

Instrumental Variables

EDLD 650: Week 6

David D. Liebowitz

Agenda

1. Roadmap and goals (9:00-9:10)

2. Discussion Questions (9:10-10:20)

- Murnane and Willett
- Angrist et al. (x2)
- Dee

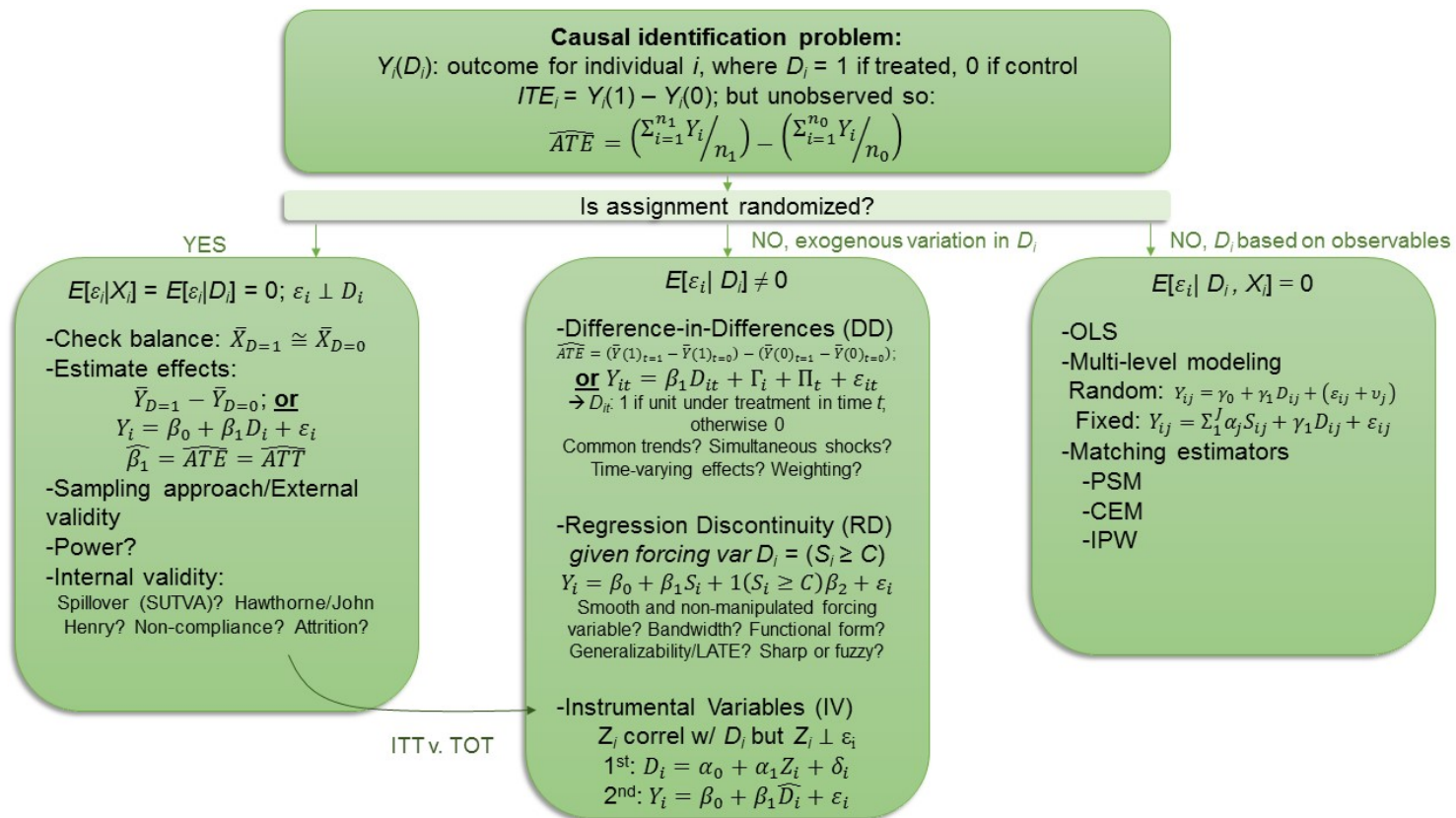
3. Break (10:20-10:30)

4. Applied instrumental variables (10:30-11:40)

5. Wrap-up (11:40-11:50)

- DARE #3 prep
- Plus/deltas

Roadmap



Goals

1. Describe conceptual approach to instrumental variables (IV) analysis
2. Assess validity of IV assumptions in applied context
3. Conduct IV analysis in simplified data and interpret results

So random...

