9
Econometric Policy Evaluation

Introduction

This chapter follows, extends, and revises Chung's (1990) work by estimating adaptive versions of our model under both classical and Keynesian identification schemes. We assume that the shock process v_t is Gaussian. We maximize a Gaussian likelihood function to estimate the free parameters $(\theta, U^*, \rho_1, \rho_2, V_v)$ of the model. Notice that, as in a rational expectations model, this list includes no free parameters describing beliefs. Our primary purpose is to use our econometric results to assess whether and how they might vindicate our model government's econometric policy evaluation procedures.

Likelihood function

To simulate the adaptive Keynesian model of the preceding chapter, we started with initial conditions for (y, U, v) and for β, R_{XK}; drew a pseudo-random sequence $\{v_t\}_{t=0}^T$; then recursively computed an artificial history $\{y_t, U_t\}_{t=0}^T$ and $\{\beta_t, R_{XK,t}\}$. and an associated history for the government's beliefs. The way to estimate the model is to reverse this procedure by starting with the data record $\{y_t, U_t\}_{t=0}^T$ together with initial conditions for the government's beliefs and for (U, y, v), and then to use them to solve for a history of residuals $\{v_t\}_{t=0}^T$ associated with a particular set of parameter values. A maximum likelihood estimator of the parameters minimizes a particular measure of the size of these residuals.

By expressing the Phillips curve and the formula for y_t as a function of $h(\gamma_{t-1})X_{t-1}$ in reverse forms, we obtain the first two equations of the following five equations that form our adaptive model under the Keynesian identification scheme:

$$\begin{aligned} v_{1t} - \theta v_{2t} &= U_t - (\rho_1 + \rho_2)U_{t-1} + \rho_1\rho_2 U_{t-2} && (105a) \\ &\quad + \rho_2 v_{1t-1} - \rho_1 \theta v_{2t-1} - U^*(1-\rho_1)(1-\rho_2) \\ v_{2t} &= y_t - h(\gamma_{t-1})\, X_{t-1} && (105b) \\ \gamma_{t-1} &= \gamma(\beta_{t-1}) && (105c) \\ \beta_t &= \beta_{t-1} + g_t R_{XK,t}^{-1} X_{Kt} \left[y_t - \beta'_{t-1} X_{Kt} \right] && (105d) \\ R_{XK,t} &= R_{XK,t-1} + g_t [X_{Kt} X'_{Kt} - R_{XK,t-1}], && (105e) \end{aligned}$$

where $Ev_t v_t' = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \equiv V_v$, and where we require initial conditions for $[v_{-1}, R_{XK,-1}, \beta_{-1}, U_{-1}, \ldots, U_{-my}, y_{-1}, \ldots, y_{-my}]$. Here (105a), (105b) are versions of the actual Phillips curve (48) and the definition of v_{2t}; (105c) applies the invert the Phillips curve operator to deduce γ_{t-1} from β_{t-1}; and (105d)–(105e) repeat (91), the recursive formulas describing the government's learning scheme. Given the initial conditions and a data record for $\{U_s, y_s\}_{s=0}^{T}$, system (105) induces $\{v_t\}_{t=0}^{T}$ and an associated set of government beliefs $\{\beta_t, R_{XK,t}\}_{t=0}^{T}$. The appendix to this chapter displays the Gaussian likelihood function, whose dependence on the data and on the parameters is entirely mediated through their influence on the v_t's via (105).

For the classical version of the model, the likelihood function is defined in a similar way, except that (105c) is dropped, and (105d)–(105e) are replaced by the recursive algorithm (85).

