Evaluating Public Programs with Close Substitutes: The Case of Head Start

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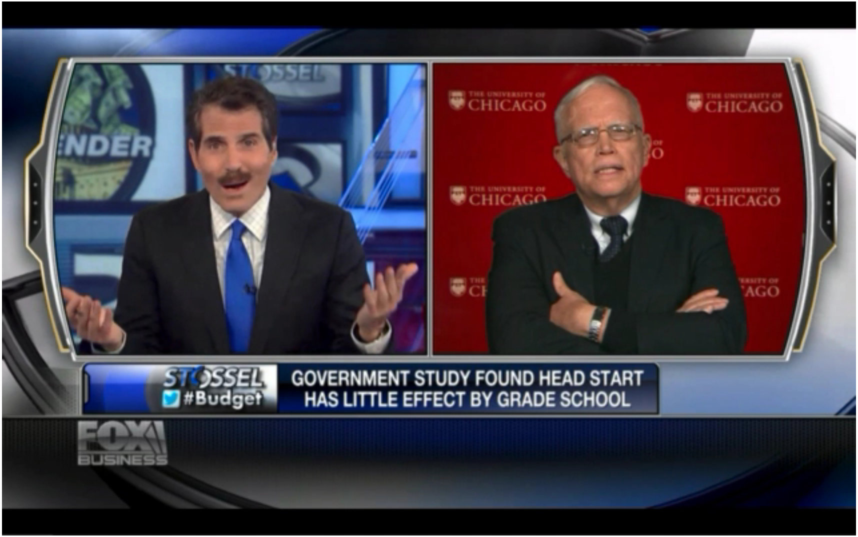
Motivation

- Many government programs provide services that can also be obtained via markets or other public organizations
  - "Substitution bias" in experiments (Heckman et al., 2000)
- Possible causal estimands of interest:
  - Effect of a program offer (ITT)
  - Effect relative to participants' next best alternative (LATE)
  - Effect relative to no program
- Which of these (if any) to use in policy evaluation?

The Case of Head Start

- Head Start (HS): Publicly-funded preschool for disadvantaged children. Largest public early childhood program in the US
- Many close public and private substitutes (state pre-K, private preschool)
- Literature evaluating impact of HS on test scores finds mixed results:
    - Observational studies based on sibling designs find large persistent impacts (Currie and Thomas, 1995; Garces et al., 2002; Deming, 2009)
    - Experimental evaluation based on lotteries, the Head Start Impact Study (HSIS), finds small impacts that fade out (Puma et al, 2010; Barnett, 2011)

Media Reaction



This Paper

Revisit HSIS results in view of wide availability of substitute preschools

Key facts:

- 1/3 of HSIS control group attended other preschools
    - Fraction increased after first year of experiment
- Most of these preschools were publicly funded

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    - IV-LATE is policy-relevant benefit
    - But costs need to be adjusted for "fiscal externalities"
  - When substitutes are rationed: LATE is not enough

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    - But costs need to be adjusted for "fiscal externalities"
  - When substitutes are rationed: LATE is not enough
- Empirical analysis:
  - PDV projected earnings impacts $\sim$ HS enrollment costs
  - But accounting for public savings $\Rightarrow$ Benefits $>$ Costs
  - With rationing: Benefits $\gg$ Costs

Technology vs Market Structure

- Develop selection model parameterizing heterogeneity in effects of Head Start vs home care / other preschools
  - Identify using interactions of experimental status with household and site characteristics
  - Decompose LATE into "subLATE's" with respect to particular alternatives
  - Predict effects of changing selection into the program

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- Findings:
  - Head Start and other preschools have roughly equivalent average impacts on test scores relative to home care
  - "Reverse-Roy" selection: those with lowest gains most likely to participate
  - Rate of return can be raised further by drawing in new populations

Outline

Background on Head Start

- Enrolls one million 3- and 4- year-olds at a cost of $8 billion per year
- Grants awarded to public, private non-profit, and for-profit organizations
- Eligibility: 100% of FPL, with some exceptions
- Competing center-based care programs are ubiquitous:
  - State preschool programs
  - TANF
  - Child Care Development Fund (CCDF)

The Head Start Impact Study

- 1998 Head Start reauthorization included a mandate to determine program's effects: resulted in the HSIS, a large-scale randomized trial

- Stratified random sample of Head Start centers
  - Baseline randomization in Fall 2002
  - Two age cohorts: 55% age 3, 45% age 4

- We focus on summary index of cognitive outcomes based upon average of PPVT and WJ III test scores
  - Normed to have mean zero, std dev. one in control group each year

Table 1: Descriptive Statistics

	By offer status		By preschool choice		
	Non-offered mean	Offer differential	Head Start	Other centers	No preschool
Variable	(1)	(2)	(3)	(4)	(5)
Black	0.298	0.010	0.317	0.353	0.250
		(0.010)			
Hispanic	0.369	0.007	0.380	0.354	0.373
		(0.010)			
Mother is high school dropout	0.397	-0.029	0.377	0.322	0.426
		(0.017)			
Mother attended some college	0.281	0.017	0.293	0.342	0.253
		(0.016)			
Test language is not English	0.239	0.016	0.268	0.223	0.231
		(0.011)			
Income (fraction of FPL)*	0.896	0.000	0.892	0.983	0.851
		(0.024)			
Age 4 cohort	0.451	-0.003	0.426	0.567	0.413
		(0.012)			
Baseline test scores	0.012	-0.009	-0.001	0.106	-0.040
Joint *p*-value		0.268			
N	3571		2043	598	930

*Household income is missing for 19 percent of observations. Missing values are excluded in statistics for income.

Table 2: Experimental Impacts on Test Scores

		Intent-to-treat			Instrumental variables	
	3-year-olds	4-year-olds	Pooled	3-year-olds	4-year-olds	Pooled
	(1)	(2)	(3)	(4)	(5)	(6)
Year 1	0.194	0.141	0.168	0.278	0.213	0.247
	(0.029)	(0.029)	(0.021)	(0.041)	(0.044)	(0.031)
N	1970	1601	3571	1970	1601	3571
Year 2	0.087	-0.015	0.046	0.245	-0.022	0.093
	(0.029)	(0.037)	(0.024)	(0.080)	(0.054)	(0.049)
N	1760	1416	3176	1760	1416	3176

Table 3: Preschool Choices by Year, Cohort, and Offer Status

		Offered			Not offered			Other center complier share
		Head Start	Other centers	No preschool	Head Start	Other centers	No preschool	
Cohort	Time period	(1)	(2)	(3)	(4)	(5)	(6)	(7)
3-year-olds	Year 1	0.851	0.058	0.092	0.147	0.256	0.597	0.282
	Year 2	0.657	0.262	0.081	0.494	0.379	0.127	0.719
4-year-olds	Year 1	0.787	0.114	0.099	0.122	0.386	0.492	0.410

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	N	1659	1336	2995	1659	1336	2995
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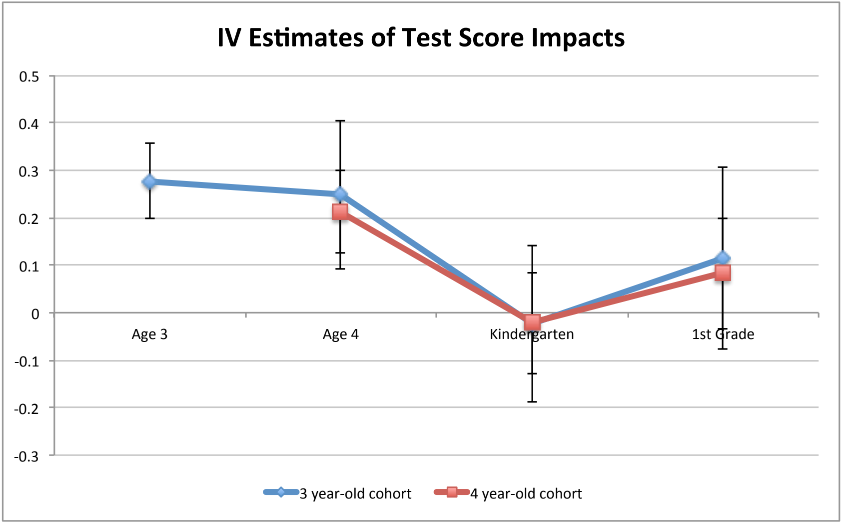

IV Estimates of Test Score Impacts
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
Age 3
Age 4
Kindergarten
1st Grade
3 year-old cohort
4 year-old cohort

Interpreting IV

- How does the presence of substitute preschools affect interpretation of the IV results?

