Model-Aided Identification of Policy Effects Using RCTs

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Motivation: The Promise and Limits of RCTs

RCTs: Gold Standard for Causal Effects

- Clean identification of treatment effects
- Foundation for evidence-based policy
- Widely used in many economic fields

But Many RCTs Have Limitations

- **Short-run duration** (SR)
  - 2-year intervention vs. permanent policy
- **Endogenous recruitment** (ER)
  - Eligibility based on outcomes

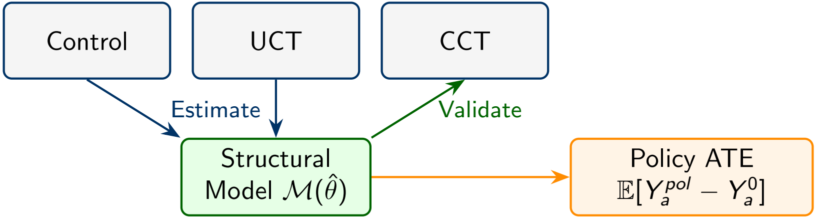
The Problem

With **forward-looking**, **heterogeneous** agents, RCTs with (SR, ER) may **not identify** the Average Treatment Effect of the *actual policy*.

This Paper: Key Contribution

Our Approach

Structural Model + Multi-Arm RCT $\Longrightarrow$ Recover policy ATE



Dual Role of RCT

- **Control + UCT**: Identification
- **CCT**: Out-of-sample validation

Policy Simulation Addresses

- **SR**: Simulate *full-duration* policy
- **ER**: Simulate *full population*

Related Literature

1. Combining Structural Models with RCTs

- Todd & Wolpin (2006): hold-out treatment for *validation*
- Attanasio, Meghir & Santiago (2012): RCT for *identification*
- Galiani, Murphy & Pantano (2015): Multi-arm RCT for *both*
- Todd & Wolpin (2023), Galiani & Pantano (2022): Surveys

2. Structural Models of CCTs and Schooling

- Todd & Wolpin (2006), Attanasio et al. (2012): Mexico's PROGRESA

Our contribution: Dual role of RCT + Correction of SR and ER

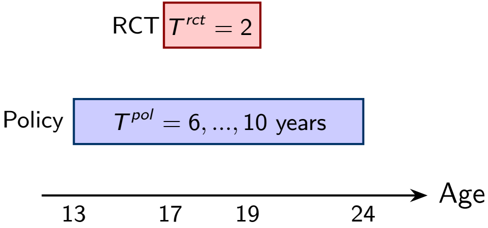
Why Short-Run RCTs Fail: The Intuition

Setup

- Policy duration: T^{pol} years (e.g., 6,7,...,10 years) until high school graduation
- RCT duration: T^{rct} years (e.g., 2 years)
- Agents are **forward-looking**

The Problem

- Agents *know* T^{rct} when experiment begins
- Their decisions account for the finite horizon
- $\Rightarrow$ Behavior under RCT $\neq$ Behavior under policy



$Y_i^{pol} \neq Y_i^{rct}$ even during RCT!

Why Endogenous Recruitment Fails: Dynamic Selection

Eligibility Criterion: E.g. girls must be **unmarried** and **in school** at recruitment

The Selection Problem

- Eligibility depends on past choices (Y_a)
- Past choices reflect *unobserved heterogeneity*
- $\Rightarrow$ RCT-Eligible sample $\neq$ Population

Implication

- Let $k \in \{\text{high, middle, low}\}$ = preference types
- Distribution of k among *eligible* girls μ_a^{elig} differs from population
- Selection intensifies with age

Eligible sample increasingly selected on high-preference types

Formalizing the Gap: RCT ATE vs. Policy ATE

What RCTs Estimate (Experimental Treatment Effect):

$$\mathrm{ATE}_a^{rct} = \int \left(Y_a^{rct} - Y_a^0\right) d\mu_a^{elig}$$

What We Want (Policy Treatment Effect):