Break

The PACES experiment

- Recall the PACES school voucher experiment (Angrist et al. 2002) from *Methods Matter*, Chapter 11
- Lottery assignment for vouchers to attend private school in Colombia
- What is the **main outcome**?
- What is the **endogenous regressor**?

Vouchers for Private Schooling in Colombia: Evidence from a Randomized Natural Experiment

By JOSHUA ANGRIST, ERIC BETTINGER, ERIC BLOOM, ELIZABETH KING,
AND MICHAEL KRAMER*

Colombia used lotteries to distribute vouchers which partially covered the cost of private secondary school for students who maintained satisfactory academic progress. These students, after the lottery, whose parents were about 10 percentage points more likely to have finished 8th grade, primarily because they were less likely to repeat grades, and scored 0.2 standard deviations higher on achievement tests. There is some evidence that winners worked less than losers and were less likely to marry or cohabitate. Moreover, benefits to participants likely exceeded the \$24 per voucher additional cost to the government of supplying vouchers instead of public school places. (JHE 122, 111, 124)

While the academic controversy over school provision and school vouchers has raged most intensely in the United States, private schools account for only about 11 percent of U.S. enrollment (U.S. Department of Education, 1996). Moreover, over half of American parents report that they are very satisfied with the public schools their children attend. In the developing world, in contrast, private enrollment as a pro-

portion of total enrollment is 2-3 times higher than in industrialized nations (Clarke Jones, 1993). Problems with public schools are usually more severe in low-income countries, since the quality and quantity of public sector service delivery is highly correlated with income levels (James E. Rauch and Peter B. Tans, 2000). In Indian schools, for example, a recent study found that one-third of headmasters were absent at the time of the researchers' visit (Pritchett, 1999), while in Kenya, Paul Glewwe et al. (2001) found that teachers were absent 24 percent of the time. The view that private schools function better than public schools in the developing world has prompted calls for governments in poor countries to experiment with demand-side financing programs such as vouchers (e.g., George Psacharopoulos et al., 1994).

This paper presents evidence on the impact of one of the largest school voucher programs to date, the Programa de Asignación de Cotización de la Educación Secundaria (PACES), a Colombian initiative that provided over 125,000 pupils with vouchers covering somewhat more than half the cost of private secondary school. Vouchers were renewable as long as students maintained satisfactory academic performance. Since many vouchers were awarded by lottery, we use a quasi-experimental research design comparing educational and other outcomes of lottery winners and losers. Subject to a variety

* Angrist: Department of Economics, MIT, 30 Memorial Drive, Cambridge, MA 02142; Bettinger: Department of Economics, Weatherhead School of Management, Case Western Reserve University, Cleveland, Ohio 44106; Bloom: Asian Development Bank, 6 ADB Avenue, Manila, Philippines; King: Development Research Group, The World Bank, 1818 H Street NW, Washington, DC 20036; Kramer: Department of Economics, Harvard University, Littauer Center 205, Cambridge, MA 02138. Special thanks go to the survey and field team in Bogotá, Colombia: Marcela Montes, Ana Gómez, and a dedicated team of interviewers from American University, in the United States, who had the help of Andy Cervero, Helen Lee, Ryan Ruggell, and especially Cristian González. We are also grateful to Jorge Echeverri for help organizing Colombian winners, and to Jose Uribe for arranging for use of a testing site. Finally, thanks go to the World Bank and the National Institute of Health for funding, and to Alberto Abadie, Ben Behrman, Adriana Wright, David Levine, Paul Pritchett, Peter Pissarides, and seminar participants at Harvard University, University of California Berkeley, Harvard University, MIT, the NBER, Northwestern University, and Princeton University for comments. This document does not necessarily reflect the position of the Asian Development Bank or the World Bank.

Estimand of interest: effect of using financial aid to attend private school

Let's replicate!

```
paces ← read.csv(here("./data/ch11_PACES.csv"))
DT::datatable(paces[,c(1:7)], fillContainer = FALSE, options =
  list(pageLength = 5))
```

Show entries

Search:

	id ↕	won_lottry ↕	male ↕	base_age ↕	finish8th ↕	use_fin_aid ↕	school ↕
1	3	1	0	11	1	1	2
2	4	0	1	11	1	1	2
3	5	0	1	11	1	0	1
4	6	0	0	9	0	0	1
5	10	1	1	11	1	1	5

