

1. Theory

Question 1

a) Given by question:

- True model: $y_i^* = x_i' \beta + \epsilon_i^*$ with $E(\epsilon_i^*|x_i) = 0$ and $V(\epsilon_i^*|x_i) = \sigma_*^2$
- Estimated model: $y_i = x_i' \beta + \epsilon_i$
- Measurement error in y_i : $y_i = y_i^* + \eta_i$ with $\eta_i \sim (0, \sigma_\eta^2)$
- Further assumption: It is a “classical measurement error”, i.e. it is uncorrelated with everything: $E(\eta_i|x_i) = 0$ and $E(\eta_i|\epsilon_i^*) = 0$

One can transform the true model as following (by knowing that $y_i = y_i^* + \eta_i$ holds):

$$y_i^* = x_i' \beta + \epsilon_i^*$$

Adding on both sides η_i :

$$\begin{aligned} y_i^* + \eta_i &= x_i' \beta + \epsilon_i^* + \eta_i \\ y_i &= x_i' \beta + \epsilon_i^* + \eta_i \\ y_i &= x_i' \beta + \epsilon_i \end{aligned}$$

Where ϵ_i is the composite error term of the true error (ϵ_i^*) and the measurement error (η_i).

Mean:

The mean of ϵ_i is:

$$E(\epsilon_i|x_i) = E(\epsilon_i^* + \eta_i) = E(\epsilon_i^*) + E(\eta_i)$$

From the (conditional-)mean-zero-error assumption one knows that $E(\epsilon_i^*|x_i) = 0$ holds and therefore:

$$E(\epsilon_i^*) = E_{x_i} E(\epsilon_i^*|x_i) = E_{x_i} \cdot 0 = 0$$

And from $\eta_i \sim (0, \sigma_\eta^2)$, it follows that:

$$E(\eta_i) = 0$$

And so, one can say that the mean of the error ϵ_i is zero:

$$E(\epsilon_i|x_i) = E(\epsilon_i^* + \eta_i) = E(\epsilon_i^*) + E(\eta_i) = 0 + 0 = \mathbf{0}$$

Variance:

The variance of ϵ_i is:

$$\begin{aligned} V(\epsilon_i) &= V(\epsilon_i^* + \eta_i) = V(\epsilon_i^*) + V(\eta_i) + 2Cov(\epsilon_i^*, \eta_i) \\ &= E((\epsilon_i^* - \mu_{\epsilon_i^*})^2) + E((\eta_i - \mu_{\eta_i})^2) + 2Cov(\epsilon_i^*, \eta_i) \end{aligned}$$

As shown before, the means of ϵ_i^* , $\mu_{\epsilon_i^*}$ and η_i , μ_{η_i} are zero and from the assumption $E(\eta_i|\epsilon_i^*) = 0$, one can say that $Cov(\epsilon_i^*, \eta_i) = 0$ must hold.

Therefore:

$$V(\epsilon_i) = E((\epsilon_i^* - 0)^2) + E((\eta_i - 0)^2) + 2 \cdot 0 = E((\epsilon_i^*)^2) + E((\eta_i)^2) = \sigma_{\epsilon_i^*}^2 + \sigma_{\eta_i}^2$$

b)

$\hat{\beta} = \beta + (X'X)^{-1}X'\epsilon$ (Estimator of β) is unbiased if $E(\hat{\beta}) = \beta$.

$$\rightarrow E(\hat{\beta}) = E(\beta + (X'X)^{-1}X'\epsilon) = E(\beta) + E((X'X)^{-1}X'\epsilon)) = \beta + E((X'X)^{-1}X'\epsilon))$$

As shown before: $E(\epsilon_i|x_i) = E(\epsilon_i^* + \eta_i) = E(\epsilon_i^*) + E(\eta_i) = 0$

Therefore:

$$E(\hat{\beta}) = \beta + E((X'X)^{-1}X'0)) = \beta + 0 = \beta$$

One can say that $\hat{\beta}$ is unbiased.

c)