$$\mathrm{ATE}_a^{pol} = \int \left(Y_a^{pol} - Y_a^0\right) d\mu_a$$

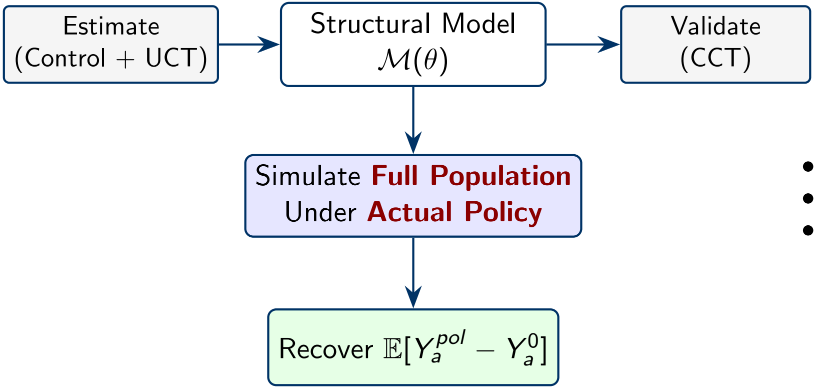
Two Sources of Bias

1. **Outcome**: $Y_a^{rct} \neq Y_a^{pol}$
   - Forward-looking agents respond to $T^{rct} \neq T^{pol}$
2. **Distribution**: $\mu_a^{elig} \neq \mu_a$
   - Eligibility selects on outcomes

Solution

$\Longrightarrow$ **Structural model needed** to map ATE_a^{rct} to ATE_a^{pol}

Our Solution: Model-Based Identification



- Forward-looking behavior
- Heterogeneous types
- No recruitment restriction

Empirical Application: Malawi Cash Transfer Program

The Zomba Cash Transfer Program (Baird, McIntosh, & Özler, 2011 *QJE*)

Design

- Target: Never-married and inschool girls, ages 13–22
- Three arms: Control, CCT, UCT
- Duration: 2 years (2008–2009)
- Randomized transfer amounts

Outcomes of Interest

- School enrollment
- Marriage
- Pregnancy

Data Collection

Round	Timing
R1	Oct 2007 – Jan 2008 (Baseline)
R2	Oct 2008 – Feb 2009 (During intervention)
R3	Feb 2010 – Jun 2010 (Post-intervention)

Key features: Short-run (SR) + Endogenous Recruitment (ER)

Dynamic Discrete Choice Model: Overview

Agents: Households with girls aged 13–24

Choices at each age a (if unmarried):

d	Marriage (m_a)	School (s_a)	Sex Partner (sp_a)
1	1	0	0
2	0	1	1
3	0	0	1
4	0	1	0
5	0	0	0

Key Model Features:

- **Forward-looking**: Agents maximize $\mathbb{E}\left[\sum_{a=13}^{25} \delta^{a-13} U(\cdot) + \delta^{12} V_{25}\right]$
- **Unobserved heterogeneity**: $K = 3$ preference types for schooling
- **Endogenous fertility**: Pregnancy probability depends on choices
- **Budget constraint**: Consumption = Income + Transfers (if treated)

Value Function and Bellman Equation

1. **Before Intervention / Control Group** (standard problem)

   - Alternative-specific value function:
     $$V_d(\Omega_a, \varepsilon_a) = U_d(c_a, s_a, m_a, sp_a, \Omega_a, \varepsilon_a) + \delta\, \mathbb{E}_{\Omega_{a+1}, \varepsilon_{a+1}} \left[V(\Omega_{a+1}, \varepsilon_{a+1}) \,\middle|\, d, \Omega_a \right]$$
   - Optimal value function: $V(\Omega_a, \varepsilon_a) = \max_{d \in \{1, \ldots, 5\}} \{ V_d(\Omega_a, \varepsilon_a) \}$

2. **During Intervention (2008–2009)** for UCT/CCT groups

   - **Re-optimization** with treatment assignment $\chi = \{Z, \tau^Z\}$:
     $$V_d^t(\Omega_a, \varepsilon_a, \chi) = U_d(c_a^Z, s_a, m_a, sp_a, \Omega_a, \varepsilon_a) + \delta\, \mathbb{E} \left[V^{t+1}(\Omega_{a+1}, \varepsilon_{a+1}, \chi) \,\middle|\, d, \Omega_a \right]$$

