In particular, in model (2) the couple for conjugate complex roots in $\phi_3(L)$ generates periodic oscillations in y_t. In univariate models the input (a_t) which generates the data (y_t) has no structure at all and is white noise. Therefore the structure in the output is due completely to the filter.

In single transfer function (TF) equations data generation can be summarized by Figure 2. The lower part of the figure shows that from a white noise u_t, through a noise filter we obtain the residual component, N_t, of y_t. In models (1) or (3) this component is

$$N_t = u_t/\phi_3(L).$$

As in the univariate model, all the structure in N_t is due to the noise filter.

In the upper part of Figure 2 the inputs x_{jt}, $j = 1, \ldots, k$, have a structure by themselves and contribute to the generation of y_t by passing through a corresponding input filter j. Thus the contribution of the rate of change of real stock prices, SR, in y_t, in models (1) or (3) is

$$SR_t^* = \frac{\omega_1(L)}{\alpha_3(L)} SR_{t-1}. \tag{4}$$

However, since the x_{jt} inputs have a structure one could think of the filter being as simple as possible. In particular, periodic oscillations in the input filters could be an indication that some relevant input is missing in the model. Therefore, before accepting a model with input filters which generate oscillations it seems worth exploring if there are relevant missing inputs.

The question is that in extending a univariate model like (2) to a single TF model like model (1) it does not seem to be always a good strategy to keep the autoregressive structure of the

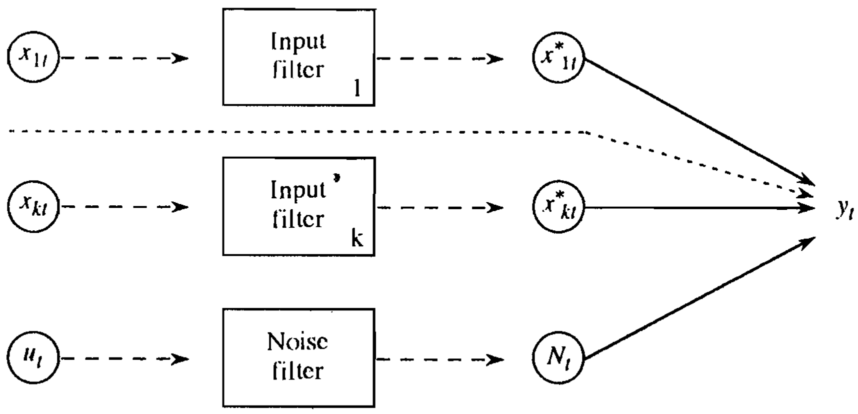

Figure 2

endogenous variable. It appears preferable to keep it only to define the noise filter and design each input filter by itself, avoiding rational filters with complex or negative autoregressive roots; for a further discussion of this point see Espasa (1982). Keeping the $\alpha_3(L)$ in the endogenous variable in model (1) implies, for instance, that a positive innovation in the rate of change of real stock prices in year t will produce positive and negative contributions in the rate of growth of real GDP in the following years. A justification for these future negative contributions does not seem clear to me.

In macroeconomic variables a missing input could be the relative price of energy. This can be illustrated with an example for the Spanish economy. Andrés *et al.* (1990) estimate the following model for real private investment (I_t):

$$I_t = \frac{-2.39}{\phi_2(L)} + \frac{(2.44 - 1.66L^2)}{\phi_2(L)} Y_{t-1} + \frac{2.24}{\phi_2(L)}(1-L)CU_t + \frac{(-1.52 + 0.57L)}{\phi_2(L)}(C/P)_{t-1} + \frac{-0.85}{\phi_2(L)}(1-L)^2\pi_t + \frac{a_t}{\phi_2(L)}, \tag{5}$$

where Y, CU, C/P, and π are real GDP, the degree of utilization of the productive capacity, the cost of use of capital, and the inflation rate, respectively. The variables are in logs and $\phi_2(L) = (1 - 0.56L + 0.27L^2)$.

Since the polynomial $\phi_2(L)$ has a couple of conjugate complex roots all the dynamic functions relating the explanatory variables to investment generate oscillations. Considering the contributions of the explanatory variables, and, in particular, the contribution of GDP

$$Y_t^* = \frac{(2.44 - 1.66L^2)}{1 - 0.56L + 0.27L^2} Y_{t-1} \tag{6}$$

and comparing Y_{t-1} with Y_t^* it can be seen that the filter generates oscillations in Y_t^* that are important in the years around the oil crises. This suggest that the relative prices of energy (RPE) could be an input that should be considered. Espasa and Senra (1992) introduce that variable and found that a dynamic relationship of investment with GDP depends on these relative prices and they estimate this relationship as:

$$Y_t^{**} = [1.25 - 0.004(1 + L + L^2)RPE_{t-1}]\,Y_{t-1} + 1.10(1+L)\,\Delta Y_{t-1}, \tag{7}$$

where $\Delta = (1 - L)$.

