Supercompliers

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Disclaimers

- Any opinions and conclusions expressed herein are those of the authors and do not necessarily reflect the views of the Joint Committee on Taxation or any Member of Congress.

- Eng performed this work prior to joining the Internal Revenue Service. All views and opinions expressed herein do not represent the Internal Revenue Service.

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  - Directly answers: who benefit from gaining treatment eligibility?
  - If supercompliers differ from compliers $\Rightarrow$ better to target pop. similar to supercompliers

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  - Illustration using two job training experiments

Introduction

- Exposition focuses on binary Y; builds on LATE assumptions + outcome monotonicity
  - Assumptions jointly testable
  - Supercomplier characteristics distribution point identified
  - Can be estimated using `ivregress`

Presentation Outline

- Introduction
- Statistical Framework
  - Set-up
  - Identification
  - Estimation
- Value in characterizing supercompliers
  - MVPF analysis
- Empirical Illustration
  - Job Corps
  - JTPA
- Conclusion

Statistical Framework: Set-up

Notations and Assumptions

Observables

- Z: treatment assignment; D: treatment take-up; Y: outcome; X: characteristics
  - Z, D, Y: binary; $Y = 1 \Rightarrow$ good outcome

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Assumptions

- *Random Assignment*: Z indep. to potential treatments/outcomes and X
- *Exclusion*: $Y_{1d} = Y_{0d} \equiv Y_d$
- *Treatment Monotonicity*: $\Pr(D_1 \geqslant D_0) = 1$
- *First Stage*: $\Pr(D_1 > D_0) > 0$

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- *Outcome Monotonicity*: $\Pr(Y_1 \geqslant Y_0) = 1$
- *Reduced Form*: $\Pr(D_1 > D_0, Y_1 > Y_0) > 0$

Defining Supercompliers

(Extended) Principal Strata

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- For treatment always takers + never takers, D does not change with Z
- For outcome always takers + never takers, Y does not change with D

Statistical Framework: Identification

Characterizing Compliers and Supercompliers

Compliers (Abadie 2003; Angrist and Pischke 2009)

$$\begin{aligned} \text{share: } & \Pr(D_1 > D_0) = E[D|Z=1] - E[D|Z=0] \\ \text{average } X\text{: } & E[X|D_1 > D_0] = E[\kappa X]/\Pr(D_1 > D_0) \\ \text{average } Y_d \ (d=0,1)\text{: } & E[Y_d|D_1 > D_0] = E[\kappa_d Y]/\Pr(D_1 > D_0) \end{aligned}$$

where $\kappa \equiv 1 - \frac{D(1-Z)}{\Pr(Z=0)} - \frac{(1-D)Z}{\Pr(Z=1)}$, $\kappa_0 \equiv \frac{(1-D)(1-Z)}{\Pr(Z=0)} - \frac{(1-D)Z}{\Pr(Z=1)}$, $\kappa_1 \equiv \frac{DZ}{\Pr(Z=1)} - \frac{D(1-Z)}{\Pr(Z=0)}$

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Supercompliers:

$$\begin{aligned} \text{share:} \quad & \Pr(D_1 > D_0, Y_1 > Y_0) = E[Y|Z=1] - E[Y|Z=0] \\ \text{average } X\text{:} \quad & E[X|D_1 > D_0, Y_1 > Y_0] = E[\pi X]/\Pr(D_1 > D_0, Y_1 > Y_0) \end{aligned}$$

where $\pi \equiv \kappa - \kappa_0 Y - \kappa_1 (1 - Y)$

Remarks on Identification: 1

Supercomplier characteristics can also be identified by a Wald-type estimand

$$E[X|D_1 > D_0, Y_1 > Y_0] = \frac{E[XY|Z = 1] - E[XY|Z = 0]}{E[Y|Z = 1] - E[Y|Z = 0]}$$

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D does not enter estimand: Identification applies regardless of degree of treatment compliance

Remarks on Identification: 2

Relaxing restriction that Y be binary; supercompliers still those with $D_1 > D_0, Y_1 > Y_0$

$$\Pr(\text{supercomplier}) \cdot E[Y_1 - Y_0 | \text{supercomplier}] = E[Y|Z=1] - E[Y|Z=0]$$

$$\frac{E[X(Y_1 - Y_0)|\text{supercomplier}]}{E[Y_1 - Y_0|\text{supercomplier}]} = \frac{E[XY|Z=1] - E[XY|Z=0]}{E[Y|Z=1] - E[Y|Z=0]}$$

Remarks on Identification: 3

Beyond averages: Replace X with $1_{[X \leqslant x]}$ for any x and identify distribution of X

