

Estimating the Effect of a Mis-measured, Endogenous, Binary Treatment

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October 17th, 2016

What is the causal effect of T^* ?

$$y_i = h(T_i^*, \mathbf{x}_i) + \varepsilon_i$$

- ▶ y – Outcome of interest
- ▶ h – Unknown function that *does not depend on i*
- ▶ T^* – Unobserved, endogenous binary treatment
- ▶ T – Observed, mis-measured binary surrogate for T^*
- ▶ \mathbf{x} – Exogenous covariates
- ▶ ε – Mean-zero error term
- ▶ z – Discrete (typically binary) instrumental variable

Target of Inference:

ATE function: $\tau(\mathbf{x}) = h(1, \mathbf{x}) - h(0, \mathbf{x})$

Example: Smoking and Birthweight (SNAP Trial)

Coleman et al. (N Engl J Med, 2012)

RCT with 1050 pregnant smokers in England: 521 given nicotine patches, the rest given placebo patches.

- ▶ y – Birthweight
- ▶ T^* – True smoking behavior
- ▶ T – Self-reported smoking behavior
- ▶ \mathbf{x} – Mother characteristics
- ▶ z – Indicator of nicotine patch

Example: Job Training Partnership Act (JPTA)

Heckman et al. (2000, QJE)

Randomized offer of job training, but about 30% of those *not* offered also obtain training and about 40% of those offered training don't attend. Estimate causal effect of *training* rather than *offer* of training.

- ▶ y – Log wage
- ▶ T^* – True training attendance
- ▶ T – Self-reported training attendance
- ▶ x – Individual characteristics
- ▶ z – Offer of job training

Example: Returns to Schooling

Oreopoulos (2006, AER)

Fuzzy RD: minimum school-leaving age in UK increased from 14 to 15 in 1947 but some already stayed until 15 before the law and others failed to comply after it.

- ▶ y – Log wage
- ▶ T^* – School attendance at age 15
- ▶ T – Self-report of school attendance at age 15
- ▶ x – Individual characteristics
- ▶ z – Indicator: born in or after 1933

Related Literature

Continuous Treatment

Lewbel (1997, 2012), Schennach (2004, 2007), Chen et al. (2005), Hu & Schennach (2008), Song (2015), Hu et al. (2015)...

Binary, Exogenous Treatment

Aigner (1973), Bollinger (1996), Kane et al. (1999), Black et al. (2000), Frazis & Loewenstein (2003), Mahajan (2006), Lewbel (2007)

Binary, Endogenous Treatment

Mahajan (2006), Shiu (2015), Ura (2015)

$$\text{Model: } y = c + \beta T^* + \varepsilon$$

Valid Instrument

$$\mathbb{E}[\varepsilon|z] = 0.$$

First-stage

$$p_k^* \equiv \mathbb{P}(T^* = 1|z = z_k) \neq \mathbb{P}(T^* = 1|z = z_\ell) \equiv p_\ell^*, \quad k \neq \ell$$

Non-differential Measurement Error

- ▶ $\mathbb{E}[\varepsilon|T^*, T, z] = \mathbb{E}[\varepsilon|T^*, z]$
- ▶ $\alpha_0 = \mathbb{P}(T = 1|T^* = 0, z)$
- ▶ $\alpha_1 = \mathbb{P}(T = 0|T^* = 1, z)$
- ▶ $\alpha_0 + \alpha_1 < 1$

Observable Moments: $y = c + \beta T^* + \varepsilon$

	$z = 1$	$z = 2$	\dots	$z = K$
$T = 0$	\bar{y}_{01} p_{01}	\bar{y}_{02} p_{02}	\dots	\bar{y}_{0K} p_{0K}
$T = 1$	\bar{y}_{11} p_{11}	\bar{y}_{12} p_{12}	\dots	\bar{y}_{1K} p_{1K}

