

## PROBLEM SET 3

### PROBLEMS DUE FRIDAY 2/11

Do the following problems:

#### Problem 1:

The regression slope  $\hat{\beta}$  in a CNLR model is distributed  $N\left(\beta, \sigma_{\hat{\beta}}^2\right)$  where  $\sigma_{\hat{\beta}}^2 = 1$ . The null hypothesis  $\beta = 0$  will be tested at the 10% significance level by using the statistic  $Z_0 = \hat{\beta}/\sigma_{\hat{\beta}}$ . That is, the null will be rejected if and only if  $|Z_0| > 1.645$ .

- (a) Write and run a program that tabulates the power of the test at the following 9 values of the true parameter  $\beta$ :  $-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2$ .
- (b) Redo (a) for the situation where  $\sigma_{\hat{\beta}}^2 = 4$ .
- (c) What do your two tables tell you about the effect of  $\sigma_{\hat{\beta}}^2$  on the power of the test?

#### Problem 2:

The regression slopes  $\hat{\beta}_1$  and  $\hat{\beta}_2$  in a CNLR model are distributed as bivariate normal:

$$\begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix} \sim N\left(\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}, \begin{pmatrix} 1 & r \\ r & 1 \end{pmatrix}\right)$$

where  $r = 0.6$ . The joint null hypothesis  $\beta_1 = \beta_2 = 0$  will be tested at the 5% significance level by using the statistic

$$W_0 = \frac{\left(\hat{\beta}_1^2 + \hat{\beta}_2^2 - 2r\hat{\beta}_1\hat{\beta}_2\right)}{(1 - r^2)}$$

That is, the null will be rejected if and only if  $|W_0| > 5.99$ .

- (a) Write and run a program that tabulates the power of the test at the following 9 pairs of the true parameter vector  $(\beta_1, \beta_2)$ :  $(-1, 1), (-1, 0), (-1, -1), (0, 1), (0, 0), (0, -1), (1, 1), (1, 0), (1, -1)$ .
- (b) Redo (a) for the situation where  $r = -0.6$ .
- (c) What do your two tables tell you about the effect of the correlation  $r$  on the power of the test?

#### Problem 3:

Suppose that  $Y_i$  is a discrete random variable (actually a *count variable*, such as, for example, number of accidents) whose conditional distribution given  $X_i$  is

$$\Pr(Y_i = y_i | X_i = x_i) = \frac{e^{-\beta x_i} (\beta x_i)^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, \dots$$

where  $X_i$  is a positive scalar random variable and  $\beta > 0$ . Assume that we have  $n$  independent observations  $\{(Y_i, X_i)\}_{i=1}^n$ .

- (a) Write down the (conditional) log-likelihood function of the sample and compute the maximum likelihood estimator of  $\beta$ ,  $\hat{\beta}_{MLE}$ .
- (b) Find the asymptotic distribution of  $\hat{\beta}_{MLE}$ .
- (c) Find the exact distribution of  $\hat{\beta}_{MLE}$ . (HINT: The sum of independent Poisson random variables with parameters  $\lambda_j$  is a Poisson variable with parameter  $\sum_j \lambda_j$ .)

**Problem 4:**

In the standard CNLR model,

$$Y_i = X_i\beta + \varepsilon_i$$

where  $\varepsilon|X \sim N(0, \sigma^2 I_n)$ , assume that  $K = 1$  and that  $\sigma^2 = \beta^2$ . Obtain the maximum likelihood estimator for  $\beta$  and the Cramér-Rao lower bound.

**Problem 5:**

Derive the log-likelihood function, the first order conditions for maximization, and the information matrix for the model:

$$\begin{aligned} Y_i &= X_i\beta + \varepsilon_i \\ \varepsilon_i|X_i &\sim N\left(0, (Z_i\gamma)^2\right) \end{aligned}$$

assuming i.i.d. sampling of  $(Y_i, X_i)$  across individuals. Here  $Z_i$  is a  $1 \times r$  subvector of  $X_i$ .

**Problem 6:**

Five sample observations are

$$\begin{array}{rcccccc} X & 4 & 1 & 5 & 8 & 2 \\ Y & 6 & 3 & 12 & 15 & 4 \end{array}$$

Assume a linear model,  $Y_i = \beta_1 + \beta_2 X_i + \varepsilon_i$ , with heteroskedasticity of the form  $Var(Y_i) \equiv Var(\varepsilon_i) \equiv \sigma_i^2 = \sigma^2 X_i^2$  where  $\sigma^2$  is a positive constant. Calculate the OLS and GLS estimates of  $\beta_1$  and  $\beta_2$  and the corresponding standard errors.

**Problem 7:**

Determine whether the following statement is true or false: Suppose that the CLR model applies to

$$E(Y|X) = X\beta$$

that  $T$  is a nonstochastic nonsingular matrix and that  $Y^* = TY$  and  $X^* = TX$ ; then the GLS regression of  $Y^*$  on  $X^*$  gives the same coefficient estimates as OLS of  $Y$  on  $X$ .