- Care environment abbreviations:
  - h - Head Start,
  - c - other preschool center
  - n - no preschool (home care)

- $D_i(z) : \{0, 1\} \rightarrow \{h, c, n\}$ gives child i's care environment as a function of experimental offer status z

- Revealed preference restriction on behavioral response to offer:

$$D_i(1) \neq D_i(0) \implies D_i(1) = h$$

Interpreting IV

$$D_i(1) \neq D_i(0) \implies D_i(1) = h$$

Five "compliance groups" of children:

1. c-compliers: $D_i(1) = h$, $D_i(0) = c$
2. n-compliers: $D_i(1) = h$, $D_i(0) = n$
3. c-never takers: $D_i(1) = D_i(0) = c$
4. n-never takers: $D_i(1) = D_i(0) = n$
5. always takers: $D_i(1) = D_i(0) = h$

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- IV identifies a weighted average of effects on $n-$ and $c-$ compliers:

$$LATE_h = E\left[Y_i(h) - Y_i(D_i(0)) | D_i(1) = h, D_i(0) \neq h\right]$$

$$= S_c LATE_{ch} + (1 - S_c) LATE_{nh}$$

where $LATE_{ch}$ and $LATE_{nh}$ are "subLATEs" measuring effects relative to specific alternative care environments

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where $LATE_{ch}$ and $LATE_{nh}$ are "subLATEs" measuring effects relative to specific alternative care environments

- Weighting term S_c is the share of compliers drawn from other preschools:

$$S_c = \frac{P\left(D_i(1) = h, D_i(0) = c\right)}{P(D_i(1) = h, D_i(0) \neq h)}$$

Fraction complying from other preschools

Wald estimator of compliance share:

$$S_c = -\frac{E\left[1\left\{D_i = c\right\}|Z_i = 1\right] - E\left[1\left\{D_i = c\right\}|Z_i = 0\right]}{E\left[1\left\{D_i = h\right\}|Z_i = 1\right] - E\left[1\left\{D_i = h\right\}|Z_i = 0\right]}$$

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Table 3: Funding Sources

Largest funding source	Head Start (1)	Other centers (2)	Other centers attended by c -> h compliers (3)
Head Start	0.842	0.027	0.038
Parent fees	0.004	0.153	0.191
Child and adult care food program	0.011	0.026	0.019
State pre-K program	0.004	0.182	0.155
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Inputs

Benefits and Costs of Head Start

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Benefits

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Tuition / time savings for parents

Reductions in crime

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Extra tax revenue from more productive children

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Health improvements

Net Costs

Administrative costs

Reduced funding of competing preschool programs

Extra tax revenue from more productive children

Extra tax revenue from parents Table

Reduced participation in transfer programs

Savings from reduced grade repetition / Special Ed

Standard approach (CEA, 2015)

Table 1: Summary of Cost-Benefit Studies

	Tulsa Full-Day Preschool	**Tulsa Half-Day Preschool**	**Oklahoma & Georgia Preschool**	**Head Start**	**Perry Preschool**
Year children entered program	2005	2005	1995/98	2002	1962
Value of earnings gains per child	$27,897	$16,683	$24,094	$14,459	$92,020
Value of total benefits per child					$180,257[b]
Cost of program per child	$9,118	$4,559	$4,086	$9,173	$20,948
Net benefit per child	$18,779	$12,124	$20,008	$5,286	$159,309[b]
Benefit to cost ratio (earnings only)	3.06	3.66	5.90	1.58[a]	4.39
Benefit to cost ratio (all benefits)	–	–	–	–	8.60[b]
Study	Bartik et al. (2012)	Bartik et al. (2012)	Cascio et al. (2013)	Duncan et al. (2010)	Heckman et al. (2010b)

A Model of Head Start Enrollment

- Continuum of applicant households on unit interval
- Government rations access to HS (ex-ante) with offers Z_i
  - Randomly assigned with probability $\delta \equiv P(Z_i = 1)$
- Competing preschools not rationed (will relax later)

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- Utilities: $\{U_i(h,z), U_i(c), U_i(n)\}$ where:

$$U_i(h,1) \geq U_i(h,0)$$

- Preferred alternative as function of offer status $z \in \{0,1\}$:

$$D_i(z) = \arg\max_{d \in \{h,c,n\}} U_i(d,z)$$

- Choices:

$$D_i = D_i(1) Z_i + D_i(0)(1 - Z_i)$$

Benefits and Costs

After-tax lifetime income of cohort:

$$(1 - \tau) p E \left[Y_i \right]$$

- $Y_i = \sum_{d \in \{n,c,h\}} Y_i\left(d\right) 1\left[D_i\left(Z_i\right) = d\right]$ is realized test score
- p is the market price of human capital
- τ is the tax rate for Head Start-eligible children

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Net Costs:

$$C \equiv \underbrace{\phi_h P(D_i = h) + \phi_c P(D_i = c)}_{\text{Costs}} - \left(\underbrace{R + \tau pE\left[Y_i\right]}_{\text{Revenue}}\right)$$

where (ϕ_h, ϕ_c) are costs of enrollment in HS / other preschool

Increasing offer probability

Marginal effect of a change in rationing probability δ on test scores:

$$\frac{dE\left[Y_i\right]}{d\delta} = LATE_h \cdot P\left(D_i\left(1\right) = h, D_i\left(0\right) \neq h\right)$$

$$LATE_h \equiv E\left[Y_i\left(h\right) - Y_i\left(D_i\left(0\right)\right) \middle| D_i\left(1\right) = h, D_i\left(0\right) \neq h\right]$$

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Marginal effect on budget:

$$\frac{dC}{d\delta} = \left(\underbrace{\phi_h}_{\text{direct cost}} - \underbrace{\phi_c S_c}_{\text{substitution}} - \underbrace{\tau p LATE_h}_{\text{tax revenue}}\right) \times \underbrace{P\left(D_i\left(1\right) = h, D_i\left(0\right) \neq h\right)}_{\text{number of compliers}}$$

Marginal Value of Public Funds

- The marginal value of public funds (MVPF) is the ratio of impacts on household welfare and the government budget (Mayshar, 1990; Hendren, 2014):

$$MVPF_\delta = \frac{(1-\tau)pLATE_h}{\phi_h - \phi_c S_c - \tau pLATE_h}$$

- MVPF gives the value of an extra dollar spent on Head Start net of fiscal externalities

- Quantifies the magnitude of "leaks" in Okun's bucket

Utility

Program Scale: Lessons

$$MVPF_{\delta} = \frac{(1-\tau)pLATE_h}{\phi_h - \phi_c S_c - \tau pLATE_h}$$

MVPF depends on:

- Test score impact $LATE_h$
  - Note: "subLATEs" not directly relevant
- Share of students drawn from competing programs, S_c
- Costs of Head Start and competing programs: ϕ_h and ϕ_c
- Conversion factor p
- Tax rate τ

What if competing schools are rationed?

