Compensation vs. Reinforcement: Identification of Parental Aversion to Inequality in Offspring

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Motivation

- Household's resource allocation among k siblings

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$$U(\underbrace{\xi_1, \xi_2, ..., \xi_k}_{\text{Endowment}}, \underbrace{e_1, e_2, ..., e_k}_{\text{Outcomes}})$$

- Becker and Tomes (1976) analyze whether better endowments are **reinforced** or poorer endowments are **compensated**.

- Behrman et al. (1982) extends Becker and Tomes (1976) by consider parental aversion to inequality in offspring outcomes.

$$\sum_{i=1}^{k} a_i (\xi_k^{\alpha_g} e_i^{\alpha_e})^{\phi}$$

- Parents might be
  - Highly averse to inequality $\rightarrow$ minimize the differences
  - Not much worried about inequality$\rightarrow$ ending up increasing it

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- Very scarce empirical evidence to test resource allocation within the household, and specially across siblings.

Research Question

How do parents allocate resources within the household?

Do they reinforce or compensate?

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- Leverage an intervention that assigned CCTs at the **student** level.
- Transfers typically assigned at the household level.
- School attendance is the parental investment
  (vs. Early entry into labor market)
- Intervention changes the opportunity cost of schooling for *some* children in the household.
- We identify parental aversion to inequality in offspring by leveraging experimental variation in relative opportunity costs of investing in each child.

Preview of Results

We find that:

Conditional Cash Trasnfer Experiment

- CCTs have clear shortrun direct effects in school attendance and enrollment.
- But effects not robust in the long run outcomes. (Millán et al., 2019)
- Negative Spillovers on Long Run Outcomes

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Dynamic Model of Siblings Education Allocations

- Identify *Low* aversion to inequality in offspring $\Longrightarrow$ reinforcement
- Parental aversion has strong impact on Intra HH inequalities
- Significant effects in both short run and long run outcomes
  once correcting for endogenous recruitment / difference in exposures
  (Galiani, Pantano, and Shi, 2022)
- Shutting down parental aversion understates the impact of the cash transfer

Preview of the Key Mechanism

- Households care about the total outcome and the inequality (Behrman, Pollak, and Taubman, 1982; Rosenzweig and Wolpin, 1988).

- Terminal value function that depends on $e_{i,h,\bar{t}_h}$:

$$V_{\bar{t}_h}(e_{1,h}, e_{2,h}, ..., e_{N_h,h}; \rho) = \rho_1 \sum_i \mathbb{I}(e_{\bar{t}_h,i} \geq 16) \ + \ \rho_2 \mathrm{Var}(e_{\bar{t}_h})$$

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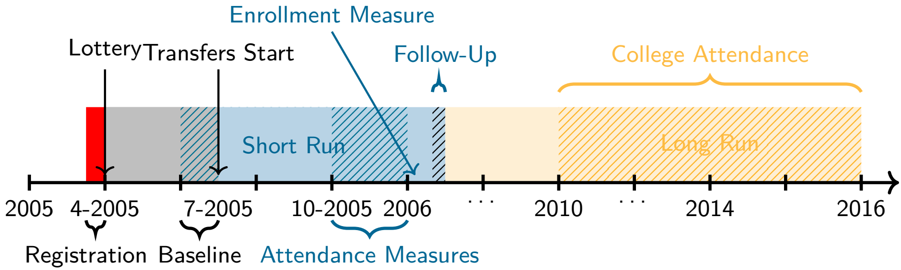
- Key structural parameter $\rho_2 \in (-\infty, 0]$:
  Degree of parental aversion to inequality in completed education among offspring
  - $\rho_2 \to -\infty$: Acheivement difference collapses
  - $\rho_2 \to 0$: sibling inequality increases in general
  - Spillover effects from experimental variation capture identify ρ_2

