# ECON220B Discussion Section 4 Midterm Review

Lapo Bini

# Roadmap

1. Question 1: Algebraic Properties of OLS

2. Question 2: Properties Empirical CDF Estimator

#### Exercise 1

Consider the following linear model:

$$y_i = \alpha + \mathbf{x}_i^T \boldsymbol{\beta} + u_i$$

where  $y_i \in \mathbb{R}$ ,  $\mathbf{x}_i \in \mathbb{R}^d$  and  $u_i \in \mathbb{R}$ . Note that the intercept is captured by  $\alpha$  and it is not included in  $\mathbf{x}_i$ . Suppose that we have an iid sample  $(y_i, \mathbf{x}_i)$  for  $i = 1, \ldots, n$ .

We will assume  $E[u_i] = 0$  and  $E[\mathbf{x}_i u_i] = 0$ .

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Write down the sample moment conditions for  $\hat{\alpha}$  and  $\hat{\beta}$ 

$$\frac{\text{EL }u: J = 0}{\text{EL }u: x: J = 0} = \sum_{i=1}^{n} \sum_{i=1}^{n} \hat{u}_{i} = 0$$

EXTRA - USEFUL FOR LATER

(1) DERIVE 
$$\hat{\alpha}$$

$$\frac{1}{m} \Sigma \hat{\mu}_{i} = 0 \implies \frac{1}{m} \Sigma (\underline{\mu}_{i} - \hat{\alpha} - \underline{x}_{i}^{T} \hat{\beta}) = 0$$

$$\frac{1}{m} \Sigma \underline{\mu}_{i} - \frac{1}{m} \Sigma \hat{\alpha} - \frac{1}{m} \Sigma \underline{x}_{i}^{T} \hat{\beta} = 0$$

$$\underline{\underline{\mu}} - \frac{m}{m} \hat{\alpha} - (\frac{1}{m} \Sigma \underline{x}_{i}^{T}) \hat{\beta} = 0 \qquad \therefore \quad \hat{\alpha} = \underline{\mu} - \underline{\overline{x}}^{T} \hat{\beta}$$

Write down the sample moment conditions for  $\hat{\alpha}$  and  $\hat{\beta}$ 

Write down the sample moment conditions for 
$$\alpha$$
 and  $\beta$ 

(2) **DERIVE**  $\hat{\beta}$ 

$$\frac{1}{m} \sum x_i \hat{u}_i = 0 \implies \frac{1}{m} \sum x_i (\underline{u}_i - \hat{\alpha} - x_i^T \hat{\beta}) = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - \frac{1}{m} \sum x_i (\bar{u}_i - \bar{\alpha}^T x_i) = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - \frac{1}{m} \sum x_i (\bar{u}_i - \bar{x}^T \hat{\beta}) - \frac{1}{m} \sum x_i x_i^T \hat{\beta} = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - \frac{1}{m} \sum x_i (\bar{u}_i - \bar{x}^T \hat{\beta}) - \frac{1}{m} \sum x_i x_i^T \hat{\beta} = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - (\frac{1}{m} \sum x_i) \bar{u}_i + (\frac{1}{m} \sum x_i) \bar{x}^T \hat{\beta} - \frac{1}{m} \sum x_i x_i^T \hat{\beta} = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - \bar{x} \bar{u}_i + \bar{x} \bar{x}^T \hat{\beta} - \frac{1}{m} \sum x_i x_i^T \hat{\beta} = 0$$

$$\frac{1}{m} \sum x_i \underline{u}_i - \bar{x} \bar{u}_i + \bar{x} \bar{x}^T \hat{\beta} - \frac{1}{m} \sum x_i x_i^T \hat{\beta} = 0$$

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Let  $\hat{u}_i$  be the regression residual, write down its expression in terms of  $y_i$ ,  $\mathbf{x}_i$  and the estimated coefficient

Now regress  $\hat{u}_i$  on an intercept and  $\mathbf{x}_i$ . Find the estimated coefficients.