- Suppose total number of competing pre-school slots is fixed
  - Now $c-$compliers spawn $n \to c$ compliers as someone takes abandoned slot
- MVPF becomes:

$$MVPF_{\delta,rat} = \frac{(1-\tau)p\left(LATE_h + S_c LATE_{nc}\right)}{\phi_h - \tau p\left(LATE_h + S_c LATE_{nc}\right)}$$

- Takeaway:
  - $LATE_{nc}$ not directly identified by experiment
  - But chances are that ignoring rationing leads to conservative assessment (will estimate later)

Program Features

- Suppose there is a Head Start program feature f that is valued by households but has no effect on potential outcomes: $\tilde{U}(h, Z_i, f) = U(h, Z_i) + f$
  - Example: Improvements in transportation services (Executive Order 13330)
- With large enough increases in f:
  - Never takers become compliers
  - Compliers become always takers

MVPF for Program Features

MVPF for reforms to program features:

$$MVPF_f = \frac{(1-\tau)pMTE_h(f)}{\phi_h(f)(1+\eta) - \phi_c \overrightarrow{S}_c(f) - \tau pMTE_h(f)}$$

where:

$$MTE_h(f) = MTE_{ch}(f)\overrightarrow{S}_c(f) + MTE_{nh}(f)\left(1 - \overrightarrow{S}_c(f)\right),$$

$$MTE_{ch}(f) = E\left[Y_i(h) - Y_i(c) | U_i(h, Z_i, f) = U_i(c) > U_i(n)\right],$$

$$\overrightarrow{S}_c(f) = P\left(U_i(c) > U_i(n) | U_i\left(h, Z_i, f\right) = \max\left\{U_i\left(c\right), U_i\left(n\right)\right\}\right),$$

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$$MVPF_f = \frac{(1-\tau)pMTE_h(f)}{\phi_h(f)(1+\eta) - \phi_c \overrightarrow{S}_c(f) - \tau pMTE_h(f)}$$

where:

$$MTE_h(f) = MTE_{ch}(f)\overrightarrow{S}_c(f) + MTE_{nh}(f)\left(1 - \overrightarrow{S}_c(f)\right),$$

$$MTE_{ch}(f) = E\left[Y_i(h) - Y_i(c) | U_i(h, Z_i, f) = U_i(c) > U_i(n)\right],$$

$$\overrightarrow{S}_c(f) = P\left(U_i(c) > U_i(n) | U_i\left(h, Z_i, f\right) = \max\left\{U_i\left(c\right), U_i\left(n\right)\right\}\right),$$

$$\eta = \frac{d\log\phi_h\left(f\right)/df}{d\log P\left(D_i = h\right)/df} \text{ (cost elasticity of enrollment)}$$

Cost-benefit Analysis

- Next use our estimates to conduct cost/benefit analysis associated with change in δ (random scaling up)

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  - Most precise estimates
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    Figure

Cost-benefit Analysis

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    Figure
- Projected earnings effects:
  - Chetty et al. (2011): 1 s.d. increase in scores $\rightarrow$ 13% increase in earnings
  - Other literature estimates: 10% or larger (Table A3)
  - To be conservative, baseline calibration uses 10%
  - Sensitivity analysis: *breakeven* conversion factor s.t. $MVPF = 1$

Table A3: Estimates of Test Score and Earnings Impacts

Study	Intervention (1)	Test score effect (std. dev.) (2)	Log earnings effect (3)	Log wage effect (4)	Ratio: wages or earnings/test scores (5)
Chetty et al. (CFHSSY, 2011)	Tennessee STAR (1 s.d. of class quality, kindergarten)	0.024	0.003	-	**0.131**
	OLS with controls (kindergarten)	1.0	0.18	-	**0.18**
Chetty, Friedman, Rockoff (2014)	Teacher value-added (1 s.d. of teacher VA, grades 3-8)	0.13	0.013	-	**0.103**
	OLS with controls (grades 3-8)	1.0	0.12	-	**0.12**
Heckman, Stixrud, Urzua (2006)	OLS with controls (males, ages 14-22)	1.0	-	0.121	**0.121**
	OLS with controls (females, ages 14-22)	1.0	-	0.169	**0.169**
Heckman et al. (HMPSY, 2010)	Perry Preschool Project (males, age 4)	0.787	0.189	-	**0.240**
	Perry Preschool Project (females, age 4)	0.980	0.286	-	**0.292**
Lindqvist and Vestman (2011)	OLS with controls (males, ages 18-19)	1.0	0.136	0.104	**0.104**

Table 6: Benefits and Costs of Head Start

Parameter (1)	Description (2)	Value (3)	Source (4)
Panel A. Parameter values			
p	Effect of a 1 SD increase in test scores on earnings	$0.1\bar{e}$	Table A3
e_{US}	US average present discounted value of lifetime earnings at age 3.4	$438,000	Chetty et al. 2011 with 3% discount rate
e_{parent}/e_{US}	Average earnings of Head Start parents relative to US average	0.46	Head Start Program Facts
IGE	Intergenerational income elasticity	0.40	Lee and Solon 2009
$\bar{e}$	Average present discounted value of lifetime earnings for Head Start applicants	$343,392	$[1 - (1 - e_{parent}/e_{US})IGE]e_{US}$
$0.1\bar{e}$	Effect of a 1 SD increase in test scores on earnings of Head Start applicants	$34,339	
$LATE_h$	Local Average Treatment Effect	0.247	HSIS

Table 6: Benefits and Costs of Head Start

Parameter (1)	Description (2)	Value (3)	Source (4)
S_c	Share of Head Start population drawn from other preschools	0.34	HSIS
ϕ_h	Marginal cost of enrollment in Head Start	\$8,000	Head Start program facts
ϕ_c	Marginal cost of enrollment in other preschools	\$0	Naïve assumption: $\phi_c = 0$
		\$4,000	Pessimistic assumption: $\phi_c = 0.5\phi_h$
		\$6,000	Preferred assumption: $\phi_c = 0.75\phi_h$

Table 6: Benefits and Costs of Head Start

Parameter	Description	Value	Source
(1)	(2)	(3)	(4)
NMB	Marginal benefit to Head Start population net of taxes	\$5,513	$(1 - \tau)pLATE_h$
MFC	Marginal fiscal cost of Head Start enrollment	\$5,031	$\phi_h - \phi_c S_c - \tau pLATE_h$, naïve assumption
		\$3,671	Pessimistic assumption
		\$2,991	Preferred assumption
MVPF	Marginal value of public funds	**1.10 (0.22)**	*NMB*/*MFC* (s.e.), **naïve assumption**
		p-value = 0.1	
		Breakeven $p/\bar{e} = 0.09$ (0.01)	
		1.50 (0.34)	**Pessimistic assumption**
		p-value = 0.00	
		Breakeven $p/\bar{e} = 0.08$ (0.01)	
		1.84 (0.47)	**Preferred assumption**
		p-value = 0.00	
		Breakeven $p/\bar{e} = 0.07$ (0.01)	

Unfinished Business

- Are Head Start and competing programs equivalent technologies?
  - Decompose $LATE_h$ into “subLATEs” for compliers drawn from c and n
- Can we boost effectiveness by targeting new populations?
  - Evaluate reforms that change the complier mix
- Answering these questions requires additional assumptions

Possible Approaches to Estimating SubLATEs

- Use $Z_i \times X_i$ interactions as additional instruments (Kling et al., 2007)
  - Requires strong restrictions on effect heterogeneity (Kirkeboen et al., 2014; Hull, 2014)
- Parametric assumption on distributions within compliance groups ("principal stratification," Feller et al. 2014)
  - Allows deconvolution of complier mix into components
  - Conditions on realized selection patterns – no predictions for effects of structural reforms
- Selection model
  - Semiparametric restriction on unselected potential outcome distributions
  - "Connect the dots" between identified distributions to interpolate/extrapolate

