

Lecture 1 Exercise Solutions

- 1.1 **Potential outcomes and treatment effects.** See Lecture 1 exercises do file for code.
- 1.2 **Estimating treatment effects with randomization.** See Lecture 1 exercises do file for code.
- 1.3 **Simulated data with selection into treatment on \mathbf{X} .** See Lecture 1 exercises do file for code.
- 1.4 **RCT of private school vouchers.** In a well-known study, Howell and Peterson (2006) evaluated the effects of a private school voucher in NYC from the School Choice Scholarships Foundation (SCSF). This program provided scholarships of up to \$1,400 for 1,300 children from low-income families to attend a private elementary school. There were more applicants to the program than vouchers, so a random lottery was used to award the scholarships. Ultimately, 1,300 families received the voucher and 960 didn't.
- (a) Let $D_i = 1$ if the student was offered a voucher and $D_i = 0$ if not. Suppose we wanted to estimate the simple population regression function below, where Y_i represents student achievement after three years of the program:

$$Y_i = \beta_0 + \beta_1 D_i + u_i$$

Under what conditions would this regression describe “differences in average potential outcomes for a well-defined population” (our criteria for causal interpretation)? Do those conditions hold here? How would you describe the relevant population? What is our *estimand* of interest (ATE, ATT, ATU, something else)?

In the population, $\beta_1 = E[Y(1)|D_i = 1] - E[Y(0)|D_i = 0]$. If the $D_i = 1$ and $D_i = 0$ groups have the same distribution of potential outcomes (e.g., $(Y_{i1}, Y_{0i}) \perp\!\!\!\perp D_i$) then this simplifies to $\beta_1 = E[Y(1) - Y(0)]$. If the randomization was successful, this condition should hold here—that is, mean potential outcomes for the treated and untreated groups should be the same. The relevant population is low-income families in NYC who applied for a private school voucher. (Note the population of applicants may differ from the general population of low-income families in NYC). The estimand of interest here would probably be considered an ATT since the focus is on applicants to a voucher program (families

that presumably would use the voucher if given the opportunity). We should also be careful about how we define “treatment.” Students were *offered* a voucher at random but did not necessarily use the voucher to attend a private school. So the treatment here is the voucher “offer,” not attending a private school. One could think of this exercise as estimating the “intent-to-treat” effect of attending a private school with a voucher.

- (b) Read the following dataset from Github which contains a subsample of 521 African-American students who participated in the lottery:

```
use https://github.com/spcorcor18/LP0-8852/raw/main/data/nyvoucher.dta, clear
```

- (c) Use `ttest` and the simple regression model above to estimate the effects of the voucher (*voucher*) on student achievement after three years of the program (*post_ach*). Is the estimated effect statistically significant? Practically significant? (The outcome variable is a composite measure of reading and math achievement, expressed as a national percentile score).

See output below. Students offered the private school voucher scored 4.9 percentile points higher, on average, than students not offered the voucher. (Note the point estimate, standard error, *t*-statistic and *p*-value are the same in this case whether one uses a *t*-test or simple regression.) The difference is statistically significant ($p < 0.004$). To assess practical significance, it is useful to compare the magnitude of the difference (4.9 points) to the overall standard deviation in the outcome (19.2). This is an effect size of 0.255, a rather large effect size in education.

```
. ttest post_ach, by(voucher) rev
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	291	26.02921	1.158	19.754	23.75006	28.30836
0	230	21.13043	1.198249	18.17234	18.76943	23.49144
Combined	521	23.8666	.841557	19.2089	22.21333	25.51987
diff		4.898775	1.682719		1.592998	8.204552
diff = mean(1) - mean(0)				t =	2.9112	
H0: diff = 0				Degrees of freedom =	519	
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0		
Pr(T < t) = 0.9981		Pr(T > t) = 0.0038		Pr(T > t) = 0.0019		

```
. reg post_ach voucher
```

Source	SS	df	MS	Number of obs	=	521
Model	3082.89021	1	3082.89021	F(1, 519)	=	8.48
Residual	188787.589	519	363.752579	Prob > F	=	0.0038
				R-squared	=	0.0161
				Adj R-squared	=	0.0142
Total	191870.479	520	368.98169	Root MSE	=	19.072

post_ach	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
voucher	4.898775	1.682719	2.91	0.004	1.592998	8.204552
_cons	21.13043	1.25759	16.80	0.000	18.65984	23.60103