Showing 1 to 5 of 1,171 entries

Previous

1

2

3

4

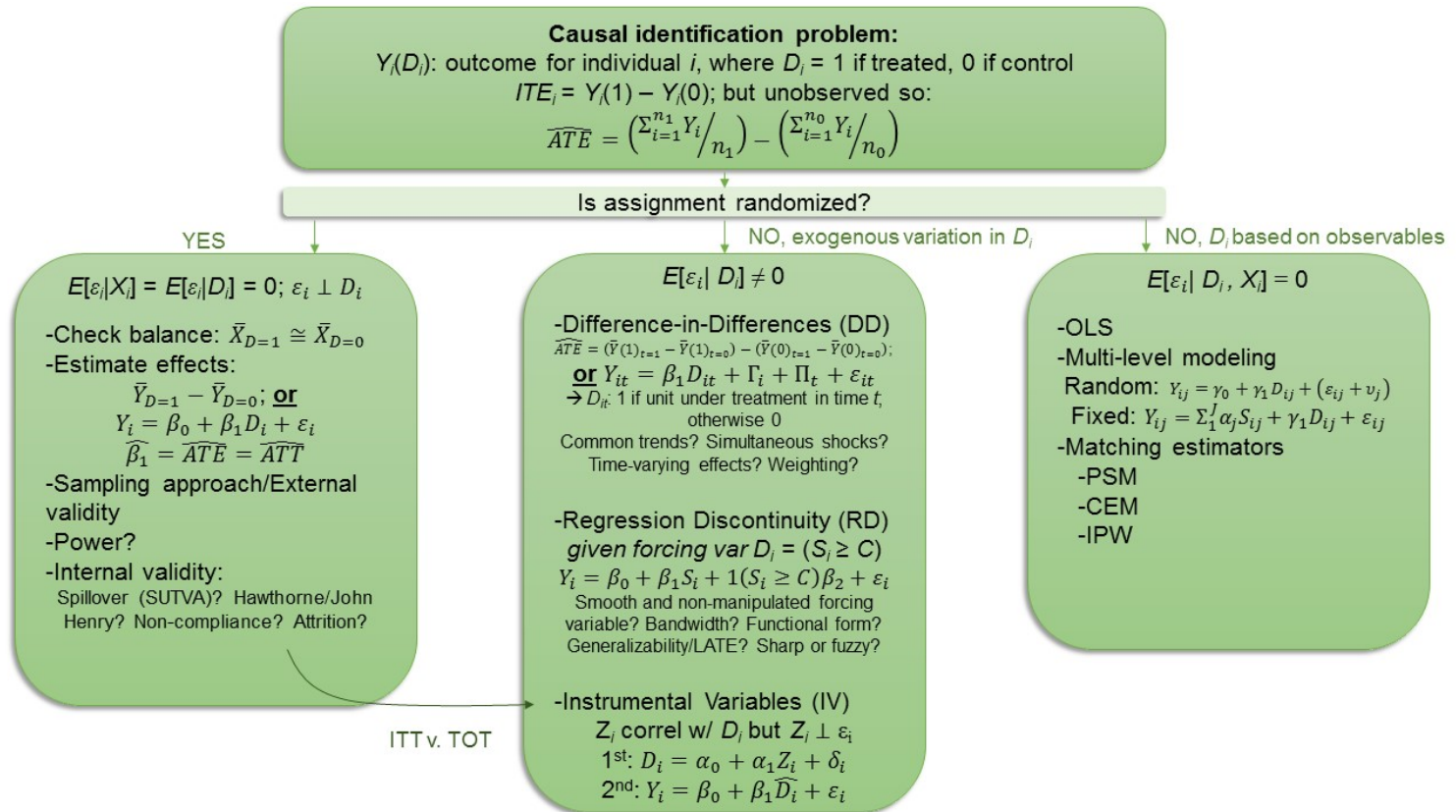
5

...

235

Next

First post-randomization task?



Balance checks

Examine by covariates:

$$\bar{X}_{D=1} \cong \bar{X}_{D=0}$$

```
random ← arsenal::tableby(won_lottry ~ male + base_age, paces)
summary(random)
```

	0 (N=579)	1 (N=592)	Total (N=1171)	p value
male				0.980
Mean (SD)	0.504 (0.500)	0.505 (0.500)	0.505 (0.500)	
Range	0.000 - 1.000	0.000 - 1.000	0.000 - 1.000	
base_age				0.422
Mean (SD)	12.036 (1.352)	11.973 (1.343)	12.004 (1.347)	
Range	7.000 - 16.000	9.000 - 17.000	7.000 - 17.000	

Balance checks

Omnibus F -test approach:

```
summary(lm(won_lottry ~ male + base_age, data=paces))
```