Choice Model

- Alternative specific indirect utilities:

$$\begin{aligned} U_i(h, Z_i) &= \psi_h(X_i, Z_i) + v_{ih}, \\ U_i(c) &= \psi_c(X_i) + v_{ic}, \\ U_i(n) &= 0 \end{aligned}$$

- Monotonicity: $\psi_h(x, 1) \geq \psi_h(x, 0)$

- Selection errors (v_{ih}, v_{ic}): unobserved tastes and constraints (e.g. accessibility) influencing participation

- Multinomial probit specification of errors:

$$(v_{ih}, v_{ic}) \,|X_i, Z_i \sim N\left(0, \begin{bmatrix} 1 & \rho(X_i) \\ \rho(X_i) & 1 \end{bmatrix}\right)$$

Potential Outcomes

Model for potential outcome CEFs:

$$E\left[Y_i\left(d\right)|X_i, Z_i, v_{ih}, v_{ic}\right] = \mu_d(X_i) + \gamma_{dh} v_{ih} + \gamma_{dc} v_{ic}$$

- $\{\gamma_{dh}, \gamma_{dc}\}$ terms capture selection on unobservables
- Possible selection patterns:
  - $\gamma_{hh} = -\gamma_{nh}$ (selection on gains)
  - $\{\gamma_{dh}\} = \gamma_h$ (selection on levels)
  - $\gamma_{hh} < \gamma_{nh}$ ("reverse Roy" selection)

Control Function Representation

By iterated expectations:

$$E\left[Y_i|X_i, Z_i, D_i = d\right] = \mu_d(X_i) + E\left[\gamma_{dh} v_{ih} + \gamma_{dc} v_{ic}|X_i, Z_i, D_i = d\right]$$

$$= \mu_d(X_i) + \gamma_{dh}\lambda_h\left(X_i, Z_i, d\right) + \gamma_{dc}\lambda_c(X_i, Z_i, d)$$

- Control function terms $\lambda_d(X_i, Z_i, D_i)$ analogous to inverse Mills terms in standard Heckman (1979) setting Review
  - Involve evaluation of bivariate normal CDFs/PDFs (formulas provided in paper)

Identification

Effect of an offer on selected outcome mean:

$$E\left[Y_i|X_i = x, Z_i = 1, D_i = d\right] - E\left[Y_i|X_i = x, Z_i = 0, D_i = d\right]$$

$$= \gamma_{dh}\left[\lambda_h(x, 1, d) - \lambda_h(x, 0, d)\right] + \gamma_{dc}\left[\lambda_c(x, 1, d) - \lambda_c(x, 0, d)\right]$$

- With two points of support x and x', we have two equations in two unknowns
- Rank condition: CF differences not linearly dependent across x groups
  - Regression based test for under-identification
- Additional support points yield over-identification
  - Score test of separability

Lessons

- Functional forms for mean utilities, correlation, and mean outcomes not essential
  - Can fully saturate and retain identification
- Key restriction is *additive separability* between observables and unobservables
  - Selection on unobservables must work "the same way" for different values of X_i
  - e.g. can't have Roy selection in some groups and "reverse Roy" in others
- $\{\gamma_{dh}, \gamma_{dc}\}$ terms measure how gaps between compliance group means vary with strength of compliance response

Parameterization

- Linear approximations to mean utilities $\psi_h(X, Z)$, $\psi_c(X)$, $\tanh^{-1}\rho(X) = \frac{1}{2}\log\left(\frac{1+\rho(X)}{1-\rho(X)}\right)$, and $\mu_d(X)$

- Key covariates interact with offer/enter correlation in the choice model, and interact with care alternative in the outcome model
  - Baseline test score, home language, mother's education, age cohort, Head Start center quality rating, transportation services, income
  - Previous studies find substantial heterogeneity on these dimensions in the HSIS (Bitler et al. 2014, Bloom and Weiland 2015, Walters 2015)

- Also substantial variation in treatment effects and substitution patterns across the hundreds of HSIS experimental sites (Walters 2015)

- But difficult to work with individual sites since samples are very small – incidental parameters problem

Site Group Fixed Effects

- To leverage variation in market shares across sites, we use a group fixed effects approach (Bonhomme and Manresa 2015; Saggio 2012)
- Constrains sites to belong to one of K discrete categories
  - K selected using Bayesian Information Criterion (BIC)
  - Site group indicators included in X
- MATLAB code available on our websites (mnpgfe routine)

Estimation / Inference

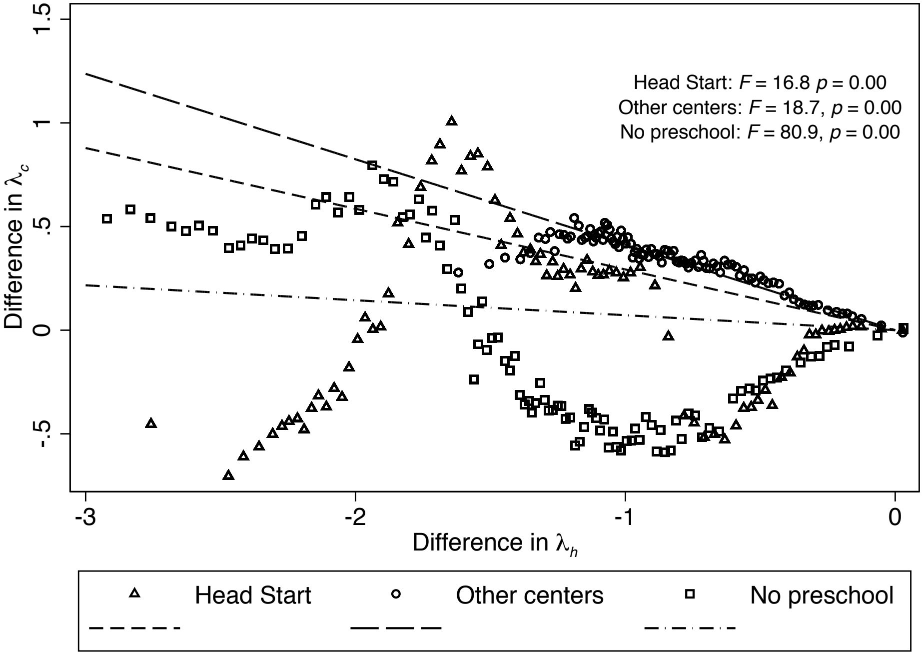
- Two-step procedure a la Heckman (1979)
- First step: estimate multinomial probit using GHK algorithm
  - Models with site groups alternate between assigning groups and maximizing likelihood
- Second step: use probit estimates to build control functions,

$$\left\{\hat{\lambda}_{dh}\left(X_i, Z_i, D_i\right), \hat{\lambda}_{dc}\left(X_i, Z_i, D_i\right)\right\}$$

- Include CFs as additional regressors in second step regression of outcomes on covariates in each choice group
- Bootstrap for inference

Table V. Two Stage Least Squares Estimates with Interaction Instruments

	One endogenous variable	Two endogenous variables	
	Head Start	Head Start	Other centers
Instruments	(1)	(2)	(3)
Offer	0.247	-	-
(1 instrument)	(0.031)		
Offer x covariates	0.241	0.384	0.419
(9 instruments)	(0.030)	(0.127)	(0.359)
First-stage *F*	276.2	17.7	1.8
Overid. *p*-value	0.007	0.006	
Offer x sites	0.210	0.213	0.008
(183 instruments)	(0.026)	(0.039)	(0.095)
First-stage *F*	215.1	90.0	2.7
Overid. *p*-value	0.002	0.002	
Offer x site groups	0.229	0.265	0.110
(6 instruments)	(0.029)	(0.056)	(0.146)
First-stage *F*	1,015.2	339.1	32.6
Overid. *p*-value	0.077	0.050	
Offer x covariates and offer x site groups (14 instruments)	0.229	0.302	0.225
	(0.029)	(0.054)	(0.134)
First-stage *F*	340.2	121.2	13.3
Overid. *p*-value	0.012	0.010	


