

# SP25 8732: Homework 2

Danbo CHEN

February 3, 2025

## 1 Question 1

(a) Solution:

```
. /// 1.A
> reg price sqrft bdrms
```

Source	SS	df	MS	Number of obs	=	88
Model	580009.152	2	290004.576	F(2, 85)	=	72.96
Residual	337845.354	85	3974.65122	Prob > F	=	0.0000
				R-squared	=	0.6319
				Adj R-squared	=	0.6233
Total	917854.506	87	10550.0518	Root MSE	=	63.045

price	Coefficient	Std. err.	t	P> t	[95% conf. interval]
sqrft	.1284362	.0138245	9.29	0.000	.1009495 .1559229
bdrms	15.19819	9.483517	1.60	0.113	-3.657582 34.05396
_cons	-19.315	31.04662	-0.62	0.536	-81.04399 42.414

```
.
. reg sqrft bdrms
```

Source	SS	df	MS	Number of obs	=	88
Model	8186960.43	1	8186960.43	F(1, 86)	=	33.85
Residual	20797100.3	86	241826.748	Prob > F	=	0.0000
				R-squared	=	0.2825
				Adj R-squared	=	0.2741
Total	28984060.7	87	333150.123	Root MSE	=	491.76

sqrft	Coefficient	Std. err.	t	P> t	[95% conf. interval]
bdrms	364.5886	62.6605	5.82	0.000	240.0236 489.1535
_cons	712.7749	229.6473	3.10	0.003	256.2513 1169.299

```
. predict e, resid
```

```
.
```

```
. reg price e
```

Source	SS	df	MS	Number of obs	=	88
Model	<b>343066.064</b>	<b>1</b>	<b>343066.064</b>	F(1, 86)	=	<b>51.33</b>
Residual	<b>574788.441</b>	<b>86</b>	<b>6683.58653</b>	Prob > F	=	<b>0.0000</b>
				R-squared	=	<b>0.3738</b>
				Adj R-squared	=	<b>0.3665</b>
Total	<b>917854.506</b>	<b>87</b>	<b>10550.0518</b>	Root MSE	=	<b>81.753</b>

  

price	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
e	<b>.1284362</b>	<b>.0179268</b>	<b>7.16</b>	<b>0.000</b>	<b>.0927989</b>	<b>.1640736</b>
_cons	<b>293.546</b>	<b>8.714921</b>	<b>33.68</b>	<b>0.000</b>	<b>276.2213</b>	<b>310.8707</b>

The coefficients of the residual's component  $e_i$  are equal to the  $\hat{\beta}_1$  estimated in the first regression. By definition, the coefficient  $\hat{\beta}_1$  is the partial effect of  $SQRFT_i$  on  $PRICE_i$  holding everything else fixed. With this procedure, estimating the residuals of  $SQRFT_i$  on  $BDRMS_i$ , we account for the variations in  $SQRFT_i$  which does not depend on the variable  $SQRFT_i$ . In other words, we keep fixed the variation of  $SQRFT_i$  due to change in  $BDRMS_i$ , and using the residuals we just see the partial effect of  $SQRFT_i$  on prices.

**(b) Solution:**

```
. /// 1.B
```

```
>
```

```
. reg bdrms sqrft
```

Source	SS	df	MS	Number of obs	=	88
Model	<b>17.3972288</b>	<b>1</b>	<b>17.3972288</b>	F(1, 86)	=	<b>33.85</b>
Residual	<b>44.1936803</b>	<b>86</b>	<b>.513880004</b>	Prob > F	=	<b>0.0000</b>
				R-squared	=	<b>0.2825</b>
				Adj R-squared	=	<b>0.2741</b>
Total	<b>61.5909091</b>	<b>87</b>	<b>.707941484</b>	Root MSE	=	<b>.71685</b>

  

bdrms	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
sqrft	<b>.0007747</b>	<b>.0001332</b>	<b>5.82</b>	<b>0.000</b>	<b>.00051</b>	<b>.0010394</b>
_cons	<b>2.008077</b>	<b>.2788063</b>	<b>7.20</b>	<b>0.000</b>	<b>1.453829</b>	<b>2.562326</b>

```
. gen delta_1 = _b[sqrft]
```

```
.
. reg price sqrft
```

