# 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*

$\Rightarrow$ We might like to know how much program impacted program **participants**

$\Rightarrow$ Not only relevant in randomized trials (who benefits from free primary education?)

*Often the case, but not always!

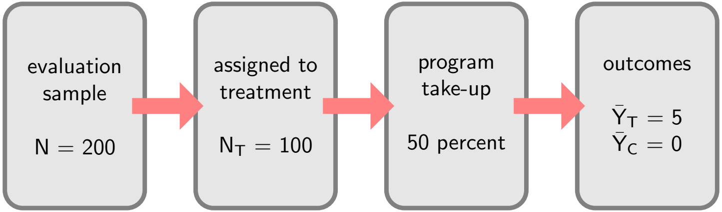
# Compliers vs. Never-Takers

| | |
|---|---|
| compliers | Will do the program if invited |
| never-takers | Will **not** do the program if invited |

# 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:

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

$$= E\left[Y_{1i} | P_i = 1\right] - E\left[Y_{0i} | P_i = 0\right]$$

$$= E\left[Y_{0i} + \delta_i | P_i = 1\right] - E\left[Y_{0i} | P_i = 0\right]$$

$$= E\left[\delta_i | P_i = 1\right] + E\left[Y_{0i} | P_i = 1\right] - E\left[Y_{0i} | P_i = 0\right]$$

$$= \underbrace{E\left[\delta_i | \text{compliers}\right]}_{\text{impact of TOT}} + \underbrace{E\left[Y_{0i} | \text{compliers}\right] - E\left[Y_{0i} | \text{never-takers}\right]}_{\text{selection bias}}$$

# 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:

$$\begin{aligned}
E\left[Y_i | T_i = 1\right] &= \lambda E\left[Y_{1i} | T_i = 1 \text{ and } P_i = 1\right] + (1-\lambda) E\left[Y_{0i} | T_i = 1 \text{ and } P_i = 0\right] \\
&= \lambda E\left[\delta_i + Y_{0i} | T_i = 1 \text{ and } P_i = 1\right] + (1-\lambda) E\left[Y_{0i} | T_i = 1 \text{ and } P_i = 0\right] \\
&= \lambda E\left[\delta_i | \text{compliers}\right] + \lambda E\left[Y_{0i} | \text{compliers}\right] + (1-\lambda) E\left[Y_{0i} | \text{never-takers}\right] \\
&= \lambda E\left[\delta_i | \text{compliers}\right] + E\left[Y_{0i}\right]
\end{aligned}$$

# The Intent-to-Treat (ITT) Effect

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

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

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

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

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

$\Rightarrow$ 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

1. Regress $Y$ on $\hat{P}$, the predicted value of $P$ from first-stage regression

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)

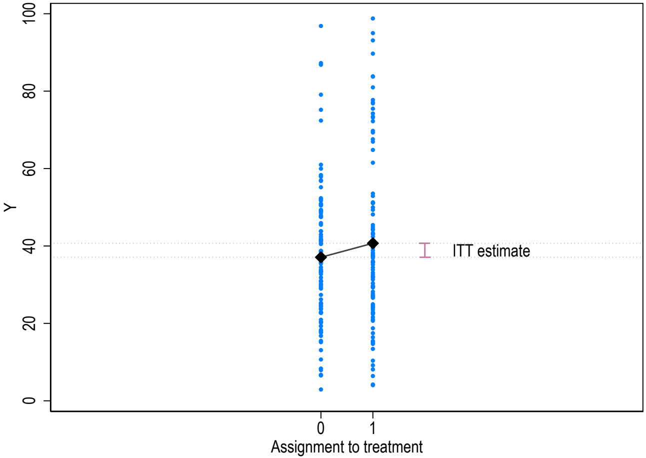
Estimated via two-stage least squares (2SLS):

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

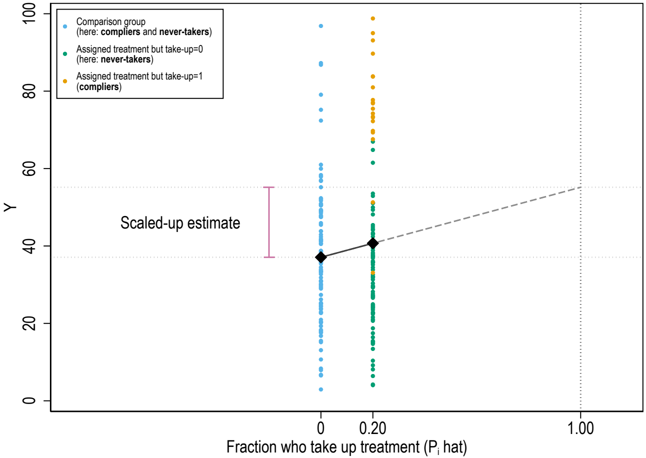
Easy to implement using Stata's `ivregress 2sls` command

- 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$\times$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

------------------------------------------------------------------------------
             |               Robust
      income | Coefficient  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:

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