The variance of $\hat{\beta}$ without the measurement error is:

$$V(\hat{\beta}) = V(\epsilon^*|X)(X'X)^{-1} = \sigma_*^2(X'X)^{-1}$$

Where σ_*^2 refers to the variance of the error term of the true model (ϵ^*). And so, this is equal to $\sigma_{\epsilon_i^*}^2$. The variance of the error term of the model with the measurement error is:

As shown already in a:

$$\sigma^2 = V(\epsilon) = \sigma_{\epsilon_i^*}^2 + \sigma_{\eta_i}^2 = \sigma_*^2 + \sigma_{\eta_i}^2$$

And therefore:

$$V(\hat{\beta}) = V(\epsilon|X)(X'X)^{-1} = (\sigma_*^2 + \sigma_{\eta_i}^2)(X'X)^{-1}$$

So, one can say that the variance of the estimator $\hat{\beta}$ is larger for the model with the measurement error in y than without.

d)

They would be right by saying it is not a big deal. A measurement error in the dependent variable y does not bias the estimator $\hat{\beta}$ but increases its variance ($V(\hat{\beta})$) as shown in c) and therefor a measurement error in the dependent variable is indeed not a big deal. But a measurement error in an independent variable biases the estimator and therefor would end up in a big deal.

2. Empirical Question

Question 1 – IV Regression

- a) See results for columns (2) and (3) below:

VARIABLES	(2) OLS	(3) IV
highqua	0.0768*** (0.0106)	0.0874*** (0.0166)
age	0.0778*** (0.0214)	0.0765*** (0.0215)
agesq	-0.000968*** (0.000266)	-0.000943*** (0.000268)
Constant	-0.428 (0.435)	-0.568 (0.467)
Observations	428	428
R-squared	0.149	0.147

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

- i) The OLS-results in column (2) show the exact same results as in BCHHS (the small discrepancy is due to rounding). The IV-results in column (3) show slightly different results than in BCHHS. Their coefficient for Education is 0.002 smaller and for Age² the difference is 0.1 (after rounding and multiplying Age² by 100). Very small discrepancies can also be found in the standard errors. However, the discrepancies are always minuscule and do not change the significance, so we consider them not serious.
- ii) In this regression, looking at the constant makes no sense. On one hand, looking at constants when log-variable are involved is pointless because these regressions focus on percental changes. On the other hand (and even with normal earnings as a variable), the constant would report the (log) average earnings with 0 years of education, which is not relevant (the minimum years of education is 10).
- iii) Assuming our IV-results are consistent, we interpret Education as follows: In the OLS-regression, our results show an increase in earnings of 7.7% with one year of additional education, controlling for age-effects. In the IV-regressions, our results show an 8.7% increase in earnings with one year of additional education, controlling for age-effects, which suggests a negative bias.

b) Biases

- i) There are three ways in which we think education could be endogenous:
 - OVB: Ability is definitively correlated with education and earnings, but it is not included in the model. We therefore have an OVB, which causes years of schooling to be endogenous.
 - Simultaneous causality: Earnings may increase education in the form of “adult education”. For example: With higher earnings, the chance of being able to afford education next to (or to some part instead of) working is higher. It also could be that only wealthy families can afford a higher education (private schools) for their children. The causality between education and earnings runs in both ways, which causes years of schooling to be endogenous.
 - Measurement error: People might overstate their years of education.
- ii) Bias signs:
 - OVB: Ability has definitively a positive effect on earnings and the covariance between ability and education is positive as well (people with high abilities go to school longer, see universities). Therefore, the likely sign of this bias is positive.
 - Simultaneous causality: If we consider education in this dataset only to include education during childhood and young adulthood, we can assume that there is no simultaneous causality and the likely sign of this bias is 0.
 - Measurement error: This would be a case of the attenuation bias (bias towards 0). With people systematically overstating their education and a positive effect of education on earnings, the likely sign of this bias is negative.
- iii) Relevance and exogeneity (without simultaneous causality):
 - OVB: The instrument of is definitively correlated with the true years of education. However, assuming that the twin’s report is also correlated with the omitted ability, this does not resolve the endogeneity issue.
 - Measurement error: The instrument is definitively correlated with the true years of education and therefore relevant. Furthermore, we suggest that this instrument “corrects” some part of the overstated education.
- iv) The difference from the IV-results to the OLS-results is -1%, therefore we have a negative bias. Even though this is suggested by bias through measurement error, we suspected the positive OVB to weigh stronger than the measurement error bias.