Head Start: $F = 16.8$ $p = 0.00$
Other centers: $F = 18.7$, $p = 0.00$
No preschool: $F = 80.9$, $p = 0.00$
Difference in λ_c
Difference in λ_h
1.5
1
.5
0
-.5
-3
-2
-1
0
Head Start
Other centers
No preschool

Panel A. Head Start participation

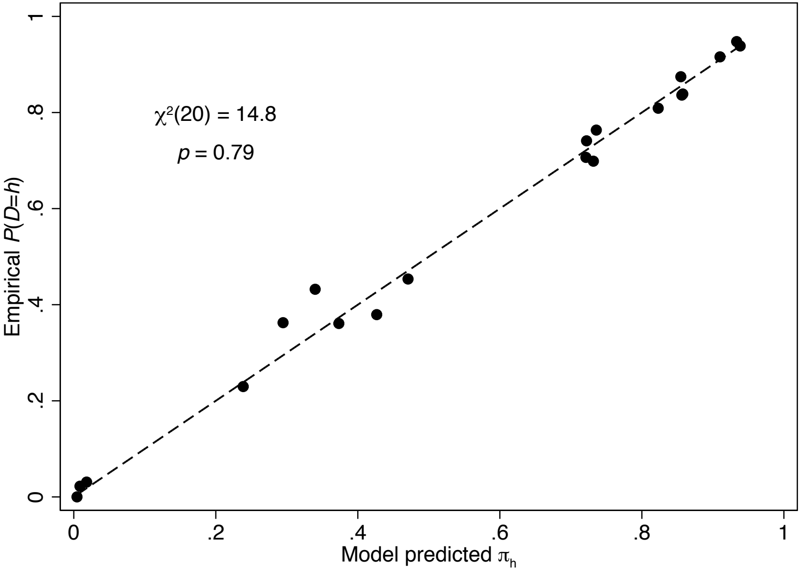
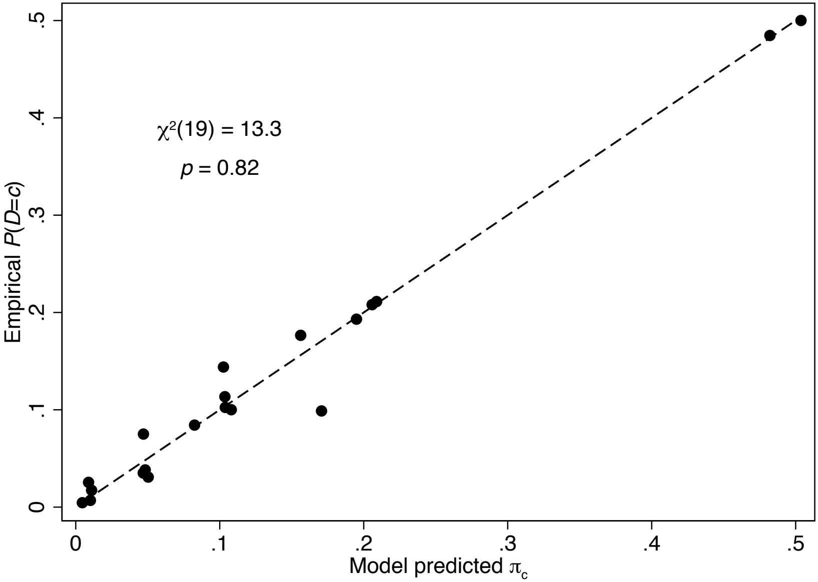


Figure A.I. Multinomial Probit Model Fit

Panel B. Substitute preschool participation



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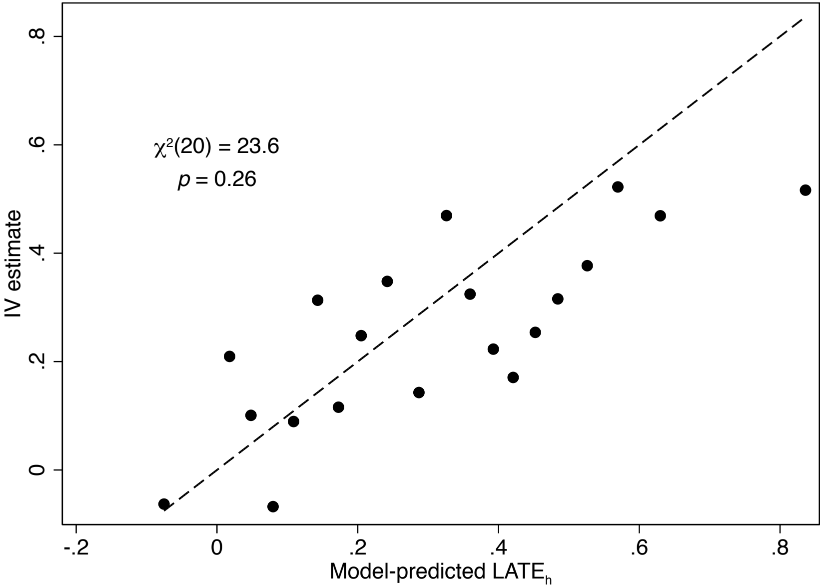

Figure A.III. Model-predicted $LATE_h$ vs. IV estimates

Table VII. Selection-corrected Estimates of Preschool Effects

	Least squares	
	No controls	Covariates
	(1)	(2)
Head Start	0.202	0.218
	(0.037)	(0.022)
Other preschools	0.262	0.151
	(0.052)	(0.035)
λ_h	-	-
Head Start x λ_h		
Other preschools x λ_h		
λ_c		
Head Start x λ_c		
Other preschools x λ_c		
P-value: Additive separability		

Table VII. Selection-corrected Estimates of Preschool Effects

	Control function		
	Covariates	Site groups	Full model
	(3)	(4)	(5)
Head Start	0.483	0.380	0.470
	(0.117)	(0.121)	(0.101)
Other preschools	0.183	0.065	0.109
	(0.269)	(0.991)	(0.253)
λ_h	0.015	0.004	0.019
	(0.053)	(0.063)	(0.053)
Head Start x λ_h	-0.167	-0.137	-0.158
	(0.080)	(0.126)	(0.091)
Other preschools x λ_h	-0.030	-0.047	0.000
	(0.109)	(0.366)	(0.115)
λ_c	-0.333	-0.174	-0.293
	(0.203)	(0.187)	(0.115)
Head Start x λ_c	0.224	0.065	0.131
	(0.306)	(0.453)	(0.172)
Other preschools x λ_c	0.488	0.440	0.486
	(0.248)	(0.926)	(0.197)
P-value: Additive separability	0.261	0.452	0.349

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Table VIII. Treatment Effects for Subpopulations

Parameter	IV (1)	Control function: Covariates (2)	Control function: Sites (3)	Control function: Full model (4)
$LATE_h$	0.247	0.261	0.190	0.214
	(0.031)	(0.032)	(0.076)	(0.042)
$LATE_{nh}$	-	0.386	0.341	0.370
		(0.143)	(0.219)	(0.088)
$LATE_{ch}$		0.023	-0.122	-0.093
		(0.251)	(0.469)	(0.154)

