

Econometrics 710
 Midterm Exam
 March 21, 2002
 Sample Answers

1. The non-parametric bootstrap estimates the distribution of $w_i = (y_i, x_i)$ by the empirical distribution function $F_n(w)$. Since the data w_i is iid, the EDF is consistent and the non-parametric bootstrap is valid. Heteroskedasticity, e.g. random $E(e_i^2 | x_i)$ is irrelevant. One way to see this is that the EDF is drawing the pairs (y_i, x_i) jointly, so the full conditional distribution of y_i given x_i matches the data. The only important caveat is to observe that heteroskedasticity affects the validity of standard errors, and this is important for the percentile-t bootstrap. The presence of heteroskedasticity means that the standard errors should be calculated using the White formula. Doing so, the t-ratio is asymptotically standard normal (and hence pivotal) which is necessary to achieve an asymptotic refinement.
2. We have

$$\begin{aligned}\hat{\beta} &= (\hat{Z}'\hat{Z})^{-1} \hat{Z}'Y \\ &= (\hat{Z}'\hat{Z})^{-1} \hat{Z}'(Z\beta + e) \\ &= (\hat{Z}'\hat{Z})^{-1} \hat{Z}'Z\beta + (\hat{Z}'\hat{Z})^{-1} \hat{Z}'e\end{aligned}$$

Since $\beta = 0$ this simplifies to

$$\sqrt{n}\hat{\beta} = \sqrt{n} (\hat{Z}'\hat{Z})^{-1} \hat{Z}'e = \left(\hat{\Gamma}' \frac{1}{n} X'X \hat{\Gamma} \right)^{-1} \hat{\Gamma}' \frac{1}{\sqrt{n}} X'e.$$

By the WLLN,

$$\frac{1}{n} X'X \rightarrow_p Q = E(x_i x_i')$$

and the CLT

$$\frac{1}{\sqrt{n}} X'e \rightarrow_d N(0, \Omega)$$

where

$$\Omega = E(x_i x_i' e_i^2).$$

Combined with $\hat{\Gamma} \rightarrow_p \Gamma$ and the CMT, we find

$$\begin{aligned}\sqrt{n}\hat{\beta} &= \left(\hat{\Gamma}' \frac{1}{n} X'X \hat{\Gamma} \right)^{-1} \hat{\Gamma}' \frac{1}{\sqrt{n}} X'e \\ &\rightarrow_d (\Gamma'W\Gamma)^{-1} \Gamma'N(0, \Omega) \\ &= N\left(0, (\Gamma'W\Gamma)^{-1} \Gamma'\Omega\Gamma (\Gamma'W\Gamma)^{-1}\right).\end{aligned}$$

This is a complete answer.

Note: The following are examples of *inappropriate* statements, because the right-hand sides are functions of the sample

$$\begin{aligned}\hat{\Gamma}' X' X \hat{\Gamma} &\rightarrow_p \Gamma' X' X \Gamma \\ \hat{\Gamma}' n^{-1} X' X \hat{\Gamma} &\rightarrow_p \hat{\Gamma}' Q \hat{\Gamma} \\ \hat{\Gamma}' n^{-1/2} X' e &\rightarrow_d \hat{\Gamma}' N(0, \Omega)\end{aligned}$$

The following is also incorrect

$$E(\hat{\beta} | X) = (\hat{\Gamma}' X' X \hat{\Gamma})^{-1} \hat{\Gamma}' X' E(e | X) = 0.$$

It is incorrect because $\hat{\Gamma}$ is not a function of X alone. (The question does not specify how $\hat{\Gamma}$ is constructed but in any event it would be highly unlikely it would be only a function of X .)

Finally, it is *very* incorrect to write Γ^{-1} , $\hat{\Gamma}^{-1}$, X^{-1} or $(X\Gamma)^{-1}$, as none of these matrices are square, so clearly do not have inverses!

