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Estimation Strategies

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Setup

The Generalized Roy Model

Potential Outcomes

$$Y_1 = \mu_1(X) + U_1$$

$$Y_0 = \mu_0(X) + U_0$$

Observed Outcome

$$Y = DY_1 + (1 - D)Y_0$$

Choice

$$D = I[\mu_D(X, Z) - V > 0]$$

Key Concept

Definition: Individuals select their treatment status based on gains unobservable by the econometrician. More formally,

$$Y_1 - Y_0 \not\perp D \mid X = x.$$

⇒ consequences for the choice of the estimation strategy

Useful Notation

$$P(X, Z) = \Pr(D = 1 \mid X, Z) = F_V(\mu_D(X, Z))$$

$$U_D = F_V(V)$$

Key Assumptions

- ▶ (U_1, U_0, V) are independent of Z conditional on X
- ▶ $\mu_D(X, Z)$ is a nondegenerate random variable conditional on X
- ▶ $0 < \Pr(D = 1 | X) < 1$
- ▶ ...

Evaluation Problem

$$Y = DY_1 + (1 - D)Y_0 = \begin{cases} Y_1 & \text{if } D = 1 \\ Y_0 & \text{if } D = 0 \end{cases}$$

Selection Problem

$$\begin{aligned} E[Y | D = 1] - E[Y | D = 0] &= \underbrace{E[Y_1 - Y_0]}_{B^{ATE}} \\ &+ \underbrace{E[Y_1 - Y_0 | D = 1] - E[Y_1 - Y_0]}_{\text{selection on gains}} \\ &+ \underbrace{E[Y_0 | D = 1] - E[Y_0 | D = 0]}_{\text{selection on levels}} \end{aligned}$$

Estimation Strategies

- ▶ Randomization
- ▶ Matching
- ▶ Instrumental Variables
 - ▶ conventional and local
- ▶ Regression Discontinuity
 - ▶ fuzzy and sharp design

Randomization

Treatment Status

D self-selected

ξ assigned

A actual

Key Identifying Assumptions

$$(Y_1, Y_0) \perp\!\!\!\perp D$$

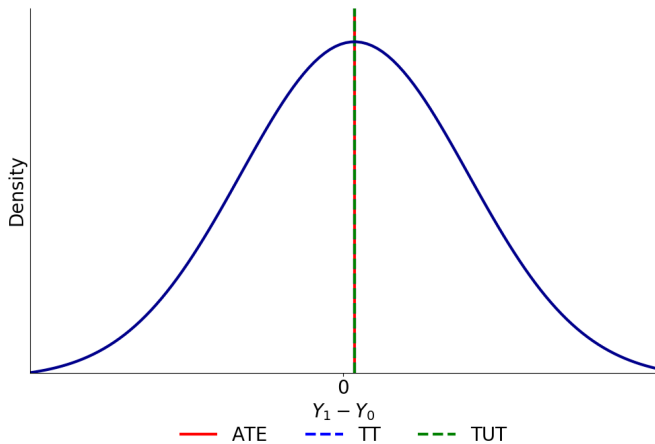
$$(Y_1, Y_0) \perp\!\!\!\perp \xi$$

$$(Y_1, Y_0) \perp\!\!\!\perp A$$

When do we have to worry about compliance?

$$\begin{aligned}
& E(Y \mid A = 1) - E(Y \mid A = 0) \\
&= E(Y_1 \mid A = 1) - E(Y_0 \mid A = 0) \quad (\text{by full compliance}) \\
&= E(Y_1) - E(Y_0) \quad (\text{by randomization}) \\
&= B^{ATE} = B^{TT} = B^{TUT}
\end{aligned}$$

Figure: Distribution of Effects



What if we can only deny program participation to individuals who are willing to participate?

$$\begin{aligned} &E(Y \mid D = 1, A = 1) - E(Y \mid D = 1, A = 0) \\ &= E(Y_1 \mid D = 1, A = 1) - E(Y_0 \mid D = 1, A = 0) \\ &= E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1) \\ &= B^{TT} \neq B^{ATE} \neq B^{TUT} \end{aligned}$$

Issues

- ▶ compliance
- ▶ imperfect randomization
- ▶ ethical concerns
- ▶ feasibility
- ▶ expenses
- ▶ external validity

Challenges to Scaling Experiments

- ▶ market equilibrium effects
- ▶ spillovers
- ▶ political reactions
- ▶ context dependence
- ▶ randomization or site-selection bias
- ▶ piloting bias

See Banerjee et al. (2017) for a discussion of these challenges and their attempts to address them in their work.