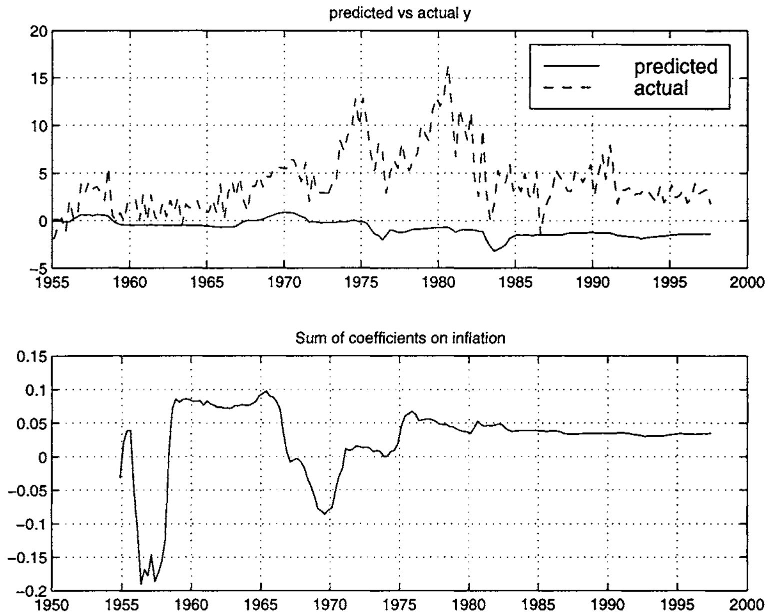

Figure 9.1. Actual inflation and outcome recommended by maximum likelihood estimates of classical model.

Estimates

I used the same measures of inflation and unemployment described in Chapter 1. For a sample period 1995I - 1997I, maximum likelihood estimates of the parameters are listed in Tables 3 and 4. I fixed $\delta = .999$ and $\lambda = .985$ to obtain these values.

Table 3
Parameter estimates under classical identification

Parameter	Estimate
θ	.1192
ρ_1	.9145
ρ_2	.5754
U^*	1.6483
$\log L$	−560

Table 4
Parameter estimates under Keynesian identification

Parameter	Estimate
θ	.163
ρ_1	.932
ρ_2	.667
U^*	2.745
$\log L$	−333

For the classical and Keynesian adaptive models, respectively, Figures 9.1 and 9.2a display the one-step ahead prediction for inflation, $\hat{y}_t$, from the best-fitting models.[1] Recall that the prediction $\hat{y}_t$ is the government's target y coming from the Phelps problem, solved at this period's estimate for γ. The top panels of Figure 9.1 and Figure 9.2a reveal that both versions of the model fit the inflation process badly. The fit is appreciably worse for the model under the classical identification scheme (Figure 9.1). The Keynesian identification scheme leads to a more promising reflection of the inflation pattern, though the gap between predicted and actual, which equals v_{2t}, is large after 1973 until 1990. The Keynesian model to some extent matches the acceleration of inflation in the 1970's but underestimates inflation for the next 15 years. The classical model fails even to match the acceleration in inflation leading up to 1970. Its better match to data caused adoption of the Keynesian identification scheme in the U.S. Phillips curve literature. The lower panel of Figure 9.2a shows how the induction hypothesis describes the government's beliefs after the mid 1970's.

Figure 9.2b displays 95% and 99% confidence ellipsoids for the sum of weights on lagged inflation and the constant for $t = 1960, 1965, 1970, 1975, 1980, 1985$. Qualitatively, they resemble the pattern found in our simulations: initially they are away

[1] These sample paths are simulations of the models at the maximum likelihood parameter values driven by sample paths of the shocks computed from the appropriate version of (105).

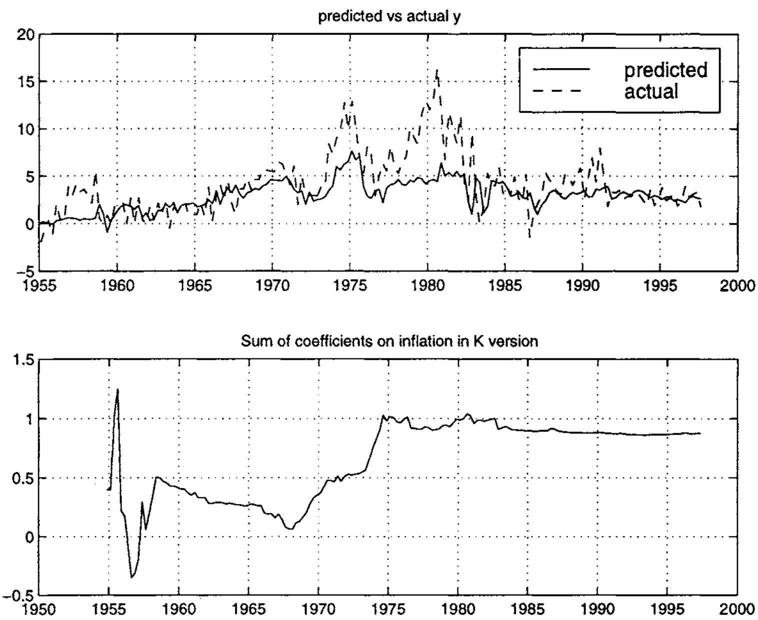

Figure 9.2a. Actual inflation and outcome recommended by maximum likelihood estimates of Keynesian model.

from the induction hypothesis, but leave room for doubt. During the 1970's, the point estimates moved, causing the centers of the ellipsoids to shift and doubt to dwindle.

