Problem Set 4

Program Evaluation and Causal Inference

Christian Birchler Fenqi Guo Mingrui Zhang Wenjie Tu Zunhan Zhang

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Names are listed in alphabetical order

Instrumental Variables

1. Bias of the IV estimator

$$y_i = \beta_0 + \beta_1 x_i + u_i$$

1(a)

$$\begin{aligned} Cov(y_i, z_i) &= Cov(\beta_0 + \beta_1 x_i + u_i, z_i) \\ &= \beta_1 Cov(x_i, z_i) + \underbrace{Cov(u_i, z_i)}_{0} \\ &= \beta_1 Cov(x_i, z_i) \end{aligned}$$

$$\beta_1 = \frac{Cov(y_i, z_i)}{Cov(x_i, z_i)}$$

where $Cov(y_i, z_i)$ can be obtained from reduced-form equation and $Cov(x_i, z_i)$ can be obtained from first-stage regression.

$$\begin{aligned} \hat{\beta}_{IV} &= \frac{\widehat{Cov(y_i, z_i)}}{\widehat{Cov(x_i, z_i)}} \\ &= \frac{\sum_{i=1}^n (z_i - \overline{z})(y_i - \overline{y})}{\sum_{i=1}^n (z_i - \overline{z})(x_i - \overline{x})} \\ &= \frac{\sum_{i=1}^n (z_i y_i - z_i \overline{y} - y_i \overline{z} + \overline{yz})}{\sum_{i=1}^n (z_i x_i - z_i \overline{x} - x_i \overline{z} + \overline{xz})} \\ &= \frac{\sum_{i=1}^n (z_i y_i - y_i \overline{z}) - \overline{y} \sum_{i=1}^n z_i + n\overline{yz}}{\sum_{i=1}^n (z_i x_i - x_i \overline{z}) - \overline{x} \sum_{i=1}^n z_i + n\overline{xz}} \\ &= \frac{\sum_{i=1}^n (z_i y_i - y_i \overline{z}) - n\overline{yz} + n\overline{yz}}{\sum_{i=1}^n (z_i x_i - x_i \overline{z}) - n\overline{xz} + n\overline{xz}} \\ &= \frac{\sum_{i=1}^n (z_i - \overline{z}) y_i}{\sum_{i=1}^n (z_i - \overline{z}) x_i} \end{aligned}$$

1(b)

$$\begin{aligned}
\hat{\beta}_{IV} &= \frac{\sum_{i=1}^{n}(z_i - \overline{z})y_i}{\sum_{i=1}^{n}(z_i - \overline{z})x_i} \\
&= \frac{\sum_{i=1}^{n}(z_i - \overline{z})(\beta_0 + \beta_1 x_i + u_i)}{\sum_{i=1}^{n}(z_i - \overline{z})x_i} \\
&= \frac{\beta_0 \sum_{i=1}^{n}(z_i - \overline{z}) + \beta_1 \sum_{i=1}^{n}(z_i - \overline{z})x_i + \sum_{i=1}^{n}(z_i - \overline{z})u_i}{\sum_{i=1}^{n}(z_i - \overline{z})x_i} \\
&= \beta_1 + \underbrace{\frac{\sum_{i=1}^{n}(z_i - \overline{z})u_i}{\sum_{i=1}^{n}(z_i - \overline{z})x_i}}_{\text{bias}}
\end{aligned}$$

$$\begin{aligned}
\mathbb{E}\left[\hat{\beta}_{IV} \mid x_i, z_i\right] &= \beta_1 + \mathbb{E}\left[\frac{\sum_{i=1}^{n}(z_i - \overline{z})u_i}{\sum_{i=1}^{n}(z_i - \overline{z})x_i}\middle| x_i, z_i\right] \\
&= \beta_1 + \frac{\sum_{i=1}^{n}(z_i - \overline{z})}{\sum_{i=1}^{n}(z_i - \overline{z})x_i} \underbrace{\mathbb{E}\left[u_i \mid x_i, z_i\right]}_{\neq 0}
\end{aligned}$$

$\mathbb{E}\left[u_i \mid x_i, z_i\right] \neq 0$ since $u_i \not\perp x_i$.