Source	SS	df	MS	Number of obs	=	88
Model	569801.074	1	569801.074	F(1, 86)	=	140.79
Residual	348053.432	86	4047.13293	Prob > F	=	0.0000
				R-squared	=	0.6208
				Adj R-squared	=	0.6164
Total	917854.506	87	10550.0518	Root MSE	=	63.617

price	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
sqrft	.140211	.0118166	11.87	0.000	.1167203	.1637017
_cons	11.20415	24.74261	0.45	0.652	-37.98253	60.39082

```
.
. reg price sqrft bdrms
```

Source	SS	df	MS	Number of obs	=	88
Model	580009.152	2	290004.576	F(2, 85)	=	72.96
Residual	337845.354	85	3974.65122	Prob > F	=	0.0000
				R-squared	=	0.6319
				Adj R-squared	=	0.6233
Total	917854.506	87	10550.0518	Root MSE	=	63.045

price	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
sqrft	.1284362	.0138245	9.29	0.000	.1009495	.1559229
bdrms	15.19819	9.483517	1.60	0.113	-3.657582	34.05396
_cons	-19.315	31.04662	-0.62	0.536	-81.04399	42.414

```
. gen beta_1_hat = _b[sqrft]
```

```
. gen beta_2_hat = _b[bdrms]
```

```
.
. gen error = beta_1_tilde - beta_1_hat - beta_2_hat*delta_1
```

Results are presented in Table 1.

Table 1: Estimation results from above steps.

$\tilde{\delta}_1$	$\tilde{\beta}_1$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\tilde{\beta}_1 - \hat{\beta}_1 - \hat{\beta}_2 \tilde{\delta}_1$
0.0007747	0.140211	0.1284362	15.19819	-3.23e-09

We can verify that:

$$\tilde{\beta}_1 = \hat{\beta}_1 + \hat{\beta}_2 \tilde{\delta}_1$$

To derive the expectation result, we take the conditional expectation on both sides and use the fact

that the \*\*OLS estimator\*\* is conditionally unbiased:

$$\mathbb{E}[\hat{\beta}_1] = \beta_1, \quad \mathbb{E}[\hat{\beta}_2] = \beta_2.$$

Furthermore,  $\tilde{\delta}_1$  is a function of the data matrix  $X$ :

$$\tilde{\delta}_1 = (X_1' X_1)^{-1} X_1' X_2.$$

Thus:

$$\mathbb{E}[\hat{\beta}_1 | X] = \mathbb{E}[\hat{\beta}_1 + \hat{\beta}_2 \tilde{\delta}_1 | X] = \beta_1 + \beta_2 \tilde{\delta}_1.$$

We consider a regression model:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i,$$

where  $X_{i2}$  is omitted from the regression. Define:

$$X_i = \begin{bmatrix} 1 \\ SQRFT_i \\ BDRMS_i \end{bmatrix}, \quad Z_{i1} = \begin{bmatrix} 1 \\ SQRFT_i \end{bmatrix}, \quad Z_{i2} = [BDRMS_i].$$

Let:

$$\gamma_1 = (\beta_0, \beta_1)', \quad \gamma_2 = (\beta_2).$$

$$\hat{\beta} = (Z_1' Z_1)^{-1} Z_1' Y.$$

Substituting  $Y = Z\beta + \varepsilon$ :

$$\hat{\beta} = (Z_1' Z_1)^{-1} Z_1' (Z\beta + \varepsilon).$$

Expanding:

$$\hat{\beta} = \gamma_1 + P_{1.2} \gamma_2 + (Z_1' Z_1)^{-1} Z_1' \varepsilon.$$

**Taking Expectation:**

$$\mathbb{E}[\hat{\beta} | X] = \gamma_1 + P_{1.2} \gamma_2.$$

Since  $Z_2$  is a scalar,  $\gamma_2 = \beta_2$ , and:

$$P_{1.2} = (\tilde{\delta}_0, \tilde{\delta}_1)'$$

Thus, we obtain:

$$\mathbb{E} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{bmatrix} \bigg| X = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \tilde{\delta}_0 \\ \tilde{\delta}_1 \end{bmatrix} \beta_2.$$

The second row confirms the required result.

