

TRACKING EXERCISE

1. OVERVIEW OF ANSWER

People seem not to have had difficulty with the first part of the problem, with $\alpha = 0$, which is a pure tracking problem case. With $\alpha = 1$, however, the problem is no longer a pure tracking problem. In the in-class discussion students argued that setting $x_t = \hat{y}_t$ is still the solution for the control, and proceeded from there. This is, however, not correct.

It turns out (I didn't realize this in setting the problem) that $\alpha = 1$ is a knife-edge special case in which the solution dynamics are in a sense degenerate, so $x_t = \hat{y}_t$ is *almost* a correct solution. With other values of α , it is more clear that $x_t = \hat{y}_t$ is not a solution.

That $x_t = y_t$ is not a solution for the certainty-equivalent (CE) problem is clear once we recognize that the state evolution equation (16) can be written as

$$y_t - x_t = \rho y_{t-1}.$$

Everything on the right-hand side of this equation at $t = 0$ is given at that date. The choice of x_0 cannot affect y_{-1} . Choosing $x_0 = y_0$ is impossible unless y_{-1} happens to be zero. As we will show below, the optimal decision rule for the CE problem is $x_t = -y_t$. This has no effect on time-0 losses $\|y_0 - x_0\|^2$, because that is fixed at $\rho^2 y_{-1}^2$. But it does mean that $y_0 = 0$ and thus that, with the optimal decision rule, $y_1 = x_1 = 0$, and indeed that thereafter $y_t = x_t = 0$ for all $t > 0$. This also means that for $t > 0$, $y_t = x_t$, so in a sense the solution does set $y_t = x_t$, but not in the initial $t = 0$ period. The decision rule that does hold at every date is $y_t = -x_t$.

The problem is tricky because I meant to put x_{t-1} , not x_t , on the right-hand-side of (16). In that case y would be the state variable, y_0 not $y_0 - x_0$, would be given at time 0, and we would be right to expect a solution that made x_t a linear function of y_t , the state. To get the problem as stated into a standard form with lagged control, not current control, on the right-hand side of the state evolution equation, we must change notation, letting $z_t = y_t - \alpha x_t$ be the state. Then the system becomes

$$\max_{\{z_t, \sigma_t^2, x_t\}} E_{t-1} \left[\sum_{t=0}^{\infty} \beta^t \|z_t - (1 - \alpha)x_t\|^2 \right] - \theta (\log W_t - \log \sigma_t^2) \quad (1)$$

$$\text{subject to } z_t = \rho z_{t-1} + \rho \alpha x_{t-1} + \varepsilon_t \quad (2)$$

$$W_t = \text{Var}(z_t | \mathcal{I}_{t-1}) = \rho^2 \sigma_{t-1}^2 + 1 \quad (3)$$

$$W_t - \sigma_t^2 \geq 0, \quad (4)$$

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2. CERTAINTY EQUIVALENT PROBLEM

The FOC's for a Lagrangian approach to the CE version of this problem are

$$\partial x : \quad -2(z_t - (1 - \alpha)x_t)(1 - \alpha) = -\beta\rho\alpha\lambda_{t+1} \quad (5)$$

$$\partial z : \quad 2(z_t - (1 - \alpha)x_t) = \lambda_t - \beta\rho\lambda_{t+1}. \quad (6)$$

When $\alpha = \rho = 0$, so we are in the pure tracking case of the first question, it is easy to check that the solution is $z_t = y_t = x_t$. More generally, the FOC's reduce to

$$(1 - \alpha)(z_t - (1 - \alpha)x_t) = \beta\rho(z_{t+1} - (1 - \alpha)x_{t+1}). \quad (7)$$

Using the fact that we know the solution will have the form $x_t = \phi z_t$ for some ϕ , this becomes

$$(1 - \alpha)z_t = \beta\rho z_{t+1}, \quad (8)$$

and the CE state evolution equation becomes

$$z_t = \rho(1 + \phi\alpha)z_{t-1}. \quad (9)$$

These two equations then imply

$$\phi = \left(\frac{1 - \alpha}{\beta\rho} - 1 \right) \frac{1}{\alpha}. \quad (10)$$

When $\alpha = 1$, this makes $\phi = -1$, as claimed above.

