

Answer key for the final exam in 2017

- 1a.) (v)  
 1b.) (vii)  
 1c.) (v) and (vi)  
 1d.) none  
 1e.) none

$$2a.) \hat{\alpha}_{OLS} = (\sum x_{1t}^2)^{-1} (\sum x_{1t} y_t) = [T^{-1} \sum (x_t^* + v_{1t})^2]^{-1} [T^{-1} \sum (x_t^* + v_{1t})(\beta x_t^* + \varepsilon_t)]$$

$$\xrightarrow{p} (\omega^2 + \lambda_1^2)^{-1} (\omega^2) \beta$$

No other assumptions needed since we have LLN for i.i.d. variables with finite mean. Only consistent if  $\lambda_1 = 0$ .

$$2b.) \hat{\alpha}_{IV} = (\sum x_{2t} x_{1t})^{-1} (\sum x_{2t} y_t) = [T^{-1} \sum (x_t^* + v_{2t})(x_t^* + v_{1t})]^{-1} [T^{-1} \sum (x_t^* + v_{3t})(\beta x_t^* + \varepsilon_t)]$$

$$\xrightarrow{p} (\omega^2)^{-1} (\omega^2) \beta = \beta$$

Consistent as long as  $\omega^2 > 0$

$$2c.) \text{Corr}(x_{1t}, x_{2t}) = \frac{E(x_t^* + v_{1t})(x_t^* + v_{2t})}{\sqrt{E(x_t^* + v_{1t})^2 E(x_t^* + v_{2t})^2}} = \frac{\omega^2}{\sqrt{(\omega^2 + \lambda_1^2)(\omega^2 + \lambda_2^2)}}$$

Instruments are strong when this is big, that is, when  $\lambda_1$  and  $\lambda_2$  are small.

2d.) Use OLS  $t$ -test of  $\gamma = 0$  in regression  $\tilde{y}_t = \gamma x_{2t} + u_t$  for  $\tilde{y}_t = y_t - 2x_{1t}$ , namely

$$\tau = \hat{\gamma} / \sqrt{s^2 / \sum x_{2t}^2} \text{ for } \hat{\gamma} = [\sum (x_{2t}^2)]^{-1} [\sum x_{2t} (y_t - 2x_{1t})] \text{ and } s^2 = (T-1)^{-1} \sum (y_t - 2x_{1t} - \hat{\gamma} x_{2t})^2.$$

The statistic  $\tau$  has an exact Student  $t$  distribution with  $T-1$  degrees of freedom under the assumptions stated. Reject  $H_0$  if the statistic is larger in absolute value than the 5% critical value.

$$3a.) \ell(\lambda) = -T \log \lambda + \sum_{t=1}^T \log y_t - \sum_{t=1}^T \frac{y_t^2}{2\lambda}$$

$$\frac{\partial \ell(\lambda)}{\partial \lambda} = \frac{-T}{\lambda} + \sum_{t=1}^T \frac{y_t^2}{2\lambda^2} \Rightarrow \hat{\lambda} = T^{-1} \sum_{t=1}^T \frac{y_t^2}{2}$$

$$3b.) s_t = \frac{-1}{\lambda} + \frac{y_t^2}{2\lambda^2} \quad E(s_t) = \frac{-1}{\lambda} + \frac{2\lambda}{2\lambda^2} = 0$$

$$3ci.) \mathbf{h}(\boldsymbol{\theta}, \mathbf{w}_t) = s_t = \frac{-1}{\lambda} + \frac{y_t^2}{2\lambda^2}$$

$$3cii.) \text{ Since i.i.d., } \mathbf{S} = E(s_t^2) = \frac{1}{\lambda^2} - \frac{4\lambda}{2\lambda^3} + \frac{8\lambda^2}{4\lambda^4} = \frac{1}{\lambda^2}$$

$$3ciii.) \mathbf{D}' = E \left[ \frac{1}{\lambda^2} - \frac{y_t^2}{\lambda^3} \right] = \frac{1}{\lambda^2} - \frac{2\lambda}{\lambda^3} = -\frac{1}{\lambda^2}$$

$$3d.) \sqrt{T}(\hat{\lambda}_{MLE} - \lambda) \xrightarrow{L} N(0, V) \text{ for } V = (1/\lambda^2)^{-1} = \lambda^2.$$

3e.) Note  $\hat{\lambda}_{MLE}$  in (a) is sample mean of the i.i.d. random variable  $y_t^2/2$  whose expectation is  $E(y_t^2)/2 = \lambda$  and whose variance is  $E(y_t^4)/4 - \lambda^2 = 2\lambda^2 - \lambda^2 = \lambda^2$  so we have immediately from the CLT that  $\sqrt{T}(\hat{\lambda}_{MLE} - \lambda) \xrightarrow{L} N(0, \lambda^2)$