Outline

Outline

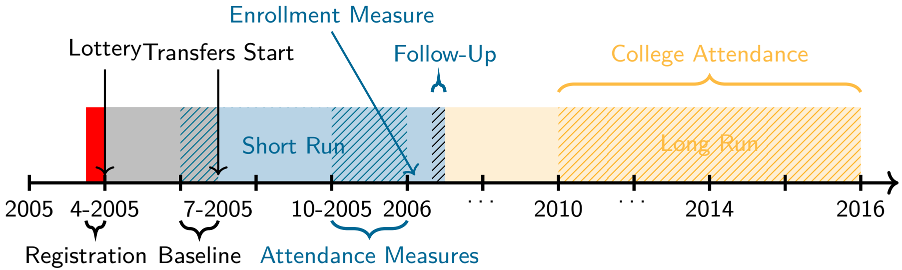
CCT and Timeline



The timeline of the intervention had several important events:

- The program was publicized in Jan-Feb 2005. Registration on March 2005
- Requisites:
  1. One parent present at moment of registration.
  2. Students with completed 5th grade.
  3. Enrolled in school but not graduated.
  4. Household categorized as poor (lowest two categories of SISBEN index).
- Recruitment based on the attendance on 2005

CCT and Timeline



- Treatment assigned ***individually*** and ***randomly*** on April 2005.
  - Transfers
    - 300k COP yearly ($ 150) (Basic)
    - 200K COP yearly + 600K COP bonus upon high school graduation (College)
  - **Conditioned on** attending 80% of the classes.
  - Short run measures (baseline, attendance, follow-up) in a subgroup of schools.
  - Long run measures in administrative data sets up to 11 years after intervention.

Outline

Total Effects

- We follow Barrera-Osorio et al. (2011, 2019).
- Simple comparison between children who win and lose the lottery, pooling all children regardless of sibling's outcome:

$$Y_i = \beta_0^T + \beta_1^T \texttt{Winner}_i + \beta_X^T X_i + \varepsilon_i^T,$$

Indirect/Spillover Effects

Sample: All losers (regardless of sibling outcome):

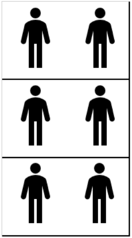
$$Y_i = \beta_0^S + \beta_1^S \texttt{Winner Sibling}_i + \beta_X^S X_i + \varepsilon_i^S,$$

- β_1^S identifies the spillover/indirect effect.

Indirect Effects

Consider three families with N = 2 :

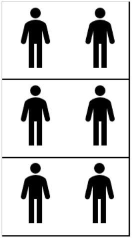
Households N = 2

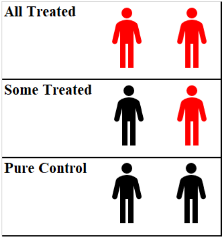


Indirect Effects

Consider three families with $N = 2$:

Households $N = 2$ Treatment Assignment





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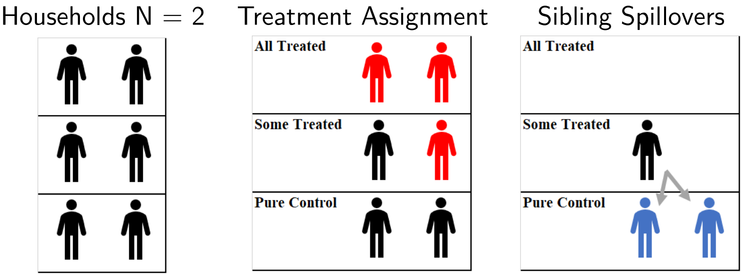

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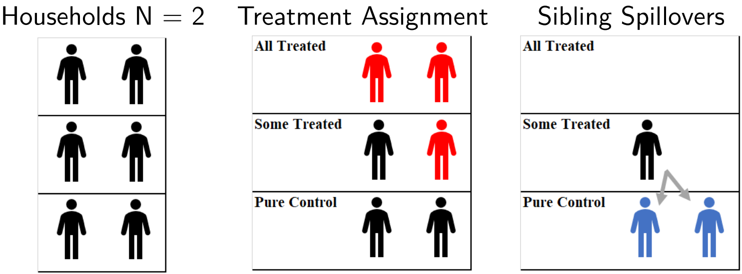

- Estimation sample for Indirect Effects restricted to Lottery Losers;:

Indirect/Spillover Effects

Sample: All losers (regardless of sibling outcome):

$$Y_i = \beta_0^S + \beta_1^S \texttt{Winner Sibling}_i + \beta_X^S X_i + \varepsilon_i^S,$$

- β_1^S identifies the spillover/indirect effect.