$$\bar{y}_{tk} = \mathbb{E}[y | T = t, z = z_k], \quad p_{tk} = q_k p_k$$

$$q_k = \mathbb{P}(z = z_k), \quad p_k = \mathbb{P}(T = 1 | z = z_k)$$

Unobservable Moments: $y = \beta T^* + u$

Define error term that absorbs constant: $u = c + \varepsilon$

	$z = 1$	$z = 2$	\dots	$z = K$
$T^* = 0$	m_{01}^* p_{01}^*	m_{02}^* p_{02}^*	\dots	m_{0K}^* p_{0K}^*
$T^* = 1$	m_{11}^* p_{11}^*	m_{12}^* p_{12}^*	\dots	m_{1K}^* p_{1K}^*

$$m_{tk}^* = \mathbb{E}[u | T^* = t, z = z_k], \quad p_{tk}^* = q_k p_k^*$$

$$q_k = \mathbb{P}(z = z_k), \quad p_k^* = \mathbb{P}(T^* = 1 | z = z_k)$$

Mahajan (2006, ECTA)

Regression Model

$$y = \mathbb{E}[y|T^*] + \nu$$

$$\mathbb{E}[\nu|T^*] = 0 \text{ by construction}$$

Causal Model

$$y = c + \beta T^* + \varepsilon$$

$$\mathbb{E}[\varepsilon|T^*] \neq 0$$

Main Result (Correct) – Exogenous Treatment

Relevant binary instrument z ($p_k^* \neq p_\ell^*$) identifies α_0, α_1 and $\mathbb{E}[y|T^*]$ provided that $\mathbb{E}[\nu|T^*, T, z] = 0$ and $\alpha_0 + \alpha_1 < 1$.

Extension (Incorrect) – Endogenous Treatment

$\mathbb{E}[\varepsilon|z] = 0$, $p_k^* \neq p_\ell^*$, $\mathbb{E}[\varepsilon|T, T^*, z] = \mathbb{E}[\varepsilon|T^*] \implies \beta$ identified.

► Details

What if z takes on more than two values?

$\mathbb{E}[\varepsilon|z] = 0 \implies$ *pair of equations for each $k = 1, \dots, K$*

$$\hat{y}_{0k} = \alpha_1(p_k - \alpha_0) \left(\frac{\beta}{1 - \alpha_0 - \alpha_1} \right) + (1 - \alpha_0)c - (p_k - \alpha_0)m_{1k}^*$$

$$\hat{y}_{1k} = (1 - \alpha_1)(p_k - \alpha_0) \left(\frac{\beta}{1 - \alpha_0 - \alpha_1} \right) + \alpha_0 c + (p_k - \alpha_0)m_{1k}^*$$

where $\hat{y}_{0k} = (1 - p_k)\bar{y}_{0k}$ and $\hat{y}_{1k} = p_k\bar{y}_{1k}$

2K Equations in $K + 4$ Unknowns

Theorem: β is unidentified regardless of K .

Proof of special case: $\alpha_0 = 0$

1. System of equations:

$$\tilde{y}_{0k} = c + p_k \left(\frac{\beta \alpha_1}{1 - \alpha_1} \right) - p_k m_{1k}^*$$

$$\tilde{y}_{1k} = p_k \beta + p_k m_{1k}^*$$

2. $\beta/(1 - \alpha_1) \equiv \beta_{IV}$ identified, $\beta \alpha_1/(1 - \alpha_1) = \beta_{IV} - \beta \implies$

$$(c + p_k \beta_{IV} - \tilde{y}_{0k})/p_k = \beta + m_{1k}^*$$

$$\tilde{y}_{1k}/p_k = \beta + m_{1k}^*$$

3. Sum equations from 1. $\implies (c + p_k \beta_{IV} - \tilde{y}_{0k}) = \tilde{y}_{1k}$

What about $\alpha_0 + \alpha_1 < 1$?

$$\beta_{IV} = \frac{\beta}{1 - \alpha_0 - \alpha_1}, \quad p_k^* = \frac{p_k - \alpha_0}{1 - \alpha_0 - \alpha_1}, \quad 1 - p_k^* = \frac{1 - p_k - \alpha_1}{1 - \alpha_0 - \alpha_1}$$

If $\alpha_0 + \alpha_1 < 1$, then:

- ▶ $Cor(T, T^*) > 0 \iff \alpha_0 + \alpha_1 < 1$
- ▶ β has same sign as β_{IV}
- ▶ $\alpha_0 < \min_k \{p_k\}$
- ▶ $\alpha_1 < \min_k \{1 - p_k\}$
- ▶ Two-sided bound for β

Non-differential Measurement Error Assumption

- ▶ $\alpha_0 = \mathbb{P}(T = 1 | T^* = 0, z)$
- ▶ $\alpha_1 = \mathbb{P}(T = 0 | T^* = 1, z)$
- ▶ $\alpha_0 + \alpha_1 < 1$

Weaker

$$\mathbb{E}[\varepsilon | T^*, T, z] = \mathbb{E}[\varepsilon | T^*, z]$$

Stronger

ε conditionally independent of T given T^* and z .

Bounds From Stronger Measurement Error Assumption

Define $F_{tk}(\tau) = \mathbb{P}(Y \leq \tau | T = t, z_k)$ and $F_k(\tau) = \mathbb{P}(Y \leq \tau | z_k)$

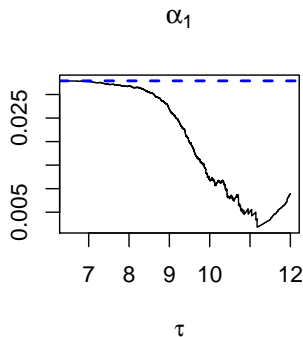
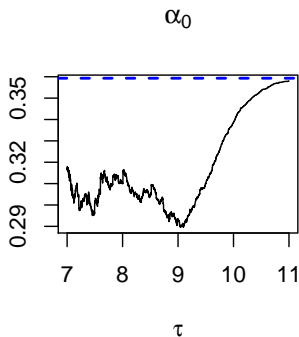
$$\alpha_0 \leq p_k \inf_{\tau} \left\{ \left[\frac{F_{1k}(\tau)}{F_k(\tau)} \right] \wedge \left[\frac{1 - F_{1k}(\tau)}{1 - F_k(\tau)} \right] \right\} \leq p_k$$

$$\alpha_1 \leq (1 - p_k) \inf_{\tau} \left\{ \left[\frac{F_{0k}(\tau)}{F_k(\tau)} \right] \wedge \left[\frac{1 - F_{0k}(\tau)}{1 - F_k(\tau)} \right] \right\} \leq (1 - p_k)$$

Bounds for (α_0, α_1) do *not* require z to be a valid instrument!

Upper Bounds for Mis-Classification Rates

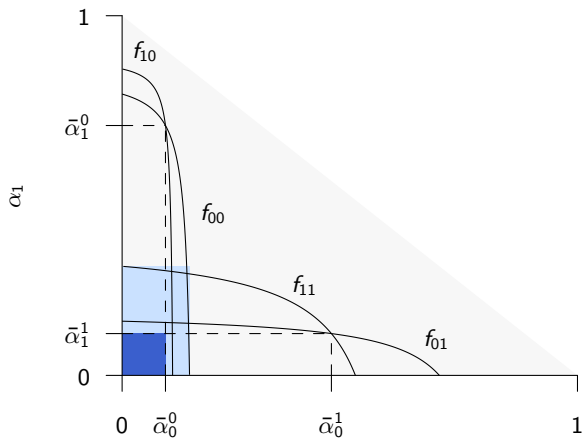
Returns to Schooling Example: Oreopoulos (2006)



Variances Only: DiTraglia & Garcia-Jimeno (2016b)

Afghan Girls RCT (Burde & Linden 2013; AEJ Applied)

$$\alpha_0 \leq 0.10, \alpha_1 \leq 0.12; \quad \min_k p_k = 0.15, \quad \min_k (1 - p_k) = 0.3$$



Sufficient Conditions To Identify α_0, α_1 , and β

Baseline Assumptions

- ▶ $\mathbb{E}[\varepsilon|z] = 0$
- ▶ $\mathbb{E}[\varepsilon|T^*, T, z] = \mathbb{E}[\varepsilon|T^*, z]$
- ▶ $\alpha_0 = \mathbb{P}(T = 1|T^* = 0, z)$, $\alpha_1 = \mathbb{P}(T = 0|T^* = 1, z)$, $\alpha_0 + \alpha_1 < 1$