1(c)

$$\begin{aligned}
p\lim(\hat{\beta}_{IV} - \beta_1) &= \frac{p\lim \sum_{i=1}^{n}(z_i - \overline{z})u_i}{p\lim \sum_{i=1}^{n}(z_i - \overline{z})x_i} \\
&= \frac{p\lim \sum_{i=1}^{n}(z_i - \overline{z})(u_i - \overline{u})}{p\lim \sum_{i=1}^{n}(z_i - \overline{z})(x_i - \overline{x})} \\
&= \frac{p\lim \frac{1}{n} \sum_{i=1}^{n}(z_i - \overline{z})(u_i - \overline{u})}{p\lim \frac{1}{n} \sum_{i=1}^{n}(z_i - \overline{z})(x_i - \overline{x})} \\
&\approx \frac{Cov(z_i, u_i)}{Cov(z_i, x_i)} = 0
\end{aligned}$$

By *Exogeneity Assumption*, $Cov(z_i, u_i) = 0$ and by *Relevance Assumption*, $Cov(z_i, x_i) \neq 0$ Therefore, $\hat{\beta}_{IV}$ is a consistent estimator of β_1.

1(d)

In a small sample, $\hat{\beta}_{IV}$ is biased. But as the sample increases, β_{IV} will probability converge to the β_1. Therefore, in a large sample, IV estimator will be a consistent estimator of β_1 regardless of whether there exists an endogeneity problem.

2. Derivation of the Wald estimator

2(a)

From question 1, we know that

$$
\begin{aligned}
\delta^W = \hat{\beta}_1 &= \frac{Cov(y_i, z_i)}{Cov(d_i, z_i)} \\
&= \frac{\mathbb{E}[y_i \mid z_i = 1] - \mathbb{E}[y_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1] - \mathbb{E}[d_i \mid z_i = 0]} \\
&= \frac{\mathbb{E}[\beta_1 + \beta_1 d_i + u_i \mid z_i = 1] - \mathbb{E}[\beta_1 + \beta_1 d_i + u_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1) - \mathbb{E}(d_i \mid z_i = 0]} \\
&= \frac{\beta_1 \mathbb{E}[d_i \mid z_i = 1] + \mathbb{E}[u_i \mid z_i = 1] - \beta_1 \mathbb{E}[d_i \mid z_i = 0] - \mathbb{E}[u_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1) - \mathbb{E}(d_i \mid z_i = 0]} \\
&= \frac{\beta_1 \left(\mathbb{E}[d_i \mid z_i = 1] - \mathbb{E}[d_i \mid z_i = 0]\right) + \mathbb{E}[u_i \mid z_i = 1] - \mathbb{E}[u_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1] - \mathbb{E}[d_i \mid z_i = 0]} \\
&= \beta_1 + \frac{\mathbb{E}[u_i \mid z_i = 1] - \mathbb{E}[u_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1] - \mathbb{E}[d_i \mid z_i = 0]}
\end{aligned}
$$

2(b)

In order to identify β_1 using the instrument, we need

$$
\frac{\mathbb{E}[u_i \mid z_i = 1] - \mathbb{E}[u_i \mid z_i = 0]}{\mathbb{E}[d_i \mid z_i = 1] - \mathbb{E}[d_i \mid z_i = 0]} = 0 \iff \begin{cases} \mathbb{E}[u_i \mid z_i = 1] = \mathbb{E}[u_i \mid z_i = 0] & \text{Exclusion Assumption} \\ \mathbb{E}[d_i \mid z_i = 1] \neq \mathbb{E}[d_i \mid z_i = 0] & \text{Relevance Assumption} \end{cases}
$$

Assumptions

- SUTVA (Stable Unit Treatment Value Assumption): outcomes of the ith individual are independent of other individuals' outcome
- Exclusion restriction: $\mathbb{E}[y_i \mid z = 1, d] = \mathbb{E}[y_i \mid z = 0, d] \quad \forall i = 0, 1$
- Relevance assumption: $\mathbb{E}[d \mid z = 1] \neq \mathbb{E}[d \mid z = 0]$
- Monotonicity assumption: $d_i(z_i = 1) \geq d_i(z_i = 0) \quad \forall i$

Only relevance assumption can be tested empirically. The vadility of other assumptions must be assessed on a case-by-case basis.