Direct Effects

Sample: winners in households where only one sibling wins and losers in the two-loser households.

$$Y_i = \beta_0^D + \beta_1^D \texttt{Winner}_i + \beta_X^D X_i + \varepsilon_i^D,$$

- β_1^D identifies the direct effect.

Dual Role of RCT: Identification + Validation

- Follow Galiani, Murphy, and Pantano (2015); Galiani and Pantano (2022)
  - Some experimental variation for estimation, some for validation.
- **Estimation**
  - "One-Winner" households
  - "Two-Losers" households (pure controls)
- **Validation**
  - "Two-Winners" households

WW vs. LL Effects

Sample: Winners in households where *both* siblings win and pure control losers.

$$Y_i = \beta_0^A + \beta_1^A \texttt{Win and Sib Wins}_i + \beta_X^A X_i + \varepsilon_i^A,$$

- β_1^A identifies the effect of a child and her sibling winning the lottery relative to none of them winning it.

Outline

Lottery: Total Effects

Table: Effects of Winning Lottery on Short and Long Run Outcomes

	Short Run			Long Run
	Attends School High Presentism	Attends School Low Presentism / No Study or Work	Works as Primary Activity	College Graduation
	(1)	(2)	(3)	(4)
A) Total Effects				
Winner	0.116***	-0.080***	-0.027***	0.004
	(0.027)	(0.026)	(0.010)	(0.013)
Observations	1162	1082	1162	2326
Control mean	0.623	0.277	0.0434	0.104

Lottery: Direct Effects

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B) Direct Effects				
Winner	0.074**	-0.055	-0.022	-0.024
	(0.037)	(0.035)	(0.014)	(0.017)
Observations	637	592	637	1283
Control mean	0.633	0.272	0.0417	0.121

Lottery: Spillover Effects

Table: Effects of Winning Lottery on Short and Long Run Outcomes

	Short Run			Long Run
	Attends School High Presentism	Attends School Low Presentism / No Study or Work	Works as Primary Activity	College Graduation
	(1)	(2)	(3)	(4)
C) Indirect Effects				
Sib Winner	-0.016	0.007	0.001	-0.037**
	(0.038)	(0.037)	(0.016)	(0.017)
Observations	645	595	645	1284
Control mean	0.633	0.272	0.0417	0.121

Lottery: WW vs. LL Effects (for Validation)

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	Short Run			Long Run
	Attends School High Presentism	Attends School Low Presentism / No Study or Work	Works as Primary Activity	College Graduation
	(1)	(2)	(3)	(4)
D) WWvLL Effects				
Win and Sib Wins	0.149***	-0.103***	-0.030**	0.002
	(0.036)	(0.034)	(0.013)	(0.019)
Observations	600	563	600	1199
Control mean	0.633	0.272	0.0417	0.121

Outline

Summary of the Structural Model

1. We model the behavior of low-income households
2. Dynamic model of the household with 2 children
3. Household differs by
   - Cohort/spacing
   - Income $(y^{p}_{h,t}, y^{c}_{1,t}, y^{c}_{2,t})$
   - Ability of the siblings (ξ_1, ξ_2)
   - Unobserved preference shocks $(\{\varepsilon^{high}_{i,t}, \varepsilon^{low}_{i,t}, \varepsilon^{home}_{i,t}, \varepsilon^{work}_{i,t}\}_{i=1}^{i=2})$

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4. Household makes decision for each kid:
   Schooling $(d^{high}_{i,t}$ or $d^{low}_{i,t})$, stay home $(d^{home}_{i,t})$, and work $(d^{work}_{i,t})$
5. In 2005, Conditional Cash Transfer comes as a surprise
6. Household becomes different in terms of CCT assignment Z and the transfer $\tau_i(Z_i, e_{it})$
7. Ability affects the probability of progression to the next grade

