

# MEI MT Problem Set 7 Part 1<sup>1</sup>

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<sup>1</sup>Available on <http://personal.lse.ac.uk/carayolt/ec402.htm>

# Question 1

## Question

- ▶  $y_t = \alpha + x_t\beta + \varepsilon_t$
- ▶  $T$  observations, 1 independent variable (plus the constant).
- ▶ Assumptions:
  - ▶  $\varepsilon_t$  are *iid* with mean 0 and variance  $\sigma_\varepsilon^2$ .
  - ▶  $x_t$  are random, *iid* with mean  $\mu_x$  and variance  $\sigma_x^2$ , and  $\forall t$   $x_t$  and  $\varepsilon_t$  are independent.
  - ▶ Also assume that  $x_t\varepsilon_t$  are independently distributed (not stated in the question, but otherwise the exercise is a bit more complicated, e.g. need to use Chebyshev-Markov *LLN4* instead of Khinshine. We use that LLN at some point in question 2, so for now stick to the simpler case  $x_t\varepsilon_t$  *iid*).
- ▶ Denote

$$Z = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_T \end{pmatrix} = \begin{pmatrix} z'_1 \\ z'_2 \\ \vdots \\ z'_T \end{pmatrix}$$

## Question 1

### Answer

$$\blacktriangleright \text{(a) } Z'Z. \quad Z'Z = \begin{pmatrix} z_1 & z_2 & \cdots & z_T \end{pmatrix} \begin{pmatrix} z'_1 \\ z'_2 \\ \vdots \\ z'_T \end{pmatrix} = \sum_{t=1}^T z_t z'_t.$$

(This is  $2 \times 2$ .)

$$\blacktriangleright Z'\varepsilon. \quad Z'\varepsilon = \begin{pmatrix} z_1 & z_2 & \cdots & z_T \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_T \end{pmatrix} = \sum_{t=1}^T z_t \varepsilon_t.$$

(This is  $2 \times 1$ .)

## Question 1

### Answer

- ▶ (b)  $E(z_t z_t')$ .

$$\begin{aligned} E(z_t z_t') &= E \left( \begin{pmatrix} 1 \\ x_t \end{pmatrix} \begin{pmatrix} 1 & x_t \end{pmatrix} \right) = \begin{pmatrix} E(1) & E(x_t) \\ E(x_t) & E(x_t^2) \end{pmatrix} \\ &= \begin{pmatrix} 1 & \mu_x \\ \mu_x & \mu_x^2 + \sigma_x^2 \end{pmatrix} = \Sigma_{zz} \end{aligned}$$

- ▶ (c)  $plim(\frac{Z'Z}{T})$ . From Khinchine LLN on  $w_t = z_t z_t'$ :  $w_t$  are *iid* (because  $z_t$  are) and have finite expected value, hence  $plim(\frac{1}{T}(\sum_t w_t)) = E(w_t) = \Sigma_{zz}$ .
- ▶ (d)  $E(z_t \varepsilon_t) = E \left( \begin{pmatrix} 1 \\ x_t \end{pmatrix} \varepsilon_t \right) = \begin{pmatrix} E(\varepsilon_t) \\ E(x_t \varepsilon_t) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$  from our assumptions.
- ▶ (e)  $Var(z_t \varepsilon_t) = E(z_t \varepsilon_t \varepsilon_t z_t') = E(\varepsilon_t^2) E(z_t z_t') = \sigma_\varepsilon^2 \Sigma_{zz}$  (from independence of  $z_t$  and  $\varepsilon_t$ ).