WHAT WE KNOW ABOUT 
$$\hat{n}_i$$
:  $\Sigma \hat{n}_i = 0$   $\Sigma x_i \hat{n}_i = 0$ 

PROPOSED SOLUTION 1:

$$\hat{\mu}$$
: =  $\chi_0 + \chi_0^{7} \chi_1 + \xi_0^{1}$  THIS IS THE REGRESSION WE WANT TO ESTIMATE. NOW DEFINE:

$$X_i = \begin{vmatrix} 1 \\ x_i \end{vmatrix}$$
  $\Gamma = \begin{vmatrix} \delta_0 \\ \delta_1 \end{vmatrix}$  Let's estimate  $\hat{u}_i = X_i^T \Gamma + \mathcal{E}_i^T$ 

$$\therefore \hat{\Gamma} = (\sum X_i X_i^T)^{-1} (\sum X_i \hat{n}_i) = \left| \sum x_i \hat{n}_i \right| = 0$$

Now regress  $\hat{u}_i$  on an intercept and  $\mathbf{x}_i$ . Find the estimated coefficients.

• PROPOSED SOLUTION 2: WE want to astumate 
$$\hat{\mu}_{i} = \delta_{0} + x_{i}^{T} \delta_{i} + \delta_{i}^{T}. \text{ FROM OUR DERIVATION BEFORE}$$

$$= 0 \qquad = \frac{1}{m} \sum \hat{\mu}_{i}^{T} = 0 \quad \text{BY PROPERTY}$$

$$\hat{\lambda}_{i} = \left(\frac{1}{m} \sum x_{i} x_{i}^{T} - \overline{x} \overline{x}^{T}\right)^{-1} \left(\frac{1}{m} \sum x_{i}^{T} \hat{\mu}_{i}^{T} - \overline{x} \overline{\lambda}^{T}\right)$$

$$\hat{\lambda}_{i} = \left(\frac{1}{m} \sum x_{i} x_{i}^{T} - \overline{x} \overline{x}^{T}\right)^{-1} \left(O - O\right) = 0$$

$$\hat{\delta}_{0} = \hat{\mu}_{0} - \overline{x}^{T} \hat{\delta}_{i} = O - \overline{x}^{T} O = 0$$
Then 
$$\hat{\delta}_{i} = \hat{\delta}_{0} = O \quad ///$$

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Let  $\bar{x}$  be the sample mean of the regressors, and define  $\check{\mathbf{x}}_i \equiv \mathbf{x}_i - \bar{x}$ . Find the estimated coefficient. Now regress  $y_i$  on an intercept and  $\check{\mathbf{x}}_i$ . Find the estimated coefficients  $\check{\alpha}$  and  $\check{\beta}$ . How are they related to the estimates  $\hat{\alpha}$  and  $\hat{\beta}$ ?

$$\underline{A} := \alpha + \underline{x} \cdot \overline{\beta} + \underline{\mu} :$$

$$\underline{A} := \alpha + \underline{x} \cdot \overline{\beta} + \underline{x} \cdot \overline{\beta} - \overline{x} \cdot \overline{\beta} + \underline{\mu} :$$

$$\underline{A} := \alpha - \underline{x} \cdot \overline{\beta} + (\underline{x} \cdot \overline{x} - \underline{x} \cdot \overline{x}) \cdot \overline{\beta} + \underline{\mu} :$$

$$\underline{A} := (\alpha - \underline{x} \cdot \overline{\beta}) + \underline{x} \cdot \overline{\beta} + \underline{\mu} :$$

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$$\underline{A} := \alpha + \underline{\mu} :$$

$$\underline{A}$$

TO BETTER SEE THIS, WE WILL DERIVE BOTH & AND B

Let  $\bar{x}$  be the sample mean of the regressors, and define  $\check{\mathbf{x}}_i \equiv \mathbf{x}_i - \bar{x}$ . Find the estimated coefficient. Now regress  $y_i$  on an intercept and  $\check{\mathbf{x}}_i$ . Find the estimated coefficients  $\check{\alpha}$  and  $\check{\beta}$ . How are they related to the estimates  $\hat{\alpha}$  and  $\hat{\beta}$ ?