In 2009 ($t = 2009$)

$$V_d^{2009} \leftarrow V(\cdot) \text{ in } 2010$$

Continuation value reverts to no-policy problem after transfers end

In 2008 ($t = 2008$)

$$V_d^{2008} \leftarrow V^{2009}(\cdot, \chi)$$

Continuation value accounts for one more year of transfers

Cash Transfers in the Model

Budget Constraint During Intervention (2008–2009)

$$c_a = y_a + sp_a \cdot g_a + \tau^{uct} \cdot \mathbf{1}\{Z = UCT\} \cdot \mathbf{1}\{t \in \{2008, 2009\}\} \cdot \mathbf{1}\{e_a < 12\}$$
$$+ \tau^{cct} \cdot \mathbf{1}\{Z = CCT\} \cdot \mathbf{1}\{t \in \{2008, 2009\}\} \cdot \mathbf{1}\{e_a < 12\} \cdot \boldsymbol{s_a}$$

UCT

- Transfer received *unconditionally*
- Pure income effect
- May delay marriage/pregnancy

CCT

- Transfer *conditional on* $s_a = 1$
- Income effect + Price effect
- Direct schooling incentive

Estimation Strategy

Method: Simulated Method of Moments (SMM)

$$\hat{\theta} = \arg\min_{\theta} \left\{ \left[m^{data} - m(\theta) \right]' W \left[m^{data} - m(\theta) \right] \right\}$$

Key Moments Targeted (Control + UCT groups only):

- School attendance rates by year (2008, 2009, 2010)
- Ever-married rates (2009, 2010)
- Ever-pregnant rates (2009, 2010)
- **Age-specific schooling ratios at recruitment (2007)** (crucial for dynamic selection)
- Auxiliary regression coefficients (indirect inference)

Parameters: 33 structural parameters matched to 91 moments

CCT group data **reserved** for out-of-sample validation

Model Fit: Main Outcomes (Targeted)

School Attendance

	'08	'09	'10
Control			
Data	.85	.68	.56
Model	.82	.67	.53
UCT			
Data	.87	.71	.57
Model	.85	.71	.59

Ever-Married

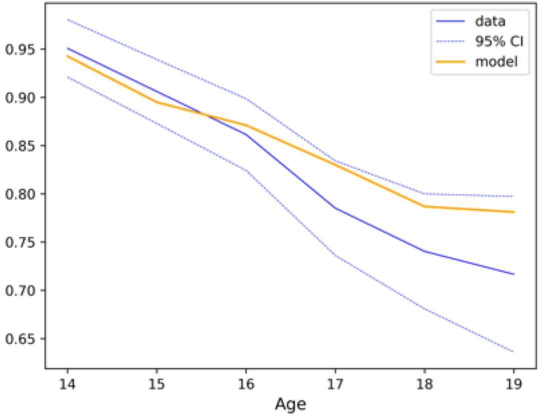
	'09	'10
Control		
Data	.052	.166
Model	.052	.133
UCT		
Data	.028	.091
Model	.041	.095

Ever-Pregnant

	'09	'10
Control		
Data	.107	.227
Model	.132	.227
UCT		
Data	.096	.168
Model	.088	.144

✓ Model captures key patterns: UCT reduces marriage/pregnancy, modest schooling effect

Model Fit: Age-Specific Schooling (Control Group, 2008)



Key Observation:

- Model within 95% CI at all ages
- Captures declining attendance with age
- Critical for **dynamic selection correction**

✓ Good fit to age profile enables reliable counterfactual simulation

Out-of-Sample Validation: CCT Group (**Not Used in Estimation**)

School Attendance

	'08	'09	'10
Data	.913	.781	.612
Model	.873	.765	.633

Ever-Married

	'09	'10
Data	.059	.163
Model	.059	.111

Ever-Pregnant

	'09	'10
Data	.102	.275
Model	.095	.167

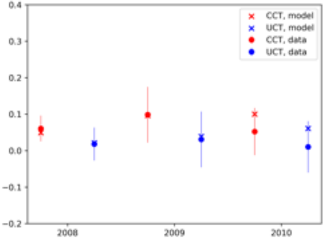
Validation Success

Model correctly predicts differential impacts of CCT vs. UCT on schooling and marriage *without seeing CCT data during estimation*.

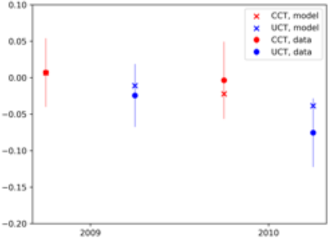
*Empirical puzzle: CCT associated with *higher* pregnancy despite higher schooling—outside standard economic mechanisms.

