ANNOUNCEMENT
A Program to Solve an Econometric Model

BY RAY C. FAIR

A computer program is available that solves the U.S. econometric model in [1]. With this program one can either perform within-sample experiments (simulations) using the model or make actual outside-sample forecasts. The program also allows the model to be changed and adjusted in various ways. The program is a useful teaching device in that it allows students to examine various issues and questions in macroeconomics within the context of an actual econometric model. (See, for example, [2] for the use of the model to examine the sensitivity of fiscal-policy effects to assumptions about monetary policy. See also [3] and [4] for other applications.) The program is also a useful forecasting or policy tool in that it allows one to make forecasts of the future course of the U.S. economy under alternative assumptions about fiscal and monetary policies.

The program is written in FORTRAN-IV. Its minimum core requirement is about 150K. A tape of the program, coefficient estimates, and data, along with the appropriate documentation, is available from the author upon request. Write Ray C. Fair, Cowles Foundation, Box 2125, Yale Station, New Haven, CT 06520. The cost is $25.00, payable to Yale University.

REFERENCES

CORRIGENDA


There is an error in Theorem 5.2 of Sarris' (1973) otherwise fine article. The theorem and its proof should read as follows.

**Theorem 5.2** The Bayesian estimator of $\theta$ is equivalent to the following sequential estimator

$$\hat{\theta}_t = \hat{\theta}_0 + \frac{T_{1}^t}{\sigma_1^2} \left( \frac{1}{P(\theta)} \right) \left( \nu - X_{t-1} \right)$$

where $\hat{\theta}_0$ is the prior mean, $\sigma_1^2$ is the prior variance, and $P(\theta)$ is the posterior density function.

**Proof** The proof hinges on observing the structure of the matrix $T$. Denote by $T_1$ the first $k$ rows of $T$, by $T_2$ the next $k$ rows, etc. up to $T_k$. It is then easy to see, having in mind the definition of $V$ by (50) that

$$V_t = TV_{t-1} + \sigma_2^2 R_t$$

where

$$F_t = \begin{bmatrix} 0 & \ldots & R & RT^t & \ldots & RT^{k-1} \end{bmatrix}$$

then

$$V_t^t = TV_{t-1} + \sigma_2^2 R_t$$

Defining $\mu_t = T^t \hat{\theta}_t$ and using (60)

$$\hat{\theta}_t = \mu_t + V_t X^t \left( \frac{1}{\sigma_1^2} \left[ P(\theta) \right]^{-1} \right) \left( \nu - X_t \mu \right)$$

where $P(\theta)$ is the posterior density function, and $\sigma_1^2$ is the prior variance.
\[ T_{\hat{\theta}, UN} + \frac{\sigma^2}{\sigma^2} R M_i(P(\theta))^{-1}(y - X\mu) \]

\[ T_{\hat{\theta}, UN} + \theta R M_i(P(\theta))^{-1}(y - X\mu) \]

by Gary M. Erickson
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In the derivation of the two stage least squares recursive algorithm, the equation at the top of page 405 should read

$$e_t = w_t \delta_t(T) = v - \delta_t(T) + \alpha_t$$

where

$$\alpha = (X'X)^{-1}X'z_t$$

The TSLS algorithm, equation (31), should be similarly amended as follows:

$$\delta_t(T + 1) = \delta_t(T) + D_t(y - a(z + \alpha t)^t[y - \delta_t(T)]) + D_t(j_{t+1} - \eta^{-1}a_{t+1})$$

Of course, $r = 0$ if the equation is just identified.