3. Self selection revisited

3(a)

$$
\begin{aligned}
D_i &= \mathbf{1}(Y_{1i} - Y_{0i} > 0) \\
&= \mathbf{1}(\beta_1 + u_{1i} - u_{0i} > 0)
\end{aligned}
$$

$$
\begin{aligned}
\Delta^{\text{ATE}} &= \mathbb{E}(Y_{1i} - Y_{0i}) \\
&= \mathbb{E}[(\beta_0 + \beta_1 + u_{1i}) - (\beta_0 + u_{0i})] \\
&= \mathbb{E}(\beta_1 + u_{1i} - u_{0i}) \\
&= \mathbb{E}(\beta_1) + \mathbb{E}(u_{1i}) + \mathbb{E}(u_{0i}) \\
&= \beta_1 > 0
\end{aligned}
$$

$$
\begin{aligned}
\Delta^{\text{ATT}} &= \mathbb{E}(Y_{1i} - Y_{0i} \mid D = 1) \\
&= \mathbb{E}(\beta_1 + u_{1i} - u_{0i} \mid D = 1) \\
&= \beta_1 + \mathbb{E}(u_{1i} - u_{0i} \mid D = 1) \\
&= \Delta^{\text{ATE}} + \mathbb{E}(u_{1i} - u_{0i} \mid D = 1) \\
\mathbb{E}(u_{1i} - u_{0i} \mid D = 1) &= \mathbb{E}(u_{1i} - u_{0i} \mid \beta_1 + u_{1i} - u_{0i} > 0) \\
&= \mathbb{E}(u_{1i} - u_{0i} \mid u_{1i} - u_{0i} > -\beta_1) > 0
\end{aligned}
$$

ATT is larger than ATE.

3(b)

$$
\begin{aligned}
\Delta^{\text{naive}} &= \mathbb{E}(Y_{1i} \mid D = 1) - \mathbb{E}(Y_{0i} \mid D = 0) \\
&= \mathbb{E}(Y_{1i} \mid D = 1) - \mathbb{E}(Y_{0i} \mid D = 0) - \mathbb{E}(Y_{0i} \mid D = 1) + \mathbb{E}(Y_{0i} \mid D = 1) \\
&= \underbrace{\mathbb{E}(Y_{1i} \mid D = 1) - \mathbb{E}(Y_{0i} \mid D = 1)}_{\Delta^{\text{ATT}}} + \underbrace{\mathbb{E}(Y_{0i} \mid D = 1) - \mathbb{E}(Y_{0i} \mid D = 0)}_{\text{selection bias}}
\end{aligned}
$$

$$
\begin{aligned}
\text{selection bias} &= \mathbb{E}(Y_{0i} \mid D = 1) - \mathbb{E}(Y_{0i} \mid D = 0) \\
&= \mathbb{E}(\beta_0 + u_{0i} \mid \beta_1 + u_{1i} - u_{0i} > 0) - \mathbb{E}(\beta_0 + u_{0i} \mid \beta_1 + u_{1i} - u_{0i} \leq 0) \\
&= \underbrace{\mathbb{E}(u_{0i} \mid u_{0i} < u_{1i} + \beta_1)}_{\text{negative}} - \underbrace{\mathbb{E}(u_{0i} \mid u_{0i} \geq u_{1i} + \beta_1)}_{\text{positive}} \\
&< 0
\end{aligned}
$$

If individuals can self-select themselves into the program, the naive estimator will be underestimated since the selection bias is negative ($\mathbb{E}(Y_{0i}|D = 1) < \mathbb{E}(Y_{0i}|D = 0)$)

3(c)

$$
\begin{cases}
D_{1i} = \mathbf{1}(Y_{1i} - Y_{0i} + Z_i > 0) & Z_i = 1 \\
D_{0i} = \mathbf{1}(Y_{1i} - Y_{0i} > 0) & Z_i = 0
\end{cases}
$$

$$
\begin{cases}
D_{1i} = \mathbf{1}(u_{1i} - u_{0i} > -\beta_1 - Z_i) & Z_i = 1 \\
D_{0i} = \mathbf{1}(u_{1i} - u_{0i} > -\beta_1) & Z_i = 0
\end{cases}
$$