Matching

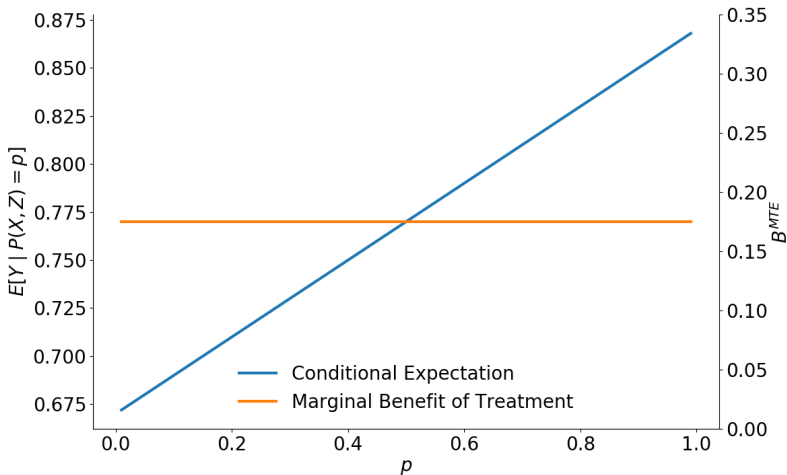
Key Identifying Assumption

$$(Y_1, Y_0) \perp\!\!\!\perp D \mid X$$

What is in the agent's and econometrician's information set?

- ▶ Heckman and Navarro-Lozano (2004) highlights the sensitivity of results to different conditioning variables.

Figure: Matching and Essential Heterogeneity



Instrumental Variables

Key Identifying Assumption

$$(Y_1, Y_0) \perp\!\!\!\perp Z \mid X$$

Even in the best cases, this is sometimes not as obvious as you think. See Heckman (1997) for a study of implicit behavioral assumptions used in making program evaluations.

Conventional Notation

$$Y = \alpha + \beta D + \epsilon,$$

where

$$\alpha = \mu_0$$

$$\beta = (Y_1 - Y_0) = \mu_1 - \mu_0 + (U_1 - U_0)$$

$$\epsilon = U_0$$

Assume for now that there is no treatment effect heterogeneity, i.e. $Y_1 - Y_0$ is the same for everybody. If we have access to a variable Z with the following properties ...

$$\text{cov}(Z, D) \neq 0$$

$$\text{cov}(Z, \epsilon) = 0$$

then the following holds

$$\text{plim } \hat{\beta}_{IV} = \frac{\text{cov}(Z, Y)}{\text{cov}(Z, D)} = \beta$$

What happens if β varies in the population?

- ▶ Do individuals select their treatment status based on gains?
⇒ essential heterogeneity

Let $\beta = \bar{\beta} + \eta$, where $U_1 - U_0 = \eta$, then

$$Y = \alpha + \bar{\beta}D + [\epsilon + \eta D].$$

and

$$\text{plim } \hat{\beta}_{IV} = \bar{\beta} + \frac{\text{cov}(Z, \epsilon + \eta D)}{\text{cov}(D, Z)}$$

So we cannot even learn about the mean effect of treatment unless we rule out essential heterogeneity, i.e. individuals selecting their treatment status based on gains.

Local Average Treatment Effect

- ▶ Average effect for those induced to change treatment because of a change in the instrument.

⇒ instrument-dependent parameter

$$\frac{E(Y | Z = z) - E[Y | Z = z']}{P(z) - P(z')} =$$
$$E(Y_1 - Y_0 | D(z) = 1, D(z') = 0)$$

Local Instrumental Variables

Local Instrumental Variable

$$\begin{aligned}\frac{\partial E(Y \mid P(Z) = p)}{\partial p} \bigg|_{p=u_D} &= E(Y_1 - Y_0 \mid U_D = u_D) \\ &= B^{MTE}(u_D)\end{aligned}$$

\Rightarrow we can only identify the $B^{MTE}(u_D)$ over the support of p in our data