## 2 Question 2

**Solution:**

$P_Z =$

$$\begin{aligned} \text{(a) when } L \times K, \quad \beta_{ZV} &= (Z'X)^{-1}Z'y = (Z'X)^{-1}Z'(X\beta + \epsilon) = (Z'X)^{-1}Z'X'\beta + (Z'X)^{-1}Z'\epsilon \\ &= \beta + (Z'X)^{-1}Z'\epsilon = \beta + \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i \epsilon_i\right) \\ &\Rightarrow \beta + \underbrace{\left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i \epsilon_i\right)}_{\xrightarrow{p} E Z_i X_i \quad E Z_i \epsilon_i} \\ &\xrightarrow{p} \beta \end{aligned}$$

$$\hat{\beta}_{ZV} - \beta = \left(\sum_{i=1}^n z_i x_i'\right)^{-1} \left(\sum_{i=1}^n z_i \epsilon_i\right), \quad \hat{\beta}_{ZLS} = (Z'X)^{-1}Z'y, \quad \text{Let } P_Z = Z(Z'Z)^{-1}Z'$$

$$\hat{X} = P_Z X = Z(Z'Z)^{-1}Z'X$$

$$\hat{\beta}_{ZLS} = (X'P_Z X)^{-1}X'P_Z y = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'X y$$

$$\hat{\beta}_{ZLS} - \beta = [X'Z(Z'Z)^{-1}Z'X]^{-1}X'Z(Z'Z)^{-1}Z'\epsilon$$

(b) Moment of  $x_i$  and  $z_i$ ,  $E[x_i x_i'] = Q_{xx} < \infty$ , rank  $Q_{xx} = K$   
 $E[z_i z_i'] = Q_{zz} < \infty$ , rank  $Q_{zz} = L$   
 $E[z_i x_i'] = Q_{zx} < \infty$  rank  $Q_{zx} = K$ .

By CLT and WLLN,

$$\begin{aligned} \sqrt{n}(\hat{\beta}_{ZLS} - \beta) &= \sqrt{n} \left[ \left( \frac{1}{n} \sum_{i=1}^n x_i z_i' \right) \left( \frac{1}{n} \sum_{i=1}^n z_i z_i' \right)^{-1} \left( \frac{1}{n} \sum_{i=1}^n z_i x_i' \right) \right]^{-1} \left( \frac{1}{n} \sum_{i=1}^n x_i z_i' \right) \left( \frac{1}{n} \sum_{i=1}^n z_i \epsilon_i \right) \\ &\xrightarrow{p} (Q_{xz} Q_{zz}^{-1} Q_{zx})^{-1} Q_{xz} Q_{zz}^{-1} \end{aligned}$$

$$\sqrt{n} \cdot \frac{Z'\epsilon}{n} = \sqrt{n} \cdot \frac{1}{n} \sum_{i=1}^n z_i \epsilon_i \xrightarrow{d} N(0, \Sigma)$$

$$\sqrt{n}(\hat{\beta}_{ZLS} - \beta) \xrightarrow{d} (Q_{xz} Q_{zz}^{-1} Q_{zx})^{-1} Q_{xz} Q_{zz}^{-1} N(0, \Sigma) = N(0, V)$$

$$V = (Q_{xz} Q_{zz}^{-1} Q_{zx})^{-1} Q_{xz} (Q_{zz}^{-1} \Sigma Q_{zz}^{-1} Q_{zx}) (Q_{xz} Q_{zz}^{-1} Q_{zx})^{-1}$$

c. If under Homoskedasticity,  $E(\epsilon_i^2) = \sigma^2$

Then  $(\sqrt{n} \frac{1}{n} \sum z_i \epsilon_i) \rightarrow_d N(0, \sigma^2 Q_{zz})$

