Williams College ECON 523:

Program Evaluation for International Development

Lecture 6: Treatment-on-the-Treated

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photo: Daniella Van Leggelo-Padilla / World Bank

Imperfect Compliance

How High Is Program Take-Up?

Even “free” programs involve opportunity costs for participants, so take-up is often low

Intervention	**Take-Up**	**Source**
Business training	65%	McKenzie & Woodruff (2013)
Deworming medication	75%	Kremer & Miguel (2007)
Microfinance	13% – 31%	JPAL & IPA (2015)

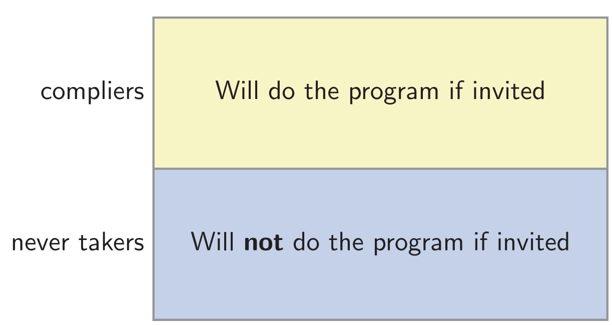
It is often the case that only people who do a program can be impacted by the program*

⇒ We might like to know how much program impacted program **participants**

⇒ Not only relevant in randomized trials (who benefits from free primary education?)

*Often the case, but not always!

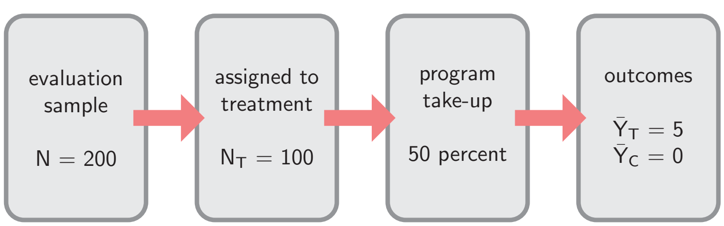
Compliers vs. Never Takers



Compliers vs. Never Takers

	$T = 0$	$T = 1$
compliers	Y_{0i}	Y_{1i}
never takers	Y_{0i}	Y_{0i}

Imperfect Compliance: A Thought Experiment



Questions:

- What can we say about the average **impact of treatment** on program participants?
- What can we say about the average **outcome** among those who did the program?

Imperfect Compliance

Suppose outcomes are impacted by program participation (P_i), not treatment status (T_i):

$$Y_i = Y_{0i} + \delta_i P_i$$

- Program take-up is endogenous conditional on treatment: $E[Y_{0i}|P_i = 1] \neq E[Y_{0i}|P_i = 0]$
- Only those randomly assigned to treatment ($T_i = 1$) are eligible: $E[P_i|T_i = 0] = 0$
- Not everyone participates: $E[P_i|T_i = 1] = \lambda < 1$

Two possible regressions:

- Regress Y on P using data from the treatment ($T_i = 1$) group
- Regress Y on T using data from the treatment and comparison groups

How Not to Estimate the Impact of Treatment on the Treated

If we estimate the regression equation $Y_i = \alpha + \beta P_i + \varepsilon_i$ using data from the treatment group:

$$\begin{aligned}
\hat{\beta} &= E\left[Y_i|P_i = 1\right] - E\left[Y_i|P_i = 0\right] \\
&= E\left[Y_{1i}|P_i = 1\right] - E\left[Y_{0i}|P_i = 0\right] \\
&= E\left[Y_{0i} + \delta_i|P_i = 1\right] - E\left[Y_{0i}|P_i = 0\right] \\
&= E\left[\delta_i|P_i = 1\right] + E\left[Y_{0i}|P_i = 1\right] - E\left[Y_{0i}|P_i = 0\right] \\
&= \underbrace{E\left[\delta_i|\text{compliers}\right]}_{\text{impact of TOT}} + \underbrace{E\left[Y_{0i}|\text{compliers}\right] - E\left[Y_{0i}|\text{never-takers}\right]}_{\text{selection bias}}
\end{aligned}$$