...

```
#> Coefficients:
```

```
#>               Estimate Std. Error t value Pr(>|t|)
#> (Intercept)  0.609897    0.131294   4.645 3.78e-06 ***
#> male         0.002568    0.029338   0.088   0.930
#> base_age     -0.008800    0.010894  -0.808   0.419
```

```
#> ---
```

```
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#>
```

```
#> Residual standard error: 0.5005 on 1168 degrees of freedom
```

```
#> Multiple R-squared:  0.000559,    Adjusted R-squared:  -0.001152
```

```
#> F-statistic: 0.3266 on 2 and 1168 DF,  p-value: 0.7214
```

...

A naïve estimate of financial aid

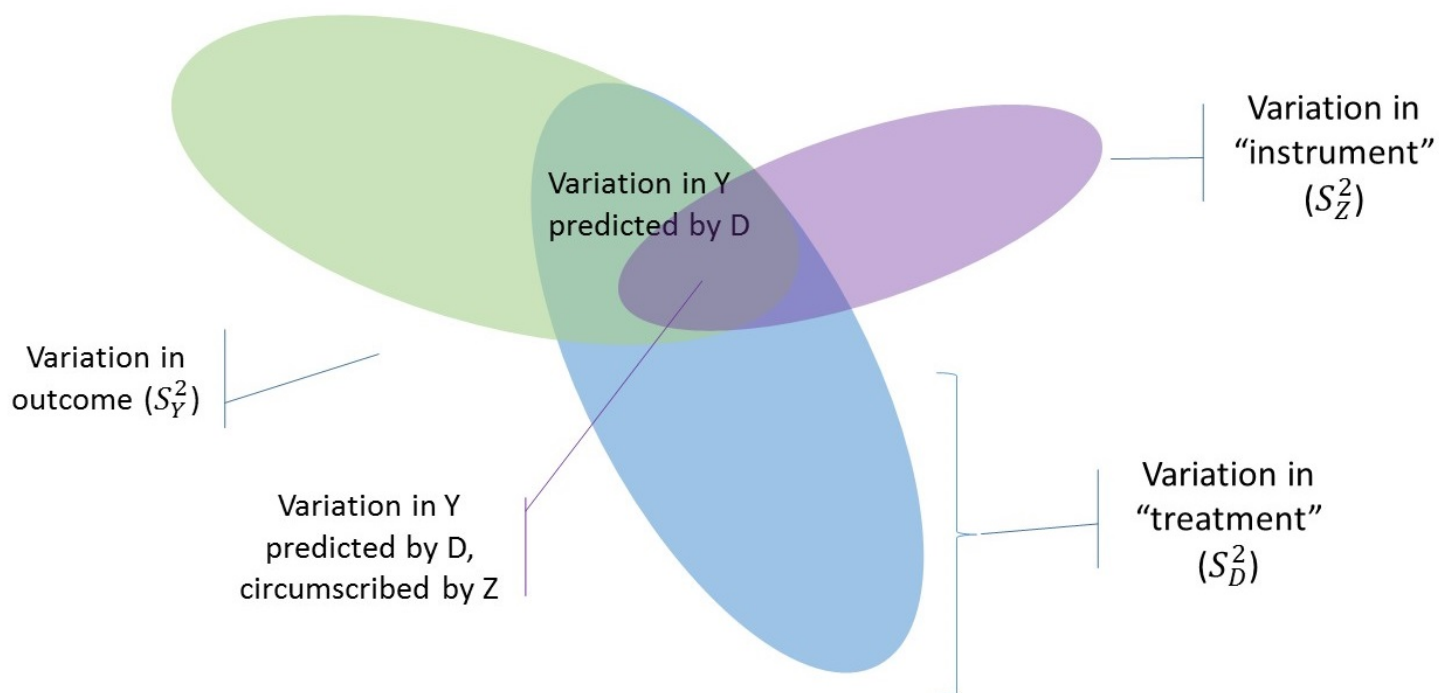
```
ols1 <- lm(finish8th ~ use_fin_aid, data=paces)
ols2 <- lm(finish8th ~ use_fin_aid + base_age + male, data=paces)
```

	(1)	(2)
use_fin_aid	0.133*** (0.027)	0.121*** (0.027)
base_age		-0.063*** (0.010)
male		-0.086** (0.026)
Observations	1,171	1,171
R ²	0.020	0.064

What's wrong with the naïve approach?