Household Preferences

Flow utility of the household is defined as

$$U = \ln(c_p) + \sum_{k=1}^{2} U_k + \alpha_{both} d_1^{high} d_2^{high}$$

where U_i is the flow utility that household h derives from child i

$$\begin{aligned} U_i = & (\alpha_{high} + \varepsilon_i^{high}) d_i^{high} \\ & + (\alpha_{low} + \varepsilon_i^{low}) d_i^{low} \\ & + (\alpha_{work} + \varepsilon_i^{work}) d_i^{work} \\ & + (\alpha_{home} + \varepsilon_i^{home}) d_i^{home} \\ & + \alpha_{reentry} (d_{i,-1}^{work} \text{ or } d_{i,-1}^{home}) \times (d_i^{high} \text{ or } d_i^{low}) \end{aligned}$$

We allow for different re-entry costs for secondary school and college

Terminal Value

- Households care about the total outcome and the inequality (Behrman, Pollak, and Taubman, 1982; Rosenzweig and Wolpin, 1988).

- Final period is when the secondborn becomes 25

  Terminal value function that depends on $e_{i,h,\bar{t}_h}$:

$$V_{\bar{t}_h}(e_{1,h}, e_{2,h}, ..., e_{N_h,h}; \rho) = \rho_1 \sum_i \mathbb{I}(e_{\bar{t}_h,i} \geq 16) \; + \; \rho_2 \, \mathrm{Var}(e_{\bar{t}_h})$$

- Households receives this value in $\bar{t}_h$ (year when youngest child (last-born) reaches age 25)

- Key structural parameter $\rho_2 \in (-\infty, 0]$:
  Degree of parental aversion to inequality in completed education among offspring (Behrman, Pollak, and Taubman, 1982; Rosenzweig and Wolpin, 1988).

Household "Business-as-Usual" Choices Before RCT

$$\max_{\{\{\mathbf{d}_t\}_{t=\underline{t}}^{t=\bar{t}_h}\}_{i=1}^{i=N_h}} \left\{ E\left[\sum_{t=\underline{t}_h}^{t=\bar{t}_h} \delta^{t-\underline{t}_h} U\left(c_t, \mathbf{d}_t, \mathbf{d}_{t-1}; \Omega_t, \varepsilon_t^u\right) + \delta^{T_h} V_{\bar{t}_h}(\Omega_{\bar{t}_h}) \middle| \chi_{\underline{t}_h} \right] \right\}$$

subject to

$$\mathbf{d}_t = \{d_{i,t}^{high}, d_{i,t}^{low}, d_{i,t}^{home}, d_{i,t}^{work}\}_i^{N_h}$$

$$c_t = y_t^p + \sum_{i=1}^{i=N_h} \left\{ d_{i,t}^{work} \times y_{it}^c \right\}$$

$$\Pr\left(e_{i,t+1} = e_{i,t} + 1 \mid d_{i,t}^{high} = 1 \text{ or } d_{i,t}^{low} = 1\right) = \pi_e\left(e_{it}, d_{i,t}^{high}, d_{i,t}^{low}, \xi_i\right)$$

$$y_t^p = y^p(X_t, \varepsilon_t^{y^p})$$

$$y_{i,t}^c = y^c(a_t, e_t, X_t, \varepsilon_{it}^{y^c})$$

$$\text{given } \Pr(X_{t+1} | X_t, d_t)$$

$\Rightarrow$ Obtain policy functions:

$$\mathbf{d}_t^* = g(\Omega_t, \varepsilon_t, \xi)$$

Household Re-optimization in 2005 upon Treatment Assignment in the RCT

$$\max_{\{\{\mathbf{d}_t\}_{t=\underline{t}}^{t=\bar{t}_h}\}_{i=1}^{i=N_h}} \left\{ E\left[\sum_{t=\underline{t}_h}^{t=\bar{t}_h} \delta^{t-\underline{t}_h} U\left(c_t, \mathbf{d}_t, \mathbf{d}_{t-1}; \Omega_t, \varepsilon_t^u\right) + \delta^{T_h} V_{\bar{t}_h}(\Omega_{\bar{t}_h}) \middle| \chi_{\underline{t}_h} \right] \right\}$$

subject to

$$\mathbf{d}_t = \{d_{i,t}^{high}, d_{i,t}^{low}, d_{i,t}^{home}, d_{i,t}^{work}\}_i^{N_h}$$

$$c_t = y_t^p + \sum_{i=1}^{i=N_h} \left\{ d_{i,t}^{work} \times y_{i,t}^c + d_{i,t}^{high} \times \mathbb{1}\{Z_i \neq \text{Control}\} \times \tau_i(Z_i, e_{i,t}) \right\}$$

$$\Pr\left(e_{i,t+1} = e_{i,t} + 1 \mid d_{i,t}^{high} = 1 \text{ or } d_{i,t}^{low} = 1\right) = \pi_e\left(e_{it}, d_{i,t}^{high}, d_{i,t}^{low}, \xi_i\right)$$

$$y_t^p = y^p(X_t, \varepsilon_t^{y^p})$$

$$y_{i,t}^c = y^c(a_t, e_t, X_t, \varepsilon_{it}^{y^c})$$

$$\text{given } \Pr(X_{t+1}|X_t, d_t)$$

$\Rightarrow$ Obtain policy functions:

Outline

1. Introduction
2. Setting
3. Identification and Empirical Strategy
4. Results
5. Model
6. Structural Estimation
7. Out-of-sample Validation
8. Counterfactual Analyses
9. Conclusions

Model Estimation

- Method of simulated moments
- Moments we match
  - School Attendance, staying home, Work decisions by age for
    1. **Observational population**
    2. **Control group** in the experiment
       $\rightarrow$ Captures Endogenous Recruitment (Galiani, Pantano, and Shi, 2022)

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  - Long-run direct/indirect effects regression moments

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  - Other moments
    1. Re-entry related moments:
       (delayed graduation, age distribution upon graduation college)
    2. Graduation penalty conditional on low attendance
    3. Graduation by birth-order

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  - Other moments
    1. Re-entry related moments:
       (delayed graduation, age distribution upon graduation college)
    2. Graduation penalty conditional on low attendance
    3. Graduation by birth-order
- We do not use All treated (WW) group for estimation

Model Fit: Direct Effects

Table: Effects of Winning Lottery: Data

	Winner Effect		Control Mean	
Outcome	Data	Model	Data	Model
High Presentism	**0.074****		**0.633**	
	[0.001, 0.147]			
Low Presentism	−0.055		**0.272**	
	[−0.124, 0.014]			
Work	−0.022		**0.042**	
	[−0.049, 0.005]			
College Grad	−0.024		**0.121**	
	[−0.057, 0.009]			

Model Fit: Direct Effects

Table: Effects of Winning Lottery: Data vs. Model

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High Presentism	**0.074****		**0.633**	0.708
	[0.001, 0.147]			
Low Presentism	−0.055		**0.272**	0.250
	[−0.124, 0.014]			
Work	−0.022		**0.042**	0.042
	[−0.049, 0.005]			
College Grad	−0.024		**0.121**	0.118
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College Grad	−0.024	−0.016	**0.121**	0.118
	[−0.057, 0.009]			

Model Fit: Spillover Effects

Table: Indirect Effects: Data

	Sibling Effect		Control Mean	
Outcome	Data	Model	Data	Model
High Presentism	−0.016		0.633	
	[−0.090, 0.058]			
Low Presentism	0.007		0.272	
	[−0.066, 0.080]			
Work	0.020		0.042	
	[−0.011, 0.051]			
College Grad	−**0.037****		0.121	
	[−0.070, −0.004]			