Table VIII. Treatment Effects for Subpopulations

		Control function		
	IV	Covariates	Sites	Full model
Parameter	(1)	(2)	(3)	(4)
Lowest predicted quintile:				
$LATE_h$		0.095	0.114	0.027
		(0.061)	(0.112)	(0.067)
$LATE_h$ with fixed S_c		0.125	0.125	0.130
		(0.060)	(0.434)	(0.119)
Highest predicted quintile:				
$LATE_h$		0.402	0.249	0.472
		(0.042)	(0.173)	(0.079)
$LATE_h$ with fixed S_c		0.364	0.289	0.350
		(0.056)	(1.049)	(0.126)

Table V. Two Stage Least Squares Estimates with Interaction Instruments

	One endogenous variable	Two endogenous variables	
	Head Start	Head Start	Other centers
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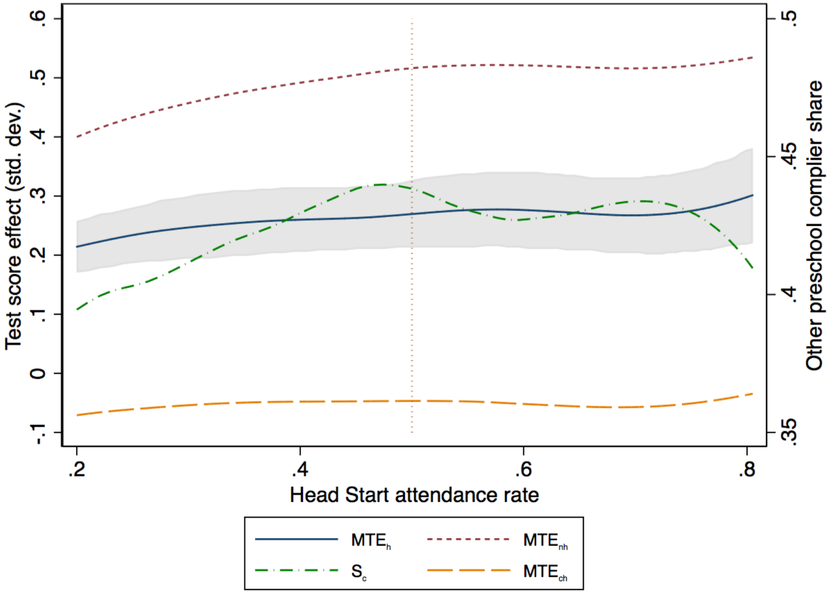
Overid. *p*-value	0.012	0.010	

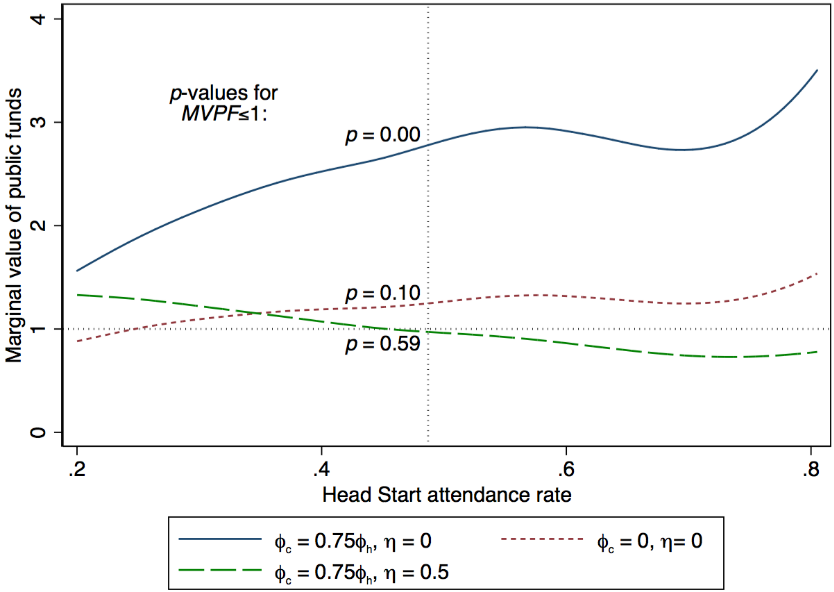
Reforms to Program Features

- Next, we evaluate returns to "structural" reforms that target new populations by increasing attractiveness of Head Start
- Use the model to predict $MTE_{ch}(f)$, $MTE_{nh}(f)$ and $\vec{S}_c(f)$

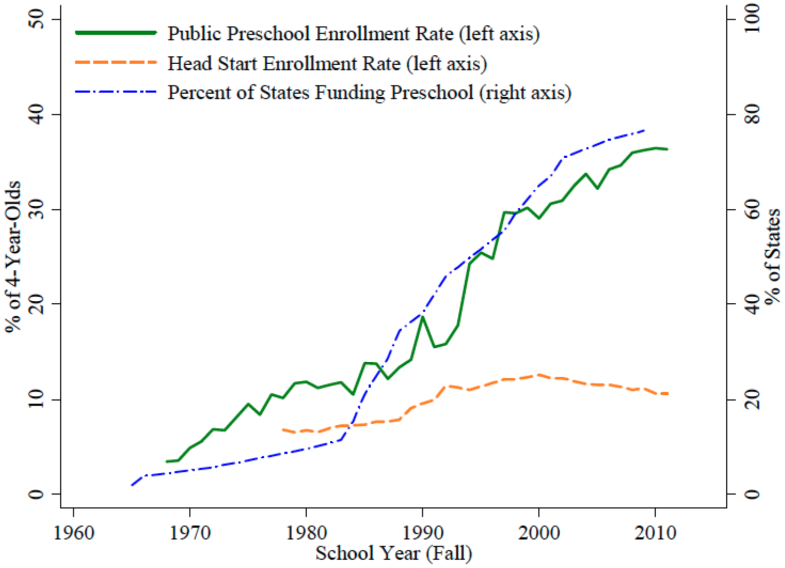
Marginal effects on test scores and program substitution

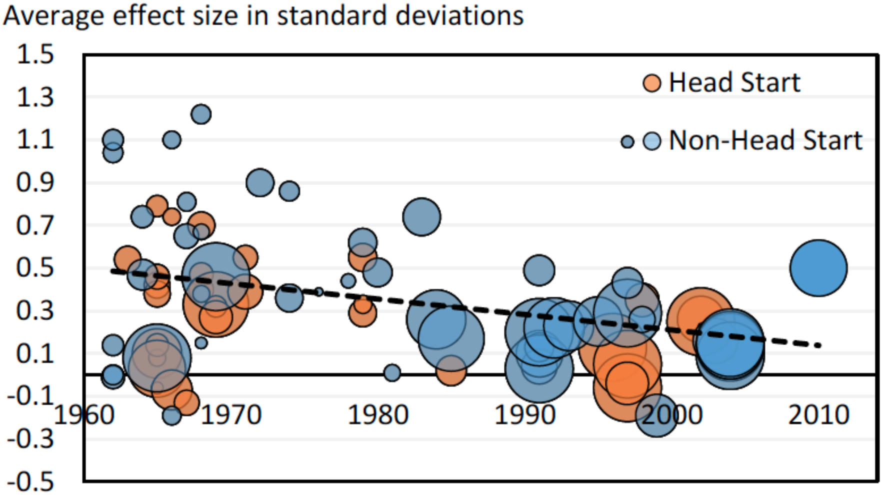


Marginal Cost-Benefit Scenarios



Cascio and Schanzenbach (2013)





Source: Duncan and Magnuson (2013); Weiland and Yoshikawa (2013).
Note: Circle sizes reflect the inverse of the squared study-level standard error. 74 of 83 studies showed positive effects, and CEA estimates that roughly 60 percent of estimates were statistically significant at the 10 percent level.