~~can be~~  $\Rightarrow V = \sigma^2 (Q_{xx} Q_{zz}^{-1} Q_{zx})^{-1}$

A sample analog  $\hat{V} = \hat{\sigma}^2 (\hat{Q}_{xx} \hat{Q}_{zz}^{-1} \hat{Q}_{zx})^{-1}$  where

$$\hat{Q}_{xx} = \frac{1}{n} X'X; \hat{Q}_{zz} = \frac{1}{n} Z'Z; \hat{Q}_{zx} = \frac{1}{n} Z'X$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \epsilon_i^2 = \frac{1}{n} \sum_{i=1}^n (y_i - x_i' \hat{\beta}_{OLS})^2$$

If under heteroskedasticity,  $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n z_i z_i' \epsilon_i^2 = \frac{1}{n} \sum_{i=1}^n z_i z_i' (y_i - x_i' \hat{\beta}_{OLS})^2$   
 $= \frac{1}{n} \sum_{i=1}^n z_i z_i' \epsilon_i^2$

d. (i) Under Homoskedasticity,  $\hat{V} = \hat{\sigma}^2 (\hat{Q}_{xx} \hat{Q}_{zz}^{-1} \hat{Q}_{zx})^{-1}$

$$\hat{\epsilon}_i = y_i - x_i' \hat{\beta} = x_i' \beta + \epsilon_i - x_i' \hat{\beta} = x_i' (\beta - \hat{\beta}) + \epsilon_i$$

$$\hat{\epsilon}_i^2 = (y_i - x_i' \hat{\beta})^2 = (x_i' (\beta - \hat{\beta}) + \epsilon_i)^2 = (\beta - \hat{\beta})' x_i x_i' (\beta - \hat{\beta}) + 2(\beta - \hat{\beta})' x_i \epsilon_i + \epsilon_i^2$$

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n \hat{\epsilon}_i^2 = \frac{1}{n} \sum_{i=1}^n \hat{\epsilon}_i^2 + 2(\beta - \hat{\beta})' \frac{1}{n} \sum_{i=1}^n x_i \epsilon_i + (\beta - \hat{\beta})' \frac{1}{n} \sum_{i=1}^n x_i x_i' (\beta - \hat{\beta})$$

By WLLN,  $\frac{1}{n} \sum_{i=1}^n \epsilon_i^2 \rightarrow_p \sigma^2$

Since  $E x_{ik}^2 < \infty$  and  $E \epsilon_i^2 < \infty$ ,  $E x_{ik} \epsilon_i < \infty$ , we can get

$$\frac{1}{n} \sum_{i=1}^n x_i \epsilon_i \rightarrow_p 0 \quad (\text{By WLLN})$$

By WLLN,  $\frac{1}{n} \sum_{i=1}^n x_i x_i' \rightarrow_p E x_i x_i' = Q_{xx}$  as  $n \rightarrow \infty$

Thus:  $\hat{\sigma} \rightarrow_p \sigma$ ,  $\hat{V} \rightarrow_p V$ .

(ii) If under heteroskedasticity,

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n z_i z_i' (y_i - x_i' \hat{\beta}_{OLS})^2$$

$$= \frac{1}{n} \sum_{i=1}^n z_i z_i' \epsilon_i^2 + 2 \frac{1}{n} \sum_{i=1}^n z_i z_i' [(\beta - \hat{\beta})' x_i \epsilon_i] + \frac{1}{n} \sum_{i=1}^n z_i z_i' [(\beta - \hat{\beta})' x_i x_i' (\beta - \hat{\beta})]$$

$$\frac{1}{n} \sum_{i=1}^n z_i z_i' \epsilon_i^2 \rightarrow_p E[z_i z_i' \epsilon_i^2] < \infty$$

$$\frac{1}{n} \sum_{i=1}^n z_i z_i' [(\beta - \hat{\beta})' x_i \epsilon_i] = (\beta - \hat{\beta})' \frac{1}{n} \sum_{i=1}^n z_i x_i z_i' \epsilon_i$$

$$\rightarrow_p E[z_i x_i z_i' \epsilon_i] < \infty$$

### 3 Question 3

Solution:

```

.
. // A
. eststo: ivregress 2sls lwage exper tenure (educ = sibs feduc meduc), first