$$\hat{\beta}?$$
(1)  $EL u_i = 0 \implies \frac{1}{m} \sum u_i = \hat{\delta}_0 + (\frac{1}{m} \sum \tilde{x}_i^*) \beta = 0$ 

$$\frac{1}{m} \sum u_i = \hat{\delta}_0 + (\frac{1}{m} \sum \tilde{x}_i^*) \beta$$

$$\frac{1}{m} \sum u_i = \hat{\delta}_0 + (\frac{1}{m} \sum \tilde{x}_i^*) \beta$$

(2) 
$$E[x_i u_i] = 0$$
  $\frac{1}{m} \sum x_i y_i = \frac{1}{m} \sum x_i \hat{y}_0 + \frac{1}{m} \sum x_i \hat{x}_i^T \hat{\beta} = 0$ 

NOW NOTICE THAT  $\sum x_i \hat{x}_i^T = \sum x_i (x_i - \bar{x})^T = \sum x_i x_i^T - \sum x_i x^T = \sum x_i x_i^T - \sum x_i x_i^T = \sum x_i x_i^T - \sum x_i x_i^T = \sum x$ 

$$\therefore \quad \frac{1}{m} \sum x_i y_i = \frac{1}{m} \sum x_i \hat{x}_0 + \left(\frac{1}{m} \sum x_i x_i T - \overline{x} \overline{x}^T\right) \hat{\beta} = 0$$

Let  $\bar{x}$  be the sample mean of the regressors, and define  $\check{\mathbf{x}}_i \equiv \mathbf{x}_i - \bar{x}$ . Find the estimated coefficient. Now regress  $y_i$  on an intercept and  $\check{\mathbf{x}}_i$ . Find the estimated coefficients  $\check{\alpha}$  and  $\check{\beta}$ . How are they related to the estimates  $\hat{\alpha}$  and  $\hat{\beta}$ ?

LASTLY SUBSTITUTE 
$$\hat{x}_{o}$$
 AND  $\hat{\beta} = \left(\frac{1}{m}\Sigma_{x,i}x_{i}^{z} - \bar{x}\bar{x}^{z}\right)^{-1}\left(\frac{1}{m}\Sigma_{x,i}y_{i}^{z} - \bar{x}\bar{y}\right) = \hat{\beta}_{ij}$ 

Claim: 
$$\check{\alpha} = \frac{1}{n} \sum_{i=1}^{n} y_{i}$$
. True or false? TRUE

WE HAVE  $\underline{M} := (\alpha + \overline{\mathbf{x}}^{\mathsf{T}} \boldsymbol{\beta}) + \widetilde{\mathbf{x}} : \boldsymbol{\beta} + \hat{\mathbf{A}} :$ 

FROM  $\frac{1}{m} \Sigma \hat{\mathbf{n}} := 0 \implies \frac{1}{m} \Sigma \underline{M} : - \overset{\checkmark}{\mathbf{x}} - \overset{\checkmark}{\mathbf{x}} : \overset{\checkmark}{\mathbf{\beta}} = 0$ 

$$\frac{1}{m} \Sigma \underline{M} : - \frac{1}{m} \Sigma \overset{\checkmark}{\mathbf{x}} : - \frac{1}{m} \Sigma \overset{\checkmark}{\mathbf{x}} : \overset{\checkmark}{\mathbf{\beta}} = 0$$

$$\overset{\widetilde{\mathbf{M}}}{\mathbf{M}} - \overset{\widetilde{\mathbf{M}}}{\mathbf{x}} + \left( \frac{1}{m} \Sigma (\mathbf{x} : - \overline{\mathbf{x}}^{\mathsf{T}}) \right) \overset{\widetilde{\mathbf{\beta}}}{\mathbf{\beta}} = 0$$

$$\vdots \quad \overset{\widetilde{\mathbf{X}}}{\mathbf{x}} = \overset{\widetilde{\mathbf{M}}}{\mathbf{M}} = \frac{1}{m} \Sigma \underline{\mathbf{M}} :$$