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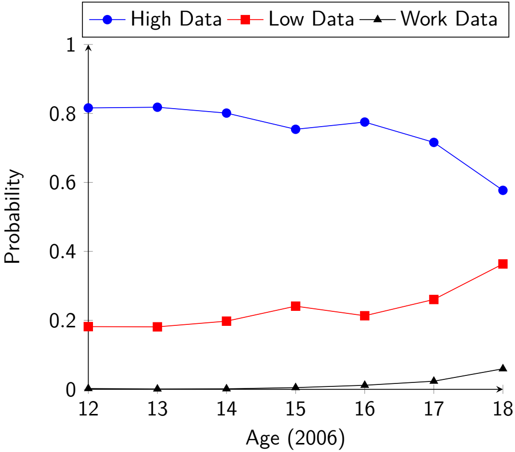
Control Group in the Experiment Moments: all



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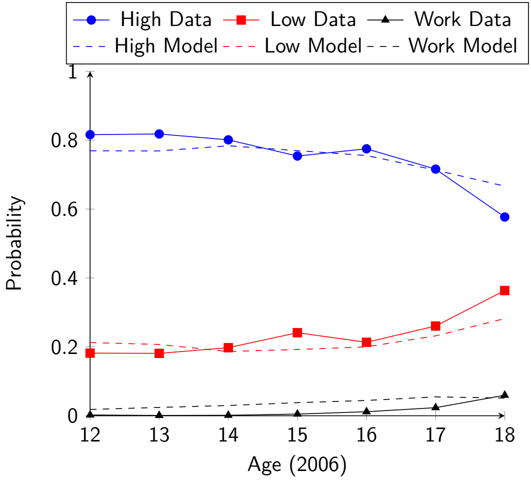
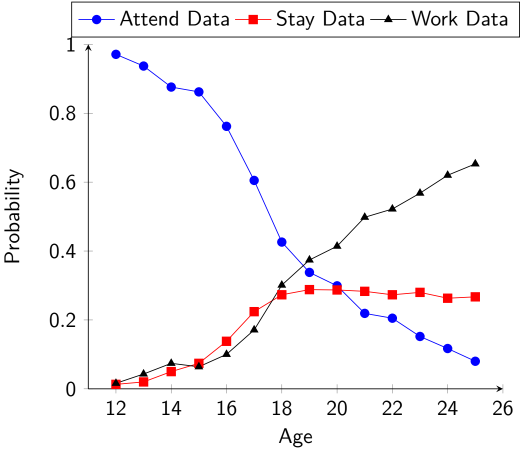


Observational Moments: all



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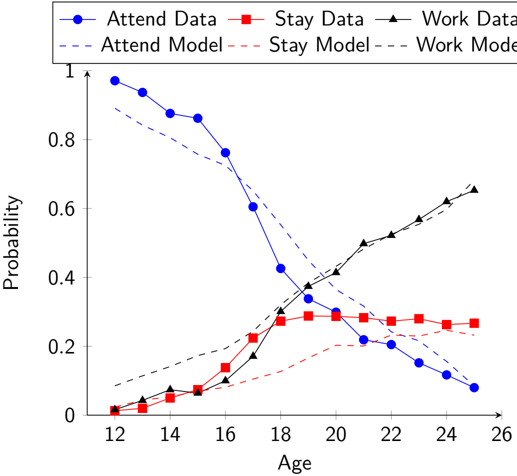

Identification of ρ_2

- Denote college graduation as Y, and treatments as D_i, and $D_{i,sib}$
- We fit the levels of the college graduation rate of the pure controls and the "indirect group"
- We fit the coefficients of the indirect effects equation

	Data	**Model**
$\frac{1}{N_{ind}} \sum Y_i(D_i = 0, D_{i,sib} = 1)$	0.082	0.085
$\frac{1}{N_{con}} \sum Y_i(D_i = 0, D_{i,sib} = 0)$	0.121	0.118
$\widehat{\beta}_{indirect}$	-0.037	-0.037