Figure: Observed Outcome and Essential Heterogeneity

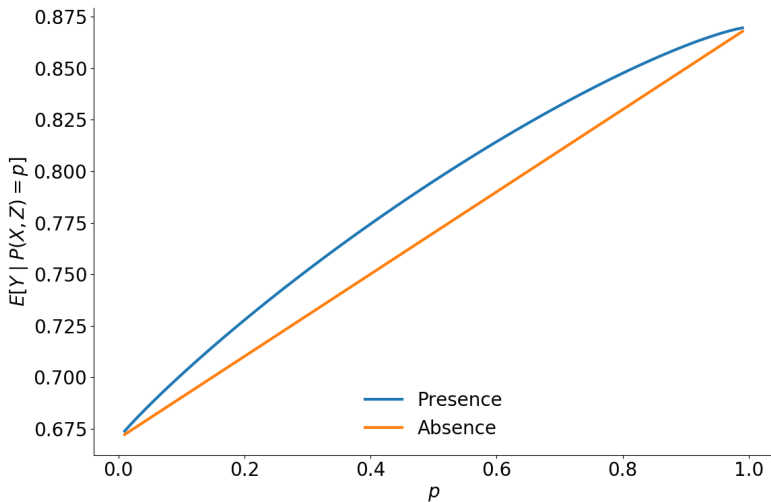
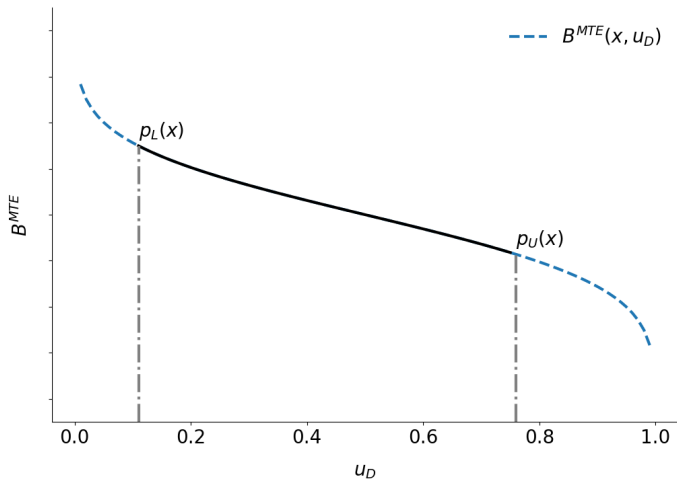


Figure: Identification I



Making $X = x$ explicit

$$\begin{aligned} E(Y_1 - Y_0 | X = x, U_D = u_D) \\ = (\mu_1(x) - \mu_0(x)) + E(U_1 - U_0 | X = x, U_D = u_D) \end{aligned}$$

but if we are willing to assume $(U_1 - U_0) \perp\!\!\!\perp X$ then

$$\begin{aligned} E(Y_1 - Y_0 | X = x, U_D = u_D) \\ = (\mu_1(x) - \mu_0(x)) + E(U_1 - U_0 | U_D = u_D) \end{aligned}$$

Figure: Identification II

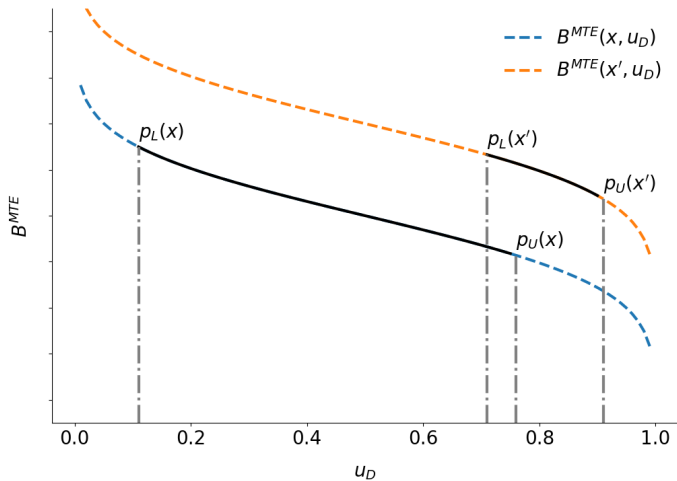
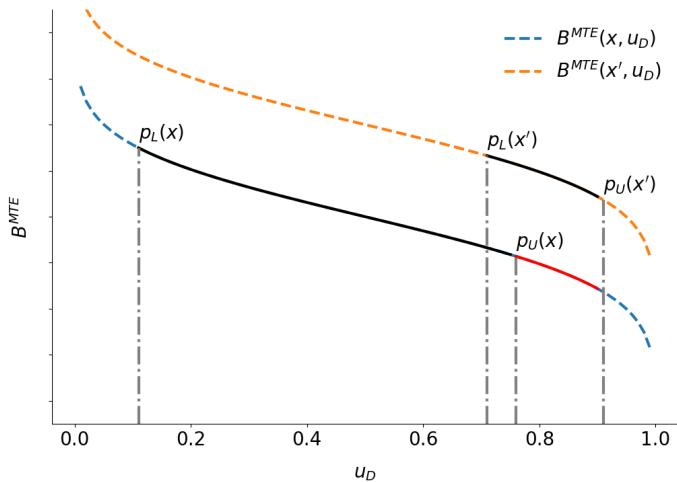


