EC402 (2023/24) RAGUR'S SPEAKING NOTES FOR CLASS

Vasihs 783 (WKH, AT)

PLAN Qr 42 (a) in detail (Q3)

$$\begin{array}{l} \left(\begin{array}{c} \left(\lambda \right) & \stackrel{\text{MATH}}{\mathbf{y}} = \mathbf{X} \mathbf{\beta} + \mathbf{z} & \text{where } \mathbf{X} \text{ is a TxK matrix. Suppose (WLOG) the last-regressor is scaled by $\mathbf{\lambda}$.
i.e. $Q := \mathbf{X} \mathbf{A}$ where $\mathbf{A} := \begin{bmatrix} \mathbf{T}_{K-1} & \mathbf{O}_{K-1} \\ \mathbf{O}_{K-1} & \mathbf{\lambda} \end{bmatrix}$
Saywe use $O(\mathbf{S} : \mathbf{y} = \mathbf{X} \mathbf{\hat{\beta}} + \mathbf{\hat{z}} \cdot \mathbf{1}$ here we scale \mathbf{X} by \mathbf{A} . That is,
we fit $\mathbf{y} = Q \mathbf{\hat{k}} + \mathbf{\hat{\eta}} \cdot \mathbf{1}$
If we force $\mathbf{\hat{z}} = \mathbf{\hat{\eta}}$ (which is another way of Saying we use $O(\mathbf{S} \text{ again})$,
then clearly: $\mathbf{X} \mathbf{\hat{\beta}} = Q \mathbf{\hat{k}} = \mathbf{X} \mathbf{A} \mathbf{\hat{k}} = \mathbf{\hat{\beta}} = \mathbf{A} \mathbf{\hat{k}}$
So that $\mathbf{A} = \mathbf{\hat{A}} \mathbf{\hat{\beta}} = \begin{bmatrix} \mathbf{I}_{K-1} & \mathbf{O}_{K-1} \end{bmatrix} \mathbf{\hat{\beta}} \\ \begin{bmatrix} \mathbf{O}_{K-1} & \mathbf{I} \mathbf{\hat{\lambda}} \end{bmatrix} \\ \vdots & \mathbf{\hat{k}}_{1} = \begin{bmatrix} \mathbf{\hat{\beta}} \\ \mathbf{\hat{\beta}} \end{bmatrix} \mathbf{\hat{\lambda}} + \mathbf{\hat{\beta}} = \mathbf{K} \cdot \mathbf{K} \end{array}$$$

INTUITION
X_K is measured originally in Emillion, and now in £000s, i.e. A=1000.
If it's confusing, see this: Salary(&m) Salary(£000)
Elon Musk 0.3 300
Raguir 92 92,000
i.e.
$$\lambda = 1000$$
 here

=> A3Rmi A3Rsm. A3F (a) $y_{ik} = \begin{cases} x_{ik} + z_{ik} \\ E \\ x_{ik} \\ z_{ik} - s \\ = 0, \text{ for } s \neq 0 \\ \neq 0, \text{ for } s > 0 \end{cases}$ (c)=> A3Rni A3Rsm.

If still Confused, here's tome extra intuition "We can't have it both ways" - either we treat zit as random in which case we cannot claim all regressor values/leads are aire giver. OR we treat zie as given so you can sensibly Condition but then why are we asking about E[.] of a non-random object? Next consider AZR Sru. Say $Y_{ik} = P_{ik-1} + E_{ik}$ and of course $E[2_{ik} + E_{ik-1}] \neq 0$. Then, $E[Y_{ik-1} + E_{ik}] = E[(P_{ik-2} + E_{ik-1}) + E_{ik}] \neq 0$. => A3Rmi A3Rsm.

Q2(a)
(1)
$$y_{t} = f_{1} \times \frac{f_{2}}{2t} \times \frac{f_{3}}{3t} \times \frac{f_{3}}{2t} \times \frac{f_{3}}$$

$$\begin{split} \log y_{k} = \log \beta_{1} + \beta_{2} \log \chi_{u} + \beta_{3} \log \chi_{3k} + \log z_{k}, \text{ or} \\ \widetilde{y}_{0} = \chi_{1} + \beta_{2} \widetilde{\chi}_{2k} + \beta_{3} \widetilde{\chi}_{3k} + M_{k}, \text{ where} \end{split}$$

ÿ_k:=log y_k; x_{hk}:=log x_{hk} for h=2,3;

 $\mathcal{T}_{k}:=\log \mathcal{L}_{k}$; and $\mathcal{T}_{1}:=\log \beta_{1}$.

Step 3: BRIEF ANALYSIS OF MODEL (2)

Model(2) is linear in parameters at far as γ , f_2 and f_3 are concerned. It is a standard multiple linear regression modul where $\hat{\gamma}_t$ is regressed on a constant, $\hat{\chi}_{15}$ and $\hat{\chi}_{35}$.

Of course the model remains non-linear with respect to β_{i} . (a) the economicts among us can maybe help explain why we may not Care about β_{i} in a loth-Douglas Catext? (b) as Varsilies' solution explains, we retain Consistency for $\beta_{i} := \exp[\{\delta_{i}]]$. Ly i.e. non-linearity With β_{i} , may not be a big deal. We also will need to ensure that a log transformation is feasible.

We also will need to ensure that a log transformation is feasible. Assumption $1: y_{t} > 0, z_{t} > 0, z_{t} > 0, z_{t} > 0, z_{t} > 0$ for all t.

Step 4: FURTHER ANALYSIS OF MODEL (2)
PROPOSITION 1: Say we had Vassilis' Al "under Model (1) and

$$x_{26}$$
 and x_{36} were not constant over t.
Then $\tilde{X} := [i \tilde{\chi}_{2} \tilde{\chi}_{2}]$ is a full rank matrix
(provided log(.) does not introduce any linear dependence)
PROPOSITION 2: Say we had Vassilis' A3Rfi and "A4GMiid"
Then, $\tilde{X} \perp \eta$, and $E[\eta\eta] = v \perp_{T}$ for a positive
constant scalar v.

Under Model (2), ... by Propositions I and 2 and Assumption I, the OLS estimator for $\theta := (\gamma_1, \beta_2, \beta_3)$ is the best linear unbiased estimator due to the Garcs Markov theorem. If additionally, we assume log-normality for ε_L , then the OLS estimator of θ is the best unbiased estimator.