```

First-stage regressions

```

Number of obs = 722
F(5, 716) = 73.49
Prob > F = 0.0000
R-squared = 0.3391
Adj R-squared = 0.3345
Root MSE = 1.8247

```

educ	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
exper	-.2009287	.0173033	-11.61	0.000	-.2348999	-.1669575
tenure	.037542	.0141963	2.64	0.008	.0096706	.0654135
sibs	-.1085301	.0317095	-3.42	0.001	-.1707849	-.0462754
feduc	.1568147	.0256903	6.10	0.000	.1063774	.2072521
meduc	.110667	.030085	3.68	0.000	.0516017	.1697323
_cons	13.17707	.4193578	31.42	0.000	12.35375	14.00039

Instrumental variables 2SLS regression

```

Number of obs = 722
Wald chi2(3) = 76.58
Prob > chi2 = 0.0000
R-squared = 0.0641
Root MSE = .40543

```

lwage	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
educ	.1376307	.0183256	7.51	0.000	.1017133	.1735482
exper	.033928	.0058711	5.78	0.000	.0224208	.0454351
tenure	.0073686	.0032532	2.27	0.024	.0009925	.0137447
_cons	4.481904	.2992201	14.98	0.000	3.895443	5.068365

```

. // B
. eststo: reg educ exper tenure sibs feduc meduc

```

Source	SS	df	MS	Number of obs	=	722
Model	1223.3278	5	244.665559	F(5, 716)	=	73.49
Residual	2383.88689	716	3.32945096	Prob > F	=	0.0000
				R-squared	=	0.3391
				Adj R-squared	=	0.3345
Total	3607.21468	721	5.00307168	Root MSE	=	1.8247

educ	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
exper	-.2009287	.0173033	-11.61	0.000	-.2348999	-.1669575
tenure	.037542	.0141963	2.64	0.008	.0096706	.0654135
sibs	-.1085301	.0317095	-3.42	0.001	-.1707849	-.0462754
feduc	.1568147	.0256903	6.10	0.000	.1063774	.2072521
meduc	.110667	.030085	3.68	0.000	.0516017	.1697323
_cons	13.17707	.4193578	31.42	0.000	12.35375	14.00039

(est2 stored)



```
. predict educ_hat
(option xb assumed; fitted values)
(213 missing values generated)
```

```
. eststo: reg lwage educ_hat exper tenure
```

Source	SS	df	MS	Number of obs	=	722
Model	12.5876366	3	4.19587887	F(3, 718)	=	26.37
Residual	114.224295	718	.159086761	Prob > F	=	0.0000
				R-squared	=	0.0993
				Adj R-squared	=	0.0955
Total	126.811931	721	.1758834	Root MSE	=	.39886

  

lwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]
educ_hat	.1376307	.0180283	7.63	0.000	.1022362 .1730252
exper	.033928	.0057759	5.87	0.000	.0225884 .0452675
tenure	.0073686	.0032004	2.30	0.022	.0010853 .0136518
_cons	4.481904	.2943666	15.23	0.000	3.903982 5.059826

```
(est3 stored)
```

```
. // For the Table
. reg educ exper tenure sibs feduc meduc
```

Source	SS	df	MS	Number of obs	=	722
Model	1223.3278	5	244.665559	F(5, 716)	=	73.49
Residual	2383.88689	716	3.32945096	Prob > F	=	0.0000
				R-squared	=	0.3391
				Adj R-squared	=	0.3345
Total	3607.21468	721	5.00307168	Root MSE	=	1.8247

  

educ	Coefficient	Std. err.	t	P> t	[95% conf. interval]
exper	-.2009287	.0173033	-11.61	0.000	-.2348999 -.1669575
tenure	.037542	.0141963	2.64	0.008	.0096706 .0654135
sibs	-.1085301	.0317095	-3.42	0.001	-.1707849 -.0462754
feduc	.1568147	.0256903	6.10	0.000	.1063774 .2072521
meduc	.110667	.030085	3.68	0.000	.0516017 .1697323
_cons	13.17707	.4193578	31.42	0.000	12.35375 14.00039