Figure: Identification III



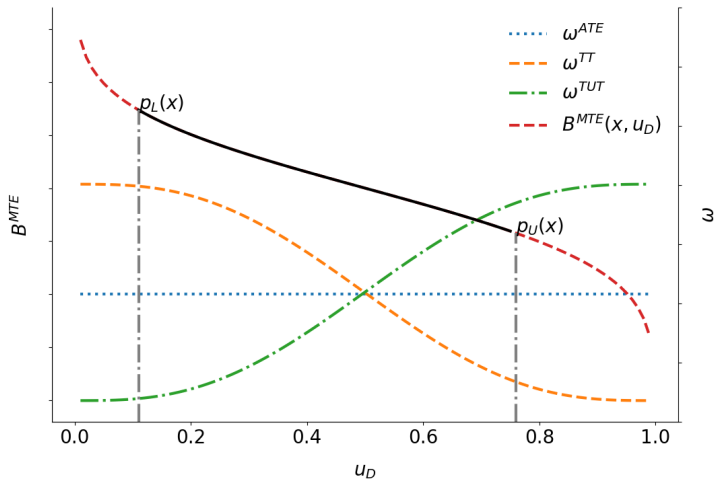
Effects of Treatment as Weighted Averages

Parameter Δ_j , can be written as a weighted average of the $B^{MTE}(x, u_D)$.

$$\Delta_j(x) = \int_0^1 B^{MTE}(x, u_D) \omega^j(x, u_D) du_D,$$

where the weights $\omega^j(x, u_D)$ are specific to parameter j and integrate to one.

Figure: Identification IV



Regression Discontinuity Design

Suppose $D = 1$ if $X \geq x_0$, and $D = 0$ otherwise

$$\Rightarrow \begin{cases} E(Y | X = x) = E(Y_0 | X = x) & \text{for } x < x_0 \\ E(Y | X = x) = E(Y_1 | X = x) & \text{for } x \geq x_0 \end{cases}$$

Suppose $E(Y_1 | X = x), E(Y_0 | X = x)$ are continuous in x .

$$\Rightarrow \begin{cases} \lim_{\epsilon \searrow 0} E(Y_0 | X = x_0 - \epsilon) = E(Y_0 | X = x_0) \\ \lim_{\epsilon \searrow 0} E(Y_1 | X = x_0 + \epsilon) = E(Y_1 | X = x_0) \end{cases}$$

$$\begin{aligned}
& \lim_{\epsilon \searrow 0} E(Y \mid X = x_0 + \epsilon) - \lim_{\epsilon \searrow 0} E(Y \mid X = x_0 - \epsilon) \\
&= \lim_{\epsilon \searrow 0} E(Y_1 \mid X = x_0 + \epsilon) - \lim_{\epsilon \searrow 0} E(Y_0 \mid X = x_0 - \epsilon) \\
&= E(Y_1 \mid X = x_0) - E(Y_0 \mid X = x_0) \\
&= E(Y_1 - Y_0 \mid X = x_0)
\end{aligned}$$

