

IV & LATE

1. Seats in Dutch medical schools are assigned through a lottery. Applicants to medical studies in the Netherlands are assigned to lottery categories based on their high school grades. The categories differ by the probability to be awarded a place (to win the lottery). If people lose a lottery they can try again the following year.

Below you find a link to a dataset that has results from peoples' first lottery outcome for participants in 1988 and 1989, and whether they attended medical school, as well as earnings from a survey that was sent out in 2007.

<https://www.dropbox.com/s/dy6cmnmvkvfv4l/lottery.dta?dl=1>

You plan to estimate the return to attending medical school (d) on earnings in 2007 (lnw) using instrumental variables using the lottery outcome (z) as your instrument.

- (a) Discuss instrument exogeneity, exclusion and monotonicity.
 - (b) Assess instrument relevance.
 - (c) Estimate the return to attending medical school on earnings in 2007 using IV, and interpret the results.
 - (d) Count the number of compliers, and compare them to the population of applicants in terms of gender.
 - (e) Is the IV estimate an estimate of the ATT? Explain why or why not.
 - (f) We want to investigate the potential outcomes $Y_i(0)$ and $Y_i(1)$ for compliers further. Estimate, for $w = 0, 1$, the conditional mean $E(Y_i(w)|X_i = x)$ and the marginal distribution of $Y_i(w)$ for compliers.
 - (g) What can you say about the marginal distribution of $Y_i(0)$ and $Y_i(1)$ for always- and never-takers?
 - (h) The lottery is within lottery category and year, so your instrument is only exogenous within these groups. Estimate lottery category * year specific LATEs and combine these in one estimate. Compare this to the specification where you control for lottery category * year dummies and also interact the instrument with these dummies.
2. We are interested in how health insurance affects out-of-pocket expenditure on drugs, and have access to an extract from the Medical Expenditure Panel Survey of individuals over the age of 65 years. We want to estimate the following equation,

$$ldrugexp = \alpha + \gamma hi_empunior + X\beta + u,$$

where $ldrugexp$ is log expenditure on prescribed medical drugs, $hi_empunior$ is equal to one if the individual has supplemental health insurance and zero otherwise,

and we control in X for *age*, *gender*, *linc* (log of household income), *totchr* (the no. of children), and *blhisp* (a dummy for being black or hispanic). Below is output from Stata with a number of results that may be useful in this exercise.

- Explain why we may worry that having supplemental health insurance is endogenous in the equation above.
- A suggested instrument is *multlc*, a dummy for whether the firm at which the individual is employed is a large operator with multiple locations. Why or why not may this be a good instrument (think about the conditions that need to hold to identify the LATE)? Using the output below, do you think that *multlc* is a weak instrument?
- Derive the indirect least squares representation of the IV-estimator using *multlc* as an instrument, and calculate it using the output below. Interpret the estimate.
- What is the share of females in the complier group? How does this compare to the overall population? How does this affect your interpretation of the estimates?
- Assuming $\beta = 0$, derive the IV-estimator using the moments (covariances), and calculate it using the output below.
- Assuming $\beta = 0$, what is the share of females in the three groups of compliers, always-takers and never-takers?
- Assuming $\beta = 0$, using the means and counts of *ldrugexp* from the output below, estimate $E[Y^0|\text{never taker}]$, $E[Y^1|\text{always taker}]$, $E[Y^0|\text{complier}]$, and $E[Y^1|\text{complier}]$, where Y^s are the potential outcomes for *ldrugexp* with and without supplemental health insurance. How do the compliers compare to the other groups, and what do you conclude about external validity?

```
. use http://fmwww.bc.edu/ec-p/data/mus/mus06data, clear

. keep if linc<.
(302 observations deleted)

. su ldrugexp hi_empunion multlc totchr age female blhisp linc
```

Variable	Obs	Mean	Std. Dev.	Min	Max
ldrugexp	10089	6.481361	1.362052	0	10.18017
hi_empunion	10089	.3821984	.4859488	0	1
multlc	10089	.0620478	.2412543	0	1
totchr	10089	1.860938	1.292858	0	9
age	10089	75.05174	6.682109	65	91
female	10089	.5770641	.4940499	0	1
blhisp	10089	.1635445	.36988	0	1
linc	10089	2.743275	.9131433	-6.907755	5.744476

```
.
. reg ldrugexp multlc totchr age female blhisp linc , robust

Linear regression                               Number of obs =   10089
```

```

F( 6, 10082) = 376.72
Prob > F      = 0.0000
R-squared     = 0.1775
Root MSE     = 1.2356