## Question 1

### Answer

- ▶ (f)  $plim\left(\frac{Z'\varepsilon}{T}\right)$ .  $v_t = z_t\varepsilon_t$  are independently distributed (i.e.,  $\forall t \neq s$ ,  $v_s$  and  $v_t$  are independent), because  $\varepsilon_t$  are *iid* and we assumed  $x_{t\varepsilon_t}$  to be independent across  $t$  as well. So we can use *LLN1* (Chebyshev); this, combined with (d), gives the results.
- ▶ (g)  $\sqrt{T}\left(\frac{Z'\varepsilon}{T}\right) \rightarrow^d \mathcal{N}(0, \sigma_\varepsilon^2 \Sigma_{zz})$ . This is *CLT1* combined with (d) and (e).
- ▶ (h)  $\sqrt{T}\left(\frac{Z'Z}{T}\right)^{-1}\left(\frac{Z'\varepsilon}{T}\right) \rightarrow^d \mathcal{N}(0, \sigma_\varepsilon^2 \Sigma_{zz}^{-1})$ . (c) implies (through Slutsky theorem)  $plim\left(\frac{1}{T}(Z'Z)\right)^{-1} = \Sigma_{zz}^{-1}$ . This combined with (g) gives the result (through Cramér).
- ▶ Clear from (c) and (f) that OLS is consistent. (Slutsky).

## Question 1

### Answer

$$\begin{aligned} \text{Var}(\hat{\beta}) &= \text{Var} \left( [(Z'Z)^{-1}Z'\varepsilon]_2 \right) \\ &= E \left( [(Z'Z)^{-1}Z'\varepsilon((Z'Z)^{-1}Z'\varepsilon)']_{22} \right) \quad (1) \\ &= E \left( [(Z'Z)^{-1}Z'\varepsilon\varepsilon'Z(Z'Z)^{-1}]_{22} \right) \\ &= E \left( [(Z'Z)^{-1}Z'E(\varepsilon\varepsilon'|Z)Z(Z'Z)^{-1}]_{22} \right) \\ &= \sigma_\varepsilon^2 E \left( [(Z'Z)^{-1}Z'Z(Z'Z)^{-1}]_{22} \right) \\ &= \sigma_\varepsilon^2 E \left( [(Z'Z)^{-1}]_{22} \right) \\ &= \sigma_\varepsilon^2 E \left( \frac{1}{\sum_t x_t^2 - \frac{1}{T}(\sum_t x_t)^2} \right) \\ &= \sigma_\varepsilon^2 E \left( \frac{1}{\sum_t (x_t - \frac{1}{T} \sum_t x_t)^2} \right) \end{aligned}$$

## Question 1

### Answer

In (1) I use  $E((Z'Z)^{-1}Z'\varepsilon) = 0$  (because  $\varepsilon$  and  $Z$  are independent). Slutsky and *LLN2* (Khinchine) allow us to conclude (also using that  $s^2$  is consistent for  $\sigma_\varepsilon^2$ , which we show in the next question).

## Question 2

### Question

- ▶  $y = X\beta + \varepsilon$ , where  $X$  is  $T \times K$ .  $\varepsilon_t$  are  $iid(0, \sigma_\varepsilon^2)$ ;  $x_t$  are random,  $iid(0, \Sigma_x)$ ;  $\forall s, t$ ,  $x_s$  independent of  $\varepsilon_t$ : very strong assumption which we relax later.
- ▶  $s^2 = \frac{1}{T-K} \sum_{t=1}^T \hat{\varepsilon}_t^2$ . Want to prove that  $s^2$  is consistent for  $\sigma_\varepsilon^2$ .

### Answer



$$\begin{aligned} s^2 &= \frac{1}{T-K} \hat{\varepsilon}' \hat{\varepsilon} = \left( \frac{T}{T-K} \right) \frac{\varepsilon' M_X \varepsilon}{T} \\ &= \left( \frac{T}{T-K} \right) \frac{\varepsilon' \varepsilon - (X' \varepsilon)' (X' X)^{-1} (X' \varepsilon)}{T} \\ &= \left( \frac{T}{T-K} \right) \left( \left( \frac{\varepsilon' \varepsilon}{T} \right) - \left( \frac{X' \varepsilon}{T} \right)' \left( \frac{X' X}{T} \right)^{-1} \left( \frac{X' \varepsilon}{T} \right) \right) \end{aligned}$$