- v) See the results from the first stage below:

VARIABLES	(1) 1S
twihigh	0.631*** (0.0371)
age	0.0531 (0.0756)
agesq	-0.000930 (0.000938)
Constant	4.835*** (1.535)
Observations	428
R-squared	0.446

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

The F-value is 290.17 (roughly the t-value squared). This is much higher than 10, so we can consider this instrument not to be weak.

- vi) We have a strong first stage, significant effect and good (well evaluated) assumptions. Therefore, we believe those results.
- c) See results for columns (4) and (5) below:

VARIABLES	(4) OLS	(5) IV
dhig	0.0394* (0.0226)	0.0774** (0.0331)
Observations	214	214
R-squared	0.014	

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

- i) Twins have the same age (difference is always 0). The difference in age drops out.

- ii) See the results in the table below:

VARIABLES	(4) OLS	(5) IV
dhigh	0.0392* (0.0226)	0.0778** (0.0330)
Constant	0.0142 (0.0471)	0.0126 (0.0474)
Observations	214	214
R-squared	0.014	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Including a constant makes no sense because earnings is again in logs. Additionally, a constant shows the average difference in earnings for 0 years difference in education, which can be expected to 0. The results in this table support the exclusion of the constant (the standard errors for example are 4 times larger than the constant itself).

- iii) Now the effect of a one-year difference in education (which is the same as one additional year of education) only leads to a 3.9% difference in earnings. The advantage of this procedure is that the OVB disappears. Assuming both twins have the same abilities (genetics and family), the difference between them is 0 and this model only shows the difference in log-earnings on the difference in education and the difference in the error terms. This is also consistent with the assumed positive OVB from b), since the OLS-results in c) are smaller. The standard errors also increase due to the smaller sample size. However, there is still a measurement error problem.
- iv) Now the effect of a one-year difference in education (which is the same as one additional year of education) only leads to a 7.8% difference in earnings, which is rather close to the results in b). The advantage of this instrument is the following: For twins with fitting differences in years of education and years of one's twin reported years of education, their difference in earnings correlate perfectly. The ones from the twins who do not fit, do not correlate perfectly. With an IV-regression, we still allow for this type of variation, but without overestimating due to twins who misreport their education. Comparing column (5) to (4), the increasing results suggest measurement error in (4). Also, the standard errors increase.
- v) We do believe these results. As in b) the results from the OLS to the IV regression shift according to our priors. The assumptions seem believable. The increased standard errors can be explained with the smaller sample size, therefore the decreased significance

compared to b) does not worry us.

- d) See the results in the table below:

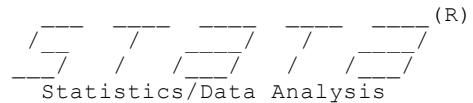
VARIABLES	(4) OLS	(5) IV
dhigh	0.0283 (0.0189)	0.0358 (0.0272)
Observations	210	210
R-squared	0.011	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- i) Both the magnitude and the significance in column (5) are heavily affected by dropping the outliers. The effect is halved, but the standard error decrease by only a little bit. This leads to non-significant results.
- ii) Now the results in (5) can be interpreted as follows: A one-year difference in education leads to a 3.8% difference in earnings.
- iii) On one hand, these decrease in the results suggest that we are overestimating the effect from education on earnings with those outliers included. However, with the standard errors nearly staying the same, we suggest that excluding these 4 observations is not a good idea.