Only about 90 percent of lottery winners used the private school voucher to pay for private school and 24 percent of lottery losers found other sources of scholarships for which to pay for private school. There are endogenous differences in the expected outcomes of children from families who chose to both use the voucher and those who secured scholarship funding from sources outside the voucher lottery. The policy relevant question is how a public subsidy of private school might affect educational attainment for children from low-income families in Bogota, Colombia. The naïve approach does not identify these effects but rather the combination of voucher subsidy and endogenous unobservables across families and individuals.

How could IV address?



IV estimate: ratio of area of overlap of Y and Z to area of overlap of D and Z . Depends entirely on variation in Z that predicts variation in Y and D :

$$\hat{\beta}_1^{IVE} = \frac{S_{YD}}{S_{DZ}}$$

a **Local Average Treatment Effect**

Recall 2SLS set-up

1st stage:

Regress the endogenous treatment (D_i) on instrumental variable (Z_i):

$$D_i = \alpha_0 + \alpha_1 Z_i + \nu_i$$

Obtain the *predicted values* of the treatment (\hat{D}_i) from this fit.

2nd stage:

Regress the outcome (Y_i) on the predicted values of the treatment (\hat{D}_i):

$$Y_i = \beta_0 + \beta_1 \hat{D}_i + \varepsilon_i$$

Think about this in the Colombia PACES experiment context. What is the **main outcome**? What is the **endogenous regressor**? What is the **instrument**? Can you write the two-stage equation without consulting the next slide or book?

The PACES Scholarship

1st stage:

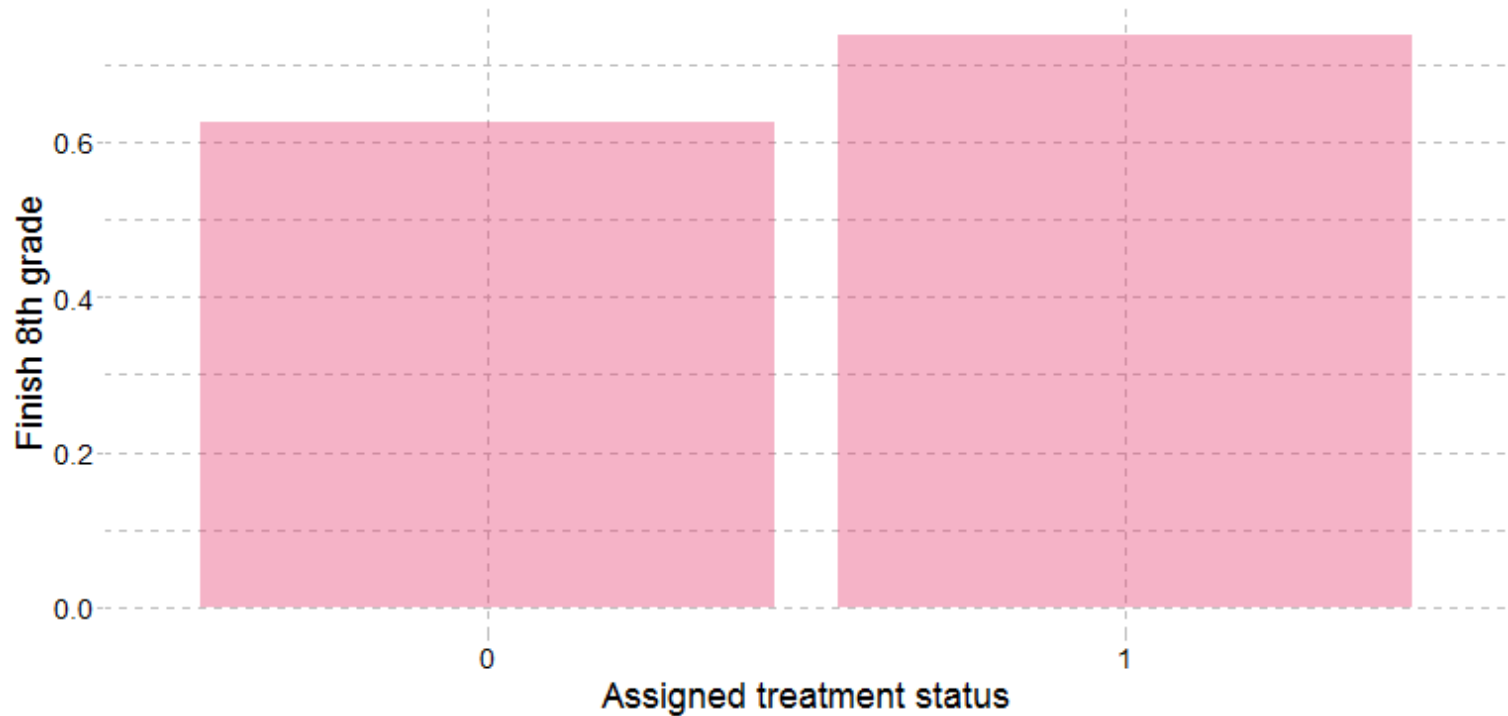
$$USEFINAID_i = \alpha_0 + \alpha_1 WONLOTTERY_i + \nu_i$$

