

Prelim Examination

Friday August 8, 2014 Time limit: 150 minutes

Instructions:

- (i) The exam consists of two parts. The total number of points for each part is 50. The number of points for each question is given below.
- (ii) The exam is closed book and closed notes.
- (iii) To receive full credit for your answers you have to explain your calculations.
You may state additional assumptions.

Part I

Question 1 (13 Points): In many areas of economics we use sample averaging to approximate expectations. The samples are often generated on the computer using random number generators. Consider the following problem:

Suppose that

$$\begin{bmatrix} X \\ Y \end{bmatrix} \sim N \left(\begin{bmatrix} \mu_X \\ \mu_Y \end{bmatrix}, \begin{bmatrix} \sigma_{XX} & \sigma_{XY} \\ \sigma_{YX} & \sigma_{YY} \end{bmatrix} \right). \quad (1)$$

Denote the joint density of (Y, X) by $p(x, y)$. To approximate the integral

$$\mathbb{E}[h(X, Y)] = \int \int h(x, y)p(x, y)dx dy \quad (2)$$

we could use a Monte Carlo average of the form:

$$\widehat{\mathbb{E}}[h(X, Y)] = \frac{1}{N} \sum_{i=1}^N h(X_i, Y_i), \quad (3)$$

where the pairs (X_i, y_i) , $i = 1, \dots, N$ are independently and identically distributed according to (1). You may assume that the function $h(x, y)$ is bounded.

- (i) (2 Points) Is $\widehat{\mathbb{E}}[h(X, Y)]$ an unbiased estimator of $\mathbb{E}[h(X, Y)]$? Explain.
- (ii) (3 Points) Derive the limit distribution of $\widehat{\mathbb{E}}[h(X, Y)]$? How exactly would you use the limit distribution to assess the accuracy of the Monte Carlo average? Explain.
- (iii) (8 Points) Suppose you can evaluate the integral

$$\int h(x, y)p(x|y)dx = g(y) \quad (4)$$

analytically. Use this ability to construct a better estimator of $\mathbb{E}[h(X, Y)]$, denoted by $\widehat{\mathbb{E}}^*[h(X, Y)]$. Show formally that your proposed estimator $\widehat{\mathbb{E}}^*[h(X, Y)]$ is more precise than the original estimator $\widehat{\mathbb{E}}[h(X, Y)]$ in (3).

Question 2 (24 Points): In golf tournaments, players play several rounds and the final score is the average score across the rounds. Suppose that we model the score of player i in round t as

$$Y_{it} = \lambda_i + U_{it}, \quad U_{it} \sim N(0, 1), \quad (5)$$

where λ_i reflects the innate skill of player i and U_{it} are some random shocks that affect the player's score in round t . We assume that the U_{it} 's are independent across i and t . There are N players in the tournament, and they play $T = 2$ rounds.

- (i) (2 Points) Let's focus on player i . Suppose you observe her/his score in round $t = 1$, Y_{i1} . Derive the maximum likelihood estimator of λ_i and call this estimator $\hat{\lambda}_i^{ml}$. What is your point prediction of the score for round $t = 2$, Y_{i2} ?
- (ii) (4 Points) Suppose that you learned that in the cross section, the distribution of skill is

$$\lambda_i \sim N(0, \sigma^2) \quad (6)$$

and someone gave you the exact value of σ^2 . Use this information to construct an alternative estimator (think Bayes!) of λ_i . Call this estimator $\hat{\lambda}_i^B$.

- (iii) (4 Points) In what sense is $\hat{\lambda}_i^B$ a better estimator than $\hat{\lambda}_i^{ml}$? Explain.
- (iv) (3 Points) In view of (5) and (6) what is the distribution of Y_{i1} conditional on σ^2 , $p(Y_{i1}|\sigma^2)$?
- (v) (4 Points) Using the cross-sectional information Y_{i1} , $i = 1, \dots, N$, from the first round of the tournament, derive a formula for the maximum likelihood estimator of σ^2 , denoted by $\hat{\sigma}_{ml}^2$.
- (vi) (4 Points) Show that $\hat{\sigma}_{ml}^2$ is a consistent estimator of σ^2 and derive its limit distribution.
- (vii) (3 Points) TRUE or FALSE? Because according to the model given by (5) and (6) performance in the tournament is independent across players, information about the performance of players $i = 2, \dots, N$ in round $t = 1$ does not help predicting the performance of player $i = 1$ in round $t = 2$. Explain carefully.

Question 3: (13 Points) Linear Regression Model

Consider the linear regression model

$$y_i = x_i' \theta + u_i, \quad u_i | x_i \sim iid(0, 1), \quad x_i \geq \epsilon > 0, \quad \mathbb{E}[x_i^2] = Q, \quad i = 1, \dots, n$$

Moreover, the x_i 's are also independent across i . Notice that we assumed that the conditional variance of u given x is known to be one.