The Intent-to-Treat (ITT) Effect

If we estimate the regression equation $Y_i = \alpha + \beta T_i + \varepsilon_i$:

$$\hat{\beta} = E\left[Y_i | T_i = 1\right] - E\left[Y_i | T_i = 0\right]$$

$E\left[Y_i | T_i = 1\right]$ is a weighted average of outcomes for complier and never-takers:

$$E\left[Y_i|T_i = 1\right] = \lambda E\left[Y_{1i}|T_i = 1 \text{ and } P_i = 1\right] + (1-\lambda)E\left[Y_{0i}|T_i = 1 \text{ and } P_i = 0\right]$$

$$= \lambda E\left[\delta_i + Y_{0i}|T_i = 1 \text{ and } P_i = 1\right] + (1-\lambda)E\left[Y_{0i}|T_i = 1 \text{ and } P_i = 0\right]$$

$$= \lambda E\left[\delta_i|\text{compliers}\right] + \lambda E\left[Y_{0i}|\text{compliers}\right] + (1-\lambda)E\left[Y_{0i}|\text{never-takers}\right]$$

$$= \lambda E\left[\delta_i|\text{compliers}\right] + E\left[Y_{0i}\right]$$

The Intent-to-Treat (ITT) Effect

Substituting this into our expression for $\hat{\beta}$:

$$\hat{\beta} = E\left[Y_i | T_i = 1\right] - E\left[Y_i | T_i = 0\right]$$

$$= \lambda E\left[\delta_i|\text{compliers}\right] + E\left[Y_{0i}\right] - E\left[Y_{0i}\right]$$

$$= \lambda \underbrace{E\left[\delta_i|\text{compliers}\right]}_{\text{impact of TOT}}$$

⇒ Low compliance ($\lambda < 1$) scales down the estimated treatment effect

⇒ ITT effect is average across population ($T_i = 1$), including zero impact on never-takers

The Impact of Treatment on the Treated

$$\text{ITT} = \lambda\text{TOT} \Leftrightarrow \text{TOT} = \text{ITT}/\lambda$$

The **treatment on the treated (TOT)** estimator: $\hat{\beta}_{tot} = \frac{E[Y_i|T_i=1]-E[Y_i|T_i=0]}{E[P_i|T_i=1]-E[P_i|T_i=0]}$

- TOT scales up ITT effect to reflect imperfect take-up
- The identifying assumption is that treatment only works through program take-up

Treatment on the Treated: Implementation (Approach #1)

Estimating the impact of treatment on the treated via two separate regressions:

Intent-to-treat (aka reduced form): impact of treatment assignment on outcome of interest

$$Y_i = \alpha_{itt} + \beta_{itt} T_i + \varepsilon_i$$

First stage: impact of assignment to treatment on program participation:

$$P_i = \alpha_{fs} + \beta_{fs} T_i + \epsilon_i$$

Combine OLS coefficients to estimate impact of treatment on the treated: $\beta_{tot} = \beta_{itt}/\beta_{fs}$

Treatment on the Treated: Implementation (Approach #2)

Approach #1 is equivalent to using treatment as an **instrument** for program participation

Assumptions required for instrumental variables estimation:

1. Instrument is exogenous (i.e. not correlated with error term in first stage)
2. Instrument is correlated with treatment (first stage)
3. Only impacts outcomes through program participation (exclusion restriction)

Treatment on the Treated: Implementation (Approach #2)

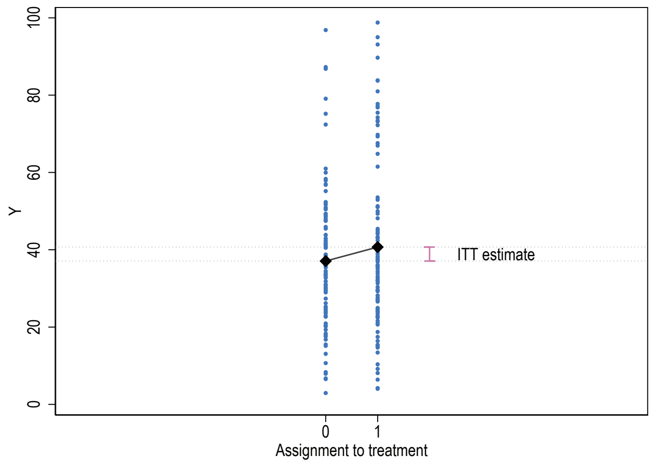
Estimated via two-stage least squares (2SLS):

- **First stage:** $P_i = \alpha_{fs} + \beta_{fs} T_i + \epsilon_i$
- **Second stage:** $Y_i = \alpha_{iv} + \beta_{iv} \hat{P}_i + \zeta_i$