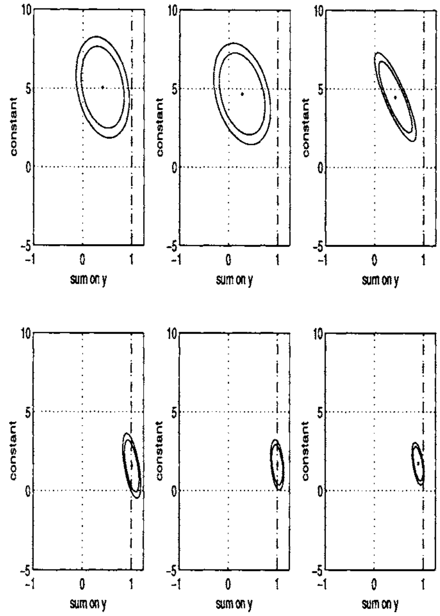

Figure 9.2b. 95% and 99% confidence ellipsoids for sum of coefficients on y (ordinate) and constant (coordinate) for first quarter of 1960, 1965, 1970, 1975, 1980, and 1985.

Interpretation

The large errors from our adaptive models are disappointing if we measure success by a good period-by-period fit. There is a long string of misses in the form of under predictions of inflation during the 1970's, even for the Keynesian model.

But such misses do not necessarily fail to vindicate econometric policy evaluation. To the contrary, the pattern of misses from the estimated models favors vindication.[2] Remembering that

[2] This section expresses opinions that I arrived at before receiving a message from Christopher A. Sims interpreting Chung's results in the same way.

the fitted value from the adaptive model is the government's recommendation as time passes extracts vindication from the econometric shortcomings. The fitted values under the Keynesian identification scheme form a sequence of recommendations that confirm the vindication story recounted above. The econometric estimates tell us that unreconstructed Keynesian Phillips curve fitters would have detected the adverse shift in the empirical Phillips curve and, through the induction hypothesis combined with the Phelps problem, would have recommended lowering the inflation rate. Those quantitative policy evaluators would not have concurred with the loosely argued recommendations current in the late 1970's that long lags in expectations made it too costly to disinflate. Our results say that recommendations under classical identification would have been even more timely.

Appendix on likelihood function

Following Chung (1990), we can compute the Gaussian likelihood function of a sample of $\{U_t, y_t\}$ conditional on the initial conditions for y, U, v, β, R_{XK}.

Because the determinant of the Jacobian of y_t, U_t with respect to v_t is unity, the Gaussian probability distribution of y_t, U_t, conditional on X_{t-1}, is:

$$L(U_t, y_t \mid X_{t-1}) = (2\pi)^{-1/2}|V_v|^{-1/2}\exp(-\frac{1}{2}\, v_t' V_v^{-1} v_t).$$

We can condition the likelihood function for a sample $U = [u_1, \cdots, u_T]$, $Y = [y_1, \cdots, y_T]$ on initial values v_{10}, v_{20} that we will typically take as zero. Then the Gaussian log likelihood function is:[3]

$$\log L(U, Y \mid X_{-1})$$

[3] As usual, we can accelerate the calculation of the likelihood by concentrating out the variance parameters to obtain the estimators, e.g., $V_v = T^{-1}\sum_{t=1}^{T} v_t v_t'$.

$$= \log \left(\sum_{t=1}^{T} (2\pi)^{-1/2} \, |V_v|^{-1/2} \exp \left[-\frac{1}{2} \left(v_t' V_v^{-1} v_t \right) \right] \right)$$

$$= -\frac{T}{2} \log 2\pi - \frac{T}{2} \log \det V_v - \frac{1}{2} \sum_{t=1}^{T} \left(v_t' V_v^{-1} v_t \right).$$