- (i) (3 Points) Derive the likelihood function and the maximum likelihood estimator $\hat{\theta}$ under the assumption that the u_i 's are in fact normally distributed.
- (ii) (10 Points) TRUE or FALSE? In this framework the Wald test of the null hypothesis $H_0 : \theta = 0$ is more powerful than the likelihood ratio test.

Note: to answer this question, formally analyze both tests. As part of your analysis, characterize the acceptance and rejection regions for both tests for a type-I error of $\alpha = 0.10$.

Part II

Question 4: (30 Points): Take a linear regression model

$$Y = X\beta + U,$$

where X is $n \times k$ and β is $k \times 1$. Assume the data is i.i.d. and $\mathbb{E}[U_i|X_i] = 0$. Suppose the parameter β is known to satisfy the restrictions

$$\beta = Q\theta,$$

where Q is $k \times m$ and θ is $m \times 1$, $m < k$. The matrix Q is known and it is of full rank. The parameter θ is unknown.

- (i) (3 Points) How to identify θ .
- (ii) (3 Points) Is there a simple way to estimate θ by least squares? If so, find this estimator $\hat{\theta}_{LS}$.
- (iii) (3 Points) Let $\hat{\beta}_{LS}$ denote the LS estimator for β . One can also estimate θ from $\hat{\beta}_{LS}$ using the minimum distance criterion. Specifically, for some symmetric positive definite $k \times k$ matrix W , define

$$C(\theta) = (\hat{\beta}_{LS} - Q\theta)' W (\hat{\beta}_{LS} - Q\theta)$$

and define $\hat{\theta}_{MD}$ as the minimizer of $C(\theta)$:

$$\hat{\theta}_{MD} = \arg \min C(\theta).$$

Find this minimum distance estimator $\hat{\theta}_{MD}$.

- (iv) (3 Points) Is $\hat{\theta}_{MD}$ consistent for θ ?
- (v) (3 Points) Find the asymptotic distribution for $\hat{\theta}_{MD}$.
- (vi) (3 Points) Is there a choice of W so that $\hat{\theta}_{LS} = \hat{\theta}_{MD}$?
- (vii) (3 Points) What is the optimal choice of W for $\hat{\theta}_{MD}$?
- (viii) (3 Points) Suppose $\hat{\theta}_{MD}^{opt}$ is constructed with the optimal weight matrix. Compare the efficiency of $\hat{\theta}_{MD}^{opt}$ and $\hat{\theta}_{LS}$.
- (ix) (3 Points) How to test the hypothesis: $H_0 : R\theta = 0$ vs $H_1 : R\theta \neq 0$, where R is a $r \times m$ matrix with rank r and $r < m$. Be specific about the test statistic, the critical value, and the decision rule.
- (x) (3 Points) How to construct a confidence interval for the first element of θ , denoted by θ_1 ?

Question 5: (7 Points) Consider the model

$$\begin{aligned} Y_i^* &= X_i\beta + U_i, \text{ where} \\ \mathbb{E}[X_i U_i] &= 0. \end{aligned}$$

We do not observe the latent variable Y_i^* . Instead we observe an i.i.d. sample of X_i and Y_i , where

$$Y_i = Y_i^* + V_i$$

for some measurement error V_i that satisfies

$$\mathbb{E}[X_i V_i] = 0 \text{ and } \mathbb{E}[U_i V_i] \neq 0.$$

Let $\widehat{\beta}_{LS}$ denote the LS estimator of regressing Y_i on X_i .

- (i) (3 Points) Is $\widehat{\beta}_{LS}$ a consistent estimator of β ? If not, how to find instruments for X_i ?
- (ii) (4 Points) Derive the asymptotic distribution of $\widehat{\beta}_{LS}$ if $\mathbb{E}[X_i V_i] = c/\sqrt{n}$ for some constant c .

Question 6 (13 Points): The Tobit model is

$$\begin{aligned} Y_i^* &= X_i' \beta + U_i, \\ U_i &\sim N(0, \sigma^2), \\ Y_i &= Y_i^* 1(Y_i^* \geq 0), \end{aligned}$$

where $1(\cdot)$ is the indicator function. Suppose X_i and U_i are independent and the data is i.i.d.

- (i) (3 Points) Find $\mathbb{E}[Y_i|X_i]$. Recall that if $Z \sim N(0, 1)$, $\mathbb{E}(Z|Z > c) = \lambda(-c)$, where $\lambda(c) = \phi(c)/\Phi(c)$ and Φ, ϕ are the cdf and pdf of a standard normal distribution, respectively.
- (ii) (3 Points) Use the result above to suggest a LS estimator for the parameter β .
- (iii) (4 Points) Construct a maximum likelihood estimator of β .
- (iv) (3 Points) Show the asymptotic distribution of this maximum likelihood estimator and estimate the its standard error.

END OF THE EXAM