Strengthen IV Assumption

- ▶ $\mathbb{E}[\varepsilon^2|z] = \mathbb{E}[\varepsilon^2]$
- ▶ $\mathbb{E}[\varepsilon^3|z] = \mathbb{E}[\varepsilon^3]$

Strengthen Measurement Error Assumption

- ▶ $\mathbb{E}[\varepsilon^2|T^*, T, z] = \mathbb{E}[\varepsilon^2|T^*, z]$
- ▶ $\mathbb{E}[\varepsilon^3|T^*, T, z] = \mathbb{E}[\varepsilon^3|T^*, z]$

Identification Argument: Part I

Impose 2nd Moment Restrictions

$$\mathbb{E}[\varepsilon^2|z] = \mathbb{E}[\varepsilon^2] \text{ and } \mathbb{E}[\varepsilon^2|T^*, T, z] = \mathbb{E}[\varepsilon^2|T^*, z]$$

Obtain New Moment Conditions

$$\mathbb{E}(y^2|z_k) - \mathbb{E}(y^2|z_\ell) \equiv \Delta \overline{y^2} = \beta[\beta_{IV}(p_k - p_\ell)] + 2\beta_{IV}\mu_{k\ell}^*$$

$$\mathbb{E}(yT|z_k) - \mathbb{E}(yT|z_\ell) \equiv \Delta \overline{yT} = (1 - \alpha_1)\beta_{IV}(p_k - p_\ell) + \mu_{k\ell}^*$$

$$\mu_{k\ell}^* = (p_k - \alpha_0)m_{1k}^* - (p_\ell - \alpha_0)m_{k\ell}^*$$

Identify $(\alpha_1 - \alpha_0)$

$$\alpha_1 - \alpha_0 = 1 + \mathcal{R}/\beta_{IV}, \quad \text{where} \quad \mathcal{R} \equiv \frac{\Delta \overline{y^2} - 2\beta_{IV}\Delta \overline{yT}}{\beta_{IV}(p_k - p_\ell)}$$

Identification Argument: Part II

Impose 3rd Moment Restrictions

$$\mathbb{E}[\varepsilon^3|z] = \mathbb{E}[\varepsilon^3] \text{ and } \mathbb{E}[\varepsilon^3|T^*, T, z] = \mathbb{E}[\varepsilon^3|T^*, z]$$

New Moment Conditions

$$\mathbb{E}(y^3|z_k) - \mathbb{E}(y^3|z_\ell) \equiv \Delta \overline{y^3} = \beta^2[\beta_{IV}(p_k - p_\ell)] + 3\beta[\beta_{IV}\mu_{k\ell}^*] + 3\beta_{IV}\lambda_{k\ell}^*$$

$$\mathbb{E}(y^2 T|z_k) - \mathbb{E}(y^2 T|z_\ell) \equiv \Delta \overline{y^2 T} = \beta(1 - \alpha_1)\beta_{IV}(p_k - p_\ell) + 2(1 - \alpha_1)\beta_{IV}\mu_{k\ell}^* + \lambda_{k\ell}^*$$

$$\lambda_{k\ell}^* = (p_k - \alpha_0)v_{1k}^* - (p_\ell - \alpha_0)v_{1\ell}^*$$

$$v_{tk}^* = \mathbb{E}(u^2|T^* = t, z_k)$$

Identification Argument: Part III

Tedious Algebra

$$2\beta_{IV}^2(1 - \alpha_1)^2 + 2\beta_{IV}\mathcal{R}(1 - \alpha_1) + (\mathcal{S} - \mathcal{R}^2) = 0$$

where

$$\mathcal{S} \equiv \frac{\Delta\overline{y^3} - 3\beta_{IV} \left[\Delta\overline{y^2T} + \mathcal{R}\Delta\overline{yT} \right]}{\beta_{IV}(p_k - p_\ell)}$$

Solve Quadratic

- ▶ Depends on $(1 - \alpha_1)$ and observables only
- ▶ Always two real roots: one is $(1 - \alpha_1)$ and the other is α_0 .
- ▶ To tell which is which, need $\alpha_0 + \alpha_1 < 1$.