- Among $\rho_2 \in (-\infty, 0]$, we identify $\widehat{\rho}_2 = -0.085$

Parameter Estimates I

(a) Terminal Value	Estimate	S.E.
Average Education (ρ_1)	8.859	(0.264)
Sibling's Inequality (ρ_2)	-0.085	(0.001)
(b) Flow Utility		
Low Attendance (α_{low})	0.380	(0.166)
Stay (α_{stay})	-0.241	(0.123)
Secondary School Reentry Cost ($\alpha^{\text{second}}_{\text{reentry}}$)	-6.199	(0.116)
College Reentry Cost ($\alpha^{\text{second}}_{\text{reentry}}$)	-0.578	(0.021)
(c) Both Kids Attendance by Types		
High-High ($\alpha^{\text{HH}}_{\text{both}}$)	1.090	(0.202)
High-Low ($\alpha^{\text{HL}}_{\text{both}}$)	0.001	(0.048)
Low-High ($\alpha^{\text{LH}}_{\text{both}}$)	0.018	(0.008)
Low-Low ($\alpha^{\text{LL}}_{\text{both}}$)	2.231	(0.438)
(d) Shock Standard Deviation		
High Attendance (σ_c)	1.167	(0.202)
Low Attendance(σ_{low})	0.639	(0.048)
Work (σ_{work})	1.209	(0.008)

- Low aversion
- More expensive re-entry cost in secondary school
- Complementarity when siblings' ability types are the same

Parameter Estimates II

(a) Progression Parameters	Estimate	S.E.
Logit - Baseline Secondary (λ_0^s)	3.742	(0.134)
Logit - High Ability Bonus in Secondary School (λ_1^s)	0.466	(0.120)
Logit - Low Attendance Penalty in Secondary School (λ^{low})	-3.717	(0.320)
Logit - Baseline College (λ_0^c)	-4.993	(0.004)
Logit - High Ability Bonus (College) (λ_1^c)	4.971	(0.051)
(b) Type Distribution		
$\Pr(c_1 = H, c_2 = H)$	0.040	(0.004)
$\Pr(c_1 = H, c_2 = L)$	0.481	(0.029)
$\Pr(c_1 = L, c_2 = H)$	0.159	(0.031)
$\Pr(c_1 = L, c_2 = L)$	0.320	-

- No huge ability bonus in progressing during secondary school
- Ability matters a lot in college graduation

Outline

WWLL: Validation

Parameter	Data	Model
(1) High Presentism	0.149***	0.108
	[0.078, 0.220]	
(2) Low Presentism	-0.103***	-0.090
	[-0.170, -0.036]	
(3) Work as Primary	-0.030**	-0.017
	[-0.055, -0.005]	
(4) College Grad	0.002	-0.023
	[-0.035, 0.039]	

Outline

Counterfactual: Motivation

Understanding **the role of** ρ_2

- **Policy 1**: Policy where both children are treated from the beginning to the end of the secondary school
- **Policy 2**: Policy where parents choose the recipent among the two children
- For different amounts of stipend (Baseline at 300,000 COP)
- With and without ρ_2 (parental aversion)

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Recover the **true policy effects** correcting for endogenous recruitment (Galiani et al., 2022)

1. Endogenous Recuritment of the RCT
    - Eligibility: Decisions prior to 2005 affects recruitment
    - Spacing/Age: different length of exposures
2. Policy starts from the first period of decision for ***all*** cohorts

Baseline Policy Analysis

		SR Attend	COL	IntraHH Ineq
Estimated Aversion	No Treatment	0.55	0.10	2.08
	Policy 1	0.62	0.11	2.14
	Policy 2	0.65	0.12	2.28
No Aversion	No Treatment	0.52	0.14	5.36
	Policy 1	0.57	0.14	5.15
	Policy 2	0.57	0.15	5.33

Notes: Policy 1: both siblings treated, Policy 2: parent chooses one recipient,
SR Attend = Short-run High Attendance; COL = College Graduation rate; IntraHH Ineq = Education Gap

- The policy effects of both children being treated is
  - 7% (vs. 14.9% in the experiment) for SR
  - 1% for COL (vs. 0.2% in the experiment)
- Shutting down aversion increases the average college graduation rate at the expense of doubled inequalities

