

## Second Midterm Review Sheet, Part I

*Ec240a – Second Half, Fall 2018*

In preparing for the exam review your lecture notes, assigned course readings, problem sets and prepare answers to the questions on the review sheet(s). You may bring to the exam a single  $8.5 \times 11$  inch sheet of paper with notes on it. No calculation aides are allowed in the exam (e.g., calculators, phones, laptops etc.). You may work in pencil or pen, however I advise the use of pencil. Please be sure to bring sufficient blue books with you to the exam if possible. Scratch paper will be provided.

[1] Available is a random sample of  $i = 1, \dots, N$  farmers. We have measures of output,  $Y_t$ , and (labor) input,  $X_t$ , for each farmer (on a per hectare basis) for each of  $t = 1, \dots, T$  years. The sample is

$$\{(Y_{i1}, \dots, Y_{iT}, X_{i1}, \dots, X_{iT})'\}_{i=1}^N.$$

We assume that, for  $Y_t = \ln O_t$  and  $X_t = \ln L_t$ , output per hectare,  $O_t$ , equals

$$O_t = L_t^\beta Q^\gamma \exp(U_t)$$

with  $L_t$  labor,  $Q_t$  soil quality – which is unobserved by the econometrician – and  $U_t$  a stochastic, and also unobserved, input outside of the farmer's control (e.g., rainfall).

Our behavioral assumption is that the farmer chooses  $L_t$  to maximize expected profits. She knows period  $t$  output and input prices, respectively  $P_t$  and  $W_t$ , as well as her soil quality,  $Q$ .

$$L_t = \arg \max_l \mathbb{E} [P_t l^\beta Q^\gamma \exp(U_t) - W_t l | P_t, W_t, Q]$$

She does not know rainfall, assumed non-forecastable by anything in her information set, with marginal distribution

$$U_t \sim N(0, \sigma_U^2).$$

You may also assume that  $(P_t, W_t)$  varies independently of all other variables in the model and is also independently and identically distributed across farms and over time.

[a] Show that the farmer's  $t$  labor input is

$$X_t = \mu + \frac{1}{1-\beta} A + V_t$$

with  $\mu = \frac{1}{1-\beta} \left( \ln \beta + \frac{\sigma_U^2}{2} \right)$ ,  $A = \gamma \ln Q$  and  $V_t = \frac{1}{1-\beta} \ln \left( \frac{P_t}{W_t} \right)$ . How does rainfall risk affect the farmer's chosen labor input level? Soil quality?

[b] Show that

$$\mathbb{E}[Y_t | X_t, A] = \beta X_t + A.$$

Why is conditioning on land quality alone sufficient to identify  $\beta$ ? What maintained assumption is important for this result?

[c] Show that, for  $\sigma_A^2 = \mathbb{V}(A)$ , and  $\sigma_V^2 = \mathbb{V}(V_t)$  for  $t = 1, \dots, T$ , that

$$\begin{aligned}\mathbb{C}(A, X_t) &= \frac{1}{1-\beta} \sigma_A^2 \\ \mathbb{V}(X_t) &= \left( \frac{1}{1-\beta} \right)^2 \sigma_A^2 + \sigma_V^2 \\ \mathbb{E}[X_t] &= \mu + \frac{1}{1-\beta} \mathbb{E}[A] + \mathbb{E}[V_t].\end{aligned}$$

[d] Next use your results in part [c] to show that

$$\mathbb{E}^*[A|X_t] = \eta_0 + \eta_1 X_t$$

where

$$\begin{aligned}\eta_1 &= (1-\beta) \left[ 1 + (1-\beta)^2 \frac{\sigma_V^2}{\sigma_A^2} \right]^{-1} \\ \eta_0 &= E[A] - \eta_1 \left[ \mu + \frac{1}{1-\beta} \mathbb{E}[A] + \mathbb{E}[V_t] \right].\end{aligned}$$

[e] Using your results from parts [b] and [d] solve for the coefficient, say  $b$ , on  $X_t$  in  $\mathbb{E}^*[Y_t|X_t]$ . Does  $b = \beta$ ? Discuss economic conditions under which  $b \approx \beta$  as well as conditions where  $b \gg \beta$ .