Simulation Example: $y = \beta T^* + \varepsilon$

Errors

$(\varepsilon, \eta) \sim$ jointly normal, mean 0, variance 1, correlation 0.3.

First-Stage

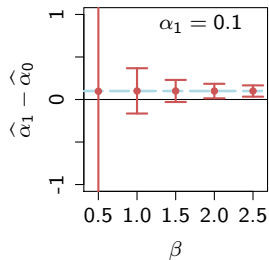
- ▶ Half of subjects have $z = 1$, the rest have $z = 0$.
- ▶ $T^* = \mathbf{1}\{\gamma_0 + \gamma_1 z + \eta > 0\}$
- ▶ $\delta = \mathbb{P}(T^* = 0|z = 1) = \mathbb{P}(T^* = 1|z = 0)$

Mis-classification

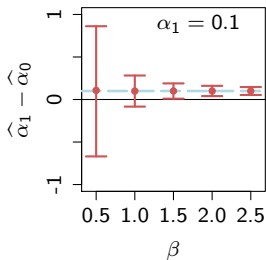
- ▶ Set $\alpha_0 = 0$ so $T^* = 0 \implies T = 0$
- ▶ $T|T^* = 1 \sim \text{Bernoulli}(1 - \alpha_1)$
- ▶ α_0, α_1 unknown to econometrician.

Sampling Distribution of $\hat{\alpha}_1 - \hat{\alpha}_0$

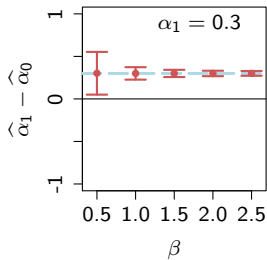
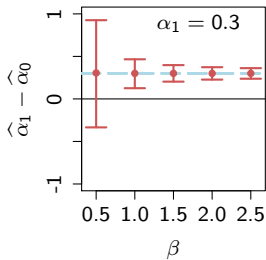
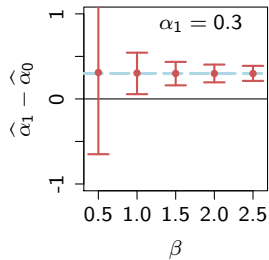
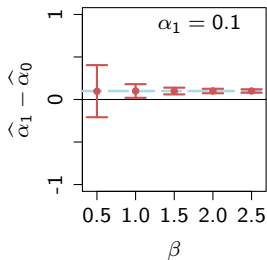
(a) $N = 500, \delta = 0.1$



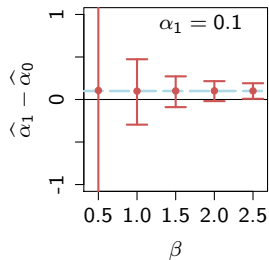
(b) $N = 1000, \delta = 0.1$



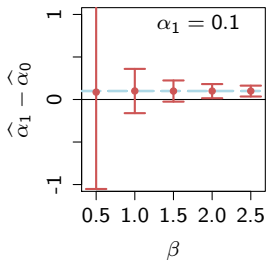
(c) $N = 5000, \delta = 0.1$



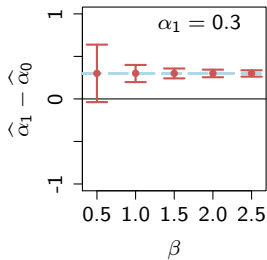
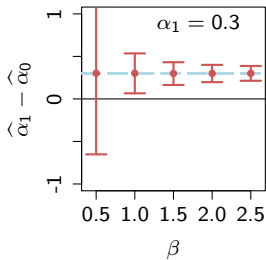
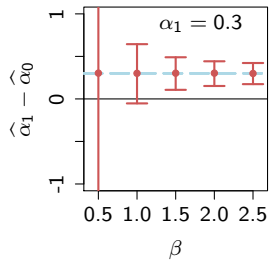
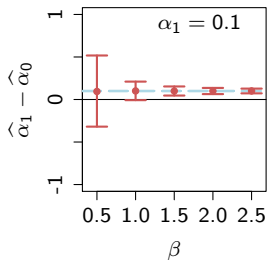
(a) $N = 500, \delta = 0.2$