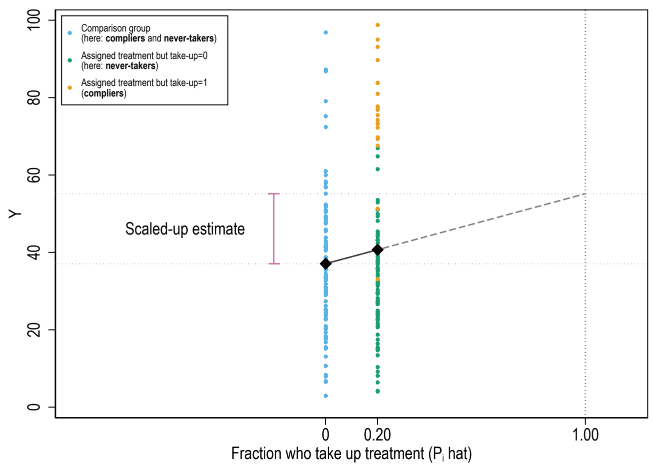
Easy to implement using Stata's `ivregress 2sls` command

- Running two (separate) regressions yields incorrect standard error

Two-Stage Least Squares (2SLS)



Two-Stage Least Squares (2SLS)



Treatment on the Treated: Implementation (Approach #3)

2SLS is also equivalent to a **control function** approach:

- **First stage:** $P_i = \alpha_{fs} + \beta_{fs} T_i + \epsilon_i$
- **Control function second stage:** $Y_i = \alpha_{iv} + \beta_{iv} P_i + \gamma \hat{\epsilon}_i + \zeta_i$

First-stage residual captures the endogenous portion of program participation

- Variation in P_i that remains is the variation explained by T_i
- Second regression equivalent to regressing Y_i on residuals from a regression of P_i on $\hat{\epsilon}_i$

Treatment on the Treated: Summary of Approaches

1. Divide ITT effect by first stage (impact of T on P)
2. Two-stage least squares (regress Y on predictions from regression of P on T)
3. Control function approach (control for residuals from regression of P on T)

Treatment on the Treated: Example

Data from a youth entrepreneurship intervention targeting young women in Nairobi, Kenya

- `treatment` is a dummy for being randomly assigned to the treatment group
- `training` is a dummy for attending at least one day of business training
- `strata` is an ID number for randomization strata (neighborhood×month)
- `income` is a measure of weekly income two years after treatment (from endline survey)

First stage, reduced form regressions take standard form

- **First stage:** `regress training treatment i.strata, r`
- **Reduced form:** `regress income treatment i.strata, r`

TOT Example: First Stage and Reduced Form Results

	(1)	**(2)**
	Training	**Income**
Treatment	0.6105267	165.9126
	(0.0260283)	(73.81483)
	[0.000]	[0.025]
Strata fixed effects	Yes	Yes
R-squared	0.470	0.030
Obs.	680	680

Robust standard errors in parentheses; p-values in square brackets.

TOT Example: Two-Stage Least Squares (2SLS)

Stata syntax for 2SLS:

```
ivregress 2sls income (training = treatment) i.strata, r
```

Generates same coefficients as two-step process, but difference standard errors

```
regress training treatment i.strata, r
predict phat, xb
regress income phat i.strata, r
```


TOT Example: Two-Stage Least Squares (2SLS)

```
. ivregress 2sls income (training = treatment) i.strata, r

Instrumental variables 2SLS regression            Number of obs   =        680
                                                  Wald chi2(14)   =      28.49
                                                  Prob > chi2     =     0.0122
                                                  R-squared       =     0.0305
                                                  Root MSE        =     950.84
```

income	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
training	271.7533	119.5059	2.27	0.023	37.52603	505.9805
strata						
494002011	243.1708	144.5925	1.68	0.093	-40.22521	526.5668
494004004	-89.89336	109.9156	-0.82	0.413	-305.324	125.5373
494004011	39.53772	151.3919	0.26	0.794	-257.185	336.2604
594004004	52.2759	155.0265	0.34	0.736	-251.5705	356.1222
594004011	-106.3099	130.9806	-0.81	0.417	-363.0272	150.4073
594012004	238.6223	146.6926	1.63	0.104	-48.88987	526.1345
594012011	319.2648	185.929	1.72	0.086	-45.14938	683.6789
694002004	-167.3286	166.5964	-1.00	0.315	-493.8515	159.1944
694002011	-187.3286	160.601	-1.17	0.243	-502.1007	127.4436
694004004	-151.1399	194.2218	-0.78	0.436	-531.8076	229.5278
694004011	-260.9	196.4015	-1.33	0.184	-645.8398	124.0398
694012004	209.9024	175.767	1.19	0.232	-134.5947	554.3994
694012011	233.7189	142.9428	1.64	0.102	-46.44377	513.8815
_cons	413.216	77.32459	5.34	0.000	261.6626	564.7694

```
Instrumented: training
 Instruments: 494002011.strata 494004004.strata 494004011.strata
              594004004.strata 594004011.strata 594012004.strata
              594012011.strata 694002004.strata 694002011.strata
              694004004.strata 694004011.strata 694012004.strata
              694012011.strata treatment
```