  

```
. reg lwage educ_hat exper tenure
```

Source	SS	df	MS	Number of obs	=	722
Model	12.5876366	3	4.19587887	F(3, 718)	=	26.37
Residual	114.224295	718	.159086761	Prob > F	=	0.0000
				R-squared	=	0.0993
				Adj R-squared	=	0.0955
Total	126.811931	721	.1758834	Root MSE	=	.39886

  

lwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]
educ_hat	.1376307	.0180283	7.63	0.000	.1022362 .1730252
exper	.033928	.0057759	5.87	0.000	.0225884 .0452675
tenure	.0073686	.0032004	2.30	0.022	.0010853 .0136518
_cons	4.481904	.2943666	15.23	0.000	3.903982 5.059826

We can notice that all estimates  $\beta_j$  are identical to those obtained before, but that the standard errors in the second equation are different. In the second case, the estimate of  $\sigma^2$  is wrong. Its



computation includes the variance of the sum of the error term in the second equation and the error term from the first stage regression. Since  $\hat{X}$  is a projection of  $X$ , 2SLS will have higher variance (even if OLS is inconsistent). This confirms the fact that, when OLS is consistent, it is better than 2SLS. But when  $X$  is endogenous, we must account for endogeneity using the 2SLS procedure. In summary, we can conclude that standard errors from the second approach are invalid.

```
. // c
. eststo: reg educ sibs feduc meduc
```

Source	SS	df	MS	Number of obs	=	722
Model	772.281437	3	257.427146	F(3, 718)	=	65.20
Residual	2834.93324	718	3.94837499	Prob > F	=	0.0000
				R-squared	=	0.2141
				Adj R-squared	=	0.2108
Total	3607.21468	721	5.00307168	Root MSE	=	1.9871

  

	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
educ						
sibs	-.0936359	.0344713	-2.72	0.007	-.1613124	-.0259594
feduc	.2100041	.0274748	7.64	0.000	.1560635	.2639447
meduc	.1307872	.032689	4.00	0.000	.0666098	.1949646
_cons	10.36426	.3585001	28.91	0.000	9.660422	11.06809

```
(est4 stored)

. predict educ_tilde
(option xb assumed; fitted values)
(213 missing values generated)

. eststo: reg lwage educ_tilde exper tenure
```

Source	SS	df	MS	Number of obs	=	722
Model	12.619224	3	4.20640799	F(3, 718)	=	26.45
Residual	114.192707	718	.159042768	Prob > F	=	0.0000
				R-squared	=	0.0995
				Adj R-squared	=	0.0957
Total	126.811931	721	.1758834	Root MSE	=	.3988

  

	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
lwage						
educ_tilde	.1129465	.0147677	7.65	0.000	.0839534	.1419396
exper	.0065613	.0037657	1.74	0.082	-.0008319	.0139544
tenure	.0126207	.0030986	4.07	0.000	.0065374	.018704
_cons	5.091582	.2153205	23.65	0.000	4.668849	5.514315

```
(est5 stored)
```

```
.
. // For the Table
. reg educ sibs feduc meduc
```

Source	SS	df	MS	Number of obs	=	722
Model	772.281437	3	257.427146	F(3, 718)	=	65.20
Residual	2834.93324	718	3.94837499	Prob > F	=	0.0000
				R-squared	=	0.2141
				Adj R-squared	=	0.2108
Total	3607.21468	721	5.00307168	Root MSE	=	1.9871

educ	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
sibs	-.0936359	.0344713	-2.72	0.007	-.1613124	-.0259594
feduc	.2100041	.0274748	7.64	0.000	.1560635	.2639447
meduc	.1307872	.032689	4.00	0.000	.0666098	.1949646
_cons	10.36426	.3585001	28.91	0.000	9.660422	11.06809

```
. reg lwage educ_tilde exper tenure
```

Source	SS	df	MS	Number of obs	=	722
Model	12.619224	3	4.20640799	F(3, 718)	=	26.45
Residual	114.192707	718	.159042768	Prob > F	=	0.0000
				R-squared	=	0.0995
				Adj R-squared	=	0.0957
Total	126.811931	721	.1758834	Root MSE	=	.3988

lwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
educ_tilde	.1129465	.0147677	7.65	0.000	.0839534	.1419396
exper	.0065613	.0037657	1.74	0.082	-.0008319	.0139544
tenure	.0126207	.0030986	4.07	0.000	.0065374	.018704
_cons	5.091582	.2153205	23.65	0.000	4.668849	5.514315