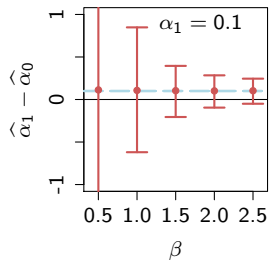
(b) $N = 1000, \delta = 0.2$



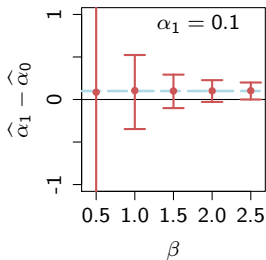
(c) $N = 5000, \delta = 0.2$



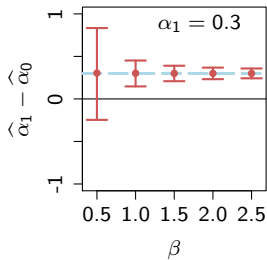
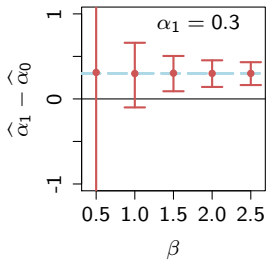
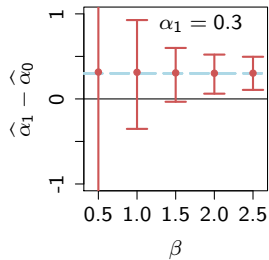
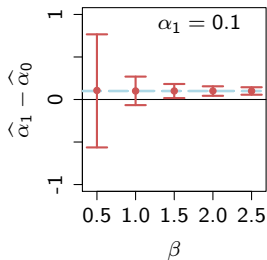
(a) $N = 500, \delta = 0.3$



(b) $N = 1000, \delta = 0.3$



(c) $N = 5000, \delta = 0.3$

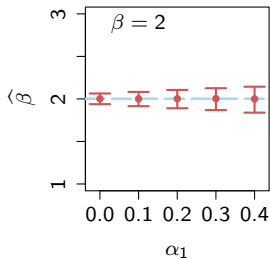
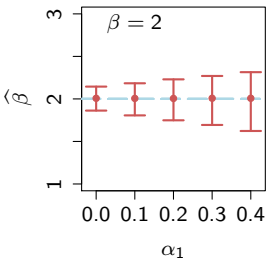
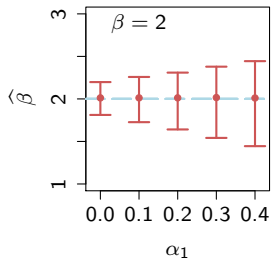
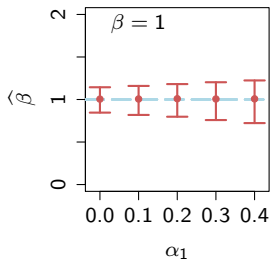
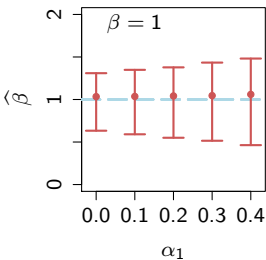
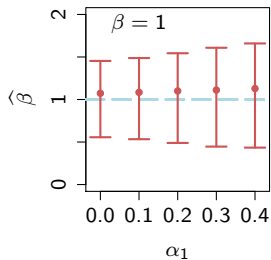


Sampling Distribution of $\hat{\beta} = (1 - \hat{\alpha}_0 - \hat{\alpha}_1)\hat{\beta}_{IV}$