Conclusion: Going forward...

$$MVPF_{\delta} = \frac{(1-\tau)pLATE_h}{\phi_h - \phi_c S_c - \tau pLATE_h}$$

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Our estimates suggest that as $S_c \to 1$:

$$(1-\tau)pLATE_h \to 0$$

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Our estimates suggest that as $S_c \to 1$:

$$(1-\tau)pLATE_h \to 0$$

$$\phi_h - \phi_c S_c - \tau pLATE_h \to \phi_h - \phi_c$$

Perhaps then we should expect that:

$$MVPF_\delta \to 0?$$

Depends critically on cost side: $\phi_h - \phi_c$

BONUS

Figure 1: Complier Shares and Head Start Effects

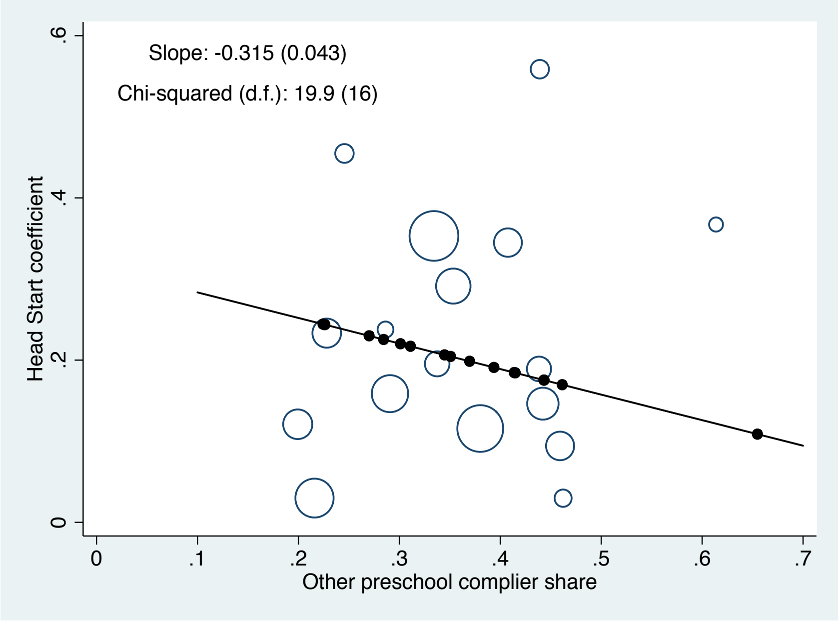

Table 4: Characteristics of Head Start and Competing Preschool Centers

	Head Start (1)	Other centers (2)	Other centers attended by *c* -> *h* compliers (3)
Quality index	0.702	0.453	0.446
Transportation provided	0.629	0.383	0.324
Fraction of staff with bachelor's degree	0.345	0.527	0.491
Fraction of staff with teaching license	0.113	0.260	0.247
Center director experience	18.2	12.2	12.6
Student/staff ratio	6.80	8.24	8.54
Full day service	0.637	0.735	0.698
More than three home visits per year	0.192	0.073	0.072
N	1848	366	

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Fraction of staff with teaching license	0.113	0.260	0.247
Center director experience	18.2	12.2	12.6
Student/staff ratio	6.80	8.24	8.54
Full day service	0.637	0.735	0.698
More than three home visits per year	0.192	0.073	0.072
N	1848	366	

Table 4: Characteristics of Head Start and Competing Preschool Centers

	Head Start (1)	Other centers (2)	Other centers attended by c -> h compliers (3)
Quality index	0.702	0.453	0.446
Transportation provided	0.629	0.383	0.324
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Table A1: Characteristics of Head Start Centers Attended by Always Takers

	Experimental center (1)	Attended center (2)
Transportation provided	0.421	0.458
Quality index	0.701	0.687
Fraction of staff with bachelor's degree	0.304	0.321
Fraction of staff with teaching license	0.084	0.099
Center director experience	19.08	18.24
Student/staff ratio	6.73	6.96
Full day service	0.750	0.715
More than three home visits per year	0.112	0.110
N	112	
p-value	0.318	

Notes: This table reports characteristics of Head Start centers for children assigned to the HSIS control group who attended Head Start. Column (1) shows characteristics of the centers of random assignment for these children, while column (2) shows characteristics of the centers they attended. The *p*-value is from a test of the hypothesis that all mean center charteristics are the same. The sample excludes children with missing values for either characteristics of the center of random assignment or the center attended.

No Parental Labor Supply Response

Table A2: Effects on Maternal Labor Supply

	Full-time	Full- or part-time
	(1)	(2)
Offer effect	0.020	-0.005
	(0.018)	(0.019)
Mean of dep. var.	0.334	0.501
N	3314	

Notes: This table reports coefficients from regressions of measures of maternal labor supply in Spring 2003 on the Head Start offer indicator. Column (1) displays effects on the probability of working full-time, while column (2) shows effects on the probability of working full- or part-time. Children with missing values for maternal employment are excluded. All models use inverse probability weights and control for baseline covariates. Standard errors are clustered at the Head Start center level.

Back

Should we value earnings impacts dollar for dollar?

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- Compensated (Hicksian) labor supply schedule:

$$l_c^*\left(\tilde{y}, \bar{u}\right) = -\frac{\partial}{\partial \tilde{y}} e\left(\tilde{y}, \bar{u}\right)$$

Dollar value of treatment effect

- *Compensating variation* $CV(\Delta)$ gives dollar value of Head Start test score impact Δ:

$$CV(\Delta) \equiv e(\tilde{y}, u_0) - e(\tilde{y} + (1-\tau)p\Delta, u_0)$$

where $u_0 \equiv V(\tilde{y})$ is utility when untreated.

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$$CV'(\Delta) = (1-\tau)pl_c^*(\tilde{y} + (1-\tau)p\Delta, u_0)$$

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- Contrast with observed earnings impacts:

$$DE(\Delta) \equiv (\tilde{y} + (1-\tau) p\Delta) l^* (\tilde{y} + (1-\tau) p\Delta, m) - \tilde{y} l^* (\tilde{y}, m)$$

$$DE'(0) = (1-\tau) p l^* (\tilde{y}, m) (1 + \eta_u)$$

where η_u is *uncompensated* labor supply elasticity

An adjustment factor

- Since, $CV(0) = DE(0) = 0$, we have first order approximation:

$$\frac{CV(\Delta)}{DE(\Delta)} \approx \frac{CV'(0)}{DE'(0)} = \frac{1}{1+\eta_u}$$

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E.g., if $\eta_u = 0.2$ would imply we need to scale observed earnings impact by 83%.

- Second order approximation implies smaller rescaling if income effects substantial ($\eta_c \gg \eta_u$):

$$\frac{CV(\Delta)}{DE(\Delta)} \approx \frac{1+\frac{1}{2}\eta_c\frac{\Delta}{y}}{1+\eta_u+\frac{1}{2}\eta_u\left(2+\eta_u^2\right)\frac{\Delta}{y}}$$

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- Also: if $u = u\left(q, \bar{l}, y\right)$ then extra term for "consumption value" of human capital.
- So $\frac{1}{1+\eta_u}$ scaling potentially very conservative.

MVPF

- In constant elasticity model, bang per net dollar spent is:

$$
\begin{aligned}
MVPF &= \frac{E\left[CV\left(\Delta_i\right)|complier\right]}{\phi_h - \phi_c S_c - \tau p \frac{\partial}{\partial \delta} E\left[Y_i I^*\left(\tilde{Y}_i\right)\right]} \\
&= \frac{E\left[CV\left(\Delta_i\right)|complier\right]}{\phi_h - \phi_c S_c - \tau LATE_h^N} \\
&\geq \frac{1}{1+\eta_u} \frac{\left(1-\tau\right) LATE_h^N}{\phi_h - \phi_c S_c - \tau LATE_h^N}
\end{aligned}
$$

where $LATE_h^N \equiv E\left[N_i\left(\tilde{Y}_i\left(h\right)\right) - N_i\left(\tilde{Y}_i\left(D_i\left(0\right)\right)\right)|complier\right]$ gives the LATE on pre-tax earnings.