#### Exercise 2

Assume  $\{x_i\}_{i=1}^n$  iid sample from a univariate distribution,  $x_i \in \mathbb{R}$ . Denote by  $F(\cdot)$  the cumulative distribution which is defined as:

$$F(x) = \mathbb{P}(x_i \leq x)$$

For simplicity we will assume that  $x_i$  is continuously distributed on the unit interval such that:

- F(x) = 0 for all x < 0.
- F(x) = 1 for all x > 1.
- F(x) continuous and strictly increasing for all  $x \in (0,1)$ .

Define the empirical CDF as:

$$\hat{F}(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}\{x_i \leq \mathbf{x}\}$$
 You get estimate CDF

• THIS IS A POINT ESTIMATOR WHEN YOU PLUG &

• YOU GET ESTIMATE CAF ITERATING OVER SUPPORT OF X

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Assume 0 < x < 1, find the asymptotic distribution of \hat{F}(x)
  STEP 1: WHERE WILL THE ASYMPTOTIC DISTRIBUTION BE
                CENTERED ?
                                                         15.3 ~ BERNOULLI (P(X: =x))
\frac{1}{2} \sum d \{ x : \leq \infty \} \xrightarrow{P} E L d \{ x : \leq \infty \} = 1 \cdot \mathbb{P} (x : \leq \infty) + O (1 - \mathbb{P} (x : \leq \infty))
                   by WLLN
                 SINCE EX: 3. IID FINITE HEAN
                 AND VARIANCE
  f(x) = \frac{1}{2} \sum A(x) \le x^3 \xrightarrow{P} P(x \le x) = f(x)
```

Assume 0 < x < 1, find the asymptotic distribution of  $\hat{F}(x)$ 

STEP 2: APPLY CLT
$$\sqrt{m} \left( \hat{F}(x) - F(x) \right) = \sqrt{m} \left( \frac{1}{m} \sum \mathbf{1} \{ X_i \le x \} - \frac{m}{m} F(x) \right)$$

$$= \sqrt{m} \left\{ \frac{1}{m} \sum \left( \mathbf{1} \{ X_i \le x \} - F(x) \right) \right\}$$

$$= \frac{1}{\sqrt{m}} \sum \left( \mathbf{1} \{ X_i \le x \} - F(x) \right) \xrightarrow{d} \mathcal{N}(0, V)$$