2nd stage:

$$FINISH8TH_i = \beta_0 + \beta_1 USE\hat{FINAID}_i + \varepsilon_i$$

What is the main outcome? What is the endogenous regressor? What is the instrument? What are the assumptions?

Outcome by lottery status



This represents an important substantive finding... **can you interpret what it is?**

A simple t -test

```
ttest ← t.test(finish8th ~ won_lottry, data=paces)
ttest
```

```
#>
```

```
#>      Welch Two Sample t-test
```

```
#>
```

```
#> data:  finish8th by won_lottry
```

```
#> t = -4.1077, df = 1153.5, p-value = 4.279e-05
```

```
#> alternative hypothesis: true difference in means between group 0 and group 1
```

```
#> 95 percent confidence interval:
```

```
#>  -0.16441869 -0.05812251
```

```
#> sample estimates:
```

```
#> mean in group 0 mean in group 1
```

```
#>      0.6252159      0.7364865
```

Can you interpret what this means?

Intent-to-Treat Estimates

```
itt1 ← lm(finish8th ~ won_lottry, data=paces)
itt2 ← lm(finish8th ~ won_lottry + base_age + male, data=paces)
itt3 ← lm(finish8th ~ won_lottry + base_age + male +
          as.factor(school), data=paces)
```

Table 1. Intent-to-Treat Estimates of Winning the PACES lottery on 8th Grade Completion

	Model 1	Model 2	Model 3
Won Lottery	0.111***	0.107***	0.108***
	(0.027)	(0.026)	(0.027)
Starting Age		-0.065***	-0.064***
		(0.010)	(0.010)
Male		-0.088***	-0.089***
		(0.027)	(0.027)
School Fixed Effects	No	No	Yes
Num.Obs.	1171	1171	1171

Notes: The table displays coefficients from Equation X and standard errors in parentheses.

Intent-to-Treat Estimates

What is our estimand of interest? Do these estimates represent that?

Table 1. Intent-to-Treat Estimates of Winning the PACES lottery on 8th Grade Completion

	Model 1	Model 2	Model 3
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	(0.027)	(0.026)	(0.027)
Starting Age		-0.065***	-0.064***
		(0.010)	(0.010)
Male		-0.088***	-0.089***
		(0.027)	(0.027)
School Fixed Effects	No	No	Yes
Num.Obs.	1171	1171	1171

Notes: The table displays coefficients from Equation X and standard errors in parentheses. 20 / 33

Implementing IV in regression

Reminder of key assumptions:

1. Instrument correlated with endogenous predictor (no "weak" instruments)
2. Instrument not correlated with 1st stage residuals ($\sigma_{Z\nu} = 0$)
3. Instrument not correlated with 2nd stage residuals ($\sigma_{Z\varepsilon} = 0$) and correlated with outcome only via predictor^[1]
 - Exclusion restriction means **NO THIRD PATH!**

Practical considerations:

Can implement this various ways. Pedagogically, we'll implement 2SLS using the `fixest` package because it allows straightforward presentation of 1st stage results. This can also be done via `ivreg` and `iv_robust` in R.

[1] Don't forget, **no defiers** too.

IV Estimation

```
# Instrument with no covariates  
# With only instrumented predictor and no covariates,  
# need to include a "1" in 2nd stage  
tot1 ← feols(finish8th ~ 1 | use_fin_aid ~ won_lottry, data=paces)  
  
# Instrument with covariates  
# Note that these are automatically included in 1st stage  
# Can include multiple instruments and multiple  
# endogenous predictors  
tot2 ← feols(finish8th ~ base_age + male |  
              use_fin_aid ~ won_lottry, data=paces)
```