```

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
ldrugexp						
multlc		-.2002194	.0540601	-3.70	0.000	-.3061878 -.0942509
totchr		.4401428	.0093589	47.03	0.000	.4217975 .4584882
age		-.0053332	.0019369	-2.75	0.006	-.0091299 -.0015366
female		.0501264	.0252882	1.98	0.047	.0005566 .0996962
blhisp		-.1481236	.0341141	-4.34	0.000	-.2149941 -.081253
linc		.0252773	.0137866	1.83	0.067	-.0017472 .0523018
_cons		6.000931	.1559161	38.49	0.000	5.695304 6.306557

```
. reg hi_empunion multlc totchr age female blhisp linc , robust
```

```

Linear regression      Number of obs = 10089
                      F( 6, 10082) = 120.25
                      Prob > F      = 0.0000
                      R-squared     = 0.0643
                      Root MSE    = .4702

```

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
hi_empunion						
multlc		.1487593	.020504	7.26	0.000	.1085674 .1889513
totchr		.0109104	.0036859	2.96	0.003	.0036853 .0181354
age		-.0091799	.0007101	-12.93	0.000	-.0105717 -.007788
female		-.0792221	.0096843	-8.18	0.000	-.0982052 -.060239
blhisp		-.0741602	.0123788	-5.99	0.000	-.0984251 -.0498953
linc		.0720981	.0062189	11.59	0.000	.0599079 .0842883
_cons		.90169	.0589985	15.28	0.000	.7860412 1.017339

```
. correlate ldrugexp hi_empunion multlc, cov
(obs=10089)
```

		ldrugexp	hi_emp~n	multlc
ldrugexp		1.85519		
hi_empunion		.021107	.236146	
multlc		-.016529	.014051	.058204

```
. reg hi_empunion multlc totchr age blhisp linc if female == 1 , robust
```

```

Linear regression      Number of obs = 5822
                      F( 5, 5816) = 75.57
                      Prob > F      = 0.0000
                      R-squared     = 0.0618
                      Root MSE    = .45887

```

		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
hi_empunion						
multlc		.1667599	.0290762	5.74	0.000	.1097599 .22376
totchr		.0031734	.0047225	0.67	0.502	-.0060845 .0124314
age		-.0101485	.0008897	-11.41	0.000	-.0118926 -.0084043
blhisp		-.0628657	.0156485	-4.02	0.000	-.0935426 -.0321888
linc		.0749594	.0084465	8.87	0.000	.0584012 .0915176
_cons		.8998824	.0745252	12.07	0.000	.7537852 1.04598

```
. reg hi_empunion multlc totchr age blhisp linc if female == 0 , robust
```

```

Linear regression      Number of obs = 4267
                      F( 5, 4261) = 43.34
                      Prob > F      = 0.0000
                      R-squared     = 0.0478
                      Root MSE    = .48478

```

hi_empunion		Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
multlc		.1352384	.0288941	4.68	0.000	.0785909	.1918859
totchr		.0221272	.0059031	3.75	0.000	.0105541	.0337004
age		-.0075946	.0011705	-6.49	0.000	-.0098894	-.0052998
blhisp		-.0885161	.0200636	-4.41	0.000	-.1278512	-.0491811
linc		.0689149	.0092015	7.49	0.000	.0508751	.0869546
_cons		.7758469	.0960955	8.07	0.000	.5874497	.9642441

```
.
. table hi_empunion multlc if female == 1
```

Insured		Multiple	
thro		locations	
emp/union		0	1
0		3,721	125
1		1,792	184

```
. table hi_empunion multlc if female == 0
```

Insured		Multiple	
thro		locations	
emp/union		0	1
0		2,267	120
1		1,683	197

```
. table hi_empunion multlc, c(mean ldrugexp N ldrugexp)
```

Insured		Multiple	locations
thro			
emp/union		0	1
0		6.464303	6.029153
		5,988	245
1		6.558737	6.3345
		3,475	381