In order to identify LATE, we need to determine the conditions for compliers. Compliers are those who are induced to switch treatment status as a result of the instrument. Therefore, D_{1i}>D_{0i}$ should hold for compliers.

$$
\text{LATE} = \mathbb{E}(Y_{1i} - Y_{0i} \mid D_{1i} > D_{0i})
$$

3(d)

$$
D_{1i} > D_{0i} \implies \begin{cases} D_{1i} = 1 \\ D_{0i} = 0 \end{cases} \implies \begin{cases} u_{1i} - u_{0i} > -\beta_1 - Z_1 \\ u_{1i} - u_{0i} < -\beta_1 \end{cases} \implies -\beta_1 - Z_1 < u_{1i} + u_{0i} < -\beta_1
$$

$$
\begin{aligned}
\text{LATE} &= \mathbb{E}(Y_{1i} - Y_{0i} \mid D_{1i} > D_{0i}) \\
&= \beta_1 + \mathbb{E}(u_{1i} - u_{0i} \mid D_{1i} > D_{0i}) \\
&= \beta_1 + \underbrace{\mathbb{E}(u_{1i} - u_{0i} \mid -\beta_1 - Z_1 < u_{1i} + u_{0i} < -\beta_1)}_{<-\beta_1} \\
&< \beta_1 \equiv \text{ATE}
\end{aligned}
$$

4. Application: Angrist's (1990) study on military service

4(a)

The OLS estimate may be biased:

- There may be a self-selection bias from participants. People may self-select themselves into or not into the program.
- There may be a self-selection bias from experimenter. The military authority can select who can join the army and who cannot.

4(b)

	$Z = 0$	$Z = 1$
$D = 0$	5,928	1,875
$D = 1$	1,400	863

Due to monotonicity:

In the observed $Z = 0$ group, the individuals who received treatment ($D = 1$) must be always-takers.

$$
p_A = \mathbb{E}(D_i \mid Z_i = 0) = \frac{\sum_i \mathbf{1}(D_i[Z_i = 0] = 1)}{\sum_i \mathbf{1}(Z_i = 0)} = \frac{1400}{5928 + 1400} = 0.191
$$

In the observed $Z = 1$ group, the individuals who did not receive treatment ($D = 0$) must be never-takers.

$$
p_N = 1 - \mathbb{E}(D_i \mid Z_i = 1) = \frac{\sum_i \mathbf{1}(D_i[Z_i = 1] = 0)}{\sum_i \mathbf{1}(Z_i = 1)} = \frac{1875}{1875 + 863} = 0.685
$$

$$
\begin{aligned}
p_C &= \mathbb{E}(D_i \mid Z_i = 1) - \mathbb{E}(D_i \mid Z_i = 0) \\
&= 1 - 0.685 - 0.191 \\
&= 0.124
\end{aligned}
$$

Due to randomization:

The proportions of compliers, always-takers, and never-takers are the same between $Z = 0$ and $Z = 1$ group.

$$
p_C = 1 - p_A - p_N = 0.124
$$

Note:

- N denotes **never takers**
- C denotes **compliers**
- A denotes **always takers**

4(c)

	$Z = 0$	$Z = 1$
$D = 0$	$\widehat{\mathbb{E}(Y)} = 6.4472$	$\widehat{\mathbb{E}(Y)} = 6.4028$
$D = 1$	$\widehat{\mathbb{E}(Y)} = 6.4076$	$\widehat{\mathbb{E}(Y)} = 6.4289$

- Average potential outcome for always-takers $\mathbb{E}(Y_{1i} \mid D_i = 1, Z_i = 0) = 6.4076$
- Average potential outcome for never-takers $\mathbb{E}(Y_{0i} \mid D_i = 0, Z_i = 1) = 6.4028$

Average potential outcome for compliers:

In $Z = 0$ group:

$$\underbrace{\mathbb{E}(Y_0 \mid D = 0, Z = 0)}_{6.4472} = \frac{p_C}{p_N + p_C} \times \mathbb{E}(Y_{0i} \mid D_{1i} > D_{0i}) + \frac{p_N}{p_N + p_C} \times \mathbb{E}(Y_{0i} \mid D_{1i} = 0)$$

$$\mathbb{E}(Y_{0i} \mid D_{1i} > D_{0i}) = 6.6867$$

In $Z = 1$ group:

$$\underbrace{\mathbb{E}(Y_1 \mid D = 1, Z = 1)}_{6.4289} = \frac{p_C}{p_A + p_C} \times \mathbb{E}(Y_{1i} \mid D_{1i} > D_{0i}) + \frac{p_A}{p_A + p_C} \times \mathbb{E}(Y_{1i} \mid D_{1i} = 0)$$

$$\mathbb{E}(Y_{1i} \mid D_{1i} > D_{0i}) = 6.4616$$

- Average potential outcome for untreated compliers $\mathbb{E}(Y_{0i} \mid D_{1i} > D_{0i}) = 6.6867$
- Average potential outcome for treated compliers $\mathbb{E}(Y_{1i} \mid D_{1i} > D_{0i}) = 6.4616$

4(d)

$$\begin{aligned}\text{LATE} &= \mathbb{E}(Y_{1i} \mid D_{1i} > D_{0i}) - \mathbb{E}(Y_{0i} \mid D_{1i} > D_{0i}) \\ &= 6.4616 - 6.6867 \\ &= -0.2251\end{aligned}$$

5. IV in action

5(a)

```r
# load relevant libraries
library(haven) # read dta file
library(lattice) # density plot
library(stargazer) # print summary statistics
library(ggplot2) # plot
library(AER) # iv regression
```

```r
d.mort <- read_dta('mortality.dta')
```

```r
demo <- subset(d.mort, select = c('before67dead', 'dist65_ageATend4emp', 'Zd_during'))
```

```r
subdata <- as.data.frame(
  subset(d.mort, select = c('before67dead', 'dist65_ageATend4emp', 'Zd_during'))
)
stargazer(subdata, header = F, title = 'Descriptive Statistics')
```

Table 3: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
before67dead	2,298	0.073	0.260	0	0	0	1
dist65_ageATend4emp	2,298	6.499	2.248	−5	5	8	11
Zd_during	2,298	0.479	0.500	0	0	1	1

5(b)

```r
model.ols1 <- lm(before67dead ~ dist65_ageATend4emp + czeit1yATage50 +
                   czeit2yATage50 + czeit5yATage50 + czeit10yATage50 +
                   czeit25yATage50 + I(czeit1yATage50^2) + I(czeit2yATage50^2) +
                   I(czeit5yATage50^2) + I(czeit10yATage50^2) +
                   I(czeit25yATage50^2) + as.factor(halfyearOFbirth) +
                   as.factor(nutsATage50), data=d.mort)

model.ols2 <- lm(before67dead ~ dist65_ageATend4emp, data=d.mort)

stargazer(model.ols1, model.ols2, keep.stat='n', header=F,
          keep='dist65_ageATend4emp', font.size='small',
          column.labels=c('Control', 'Non-control'), digits=4,
          title='Comparison between control and non-control')
```

5(c)

As we can see, the coefficient on the treatment slightly increases from column 1 (with control variables) to column 2 (without control variables).

Significance

- With control variables, *p-value* is smaller than 10

Table 4: Comparison between control and non-control

	Dependent variable:	
	before67dead	
	Control	Non-control
	(1)	(2)
dist65_ageATend4emp	0.0046*	0.0049**
	(0.0026)	(0.0024)
Observations	2,298	2,298
Note:	*p<0.1; **p<0.05; ***p<0.01	

- Without control variables, *p-value* is smaller than 5

We can reject the null hypothesis in both cases but we are more confident to reject $\beta_1 = 0$ with control variables.