X can be multi-dimensional

Remarks on Identification: 4

Violation of outcome monotonicity: bias $\propto$ share of "outcome defiers" $(D_1 > D_0, Y_1 < Y_0)$

$$\text{Bias} = \xi \cdot \{E[X|D_1 > D_0, Y_1 > Y_0] - E[X|D_1 > D_0, Y_1 < Y_0]\}$$

where

$$\xi \equiv \frac{\Pr(D_1 > D_0, Y_1 < Y_0)}{\Pr(D_1 > D_0, Y_1 < Y_0) + \Pr(D_1 > D_0, Y_1 > Y_0)}$$

Remarks on Identification: 5

- Shares/characteristics of two remaining groups within treatment compliers identified

$$\Pr(D_1 > D_0, Y_0 = Y_1 = 1) = E[\kappa_0 Y] = E[(1-D)Y|Z=1] - E[(1-D)Y|Z=0]$$

$$E[X|D_1 > D_0, Y_0 = Y_1 = 1] = \frac{E[\kappa_0 YX]}{E[\kappa_0 Y]} = \frac{E[(1-D)YX|Z=1] - E[(1-D)YX|Z=0]}{E[(1-D)Y|Z=1] - E[(1-D)Y|Z=0]}$$

$$\Pr(D_1 > D_0, Y_0 = Y_1 = 0) = E[\kappa_1(1-Y)] = E[D(1-Y)|Z=1] - E[D(1-Y)|Z=0]$$

$$E[X|D_1 > D_0, Y_0 = Y_1 = 0] = \frac{E[\kappa_1(1-Y)X]}{E[\kappa_1(1-Y)]} = \frac{E[D(1-Y)X|Z=1] - E[D(1-Y)X|Z=0]}{E[D(1-Y)|Z=1] - E[D(1-Y)|Z=0]}$$

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If we extend exclusion restriction and monotonicity assumption to cover M,

- i.e., $Y_{zdm} = Y_m$, $M_{zd} = M_d$, and $M_1 \geqslant M_0$,

then previous estimands identify share + characteristics of superdupercompliers

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Can also identify shares and characteristics of those with

- $D_1 > D_0, M_1 = M_0 = m$
- $D_1 > D_0, M_1 > M_0, Y_1 = Y_0 = y$

Outcome Monotonicity Assumption

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  - Ambiguous: health insurance coverage and out-of-pocket spending

Outcome Monotonicity Assumption: Test

(i) Under our assumptions, the following inequalities hold

$$
\begin{aligned}
\Pr(Y=0, D=1|Z=1) - \Pr(Y=0, D=1|Z=0) &\geqslant 0 \\
\Pr(Y=1, D=0|Z=0) - \Pr(Y=1, D=0|Z=1) &\geqslant 0 \\
\Pr(Y=1|Z=1) - \Pr(Y=1|Z=0) &\geqslant 0
\end{aligned}
$$

(ii) If these inequalities hold, there exists a joint distribution of $(Y_{11}, Y_{10}, Y_{01}, Y_{00}, D_1, D_0, Z)$ that satisfies our assumptions and induces the observed distribution of (Y, D, Z).

Statistical Framework: Estimation

Estimating Complier Characteristics

- Alternative estimands for average complier characteristics
  1. $E[\kappa X] / \{E[D|Z = 1] - E[D|Z = 0]\}$

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  - Sample analogs of 2 and 3 are equal
  - implementation: `ivregress 2sls DX (D = Z)`

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- Sample analog of 1 is the same as that of

$$\frac{E[\tilde{D}X|Z=1] - E[\tilde{D}X|Z=0]}{E[\tilde{D}|Z=1] - E[\tilde{D}|Z=0]}$$

where $\tilde{D} = D - \Pr(Z=0)$

  - implementation: `ivregress 2sls DtildeX (Dtilde = Z)`

Estimating Supercomplier Characteristics

Supercompliers characteristics can be analogously estimated, e.g., with

- `ivregress 2sls YX (Y = Z)`

Stratified Randomization

Randomization in many experiments is stratified

- Common practice to include strata fixed effects W in regressions

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How does inclusion of W affect interpretation of supercomplier characteristics?

- Assuming
  1. Conditional independence
  2. Non-zero conditional reduced form
  3. Saturation of strata fixed effects

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- 2sls estimand identifies a nonnegatively weighted average of supercomplier characteristics:

$$\beta_{2SLS} = E\left[\omega_W E[X|\text{supercomplier}, W]\right]$$

with $\omega_W \geq 0$ across all strata W.