(a) $N = 500, \delta = 0.1$

(b) $N = 1000, \delta = 0.1$

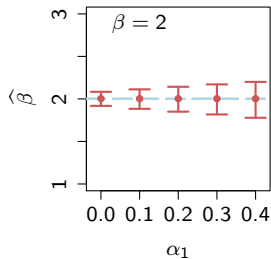
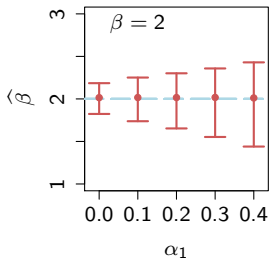
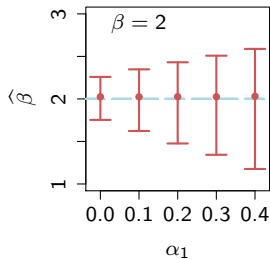
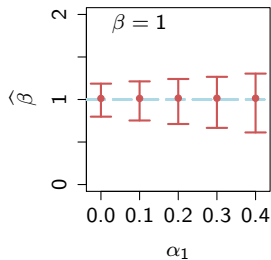
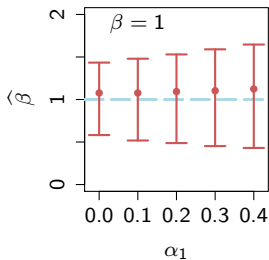
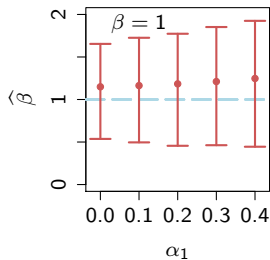
(c) $N = 5000, \delta = 0.1$



(a) $N = 500, \delta = 0.2$

(b) $N = 1000, \delta = 0.2$

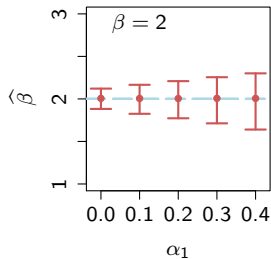
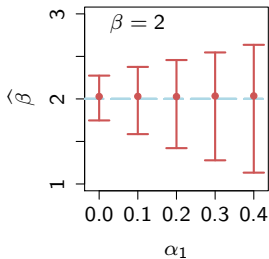
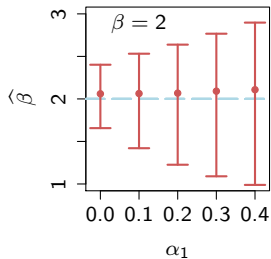
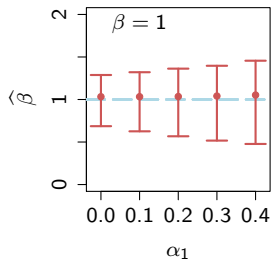
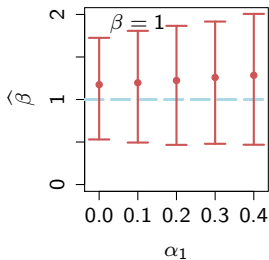
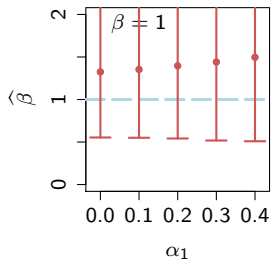
(c) $N = 5000, \delta = 0.2$



(a) $N = 500, \delta = 0.3$

(b) $N = 1000, \delta = 0.3$

(c) $N = 5000, \delta = 0.3$



$(z \perp \varepsilon)$ and $(T \perp \varepsilon | T^*, z) \Rightarrow$ Continuum of MCs

Characteristic Functions

$$e^{i\omega\beta} [(1 - \alpha_1) - \xi(\omega)] = \alpha_0 - \xi(\omega)$$

$$\xi(\omega) \equiv \frac{\varphi_k(\omega) - \varphi_\ell(\omega)}{p_k \varphi_{1k}(\omega) - p_\ell \varphi_{1\ell}(\omega)}$$