3. Log-file

See attachment



```

name: <unnamed>
log: C:\Users\ramon\Desktop\UZH\Empirical Methods\Problem Sets\Problem Set 3\Stata\log_gm
log type: smcl
opened on: 2 Dec 2019, 16:01:51

```

```

1 .
2 . insheet using "C:\Users\ramon\Desktop\UZH\Empirical Methods\Problem Sets\Problem Set 3\Stata\BCI"
(18 vars, 428 obs)

3 .
4 . *1)
5 .
6 . gen lnearn = log(earning)

7 . gen agesq = age^2

8 .
9 .
10 . **a)
11 .
12 . reg lnearn highqua age agesq

```

Source	SS	df	MS	Number of obs	=	428
Model	20.7258534	3	6.9086178	F(3, 424)	=	24.72
Residual	118.492426	424	.279463268	Prob > F	=	0.0000
Total	139.218279	427	.326038124	R-squared	=	0.1489

lnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
highqua	.0767543	.0105917	7.25	0.000	.0559355 .0975731
age	.0778154	.0213949	3.64	0.000	.0357622 .1198687
agesq	-.0009675	.0002658	-3.64	0.000	-.0014899 -.0004451
_cons	-.4282208	.4347756	-0.98	0.325	-1.282805 .4263631

```

13 . outreg2 using "regressiona.doc", replace ctitle(OLS)
regressiona.doc
dir : seeout

```

```
14 . ivreg lnearn age agesq (highqua = twihigh)
```

Instrumental variables (2SLS) regression

Source	SS	df	MS	Number of obs	=	428
Model	20.4445064	3	6.81483547	F(3, 424)	=	16.40
Residual	118.773773	424	.280126822	Prob > F	=	0.0000
Total	139.218279	427	.326038124	R-squared	=	0.1469

lnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
highqua	.0873817	.0166363	5.25	0.000	.0546818 .1200815
age	.0764781	.0214809	3.56	0.000	.0342558 .1187005
agesq	-.0009428	.0002677	-3.52	0.000	-.0014691 -.0004165
_cons	-.5684209	.4669861	-1.22	0.224	-1.486317 .3494751

Instrumented: highqua

Instruments: age agesq twihigh

```
15 . outreg2 using "regressiona.doc", append ctitle(IV)
regressiona.doc
dir : seeout
```

```
16 .
17 . **b)
18 .
19 . ***v)
20 . reg highqua twihigh age agesq
```

Source	SS	df	MS	Number of obs	=	428
Model	1190.87218	3	396.957394	F(3, 424)	=	113.80
Residual	1478.9666	424	3.48812878	Prob > F	=	0.0000
Total	2669.83879	427	6.25254985	R-squared	=	0.4460
				Adj R-squared	=	0.4421
				Root MSE	=	1.8677

highqua	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
twihigh	.6312721	.0370589	17.03	0.000	.5584302 .7041141
age	.0531199	.0755603	0.70	0.482	-.0953996 .2016394
agesq	-.0009302	.0009385	-0.99	0.322	-.0027749 .0009144
_cons	4.83493	1.535057	3.15	0.002	1.817661 7.852198

```
21 . outreg2 using "regressionb.doc", replace ctitle(1S)
regressionb.doc
dir : seeout
```

```
22 . test _b[twihigh]=0
```

```
( 1) twihigh = 0

F( 1, 424) = 290.17
Prob > F = 0.0000
```

```
23 .
24 . **c)
25 .
26 . drop schyear lnandse part full self married own_exp bweight exp_par parted sm16 sm18
27 . reshape wide lnearn highqua twihigh earning, i(family) j(twinno)
(note: j = 1 2)
```

Data	long	->	wide
Number of obs.	428	->	214
Number of variables	8	->	11
j variable (2 values)	twinno	->	(dropped)
xij variables:			
	lnearn	->	lnearn1 lnearn2
	highqua	->	highqual highqua2
	twihigh	->	twihigh1 twihigh2
	earning	->	earning1 earning2

```
28 .
29 . gen dlnearn = lnearn1 - lnearn2
30 . gen dhigh = highqual - highqua2
```

```

31 . gen dtwihigh = twihigh1 - twihigh2
32 .
33 . gen dearn = earning1 - earning2
34 . *This one is for d)
35 .
36 . reg dlnearn dhig, nocons