The first stage is used to estimate the endogenous variable, and if the first stage is not correctly specified, the second stage will not be consistent. The error term in the second stage will not be orthogonal to the exogenous regressors and the estimator will be inconsistent.

```
. // D
. eststo: reg lwage educ exper tenure
```

Source	SS	df	MS	Number of obs	=	935
Model	25.6953278	3	8.56510927	F(3, 931)	=	56.97
Residual	139.960966	931	.150334013	Prob > F	=	0.0000
				R-squared	=	0.1551
				Adj R-squared	=	0.1524
Total	165.656294	934	.177362199	Root MSE	=	.38773

lwage	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
educ	.0748638	.0065124	11.50	0.000	.062083	.0876446
exper	.0153285	.0033696	4.55	0.000	.0087156	.0219413
tenure	.0133748	.0025872	5.17	0.000	.0082974	.0184522
_cons	5.496696	.1105282	49.73	0.000	5.279782	5.713609

(est6 stored)

```
. esttab, se ar2 replace
```

> _____	(1)	(2)	(3)	(4)
> (5)	(6)			
> lwage	lwage	educ	lwage	educ
> _____				
educ	<b>0.138***</b>			
>	<b>0.0749***</b>			
	(0.0183)			
>	(0.00651)			
exper	<b>0.0339***</b>	<b>-0.201***</b>	<b>0.0339***</b>	
> <b>0.00656</b>	<b>0.0153***</b>			
	(0.00587)	(0.0173)	(0.00578)	
> (0.00377)	(0.00337)			
tenure	<b>0.00737*</b>	<b>0.0375**</b>	<b>0.00737*</b>	
> <b>0.0126***</b>	<b>0.0134***</b>			
	(0.00325)	(0.0142)	(0.00320)	
> (0.00310)	(0.00259)			
sibs		<b>-0.109***</b>		<b>-0.0936**</b>
>				
		(0.0317)		(0.0345)
>				
feduc		<b>0.157***</b>		<b>0.210***</b>
>				
		(0.0257)		(0.0275)
>				
meduc		<b>0.111***</b>		<b>0.131***</b>
>				
		(0.0301)		(0.0327)
>				
educ_hat			<b>0.138***</b>	
>				
			(0.0180)	
>				
educ_tilde				
> <b>0.113***</b>				
> (0.0148)				
_cons	<b>4.482***</b>	<b>13.18***</b>	<b>4.482***</b>	<b>10.36***</b>
> <b>5.092***</b>	<b>5.497***</b>			
	(0.299)	(0.419)	(0.294)	(0.359)
> (0.215)	(0.111)			
> _____				
N	722	722	722	722
> 722	935			
adj. R-sq	<b>0.060</b>	<b>0.335</b>	<b>0.095</b>	<b>0.211</b>
> <b>0.096</b>	<b>0.152</b>			
> _____				

## 4 Question 4

Solution:

(4) From the conclusion in prob (2), we have

$$\begin{aligned}\hat{\beta}_{2SLS} &= (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'Y \\ &= \begin{bmatrix} 219.4 & 115.4 & 49.6 \\ 52.4 & 34.6 & 61.4 \end{bmatrix} \cdot \begin{bmatrix} 526 & 118.7 & 59.2 \\ 188.7 & 211.9 & 42.9 \\ 59.2 & 42.9 & 194.7 \end{bmatrix}^{-1} \begin{bmatrix} 219 & 52.4 \\ 115.4 & 34.6 \\ 49.6 & 61.4 \end{bmatrix} \dots \\ &= \begin{pmatrix} 1.728 \\ 1.654 \end{pmatrix} \quad (\text{By Matlab})\end{aligned}$$