[f] Let  $X = (X_1, \dots, X_T)'$ . Solve for  $\mathbb{V}(X)$ ,  $\mathbb{C}(A, X)$  and hence the coefficients  $\delta = (\delta_1, \dots, \delta_T)'$  on  $X_1, \dots, X_T$  in the linear regression

$$\mathbb{E}^*[A|X] = \lambda + X'\delta.$$

[g] Let  $Y = (Y_1, \dots, Y_T)'$  and  $W = (\mathbf{1}, X')'$  Solve for the multivariate linear predictor

$$\mathbb{E}^*[Y|X] = \Pi W.$$

Specifically, express the elements of the  $T \times (1+T)$  matrix  $\Pi$  in terms of  $\beta$ ,  $\lambda$  and  $\delta$ .

[h] Let  $\theta = (\beta, \lambda, \delta)'$ . Let  $\pi = \text{vec}(\Pi')$  be the  $T(T+1) \times 1$  vector constructed by vertically stacking the columns of  $\Pi$ . Let  $G$  be a  $T(T+1) \times (1+1+T)$  matrix such that

$$\pi = G\theta.$$

Derive the form of  $G$ .

[i] Consider the estimator

$$\hat{\pi} = \left[ \frac{1}{N} \sum_{i=1}^N (I_T \otimes W_i) (I_T \otimes W_i)' \right]^{-1} \times \left[ \frac{1}{N} \sum_{i=1}^N (I_T \otimes W_i) Y_i \right].$$

Further define  $U = Y - (I_T \otimes W_i)' \pi$  and

$$\Gamma = I_T \otimes \mathbb{E}[WW']$$

and

$$\Omega = \mathbb{E} \left[ (I_T \otimes W_i) U U' (I_T \otimes W_i)' \right].$$

Argue that  $\hat{\pi} \xrightarrow{P} \pi$  and furthermore also argue that  $\sqrt{N}(\hat{\pi} - \pi) \xrightarrow{D} \mathcal{N}(0, \Lambda)$  for  $\Lambda = \Gamma^{-1} \Omega \Gamma^{-1}$ .

[j] Construct a minimum distance estimate of  $\theta$  and derive its asymptotic sampling distribution.

[2] Let  $\mathbf{Y} = (Y_1, \dots, Y_N)'$  be  $N$  independent measurements of the same outcome, each distributed

$$Y_i \sim \mathcal{N}(\mu, \sigma_i^2).$$

Let  $\mathbf{c}$  be an  $N \times 1$  vector of constants. Consider estimates of  $\mu$  in the family

$$\hat{\mu} = \mathbf{c}' \mathbf{Y}. \tag{1}$$

[a] Show that the sample mean  $\bar{Y} = \frac{1}{N} \sum_{i=1}^N Y_i$  is a member of (1).

[b] Show that the mean squared error minimizing choice of  $\mathbf{c}$  is

$$\mathbf{c} = \mu^2 (\text{diag} \{ \sigma_1^2, \dots, \sigma_N^2 \} + \mu^2 \iota_N \iota_N')^{-1} \iota_N$$

with  $\iota_N$  an  $N \times 1$  vector of ones and  $\text{diag} \{ \sigma_1^2, \dots, \sigma_N^2 \}$  denoting a diagonal matrix.

[c] Further show that the  $i^{\text{th}}$  element of  $\mathbf{c}$  is

$$c_i = \frac{\mu^2}{\sigma_i^2} \frac{\left[ \sum_{i=1}^N \frac{1}{\sigma_i^2} \right]^{-1}}{\left[ \sum_{i=1}^N \frac{1}{\sigma_i^2} \right]^{-1} + \mu^2}.$$

**HINT:** For  $A$  an invertible matrix,  $u$  and  $v$  column vectors and  $b$  a scalar:

$$(A + buv')^{-1} = A^{-1} - \frac{b}{1 + bv' A^{-1} u} A^{-1} u v' A^{-1}.$$

[d] Assume that  $\sigma_i^2 = \sigma^2$  for all  $i = 1, \dots, N$ . Show that in this case the mean squared error minimizing estimate of  $\mu$  is

$$\hat{\mu} = \frac{\mu^2}{\frac{\sigma^2}{N} + \mu^2} \bar{Y}$$

Prove that this estimate converges in mean square to  $\mu$  (and hence also converges in probability).

[e] The estimate in part [d] is infeasible. Assume that  $\sigma^2$  is known and consider the feasible estimator

$$\hat{\mu} = \left( 1 - \frac{\frac{\sigma^2}{N}}{\bar{Y}^2} \right) \bar{Y}.$$

Provide a justification for this estimate. Argue that  $\hat{\mu} \xrightarrow{P} \mu$ . Do you think its mean squared error will be lower than that of the sample mean's in finite samples? Why?

[f] Rebut the assertion that “the sample mean’s day has come and gone”.