## Question 2

### Answer

- ▶ Hence, using the Slutsky theorem:

$$plim(s^2) = 1 \left( \sigma_\varepsilon^2 - \left( 0'_K \Sigma_X^{-1} 0_K \right) \right) = \sigma_\varepsilon^2$$

because

- ▶  $plim \left( \frac{T}{T-K} \right) = 1$  trivial.
- ▶  $plim \left( \frac{\varepsilon' \varepsilon}{T} \right) = E(\varepsilon_t^2) = \sigma_\varepsilon^2$  from Khinchine LLN2.
- ▶  $plim \left( \frac{X' \varepsilon}{T} \right) = E(x_t \varepsilon_t) = 0$  from Khinchine LLN2 (because  $\forall s, t, v_s = x_s \varepsilon_s$  is independent from  $v_t$  from our assumptions, i.e. the  $v_t$  are iid).
- ▶ And finally,  $plim \left( \frac{X' X}{T} \right) = E(x_t x_t') = \Sigma_X$  from Khinchine LLN2.

## Question 2

### Answer

- ▶ Now relax our assumption that  $\forall s, t, x_s$  independent of  $\varepsilon_t$ .
- ▶ We have instead  $y = X\beta + \varepsilon$ , where  $X$  is  $T \times K$ .  $\varepsilon_t$  are  $iid(0, \sigma_\varepsilon^2)$ ;  $x_t$  are random,  $iid(0, \Sigma_x)$ ;  $E(x_t \varepsilon_t) = 0$ .
- ▶ Still the case that

$$s^2 = \left( \frac{T}{T-K} \right) \left( \left( \frac{\varepsilon' \varepsilon}{T} \right) - \left( \frac{X' \varepsilon}{T} \right)' \left( \frac{X' X}{T} \right)^{-1} \left( \frac{X' \varepsilon}{T} \right) \right)$$

- ▶ More tricky than previously: cannot use Chebyshev or Khinshine *LLN* for  $x_t \varepsilon_t$  anymore. Instead we'll have to use Chebyshev-Markov (*LLN4*).

## Question 2

### Answer

- ▶ To use Chebyshev-Markov on  $\frac{1}{T} \sum_t x_t \varepsilon_t = \frac{1}{T} \sum_t u_t$ : need  
$$\text{Var} \left( \frac{1}{T} \sum_t u_t \right) = \frac{1}{T^2} \left( \sum_t \sigma_t^2 + 2 \sum_{t \neq s} \sigma_{ts} \right) \rightarrow 0 \text{ as } T \rightarrow \infty$$
with  $V(u_t) = \sigma_t^2$  and  $\text{cov}(u_t, u_s) = \sigma_{ts}$

## Question 2

### Answer

$$\begin{aligned}\text{Var} \left( \frac{1}{T} \sum_t u_t \right) &= \frac{1}{T^2} \text{Var} \left( \sum_t x_t \varepsilon_t \right) \\ &= \frac{1}{T^2} \text{Var} (X' \varepsilon) \\ &= \frac{1}{T^2} E \left( [X' \varepsilon - E(X' \varepsilon)][X' \varepsilon - E(X' \varepsilon)]' \right) \\ &= \frac{1}{T^2} E (X' \varepsilon \varepsilon' X) \\ &= \frac{1}{T^2} E (X' E(\varepsilon \varepsilon' | X) X) \\ &= \frac{1}{T^2} E (X' \sigma_\varepsilon^2 X) \\ &= \frac{1}{T} \left( \sigma_\varepsilon^2 \Sigma_X \right) \rightarrow_{T \rightarrow \infty} 0\end{aligned} \tag{2}$$

## Question 2

### Answer

- ▶ In (2) I use  $E(\varepsilon\varepsilon'|X) = \sigma_\varepsilon^2 I_T$ , which is not explicitly mentioned in the question (we only know it is true unconditional on  $X$ ). But we cannot conclude without making an additional assumption.