$$(b) \quad \hat{\chi}^2 = \frac{e'e}{n} = \frac{Y'Y + \hat{\beta}'_{2SLS} X'X \hat{\beta}_{2SLS} - 2(X\hat{\beta}_{2SLS})'Y}{n} = 7.788$$

$$\hat{\sigma}^2 [X'Z(Z'Z)^{-1}Z'X]^{-1} = \begin{bmatrix} 0.13328 & -0.1884 \\ -0.1884 & 0.6168 \end{bmatrix}$$

$$t\text{-statistic: } \frac{\hat{\beta}_{2SLS,1} - \beta_1}{\text{se}(\hat{\beta}_{2SLS})} = \frac{1.7279 - 1}{\sqrt{0.13328}} = 1.9939, \quad \text{By checking with F-table, the p-value is 0.023}$$

$\Rightarrow$  we can reject  $H_0$  at 5% level.

$$(c) \Rightarrow CI = (1.6535 \pm 1.96 \cdot \sqrt{0.6168}), (1.6535 + 1.96 \cdot \sqrt{0.6168})$$

(d)  $H_0: \beta_1 = 1$  and  $\beta_2 = 2$ . under  $H_0$ .

$$\begin{pmatrix} \hat{\beta}_1 - \beta_1 \\ \hat{\beta}_2 - \beta_2 \end{pmatrix} = \begin{pmatrix} 1.728 - 1 \\ 1.654 - 2 \end{pmatrix} = \begin{pmatrix} 0.728 \\ -0.347 \end{pmatrix}, \quad \text{var} \begin{pmatrix} \hat{\beta}_1 - \beta_1 \\ \hat{\beta}_2 - \beta_2 \end{pmatrix} = \begin{pmatrix} 0.1333 & -0.1884 \\ -0.1884 & 0.6168 \end{pmatrix}$$

By using Wald test,

$$(\hat{\beta} - \beta)' \text{var}(\hat{\beta})^{-1} (\hat{\beta} - \beta) = 5.3056, \quad p\text{-value} = 0.07045 > 0.01$$

reject  $H_0$  at 1%

## 5 Question 5

Solution:

pt.

$$y_i = z_i' \beta + \eta_i$$

(a) First, we regress  $z_i$  on  $W_i$  (IV) to get  $\hat{z}_i$

$$z_i = X_i = \delta_0 + \delta_1 W_i + u_i$$

Since  $X_i = W_i = X_i + v_i$ ,  $z_i = X_i = \delta_0 + \delta_1 (X_i + v_i) + u_i$

$$\hat{\delta}_1 = \frac{\text{Cov}(z_i, W_i)}{\text{Var}(W_i)} = \frac{\text{Cov}(X_i, X_i + v_i)}{\text{Var}(X_i + v_i)} = \frac{\text{Cov}(X_i, X_i) + 0}{\text{Var}(X_i) + \sigma_v^2} < 1$$

(b) In second stage, we regress  $y_i$  on  $\hat{z}_i$  which  $\hat{z}_i = \hat{\delta}_0 + \hat{\delta}_1 W_i$ , And under homoskedasticity assumption,  $\sqrt{n}(\hat{\beta}_{IV} - \beta) \rightarrow_d N(0, V_{IV})$

$$V_{IV} = \sigma_\epsilon^2 E[W_i z_i']^T E[W_i W_i'] E[z_i W_i']^{-1}$$

$$E[W_i z_i'] = E[(X_i + v_i) X_i] = E[X_i^2] + E[v_i X_i] = E[X_i^2]$$

$$E[W_i W_i'] = E[(X_i + v_i)^2] = E[X_i^2] + 2E[X_i v_i] + E[v_i^2] = E[X_i^2] + \sigma_v^2$$

$$\therefore V_{IV} = \sigma_\epsilon^2 \cdot \frac{1}{E[X_i^2]} (E[X_i^2] + \sigma_v^2) \cdot \frac{1}{E[X_i^2]} = \sigma_\epsilon^2 \cdot \frac{E[X_i^2] + \sigma_v^2}{E[X_i^2]^2}$$

(c) From (b), when  $\sigma_v^2 = 0$ ,  $V_{IV}$  have same <sup>limiting</sup> distribution as OLS estimation.