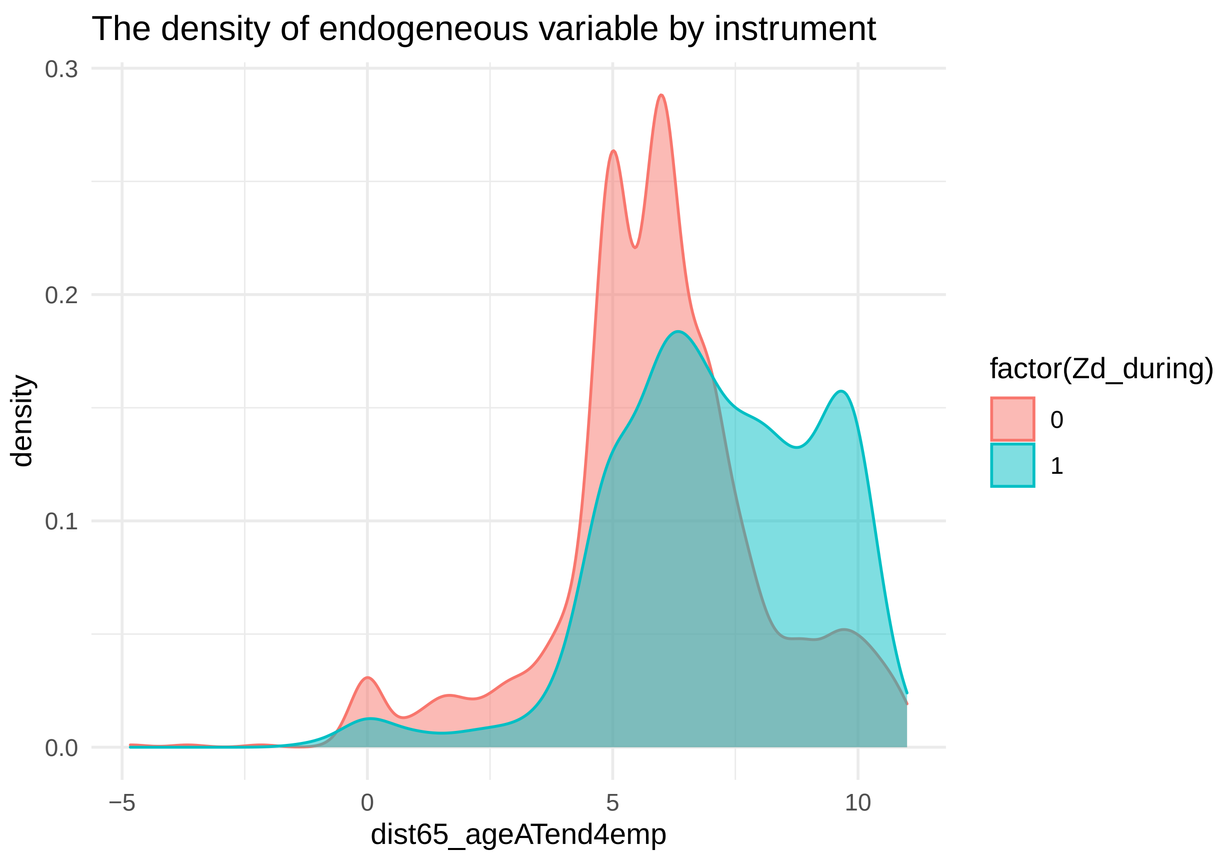
5(d)

Omitted-variable bias

Health status. If people are in a bad physical condition, they are more likely to spend less years in their early retirement or even die before retirement. Therefore, the estimator for β_1 is biased upwards and we expect a positive bias.

5(e)

```
ggplot(d.mort, aes(x = dist65_ageATend4emp)) +
  geom_density(aes(group = factor(Zd_during),
                   color = factor(Zd_during),
                   fill = factor(Zd_during)), alpha = 0.5) +
  theme_minimal() + ggtitle('The density of endogeneous variable by instrument')
```



5(f)

```
# first stage regression
iv.1st.stage <- ivreg(dist65_ageATend4emp ~ Zd_during*as.factor(halfyearOFbirth) +
                        czeit1yATage50 + czeit2yATage50 + czeit5yATage50 +
                        czeit10yATage50 + czeit25yATage50 + I(czeit1yATage50^2) +
                        I(czeit2yATage50^2) + I(czeit5yATage50^2) + I(czeit10yATage50^2) +
                        I(czeit25yATage50^2) + as.factor(halfyearOFbirth) +
                        as.factor(nutsATage50), data=d.mort)

stargazer(iv.1st.stage, keep='Zd_during', keep.stat='n', header=F,
          font.size='small', title='First stage regression', no.space=T)
```

5(g)

```
# second stage regression
iv.2nd.stage <- lm(before67dead ~ predict(iv.1st.stage) + czeit1yATage50 +
                     czeit2yATage50 + czeit5yATage50 + czeit10yATage50 +
                     czeit25yATage50 + I(czeit1yATage50^2) + I(czeit2yATage50^2) +
                     I(czeit5yATage50^2) + I(czeit10yATage50^2) +
                     I(czeit25yATage50^2) + as.factor(halfyearOFbirth) +
```