Figure: Probability

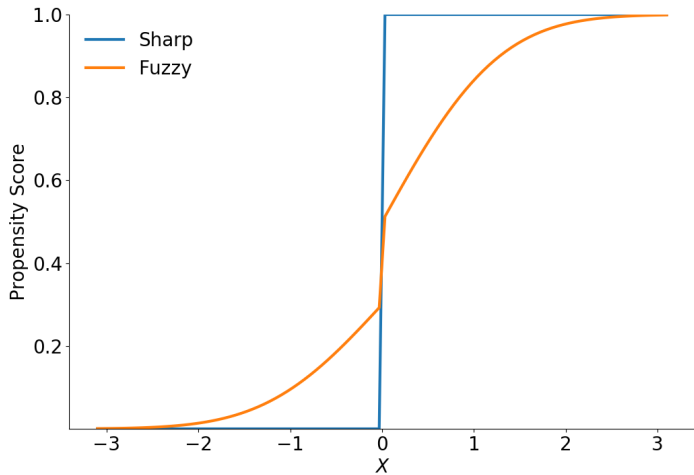


Figure: Observed Outcome in a Sharp Design

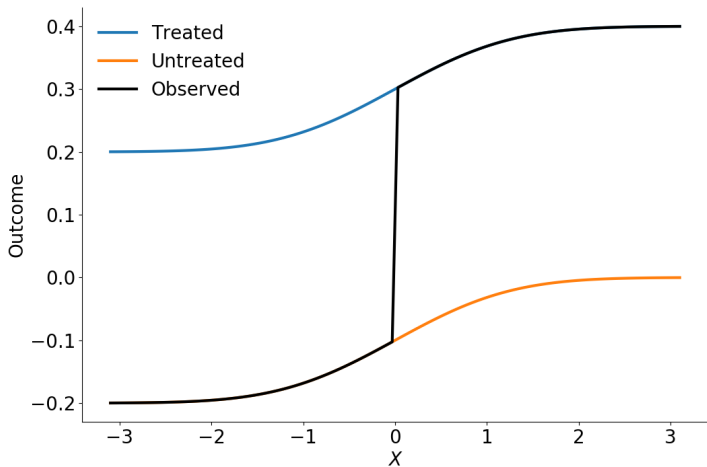
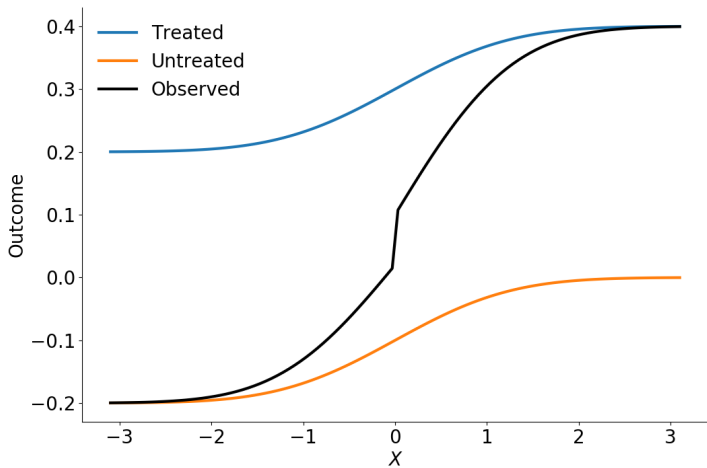


Figure: Observed Outcome in a Fuzzy Design



Conclusion

Appendix

References

- Banerjee, A., Banerji, R., Berry, J., Duflo, E., Kannan, H., Mukerji, S., ... Walton, M. (2017). From proof of concept to scalable policies: Challenges and solutions, with an application. *Journal of Economic Perspectives*, 31(4), 73–102.
- Carneiro, P., Heckman, J. J., & Vytlacil, E. J. (2011). Estimating marginal returns to education. *American Economic Review*, 101(6), 2754–2781.
- Heckman, J. J. (1990). Selection bias and self-selection. In J. Eatwell, M. Milgate, & P. Newman (Eds.), *Econometrics* (pp. 201–224). London: Palgrave Macmillan.

- Heckman, J. J. (1997). Instrumental variables: A study of implicit behavioral assumptions used in making program evaluations. *The Journal of Human Resources*, 32(3), 441.
- Heckman, J. J., & Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and Statistics*, 86(1), 30–57.
- Heckman, J. J., & Taber, C. (2010). Roy model. In L. E. Blume & S. N. Durlauf (Eds.), *Microeconometrics* (pp. 221–228). London: Palgrave Macmillan.