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- Characterizing supercompliers offers description of beneficiaries
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- Characterizing supercompliers useful for MVPF analysis
  - Facilitate incorporation of social welfare weights

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- Impact of a policy change, denoted by dp, on social welfare:

$$\frac{\mathrm{dWelfare}}{\mathrm{d}p} = \sum_i \eta_i \frac{\mathrm{d}U_i}{\mathrm{d}p} \equiv \sum_i \eta_i WTP_i$$

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  - WTP = willingness to pay; Captures benefits of policy change
- HSK MVPF definition

$$\mathrm{MVPF} = \sum_i WTP_i / G$$

  - G: impact of dp on government budget
- Note: η not in MVPF definition, presumably due to difficulty in implementation

Marginal Value of Public Funds: 2

MVPF calculation (focusing on WTP)

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- For policies that include a transfer
  - WTP includes dollar value of transfer
- If policies affect later life outcomes, e.g., human capital, health
  - WTP includes dollar values of these causal impacts
  - Causal impacts possibly measured on a subpopulation, e.g., LATE

Supercompliers and MVPF

- If WTP is measured as the effect of policy on outcome Y
  - $WTP_i = Y_{1i} - Y_{0i}$

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- Weighted average WTP for the complier group is

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  - If $\eta_i = h(X_i)$ one can estimate it with our machinery
- If $E[X_i|\text{supercomplier}]$ is systematically reported
  - Reader may construct weighted WTP with own weights without microdata access

Empirical Illustration

National Job Corps Study and National JTPA Study

National Job Corps Study: Randomized experiment to evaluate Job Corps

- Job Corps: residential ed and voc training program targeting disadvantaged youth

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National JTPA Study: Randomized experiment to evaluate JTPA training programs

- JTPA: target economically disadvantaged adults and out-of-school youths
- Participants randomized between 1987 and 1989
- We use data from the 30-month follow-up analysis sample
  - Focusing on adult females ($N = 6,102$)

Job Corps Supercomplier Characteristics; Outcome: Receiving GED

	Population Mean	Complier Mean	Supercomplier Mean	Diff Pop-SC	Diff C-SC
Female	38%	38%	48%	**	***
White	25%	25%	34%	**	**
Age >=20	17%	16%	21%		*
Never Arrested	69%	71%	78%	**	
Prev. Empl.	60%	61%	75%	***	***
Income <$3K	16%	15%	11%	*	*
Income $3-6K	13%	12%	9%		
Income $6-9K	6%	7%	5%		
Income $9-12K	6%	6%	9%		
Income >$12K	59%	60%	67%	*	*

Job Corps Supercomplier Characteristics; Outcome: Voc. Certificate

	Population Mean	Complier Mean	Supercomplier Mean	Diff Pop-SC	Diff C-SC
Female	41%	39%	44%		**
White	27%	27%	31%	**	***
Age >=20	27%	25%	28%		
Never Arrested	71%	73%	78%	***	***
Prev. Empl.	64%	64%	69%	**	***
Income <$3K	16%	15%	16%		
Income $3-6K	13%	12%	12%		
Income $6-9K	7%	7%	9%		
Income $9-12K	6%	6%	6%		
Income >$12K	59%	59%	57%		

Job Corps Supercomplier Characteristics; Outcome: Qtr16 Earnings

	Population	Complier	Supercomplier	Diff	
	Mean	Mean	Mean	Pop-SC	C-SC
Female	41%	39%	38%		
White	27%	27%	65%	***	***
Age >=20	27%	25%	55%	**	**
Never Arrested	72%	74%	79%		
Prev. Empl.	64%	64%	75%		
Income <$3K	16%	15%	10%		
Income $3-6K	13%	12%	1%		
Income $6-9K	7%	7%	1%		
Income $9-12K	6%	6%	7%		
Income >$12K	58%	59%	81%		

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- Our survey data based results tentatively suggest weighted MVPF would be even smaller

JTPA Supercomplier Characteristics; Outcome: Total 30-Month Earnings

	Population	Complier	Supercomplier	Diff	
	Mean	Mean	Mean	Pop-SC	C-SC
Black	26%	24%	37%		
Hispanic	12%	13%	2%		
High School/GED	68%	69%	70%		
Ever Rec Voc Train	45%	45%	48%		
Annual Earnings	2489	2461	1773		
Worked 1-12 Weeks	16%	16%	21%		
Worked 13-52 Weeks	43%	45%	13%		*
Received AFDC	38%	38%	49%		
Income <$3K	31%	29%	46%		
Income $3-6K	34%	35%	15%		
Income $6-9K	16%	16%	26%		
Income $9-12K	9%	9%	4%		
Income >$12K	9%	10%	8%		

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  - 1.63 when $\phi = 0.5$
  - 1.97 when $\phi = 1$
- Reader can compute own weighted MVPF if relevant supercomplier char. are reported

Conclusion

- We study what we call "supercompliers"
  - Whose D responds positively to Z and whose Y responds positively to D
  - Supercompliers are the only ones who benefit from gaining treatment eligibility
- Supercomplier characteristics identified under LATE assumptions + outcome monotonicity
- Identification result leads to natural IV estimators
- Illustrate the value of our tools in two training programs
  - Describing supercompliers can facilitate calculation of MVPF with social weights

Thank you!