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Selection into the Experiment: Ability Types

Table: Distribution of Household Ability Types

Ability Config	Experiment	Population
HH	0.044	0.040
HL	0.397	0.482
LH	0.202	0.160
LL	0.357	0.319

- The experiment has fewer “first-high / second-low” (HL) households.
- Selection of Households with High ability secondborn (LH and HH)
- LL Households are overrepresented

Selection into the Experiment: Spacing

Table: Distribution of Sibling Spacing

Spacing	Experiment	Population
1	0.305	0.303
2	0.355	0.528
3	0.160	0.105
4	0.126	0.034
5	0.051	0.013
6	0.003	0.007
7$\geq$	0.000	0.010

- Very long spacing is rare (by the design)
- HH with more widely spaced siblings are more likely to participate.

Baseline Policy Analysis

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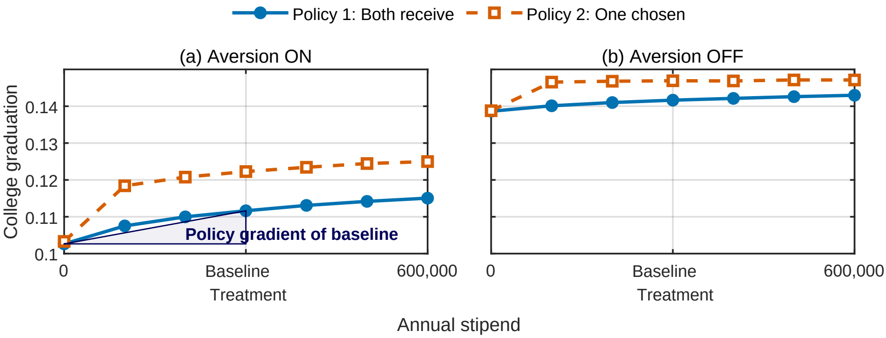
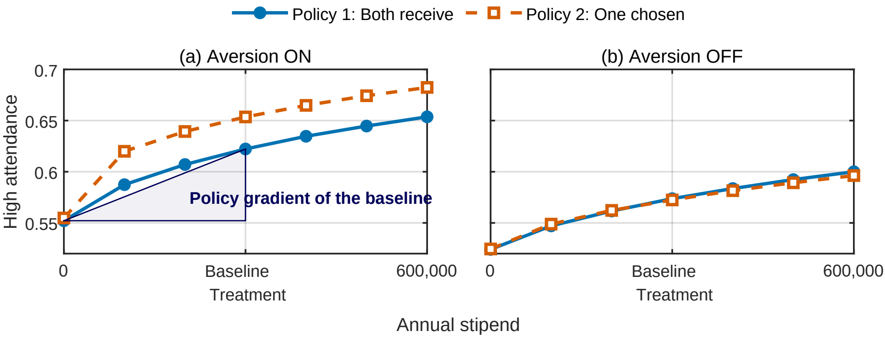
Effects of Policies by Stipend: College Graduation



- The policy gradient of college graduation is steeper with the presence of aversion
- Shutting down ρ_2 understates the impact of the policy on college graduation
- Policy 1 and 2 are not that different under ***No Aversion***

Effects of Policies by Stipend: Attendance



- The policy gradient of short-run attendance for all students is steeper with the presence of aversion
- Shutting down ρ_2 understates the impact of the policy on SR attendance
- Policy 1 and 2 are not that different under ***No Aversion***

Outline

Conclusions

- Economic theory typically treats households as units.
- But resources are allocated within the household.
- We leverage random variation to analyse how resources are allocated within the household.
- Intervention was assigned at the individual level, thereby introducing identifying variation.
- We find negative long-run spillovers effects from CCTs, consistent with moderate aversion to inequality.
- We develop, estimate, and validate a dynamic structural model.
- Counterfactual analyses suggest that aversion plays a big role in intra HH inequalities
- Shutting down aversion understates the impacts of policy

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