Table 5: First stage regression

	Dependent variable:
	dist65_ageATend4emp
Zd_during	0.664^{*}
	(0.345)
Zd_during:as.factor(halfyearOFbirth)-50	-0.448
	(0.492)
Zd_during:as.factor(halfyearOFbirth)-49	-0.070
	(0.505)
Zd_during:as.factor(halfyearOFbirth)-48	0.179
	(0.506)
Zd_during:as.factor(halfyearOFbirth)-47	-0.280
	(0.492)
Zd_during:as.factor(halfyearOFbirth)-46	0.424
	(0.471)
Zd_during:as.factor(halfyearOFbirth)-45	0.253
	(0.509)
Zd_during:as.factor(halfyearOFbirth)-44	0.525
	(0.504)
Zd_during:as.factor(halfyearOFbirth)-43	0.558
	(0.495)
Zd_during:as.factor(halfyearOFbirth)-42	0.150
	(0.460)
Zd_during:as.factor(halfyearOFbirth)-41	1.229^{***}
	(0.450)
Zd_during:as.factor(halfyearOFbirth)-40	0.681
	(0.451)
Zd_during:as.factor(halfyearOFbirth)-39	0.608
	(0.463)
Zd_during:as.factor(halfyearOFbirth)-38	0.524
	(0.479)
Zd_during:as.factor(halfyearOFbirth)-37	0.345
	(0.459)
Observations	2,298
Note:	*p<0.1; **p<0.05; ***p<0.01

```
                    as.factor(nutsATage50), data=d.mort)

# iv regression
model.iv <- ivreg(before67dead ~ dist65_ageATend4emp + czeit1yATage50 +
                    czeit2yATage50 + czeit5yATage50 + czeit10yATage50 +
                    czeit25yATage50 + I(czeit1yATage50^2) + I(czeit2yATage50^2) +
                   I(czeit5yATage50^2) + I(czeit10yATage50^2) + I(czeit25yATage50^2) +
                   as.factor(halfyearOFbirth) + as.factor(nutsATage50) |
                   Zd_during*as.factor(halfyearOFbirth) + czeit1yATage50 +
                   czeit2yATage50 + czeit5yATage50 + czeit10yATage50 +
                   czeit25yATage50 + I(czeit1yATage50^2) + I(czeit2yATage50^2) +
                   I(czeit5yATage50^2) + I(czeit10yATage50^2) + I(czeit25yATage50^2) +
                   as.factor(halfyearOFbirth) + as.factor(nutsATage50), data=d.mort)

stargazer(iv.2nd.stage, model.iv, font.size='small', header=F,
          keep.stat=c('n', 'f'), title='Comparsion between 2SLS and ivreg',
          keep=c('iv.1st.stage', 'dist65_ageATend4emp'), digits=4)
```

Table 6: Comparsion between 2SLS and ivreg

	Dependent variable:	
	before67dead	
	OLS	*instrumental variable*
	(1)	(2)
predict(iv.1st.stage)	−0.0143	
	(0.0109)	
dist65_ageATend4emp		−0.0143
		(0.0110)
Observations	2,298	2,298
F Statistic	1.3992* (df = 32; 2265)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

As we can see, **2SLS** and **ivreg** yield exactly the same estimate but with different standard errors.

5(h)

```
stargazer(model.ols1, model.iv, font.size='small', header=F,
          keep.stat=c('n', 'f'), keep='dist65_ageATend4emp',
          title='Comparison between OLS and 2SLS results', digits=4)
```

As expected, from column(1) to column(2), we see a decrease in the coefficient on *dist65_ageATend4emp*, which verifies our statement in 5(d) - a positive bias in the OLS estimator.

Table 7: Comparison between OLS and 2SLS results

	Dependent variable:	
	before67dead	
	OLS	*instrumental variable*
	(1)	(2)
dist65_ageATend4emp	0.0046*	−0.0143
	(0.0026)	(0.0110)
Observations	2,298	2,298
F Statistic	1.4431* (df = 32; 2265)	
Note:	*p<0.1; **p<0.05; ***p<0.01	