```

Source	SS	df	MS	Number of obs	=	214
Model	1.43564569	1	1.43564569	F(1, 213)	=	3.04
Residual	100.55228	213	.472076434	Prob > F	=	0.0826
Total	101.987926	214	.476579094	R-squared	=	0.0141
				Adj R-squared	=	0.0094
				Root MSE	=	.68708

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0393535	.0225666	1.74	0.083	-.0051289 .083836

```

37 . outreg2 using "regressionnc.doc", replace ctitle(OLS)
regressionnc.doc
dir : seeout

```

```
38 . ivreg dlnearn (dhigh = dtwihigh), nocons
```

Instrumental variables (2SLS) regression

Source	SS	df	MS	Number of obs	=	214
Model	.096383507	1	.096383507	F(1, 213)	=	.
Residual	101.891543	213	.47836405	Prob > F	=	.
Total	101.987926	214	.476579094	R-squared	=	.
				Adj R-squared	=	.
				Root MSE	=	.69164

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0773631	.0330598	2.34	0.020	.0121968 .1425294

Instrumented: dhigh
Instruments: dtwihigh

```

39 . outreg2 using "regressionnc.doc", append ctitle(IV)
regressionnc.doc
dir : seeout

```

```

40 .
41 . ***ii)
42 .
43 . reg dlnearn dhig

```

Source	SS	df	MS	Number of obs	=	214
Model	1.4249932	1	1.4249932	F(1, 212)	=	3.01
Residual	100.508895	212	.47409856	Prob > F	=	0.0844
Total	101.933888	213	.478562854	R-squared	=	0.0140
				Adj R-squared	=	0.0093
				Root MSE	=	.68855

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0392153	.0226195	1.73	0.084	-.0053727 .0838032
_cons	.0142415	.0470778	0.30	0.763	-.0785591 .107042

44 . outreg2 using "regressionc2.doc", replace ctitle(OLS)
regressionc2.doc

dir : seeout

45 . ivreg dlnearn (dhigh = dtwihigh)

Instrumental variables (2SLS) regression

Source	SS	df	MS	Number of obs	=	214
Model	.04558248	1	.04558248	F(1, 212)	=	5.54
Residual	101.888306	212	.480605215	Prob > F	=	0.0195
Total	101.933888	213	.478562854	R-squared	=	0.0004

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0777982	.0330489	2.35	0.019	.0126517 .1429448
_cons	.0126188	.0474104	0.27	0.790	-.0808375 .1060751

Instrumented: dhigh

Instruments: dtwihigh

46 . outreg2 using "regressionc2.doc", append ctitle(IV)

regressionc2.doc

dir : seeout

47 .

48 . **d)

49 .

50 . gen absearn = abs(dearn)

51 . preserve

52 . drop if absearn > 60
 (4 observations deleted)

53 .

54 . reg dlnearn dhigh, nocons

Source	SS	df	MS	Number of obs	=	210
Model	.736676732	1	.736676732	F(1, 209)	=	2.24
Residual	68.7836569	209	.329108406	Prob > F	=	0.1361
Total	69.5203336	210	.331049208	R-squared	=	0.0106

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0282666	.0188931	1.50	0.136	-.008979 .0655121

55 . outreg2 using "regressionond.doc", replace ctitle(OLS)

regressionond.doc

dir : seeout

56 . ivreg dlnearn (dhigh = dtwihigh), nocons

Instrumental variables (2SLS) regression

Source	SS	df	MS	Number of obs	=	210
Model	.684658057	1	.684658057	F(1, 209)	=	.
Residual	68.8356756	209	.329357299	Prob > F	=	.
Total	69.5203336	210	.331049208	R-squared	=	.

Adj R-squared

Root MSE

dlnearn	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dhigh	.0357778	.0272474	1.31	0.191	-.0179371 .0894928

Instrumented: dhhigh
Instruments: dtwihigh

```
57 . outreg2 using "regressiond.doc", append ctitle(IV)
regressiond.doc
dir : seeout

58 .
59 . restore

60 .
end of do-file
```