IV results - First Stage

```
summary(tot2, stage = 1)
```

```
#> TSLS estimation, Dep. Var.: use_fin_aid, Endo.: use_fin_aid, Instr.: won_
#> First stage: Dep. Var.: use_fin_aid
#> Observations: 1,171
#> Standard-errors: IID
#>
#>           Estimate Std. Error   t value   Pr(>|t|)
#> (Intercept)  0.432760   0.095159  4.547738 5.9880e-06 ***
#> won_lottry   0.674527   0.021014 32.098773 < 2.2e-16 ***
#> base_age    -0.015160   0.007826 -1.937178 5.2965e-02 .
#> male        -0.020257   0.021070 -0.961417 3.3654e-01
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.358813   Adj. R2: 0.469577
#> F-test (1st stage): stat = 1,030.3, p < 2.2e-16, on 1 and 1,167 DoF.
```

You will see some rules of thumb about what makes for a strong instrument (e.g., $t_F > 10$), but recent work has found that with t -ratios lower than 100 one should adjust critical value (Lee et al., 2021).

IV results - Second Stage

```
summary(tot2)
```

```
#> TSLS estimation, Dep. Var.: finish8th, Endo.: use_fin_aid, Instr.: won_lo
#> Second stage: Dep. Var.: finish8th
#> Observations: 1,171
#> Standard-errors: IID
#>
#>               Estimate Std. Error  t value   Pr(>|t|)
#> (Intercept)    1.378128    0.123090  11.19614 < 2.2e-16 ***
#> fit_use_fin_aid 0.159000    0.039173   4.05890 5.2589e-05 ***
#> base_age       -0.062157    0.009872  -6.29603 4.3146e-10 ***
#> male           -0.085145    0.026504  -3.21258 1.3515e-03 **
#> ---
#> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#> RMSE: 0.451177  Adj. R2: 0.059822
#> F-test (1st stage), use_fin_aid: stat = 1,030.3      , p < 2.2e-16 , on 1 d
#>                               Wu-Hausman: stat =      1.78464, p = 0.181841, on 1 d
```

Can you interpret what this means?

A taxonomy of IV estimates

```
# Include school fixed effects
```

```
tot3 ← feols(finish8th ~ base_age + male | as.factor(school) |  
             use_fin_aid ~ won_lottry,  
             vcov = "iid", data=paces)
```

```
# Cluster-robust standard errors
```

```
tot4 ← feols(finish8th ~ base_age + male | as.factor(school) |  
             use_fin_aid ~ won_lottry,  
             vcov = ~ school, data=paces)
```

Estimate voucher use effects

Table 2. Instrumental variable estimates of using financial aid to attend private school due to winning the PACES lottery on 8th grade completion

	(1)	(2)	(3)	(4)
Use Fin. Aid	0.165***	0.159***	0.161***	0.161*
	(0.040)	(0.039)	(0.039)	(0.052)
Starting Age		-0.062***	-0.062***	-0.062**
		(0.010)	(0.010)	(0.009)
Male		-0.085**	-0.086**	-0.086
		(0.027)	(0.027)	(0.037)
School FE	No	No	Yes	Yes
Num.Obs.	1171	1171	1171	1171

The table displays coefficients from Equation X and standard errors in parentheses. Model 4 uses cluster-robust standard errors at school level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS, ITT and TOT estimates

Table 3. Comparison of OLS, ITT and IV estimates of using financial aid to attend private school due to winning the PACES lottery

	(1)	(2)	(3)	(4)	(5)
	OLS	ITT	TOT	TOT	TOT
Use Fin. Aid	0.121*** (0.027)		0.165*** (0.040)	0.159*** (0.039)	0.161* (0.052)
Win Lottery		0.107*** (0.026)			
School FE	No	No	No	No	Yes
Student Chars.	Yes	Yes	No	Yes	Yes
Clust. SEs	No	No	No	No	Yes
Num.Obs.	1171	1171	1171	1171	1171

The table displays coefficients from Equation X and standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Interpretation of results

The naïve OLS estimates **understate** the effects of a public voucher subsidy for private school attendance for over 125,000 children from low-income families in Bogota, Colombia. Our preferred estimates of the effect of voucher use on eighth-grade completion imply an increase in the on-time completion rate of 16 percentage points.