3. By definition,

$$\hat{V}_n = (X'X)^{-1} X' \hat{D} X (X'X)^{-1}$$

where $D = \text{diag}\{\hat{e}_i^2\}$. Thus

$$E(\hat{V}_n | X) = (X'X)^{-1} X' E(\hat{D} | X) X (X'X)^{-1}$$

where

$$E(\hat{D} | X) = \text{diag}\{E(\hat{e}_i^2 | X)\}.$$

Thus the main problem is to find $E(\hat{e}_i^2 | X)$. There are two different ways to do this. First, you can observe that \hat{e}_i^2 are the diagonal elements of the $n \times n$ matrix

$$\hat{e}\hat{e}' = Mee'M$$

where

$$M = I_n - X(X'X)^{-1}X'$$

Under the homoskedasticity assumption,

$$E(\hat{e}\hat{e}' | X) = ME(ee' | X)M = MI_n\sigma^2M = M\sigma^2.$$

Hence

$$E(\hat{e}_i^2 | X) = [M]_{ii}\sigma^2 \equiv \lambda_i\sigma^2,$$

where $[M]_{ii}$ is the i 'th diagonal element of M . This is

$$\lambda_i = [M]_{ii} = 1 - x_i'(X'X)^{-1}x_i.$$

The second way to calculate this is to observe that

$$\hat{e}_i = y_i - x_i'\hat{\beta} = e_i - x_i'(\hat{\beta} - \beta)$$

so

$$\hat{e}_i^2 = e_i^2 - 2e_i x_i' (\hat{\beta} - \beta) + x_i' (\hat{\beta} - \beta) (\hat{\beta} - \beta)' x_i.$$

Hence

$$E(\hat{e}_i^2 | X) = E(e_i^2 | X) - 2E(e_i x_i' (\hat{\beta} - \beta) | X) + E(x_i' (\hat{\beta} - \beta) (\hat{\beta} - \beta)' x_i | X).$$

Note that

$$E(e_i^2 | X) = \sigma^2,$$

and

$$\begin{aligned} E(e_i x_i' (\hat{\beta} - \beta) | X) &= E(e_i (\hat{\beta} - \beta)' x_i | X) \\ &= E(e_i e' X (X' X)^{-1} x_i | X) \\ &= \sigma^2 x_i' (X' X)^{-1} x_i, \end{aligned}$$

and

$$\begin{aligned} E(x_i' (\hat{\beta} - \beta) (\hat{\beta} - \beta)' x_i | X) &= x_i' E((\hat{\beta} - \beta) (\hat{\beta} - \beta)' | X) x_i \\ &= x_i' (X' X)^{-1} \sigma^2 x_i \end{aligned}$$

Together

$$\begin{aligned} E(\hat{e}_i^2 | X) &= \sigma^2 - 2\sigma^2 x_i' (X' X)^{-1} x_i + \sigma^2 x_i' (X' X)^{-1} x_i \\ &= \sigma^2 (1 - x_i' (X' X)^{-1} x_i) \\ &= \sigma^2 \lambda_i \end{aligned}$$

as derived above.

Okay, now we know $E(\hat{e}_i^2 | X)$. Let $\Lambda = \text{diag}\{\lambda_i\}$. Then $E(\hat{D} | X) = \Lambda \sigma^2$, and we find

$$\begin{aligned} E(\hat{V}_n | X) &= (X' X)^{-1} X' \Lambda \sigma^2 X (X' X)^{-1} \\ &= \sigma^2 (X' X)^{-1} \sum_{i=1}^n x_i x_i' \lambda_i (X' X)^{-1} \\ &= \sigma^2 (X' X)^{-1} \sum_{i=1}^n x_i x_i' (1 - x_i' (X' X)^{-1} x_i) (X' X)^{-1}. \end{aligned}$$

It is interesting to observe that $E(\hat{V}_n | X)$ does not equal $V_n^0 = \sigma^2 (X' X)^{-1}$, the actual conditional covariance matrix under the stated conditions. Thus \hat{V}_n is biased. What this calculation shows is that even under the strong assumption of homoskedasticity, the White covariance matrix estimator is biased.

Note: A very incorrect answer is to write

$$E(e_i^2 | x_i) = \sigma^2 \text{ implies that } \hat{V}_n = s^2 (X'X)^{-1}$$

This is incorrect. An estimator, such as \hat{V}_n , is not affected by the distribution of the data. An estimator is a particular function of the data. The distribution of the data affects the distribution of the estimator, but not its definition. So $E(e_i^2 | x_i) = \sigma^2$ affects the distribution of \hat{V}_n (including its expectation) but not the way it is constructed.