With this factor the resulting model for investment is

$$I_t = -5.83 + Y_t^{**} + 1.04(1-L)U_{t-1} - 0.83(C/P)_{t-1} - 0.27(1-L)^2\pi_t + e_t/(1 + 0.79L^2). \tag{8}$$

Model (8) says that under stable relative prices of energy (RPE equals zero) the dynamic function relating investment with GDP and its rate of growth is very simple and does not generate oscillations. On the other hand, the dynamic functions for all the inputs do not contain an autoregressive part. The autoregressive factor only appears in the residuals. Model (8) improves considerably the fit by reducing by one third the error variance, $\text{var}(e_t) = 0.66 \text{ var } (a_t)$.

With respect to the question of forecasting an aggregate variable directly from a model that explains it or by aggregating the forecasts from models which explain the components of this aggregate, I would like to comment from my experience in forecasting different variables of the Spanish economy for several years. The experience shows that if the components have different seasonal behaviour or trends then it is worth forecasting the aggregate from the component models. In other words, if the components are not co-integrated then the forecast of the aggregate can be improved by modelling the components. In Espasa and Pérez (1979), Espasa *et al.* (1984), and Espasa y Matea (1991) there is evidence of improving the forecast of money aggregates and inflation in the CPI by decomposing these aggregates into a few components which have quite different trends and/or seasonal behaviour.

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Author's biography:
Antoni Espasa is Professor of Econometrics at the Universidad Carlos III, Madrid. He obtained his PhD from the London School of Economics in 1975. He has been Chief Economist at the Research Unit of the Banco de España. His published research includes studies in spectral econometrics, dynamic models, applied econometrics, forecasting, and signal extraction in time series.

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Response to Comments of A. Espasa

A. ZELLNER

I thank Professor Espasa for his thoughtful comments on my paper. He provides a brief summary of our structural econometric modelling, time-series analysis (SEMTSA) approach to econometric model construction. Then he goes on to discuss one of our autoregressive leading indicator models in the context of transfer function modelling, the possibility of adding an additional input variable and aggregation issues.

General transfer function modelling techniques were employed in Zellner and Palm (1974, 1975). In the latter work we found that even with a large sample of monthly data for the USA, '... the parameter estimates are in general rather imprecise. This is somewhat disquieting as the sample size is relatively large' (p. 46). Looking back on this finding in the light of later work, it may be that the transfer functions' parameters are not constant but time varying. As noted in my paper, there are many reasons for parameters to be time varying and time-varying parameter models tended to perform better in forecasting than did fixed-parameter models. Also, Palm and I noted difficulties in selecting a particular transfer function specification from a multitude of possibilities even with a large sample of data. In our present work with annual macroeconomic data, for each country, we have a small sample of just 20 observations with which to begin our forecasting experiments and thus cannot entertain extremely complicated models with many parameters.

As regards Espasa's query regarding an innovation in the growth rate of real stock prices producing positive and negative contributions to the rate of growth of GDP in following years, it is well known in economics and other areas that when a shock hits a system it can produce oscillations, a characteristic of many physical systems and of many models of the business cycle. Further, innovations in the stock price variable might be produced from a variety of sources, as explained in my paper, including changes in the relative price of energy. This 'catch-all' property of the stock price leading indicator variable is a major reason for including it in our models.

While it is possible to view the transfer function model-building process as shown in Figure 2 in Professor Espasa's comments, it should be appreciated that this approach does not take account of the relation of the transfer functions to structural econometric models, as explained in my paper and illustrated with examples in previous work. Neglecting the link with structural equations can result in loss of important information about the system being modelled. Also, as indicated in my paper, the input x-variables need not be generated by independent processes. Intercorrelations among input variables can cause well-known problems in usual transfer function model identification and estimation procedures. While there are index, component, etc. techniques for attempting to cope with this range of problems, with just 20–30 observations, they did not appear to be feasible, and instead we opted for use of several 'catch-all' leading indicator variables that Burns and Mitchell discovered in their research with pre-Second World War data for several countries. Note, however, that addition of a measure of world output growth led to an elaboration of our model that produced improvement in forecasting performance for many countries.

Clearly, there are many additional variables that may lead to improved forecasts. However, including them all in a single relation with limited data is impractical. As I indicated in my paper, what is practical is to disaggregate by industrial sector and to develop sectoral econometric models with their associated transfer functions incorporating specific and general input variables. Then forecasts of sectors' outputs as well as forecasts of aggregate output can be obtained. It will be of great interest to determine whether disaggregation will lead to good sector forecasts and better aggregate forecasts as indicated in some of Espasa's and our theoretical work. Finally, I believe that the sectoral models so developed will be of great interest and value. Our preliminary work on this problem, involving use of demand, supply, and entry equations for each industrial sector, has yielded interesting non-linear models that are currently being analysed.

Thanks again to Professor Espasa for his stimulating comments and to the organizers of this productive meeting for inviting me to participate in it.