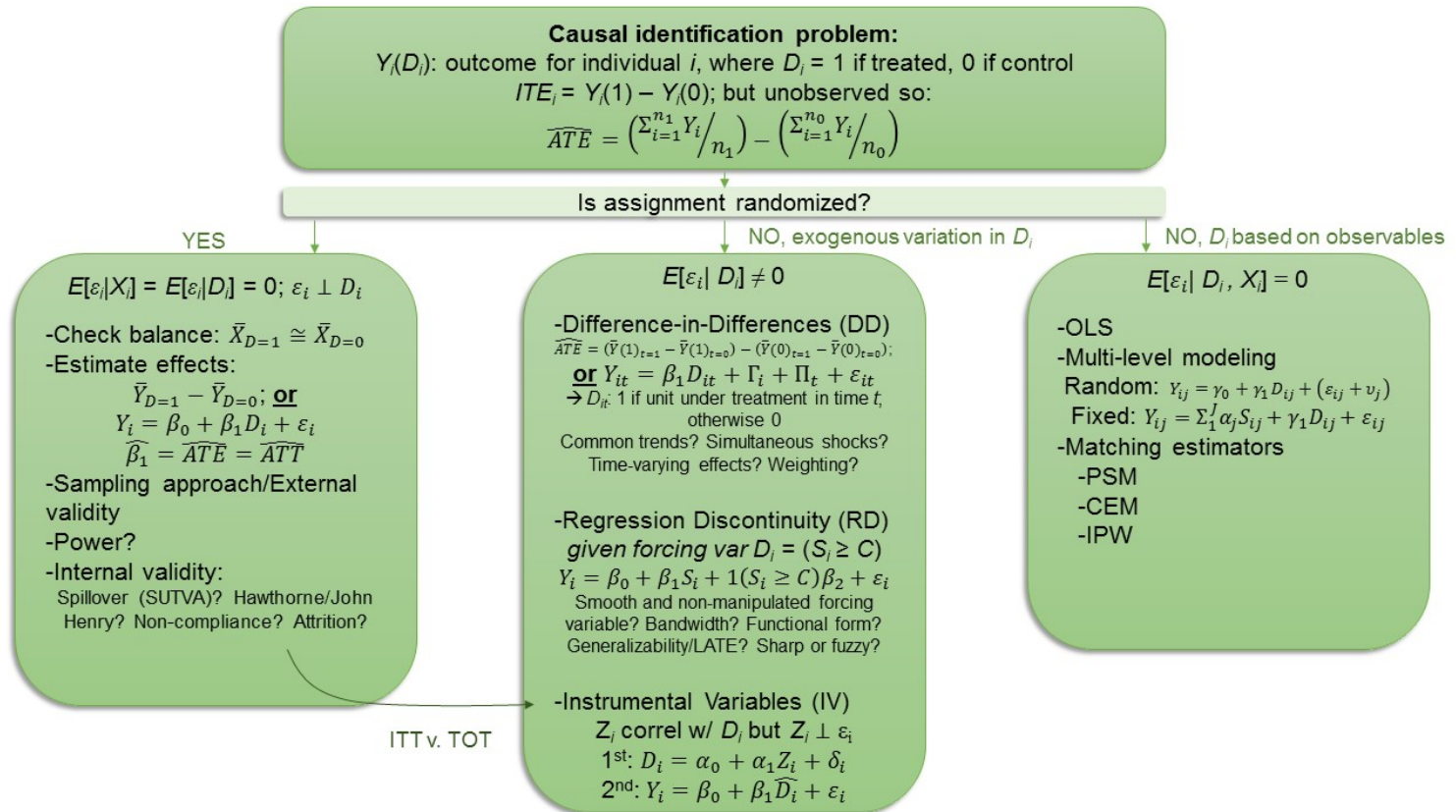
The estimates of the endogenous relationship between the use of financial aid to attend private school and school attainment (Model 1) imply that students who use any form of external scholarship are 12 percentage points more likely to complete eighth grade. In Model 2, we present results of winning an unbiased lottery to receive vouchers covering slightly more than half the cost of average private school attendance. We find that the offer of the voucher increased eighth-grade completion rates by just less than 11 percentage points. Finally, Models 3-5 present a taxonomy of Treatment-on-the-Treated estimates in which we use the randomized lottery as an instrument for the use of financial aid to attend private school. We find consistent effects 50 percent larger than the Intent-to-Treat estimates. These models are robust to the inclusion of baseline student characteristics, cohort fixed effects, and the clustering of standard errors at the level of randomization (within school).

Synthesis and wrap-up

Goals

1. Describe conceptual approach to instrumental variables (IV) analysis
2. Assess validity of IV assumptions in applied context
3. Conduct IV analysis in simplified data and interpret results

Can you explain this figure?



To-Dos

Week 7: Instrumental Variables

Readings:

- Kim, Capotosto, Hartry & Fitzgerald (2011)

Assignments Due

DARE 3

- Due 9:00am, Feb. 14

Final Research Project

- Presentation, March 8
- Paper, March 18 (submit early [March 10] for feedback)

Feedback

Plus/Deltas

Front side of index card

Clear/Murky

On back