3. PROBLEM WITH CE SOLUTION PLUGGED IN FOR x_t

Using the $x_t = \phi\hat{z}_t$ CE solution, we can rewrite the objective function (1) as

$$\begin{aligned} E_{-1} \left[\sum_{t=0}^{\infty} \beta^t ((z_t - \hat{z}_t)^2 + (1 - \phi + \alpha\phi)^2 \hat{z}_t^2 + \theta(\log W_t - \log \sigma_t^2)) \right] \\ = E_{-1} \left[\sum_{t=0}^{\infty} \beta^t (\sigma_t^2 + (1 - \phi + \alpha\phi)^2 \text{Var}_{-1}(\hat{z}_t) + \theta(\log W_t - \log \sigma_t^2)) \right] \end{aligned} \quad (11)$$

In the pure tracking case, where $\alpha = 0$ and $\phi = 1$, the $\text{Var}_{-1} \hat{z}_t$ drops out, and we end up with a deterministic problem in σ_t^2 and W_t . But when $\alpha \neq 0$, even when it is 1, the $\text{Var}_{-1} \hat{z}_t$ is present. It does depend on W_t and z_t , but it depends on the whole sequence of them at dates between 0 and t . There is therefore much work remaining to get the objective function into a standard form, depending only on the W_t, σ_t^2 sequence.

Here again, $\alpha = 1$ is a knife-edge special case. We have verified that in this case $E_{t-1} \hat{z}_t = 0$, so $\text{Var}_{-1}(z_t) = \text{Var}_{t-1}(\hat{z}_t) = W_t - \sigma_t^2$. Thus in this case the objective function becomes

$$E_{-1} \left[\sum_{t=0}^{\infty} \beta^t W_t \right] \quad (12)$$

and allowing straightforward (but tedious! I'm only 80% sure it's correct) solution, when combined with (3), to obtain

$$\sigma_t^2 = \frac{W_t}{W_t + \theta} \frac{\theta}{\beta \rho^2} \quad (13)$$

$$\therefore \sigma_t^2 = \frac{(\rho^2 \sigma_{t-1}^2 + 1)\theta}{(\rho^2 \sigma_{t-1}^2 + 1 + \theta)\beta \rho^2}. \quad (14)$$

So we see that in general σ_t^2 varies over time and converges to a steady state. This contrasts with the $\alpha = 0$ case, where the solution jumps to the steady state at $t = 1$. So long as $\beta \rho^2 < 1$, there will be a θ so large that the no-forgetting constraint always binds.

4. ORIGINAL PROBLEM STATEMENT

The problem is

$$\max_{\{y_t\}, \{\sigma_t^2\}} E_{t-1} \left[\sum_{t=0}^{\infty} \beta^t \|y_t - x_t\|^2 \right] - \theta (\log W_t - \log \sigma_t^2) \quad (15)$$

$$\text{subject to } y_t = \rho y_{t-1} + \alpha x_t + \varepsilon_t \quad (16)$$

$$W_t = \text{Var}(y_t | \mathcal{I}_{t-1}) = \rho^2 \sigma_{t-1}^2 + 1 \quad (17)$$

$$W_t - \sigma_t^2 \geq 0, \quad (18)$$

where $\varepsilon_t | \{y_s, x_s, s \geq 1\} \sim N(0, 1)$.

x_t is chosen with the \mathcal{I}_t information set and σ_t^2 is chosen with the \mathcal{I}_{t-1} information set. The information set \mathcal{I}_t consists of all values of x_s dated $s = t$ or earlier, or equivalently the value of all the noisy signals about y received up to time t .

- (1) Solve the problem for $\beta = .9, \rho = .9, \alpha = 0$ and various values of θ . Is there a value of θ so high that no information is collected? So low that the problem is deterministic?
- (2) Write out the Bellman equation for this problem for the same parameter values except now with $\alpha = 1$. Explain why your previous solution method doesn't work on this version of the problem.