```
Assume 0 < x < 1, find the asymptotic distribution of \hat{F}(x)
STEP 3: FIND ASYMPTOTIC VARIANCE
V = Vor\left(\sqrt{m}\left(\hat{\mathbf{F}}(\mathbf{x}) - \mathbf{F}(\mathbf{x})\right)\right) = Vor\left(\frac{1}{\sqrt{m}}\sum\left(\mathbf{1}\left\{\mathbf{x}\right\} \leq \mathbf{x}\right\} - \mathbf{F}(\mathbf{x})\right)
        = \frac{1}{m} \text{Vor} \left( \sum \left( \underbrace{1} \{ X : \leq \pi \} - F(x) \right) \right) 
= \frac{1}{m} \sum \text{Vor} \left( \underbrace{1} \{ X : \leq \pi \} - F(x) \right) 
= \frac{1}{m} \sum \text{Vor} \left( \underbrace{1} \{ X : \leq \pi \} - F(x) \right) 
= \frac{1}{m} \sum \text{Vor} \left( \underbrace{1} \{ X : \leq \pi \} - F(x) \right) 
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= \frac{m}{m} \text{Vor} \left( \underbrace{1} \{ X : \leq \pi \} - F(x) \right) 
                                                                                                                                                                                                                                                    JUST A CONSTANT
          = Vor (11 {X: < > x 3}) ~ BERNOULLI
                                                                                                                                                                                                                                                    a E IK, X RANDOM VAR.
                                                                                                                                                                                                                                                   Vor (X+a) = X
          = \mathbb{P}(X: \leq x) (1 - \mathbb{P}(X: \leq x)) = \mathbb{P}(x) (1 - \mathbb{P}(x))
```

Assume  $0 < x \neq x' < 1$ , find the asymptotic distribution of  $\hat{F}(x)$  and  $\hat{F}(x')$ 

STEP 1: FIND PLIM. WE KNOW FROM BEFORE THAT 
$$\hat{F}(x) \xrightarrow{P} F(x) \quad \text{Then we get} \quad \begin{vmatrix} \hat{f}(x) \\ \hat{f}(x) \end{vmatrix} \xrightarrow{P} \begin{vmatrix} f(x) \\ f(x) \end{vmatrix}$$

STEP 2: APPLY CLT (MULTIVARIATE):  $\{x:3:^{\infty}_{-}, \text{ IIB}, \text{ onc.}$ ASYMPTOTIC VARIANCE  $\hat{\mathbf{f}}(\mathbf{x})$  FINITE SINCE  $\hat{\mathbf{f}}(\mathbf{x}) \in [0,1]$ THEN COVARIANCE  $\hat{\mathbf{f}}(\mathbf{x})$  AND  $\hat{\mathbf{f}}(\mathbf{x})$  FINITE AND

$$\operatorname{Vm}\left(\left|\begin{array}{c} \hat{\mathbf{f}}\left(\mathbf{x}^{i}\right) \\ \hat{\mathbf{f}}\left(\mathbf{x}^{i}\right) \end{array}\right| - \left|\begin{array}{c} \mathbf{f}\left(\mathbf{x}^{i}\right) \\ \mathbf{f}\left(\mathbf{x}^{i}\right) \end{array}\right|\right) \xrightarrow{\delta} \mathcal{N}\left(\left|\begin{array}{c} \mathbf{0} \\ \mathbf{0} \end{array}\right|; \left|\begin{array}{c} \mathbf{f}\left(\mathbf{x}\right)\left(\mathbf{1} - \mathbf{f}\left(\mathbf{x}\right)\right) \\ \operatorname{cov} & \mathbf{f}\left(\mathbf{x}^{i}\right)\left(\mathbf{1} - \mathbf{f}\left(\mathbf{x}^{i}\right)\right) \end{array}\right|\right)$$