```
. summ post_ach
```

Variable	Obs	Mean	Std. dev.	Min	Max
post_ach	521	23.8666	19.2089	0	89

```
. display b/r(sd)
.25502636
```

- (d) Randomization in theory should prevent omitted variables bias. However, in finite samples, there may be *incidental* (chance) correlation between treatment assignment and other predictors of the outcome. The first step in the analysis of any RCT is to “check for balance” between the treated and untreated group on a host of baseline predictors. (This can also be revealing about whether the randomization “worked.”) The only other variable in this dataset is a measure of baseline achievement, *pre_ach*. How does this measure differ between the treated and untreated group? (You can compare both means and other features of the distribution).

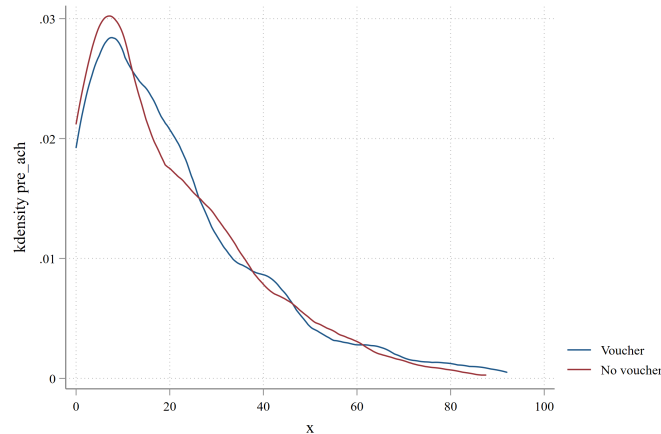
See output below. At *baseline*, students offered the voucher scored 1.17 percentile points higher than students not offered the voucher. The difference is not statistically significant, however ($p = 0.4698$). In larger samples, one would not expect to see a mean difference between these groups. However, in finite samples, there may be chance differences between them. It is good practice to compare more than just the means of the two groups. The code below includes an overlapping kernel densities for the voucher and no voucher groups.

```
. ttest pre_ach, by(voucher) rev
```

Two-sample t test with equal variances

Group	Obs	Mean	Std. err.	Std. dev.	[95% conf. interval]	
1	291	20.67869	1.097621	18.72401	18.51838	22.83901
0	230	19.51304	1.164686	17.66333	17.21817	21.80791
Combined	521	20.16411	.799776	18.25523	18.59292	21.7353
diff		1.165651	1.611368		-1.999956	4.331257
diff = mean(1) - mean(0)				t = 0.7234		
H0: diff = 0				Degrees of freedom = 519		
Ha: diff < 0		Ha: diff != 0		Ha: diff > 0		
Pr(T < t) = 0.7651		Pr(T > t) = 0.4698		Pr(T > t) = 0.2349		

. twoway (kdensity pre_ach if voucher==1) (kdensity pre_ach if voucher==0)



- (e) Add the *pre_ach* measure to the regression function below (as X). What purpose does this serve? How does this additional covariate change your point estimate for β_1 (if at all)? How does it change the standard error for β_1 (if at all)?

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + u_i$$

See results below. If the randomization was successful, inclusion of *pre_ach* as a covariate should have little effect on the point estimate of *voucher*. However, as noted above, in finite samples there can be incidental correlation between treatment status and the baseline covariates. Controlling for these can help “purge” any chance correlation.

Inclusion of baseline covariates should also increase the *precision* of your estimator of the treatment effect. Note that the standard error fell from 1.68 (without covariates) to 1.27 (with the *pre_ach* control).

```
. reg post_ach voucher pre_ach
```

Source		SS	df	MS	Number of obs	=	521
-----+-----					F(2, 518)	=	205.40
Model		84863.1705	2	42431.5852	Prob > F	=	0.0000
Residual		107007.308	518	206.577815	R-squared	=	0.4423
-----+-----					Adj R-squared	=	0.4401
Total		191870.479	520	368.98169	Root MSE	=	14.373

post_ach		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----							
voucher		4.097609	1.26873	3.23	0.001	1.60512	6.590097
pre_ach		.6873125	.0345439	19.90	0.000	.619449	.7551759
_cons		7.718877	1.162978	6.64	0.000	5.434143	10.00361
-----+-----							