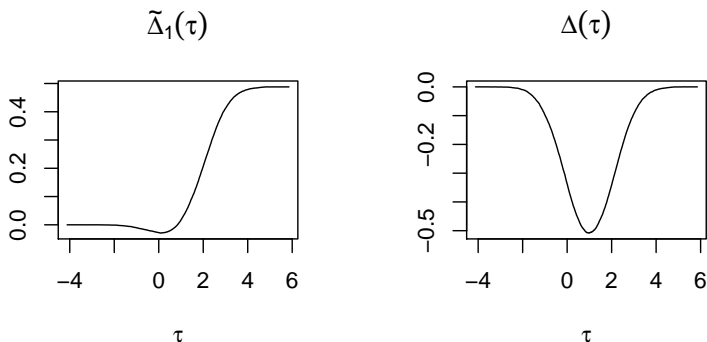
Distribution Functions

$$\tilde{\Delta}_1(\tau + \beta) - \tilde{\Delta}_1(\tau) = \alpha_0 \Delta(\tau + \beta) - (1 - \alpha_1) \Delta(\tau)$$

$$\Delta(\tau) = F_k(\tau) - F_\ell(\tau)$$

$$\tilde{\Delta}_1(\tau) = p_k F_{1k}(\tau) - p_\ell F_{1\ell}(\tau)$$

CDF Conditions for Simulation DGP



$$\tilde{\Delta}_1(\tau + \beta) - \tilde{\Delta}_1(\tau) = \alpha_0 \Delta(\tau + \beta) - (1 - \alpha_1) \Delta(\tau)$$

Conclusion

Summary

- ▶ Endogenous, mis-measured binary treatment.
- ▶ Important in applied work but no solution in the literature.
- ▶ Usual (1st moment) IV assumption fails to identify β
- ▶ Bounds for mis-classification probabilities and β .
- ▶ Higher moment / independence restrictions identify β

Extensions / Work in Progress

- ▶ Efficient estimation w/ continuum of MCs
- ▶ Inference / Specification Testing
- ▶ LATE interpretation

Mahajan (2006, ECTA)

Regression Model

$$y = \mathbb{E}[y | T^*] + \nu$$

$$\mathbb{E}[\nu | T^*] = 0 \text{ by construction}$$

Causal Model

$$y = c + \beta T^* + \varepsilon$$

$$\mathbb{E}[\varepsilon | T^*] \neq 0$$

Ingredients

1. If $p_k^* \neq p_\ell^*$, $\mathbb{E}[\varepsilon | z] = 0$ then, since $\beta_{IV} = \beta / (1 - \alpha_0 - \alpha_1)$, knowledge of α_0, α_1 is sufficient to recover β . (Correct)
2. If $p_k^* \neq p_\ell^*$, $\mathbb{E}[\nu | T^*, T, z] = 0$, α_0, α_1 are identified. (Correct)

How to satisfy both 1 and 2 while allowing $\mathbb{E}[\varepsilon | T^*] \neq 0$?

3. Assume that $\mathbb{E}[\varepsilon | T^*, T, z] = \mathbb{E}[\varepsilon | T^*]$
(i.e. $m_{0k}^* = m_{0\ell}^*$ and $m_{1k}^* = m_{1\ell}^*$)

Flaw in the Argument

Proposition

If $\mathbb{E}[\varepsilon | T^*] \neq 0$ then $\mathbb{E}[\varepsilon | T^*, T, z] = \mathbb{E}[\varepsilon | T^*]$ combined with $\mathbb{E}[\varepsilon | z] = 0$ implies $p_k^* = p_\ell^*$, i.e. z is irrelevant for T^* .

Proof

$\mathbb{E}[\varepsilon | z] = 0$ implies

$$(1 - p_1^*)m_{0k}^* + p_1^*m_{1k}^* = c$$

$$(1 - p_2^*)m_{0\ell}^* + p_2^*m_{1\ell}^* = c$$

while Mahajan's assumption implies $m_{0k}^* = m_{0\ell}^*$ and $m_{1k}^* = m_{1\ell}^*$.

Therefore either $m_{0k}^* = m_{0\ell}^* = m_{1k}^* = m_{1\ell}^* = c$, which is ruled out by $E[\varepsilon | T^*] = 0$, or $p_k^* = p_\ell^*$.