

# Midterm ECO 521

Haixiang Zhu

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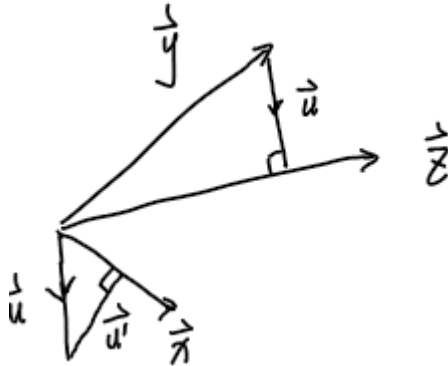
## 1. Omitted Variables

$$\begin{aligned}
 \hat{b} &= (X'X)^{-1}X'y \\
 &= \beta + (X'X)^{-1}X'Z\gamma + (X'X)^{-1}X'u \\
 plim\hat{b} &= \beta + plim\left(\frac{X'X}{n}\right)^{-1} plim\left(\frac{X'Z}{n}\right)\gamma + plim\left(\frac{X'X}{n}\right)^{-1} plim\left(\frac{X'u}{n}\right) \\
 &= \beta + plim\left(\frac{X'X}{n}\right)^{-1} plim\left(\frac{X'Z}{n}\right)\gamma \\
 Var(\hat{b}) &= E(\hat{b} - plim\hat{b})(\hat{b} - plim\hat{b})' \\
 &= E\left[plim\left(\frac{X'X}{n}\right)^{-1} plim\left(\frac{X'u}{n}\right) plim\left(\frac{u'X}{n}\right) plim\left(\frac{X'X}{n}\right)^{-1}\right] \\
 &= \frac{1}{n}\sigma^2 plim\left(\frac{X'X}{n}\right)^{-1}
 \end{aligned}$$

Its asymptotic properties

$$\sqrt{n}(\hat{b} - plim\hat{b}) \sim N\left(0, \sigma^2 plim\left(\frac{X'X}{n}\right)^{-1}\right)$$

## 2. Projection of residuals



### 3. Dummy Variables

$$e_i = \sum_j X_{ij}\beta_j + A_i\gamma + A_i \sum_j X_{ij}\delta_j + u_i$$

where  $X_{ij}$  is a dummy variable, which equals to 1 if person  $i$  injected with vaccine  $j$ ,  $\beta_j$  is the effectiveness of the vaccine holding everything else constant and  $\delta_j$  is the interaction of age with different common vaccines.

### 4. DID Model

$$\begin{aligned} \log w_i &= X_i\beta + u_i \\ \text{Var}(u_i) &= e^{\lambda + Age_i\delta + Female_i\alpha + Age_iFemale_i\theta + e_i} \\ \Rightarrow \log(u_i^2) &= \lambda + Age_i\delta + Female_i\alpha + Age_iFemale_i\theta + e_i \end{aligned}$$

### 5. ARMA(2,2)

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2}$$

Let  $\gamma(k) = E(u_t u_{t-k})$ . For simplicity, we first calculate  $E(u_t e_t)$ ,  $E(u_t e_{t-1})$  and  $E(u_t e_{t-2})$  respectively.

$$\begin{aligned} E(u_t e_t) &= \rho_1 E(u_{t-1} e_t) + \rho_2 E(u_{t-2} e_t) + a_0 E(e_t^2) + a_1 E(e_{t-1} e_t) + a_2 E(e_{t-2} e_t) \\ &= a_0 \sigma_e^2 \\ &= E(u_{t-1} e_{t-1}) = E(u_{t-2} e_{t-2}) \end{aligned} \tag{1}$$

$$\begin{aligned} E(u_t e_{t-1}) &= \rho_1 E(u_{t-1} e_{t-1}) + \rho_2 E(u_{t-2} e_{t-1}) + a_0 E(e_t e_{t-1}) + a_1 E(e_{t-1}^2) + a_2 E(e_{t-2} e_{t-1}) \\ &= (\rho_1 a_0 + a_1) \sigma_e^2 \\ &= E(u_{t-1} e_{t-2}) \end{aligned} \tag{2}$$

$$\begin{aligned} E(u_t e_{t-2}) &= \rho_1 E(u_{t-1} e_{t-2}) + \rho_2 E(u_{t-2} e_{t-2}) + a_0 E(e_t e_{t-2}) + a_1 E(e_{t-1} e_{t-2}) + a_2 E(e_{t-2}^2) \\ &= \rho_1 (\rho_1 a_0 + a_1) \sigma_e^2 + \rho_2 a_0 \sigma_e^2 + a_2 \sigma_e^2 \\ &= (\rho_1^2 a_0 + \rho_1 a_1 + \rho_2 a_0 + a_2) \sigma_e^2 \end{aligned} \tag{3}$$