- So, we have an overestimate of MVPF by a factor of (at most) $\frac{1}{1+\eta_u}$.

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CFHSSY (2011)

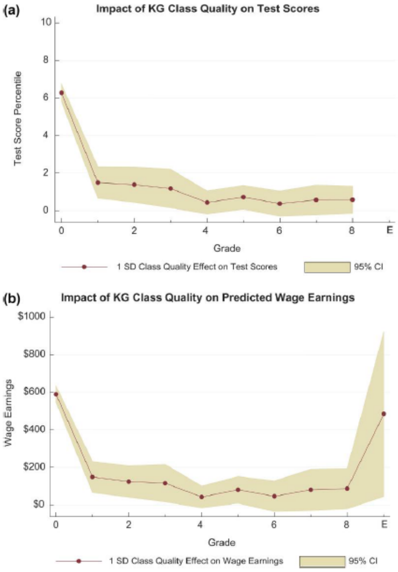

FIGURE VI

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Review: know your Heckit

- Potential outcomes

$$\begin{aligned} Y_{1i} &= \mu_1 + U_{i1} \\ Y_{0i} &= \mu_0 + U_{i0} \end{aligned}$$

- Regime switching:

$$\begin{aligned} D_i^* &= \psi_0 + \psi_1 Z_i + V_i, \\ D_i &= 1\left\{D_i^* > 0\right\}, \end{aligned}$$

- Random assignment:

$$(U_{i1}, U_{i0}, V_i) \perp Z_i$$

- Result:

$$\begin{aligned} E\left[Y_i | Z_i = z, D_i = d\right] &= \mu_d + E\left[U_{id} | Z_i = z, D_i = d\right] \\ &= \mu_d + \gamma_d \underbrace{\lambda_d\left(\pi\left(z\right)\right)}_{\text{Control Fn}} \end{aligned}$$

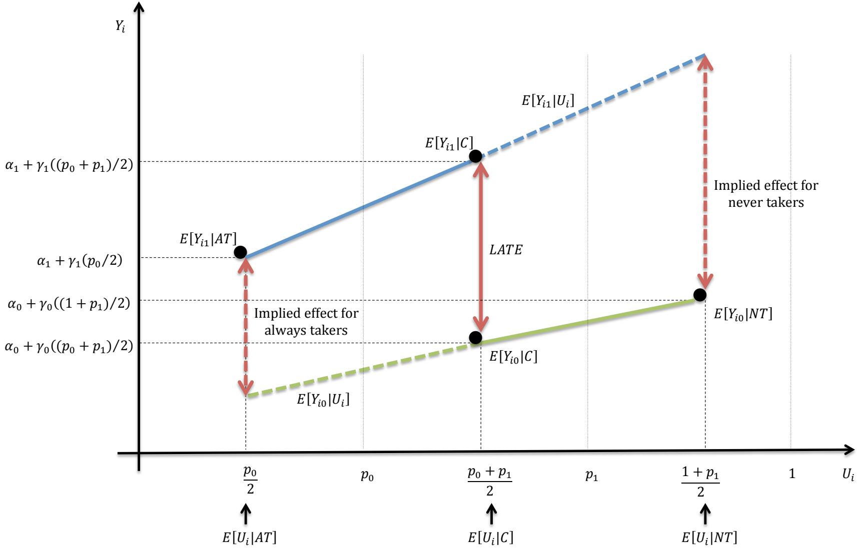
where $\pi\left(z\right) = P\left(D_i = 1 | Z_i = z\right)$.

Review: control functions

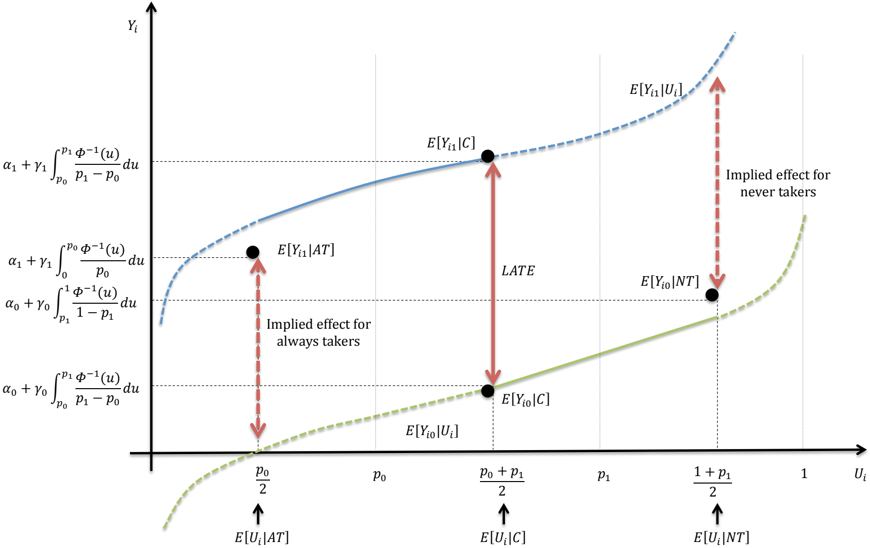
$$E\left[Y_i | Z_i = z, D_i = d\right] = \mu_d + \lambda_d\left(\pi\left(z\right)\right)$$

- Standard causal estimands functions of $\{\mu_0, \mu_1, \lambda_0\left(.\right), \lambda_1\left(.\right), \pi\left(.\right)\}$:
  - $ATE = \mu_1 - \mu_0$
  - $MTE\left(z\right) = \mu_1 - \mu_0 + \gamma_1 \lambda_1'\left(\pi\left(z\right)\right) - \gamma_0 \lambda_0'\left(\pi\left(z\right)\right)$
  - $LATE =$
    $\mu_1 - \mu_0 - \left(\gamma_1 - \gamma_0\right)\left(\frac{\pi\left(0\right)\lambda_1(\pi\left(0\right)) + (1 - \pi\left(1\right))\lambda_0\left(\pi\left(1\right)\right)}{\pi\left(1\right) - \pi\left(0\right)}\right)$

- Identification challenges:
  - Getting $\left(\lambda_0\left(.\right), \lambda_1\left(.\right)\right)$ requires "identification at infinity"
  - With binary instrument, need parametric structure
    - Classic "two-step" Heckit: $\lambda_d\left(\pi\right) = \rho_d \frac{\phi\left(\Phi^{-1}\left(\pi\right)\right)}{\pi}$



Linear selection model: $E[Y_{id}|U_i] = \alpha_d + \gamma_d U_i$



Heckit model: $E[Y_{id}|U_i] = \alpha_d + \gamma_d \Phi^{-1}(U_i)$

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- Kline and Walters (2015): with binary Z, fully saturated two-step Heckit gives LATE estimate numerically equivalent to IV!
- Heckit MTE estimate is discrete approx to derivative over range of compliance traced out by instrument.
  - In limiting case where $\pi(z') \to \pi(z)$ interpolation is exact because $LATE = MTE(z)$

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CF differences nearly linear

Relationship between control function differences and choice probability differences

Preschool choice	Control function difference	Total R^2 (1)	Partial R^2: Difference in π_h (2)	Partial R^2: Difference in π_c (3)
Head Start	v_h	0.887	0.886	0.047
	v_c	0.483	0.002	0.473
Other centers	v_h	0.930	0.929	0.549
	v_c	0.764	0.505	0.606
No preschool	v_h	0.826	0.816	0.060
	v_c	0.044	0.005	0.035

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