```
Assume 0 < x \neq x' < 1, find the asymptotic distribution of \hat{F}(x) and \hat{F}(x')
Cov = Cov \left( \sqrt{m} \left( \hat{F}(x) - F(x) \right); \sqrt{m} \left( \hat{F}(x') - F(x') \right) \right)
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       a, belk
                                   = COV \left( \frac{1}{\sqrt{m}} \sum \left( \frac{1
                                   = \frac{1}{2\pi} \left( \sum \left( \mathbf{1} \left\{ \mathbf{1} \left\{ \mathbf{X} : \mathbf{x} \cdot \mathbf{X} - \mathbf{F} \left( \mathbf{x} \right) \right\} \right) : \sum \left( \mathbf{1} \left\{ \mathbf{1} \left\{ \mathbf{X} : \mathbf{x} \cdot \mathbf{x} \right\} - \mathbf{F} \left( \mathbf{x} \right) \right\} \right) \right)
                                  =\frac{1}{m} \operatorname{Cov} \left( \sum_{i=1}^{n} \operatorname{Ai} \{X_{i} \leq x_{i}\}; \sum_{i=1}^{n} \operatorname{Ai} \{X_{i} \leq x_{i}\} \right) \qquad \qquad \operatorname{Cov} \left( a+Y_{i}b+Y_{i} \right) = \operatorname{Cov} \left( X_{i}Y_{i} \right)
                                                                                          · M TIMES COV (1 { X; < x }, 1 { X; < x }) SINCE IDENTICALLY DISTRIBUTED
                                                                                        • m(m-1) TIMES COV (1 { X: < x }, 1 { X; < x } } WITH i = BUT ALL
                                                                                                                                                                                                                                          ZEROS SINCE X: LX; V; +;
                           = m (1 { X: < x }, 1 { X: < x })
```

Assume  $0 < x \neq x' < 1$ , find the asymptotic distribution of  $\hat{F}(x)$  and  $\hat{F}(x')$ 

$$COV = EL \underbrace{1 \{X: \leq x \} 1 \{X: \leq x' \}}_{:= K} - EL 1 \{X: \leq x \} ]EL 1 \{X: \leq x' \}]_{:= K} = \begin{cases} 1 & \text{if } \{x: \leq x' \} \\ 0 & \text{otherwise} \end{cases} = \begin{cases} 1 & \text{if } \{x: \leq x' \} \\ 0 & \text{otherwise} \end{cases}$$

$$COV = EL \underbrace{1 \{X: \leq m \text{im } \{x, x' \}\}}_{N} - F(x) F(x')$$

$$N \text{ BERNOULL}$$

$$COV = P(X: \leq m \text{im } \{x, x' \}) - F(x) F(x')$$

=  $F(m_1 + 2x, x + \xi) - F(x)F(x+\xi)$ 

(\*) CALL THIS & AND PROOF Exercise 2 - Question 3 IS COMPLETE

Consider the hypothesis  $H_0: F(x) = G(x)$  and define the following statistic:

$$KS = \sup_{x \in [0,1]} \sqrt{n} |\hat{F}(x) - G(x)|$$

Show that under the null, the KS statistic can be rewritten as:

$$KS = \sup_{x \in [0,1]} \sqrt{n} \left| \frac{1}{n} \sum_{i=1}^{n} \left( \mathbb{I}\{F(x_i) \leq x\} - x \right) \right| \quad \text{define } \underline{y} := \mathbf{f}(\mathbf{x})$$
WE KNOW  $\underline{y} \in \mathbf{IO}_1\mathbf{1}\mathbf{1}$ . Since  $\mathbf{f}(\cdot)$  strictly increasing and continuous

3F-1/1, THEN  $= \underset{x \in [0,1]}{\text{mb}} \sqrt{w} \left| \frac{w}{1} \sum \{ E(x^2) \in E(E_{-1}(R)) \} - R \right\} = \underset{x \in [0,1]}{\text{mb}} \sqrt{w} \left| \frac{w}{1} \sum \{ E(x^2) \in E(E_{-1}(R)) \} - R \right\} = \underset{x \in [0,1]}{\text{mb}} \sqrt{w} \left| \frac{w}{1} \sum \{ E(x^2) \in R \} - R \right|$ (\*\*)

WE KNOW y & [0,1]. SINCE £ (-) STRICTLY INCREASING AND CONTINUOUS 
$$\exists F^{-1}(\cdot)$$
, THEN

Consider the hypothesis  $H_0: F(x) = G(x)$  and show that the KS statistic does not depend on the underlying distribution  $F(\cdot)$ .

$$\sup_{x \in [0,1]} \sqrt{m} \left| \frac{1}{m} \sum \mathbf{1} \{x, \pm x\} - F(x) \right| \quad \text{Now call } Y := F(x)$$

WHAT IS ITS LDF?

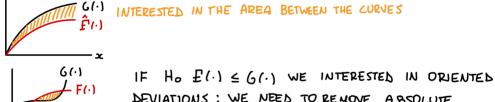
WHAT IS ITS CDF:  

$$E(y) = \mathbb{P}(Y \leq y) = \mathbb{P}(E(x) \leq y) = \mathbb{P}(X \leq E^{-1}(y)) = F(E^{-1}(y)) = y$$



WE DON'T CARE ABOUT  $\, f(\cdot) \,$ , by Chance of Variable always uniform

Discuss how you can modify the KS statistic to test FOSD.



DEVIATIONS : WE NEED TO REMOVE A BSOLUTE VALUE

.. 
$$t = \int_{0}^{\infty} (\hat{E}(x) - G(x))^{+} dx$$
 => IF t>0 THEN EVIDENCE

TO REJECT HO