The Yule-Walker equations for an ARMA(2,2) process is

$$\begin{aligned} \gamma(0) &= E u_t^2 \\ &= E(\rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2})^2 \\ &= (\rho_1^2 + \rho_2^2) \gamma(0) + 2\rho_1 \rho_2 \gamma(1) + (a_0^2 + a_1^2 + a_2^2) \sigma_e^2 + 2\rho_1 a_1 E(u_{t-1} e_{t-1}) \\ &\quad + 2\rho_2 a_2 E(u_{t-2} e_{t-2}) + 2\rho_1 a_2 E(u_{t-1} e_{t-2}) \\ &= (\rho_1^2 + \rho_2^2) \gamma(0) + 2\rho_1 \rho_2 \gamma(1) + (a_0^2 + a_1^2 + a_2^2 + 2\rho_1 a_1 a_0 + 2\rho_2 a_2 a_0 + 2\rho_1 a_2 a_1 + 2\rho_1^2 a_2 a_0) \sigma_e^2 \end{aligned}$$

Alternatively

$$\begin{aligned}
\gamma(0) &= Eu_t^2 \\
&= E[u_t(\rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2})] \\
&= \rho_1 E(u_t u_{t-1}) + \rho_2 E(u_t u_{t-2}) + a_0 E(u_t e_t) + a_1 E(u_t e_{t-1}) + a_2 E(u_t e_{t-2}) \\
&\quad \underline{\text{plugging in (1),(2) and (3)}} \quad \rho_1 \gamma(1) + \rho_2 \gamma(2) + (a_0^2 + a_1^2 + a_2^2 + a_1 \rho_1 a_0 + a_2 \rho_2 a_0 + a_2 \rho_1 a_1 + a_2 \rho_1^2 a_0) \sigma_e^2 \\
\gamma(1) &= E(u_t u_{t-1}) \\
&= E[u_{t-1}(\rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2})] \\
&= \rho_1 E u_{t-1}^2 + \rho_2 E(u_{t-1} u_{t-2}) + a_0 E(u_{t-1} e_t) + a_1 E(u_{t-1} e_{t-1}) + a_2 E(u_{t-1} e_{t-2}) \\
&\quad \underline{\text{plugging in (1) and (2)}} \quad \rho_1 \gamma(0) + \rho_2 \gamma(1) + (a_1 a_0 + a_2 a_1 + a_2 \rho_1 a_0) \sigma_e^2 \\
\gamma(2) &= E(u_t u_{t-2}) \\
&= E[u_{t-2}(\rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2})] \\
&= \rho_1 E(u_{t-2} u_{t-1}) + \rho_2 E u_{t-2}^2 + a_0 E(u_{t-2} e_t) + a_1 E(u_{t-2} e_{t-1}) + a_2 E(u_{t-2} e_{t-2}) \\
&\quad \underline{\text{plugging in (1)}} \quad \rho_1 \gamma(1) + \rho_2 \gamma(0) + a_2 a_0 \sigma_e^2 \\
\gamma(k) &= E(u_t u_{t-k}) \\
&= E[u_{t-k}(\rho_1 u_{t-1} + \rho_2 u_{t-2} + a_0 e_t + a_1 e_{t-1} + a_2 e_{t-2})] \\
&= \rho_1 \gamma(k-1) + \rho_2 \gamma(k-2) \quad k \geq 3
\end{aligned}$$

## 6. Random Effect Model

Rewrite the error as

$$v = u + e$$

where  $e$  is a AR(1) process and  $u$  is a random effect.

$$\begin{aligned}
\Omega &= E(vv') \\
&= \begin{pmatrix} A & 0_T & \cdots & 0_T \\ 0_T & A & \cdots & 0_T \\ \vdots & \vdots & \ddots & \vdots \\ 0_T & 0_T & \cdots & A \end{pmatrix}
\end{aligned}$$

where

$$A_{T \times T} = \begin{pmatrix} \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \rho \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \cdots & \rho^{T-1} \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 \\ \rho \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \cdots & \rho^{T-2} \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 \\ \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \rho^{T-2} \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 & \cdots & \frac{\sigma_\varepsilon^2}{1-\rho^2} + \sigma_u^2 \end{pmatrix}$$

There are three unknown parameters:  $\rho, \sigma_\varepsilon, \sigma_u$ . Using MOM, we compute first three moments to estimate them and get  $\hat{\Omega}$ . Therefore,

$$\beta_{FGLS} = \left( X' \hat{\Omega}^{-1} X \right)^{-1} X' \hat{\Omega}^{-1} y$$

Alternatively, following Andrews (1991) and Newey & West (1987,1994), we can construct a heteroskedasticity and autocorrection consistent variance-covariance matrix estimator to estimate  $\Omega$ .