TOT Example: Two-Stage Least Squares (2SLS)

```
. quietly regress training treatment i.strata, r

. predict phat, xb

. regress income phat i.strata, r

Linear regression                               Number of obs     =        680
                                                F(14, 665)        =       1.97
                                                Prob > F          =     0.0177
                                                R-squared         =     0.0295
                                                Root MSE          =        962

------------------------------------------------------------------------------
             |               Robust
      income | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
        phat |   271.7533   120.9035     2.25   0.025     34.35466    509.1519
             |
      strata |
   494002011 |   243.1708   147.3034     1.65   0.099    -46.06501    532.4066
   494004004 |  -89.89336   112.5547    -0.80   0.425    -310.8988    131.1121
```


TOT Example: The Control Function Approach

```
. quietly regress training treatment i.strata, r

. predict presid, resid

. regress income training presid i.strata, r

Linear regression                               Number of obs     =        680
                                                F(15, 664)        =       1.98
                                                Prob > F          =     0.0144
                                                R-squared         =     0.0322
                                                Root MSE          =     961.36

------------------------------------------------------------------------------
             |               Robust
      income | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
    training |   271.7533   120.8254     2.25   0.025     34.50743    508.9991
      presid |  -120.5366   173.7454    -0.69   0.488    -461.6932    220.6199
             |
      strata |
   494002011 |   243.1708   146.5754     1.66   0.098    -44.63639     530.978
   494004004 |  -89.89336   111.6222    -0.81   0.421    -309.0684    129.2816
```

TOT Example: Interpretation

The entrepreneurship promotion intervention increases income

- TOT effects are larger than ITT effects (is this always true?)
- Assumption: program has no impact on women who do not participate
  - When might this be a reasonable assumption?
  - When might this **not** be a reasonable assumption?
- Which is more policy relevant: the ITT estimates or the TOT estimates?
- Could you estimate the TOT impacts of self-employment? Why or why not?

Two-Sided Non-Compliance

Two-Sided Non-Compliance

We sometimes evaluate programs that are available to those in the treatment group

- Examples: medical/health treatment, schooling, vocational/business training, childcare, access to credit, migration, agricultural inputs, management consulting, export contracts
- In such settings, an intervention involves encouraging/facilitating takeup
- Treatment is random and (one hopes) strongly associated with program participation
  - Compliers participate when assigned to treatment, but not when assigned to control
  - Some people in the treatment group may choose not to participate
  - Some people in the control group may still participate in the program

IV Estimates with Two-Sided Non-Compliance

$T = 0$	$T = 1$
always takers	always takers
compliers	compliers
never takers	never takers

IV estimates tell us local average treatment effect (LATE) on **compliers**

- Monotonicity assumption: there are no **defiers**
- We can't estimate impacts on **always takers** and **never takers** because being assigned to treatment doesn't change their take-up (i.e. program participation) decision

Assumptions Required for IV Estimation of LATE

1. Instrument is exogenous (OK in an RCT)
2. Instrument is correlated with treatment (first stage)
3. Only impacts outcomes through take-up (exclusion restriction)
4. Monotonicity (i.e. no defiers)
   - Treatment either moved people into participation or out of participation, not both
   - Not required if treatment effects are homogeneous

Characteristics of the Compliers

The impact of treatment on program participation indicates the proportion compliers

$$E[P_i|T_i = 1] - E[P_i|T_i = 0] \;=\; \frac{\text{number of compliers}}{N} \;=\; \frac{C}{N}$$

This is also true in sub-populations, e.g. among observations with $X = 1$ for some X

$$E[P_i|T_i = 1 \text{ and } X_i = 1] - E[P_i|T_i = 0 \text{ and } X_i = 1] = \frac{C_{X=1}}{N_{X=1}}$$

Relative frequency of characteristics $X = 1$ among compliers, relative to entire population:

$$\frac{E[P_i|T_i{=}1 \text{ and } X_i{=}1] - E[P_i|T_i{=}0 \text{ and } X_i{=}1]}{E[P_i|T_i{=}1] - E[P_i|T_i{=}0]}$$