Validation: Treatment Effects (CCT & UCT vs Control)

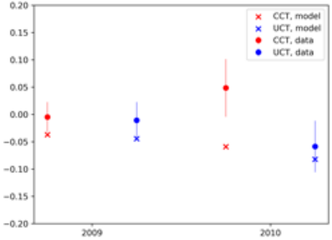
School Attendance



Ever-Married

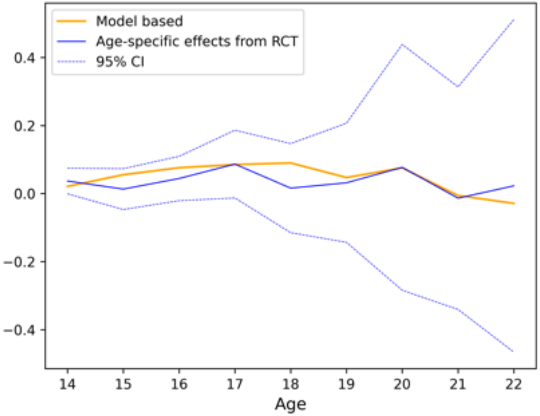


Ever-Pregnant



Model predictions align with RCT estimates within confidence intervals.

Validation: Age-Specific Treatment Effects on Schooling (CCT vs Control)

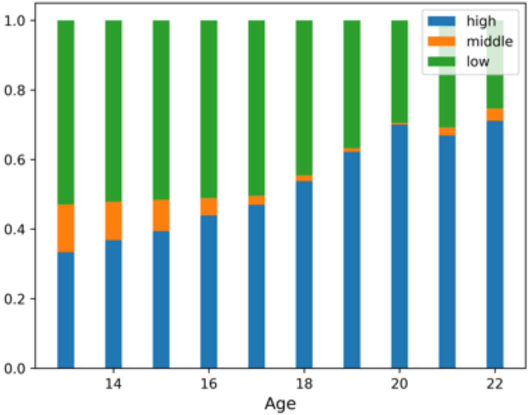


Key Finding:

- Model predictions within confidence intervals
- Captures age pattern of effects
- Wide CIs at older ages due to small samples

✓ Strong out-of-sample validation supports model credibility for counterfactual analysis

Dynamic Selection: Composition of Eligible Sample



Key Insight:

- At age 14: ∼33% high-preference types
- At age 22: ∼70% high-preference types
- Low-preference girls *selected out* (married or dropped out)

Implication

RCT treatment effects reflect *selected sample*, not population. Selection bias increases with age.

Counterfactual Experiment: Design

Goal: Simulate full-duration cash transfer policy for *full population*

Simulation Setup

- **Starting population**: All girls at age 13
  - No eligibility selection
  - All unmarried, in school
  - Includes all preference types
- **Policy duration**: Varies
  - 2 yrs, 3 yrs, ..., 11 yrs
  - Support ends at ages 15, 16, ..., 24

Key Comparisons

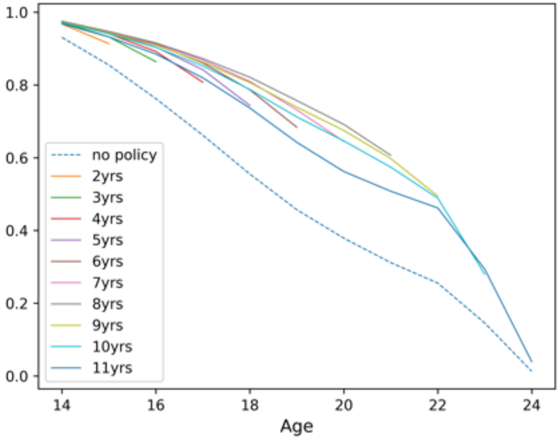
- **No policy**: Baseline trajectory
- **2-year policy**: Mimics RCT duration
- **Full duration (11 yrs)**: Policy from age 13 to 24

Outcome: School attendance rate by age

Why This Matters

Addresses both RCT limitations: (1) short duration → simulate longer policies; (2) endogenous recruitment → start from unselected population

Counterfactual Experiment: Results



Without Policy (dashed):

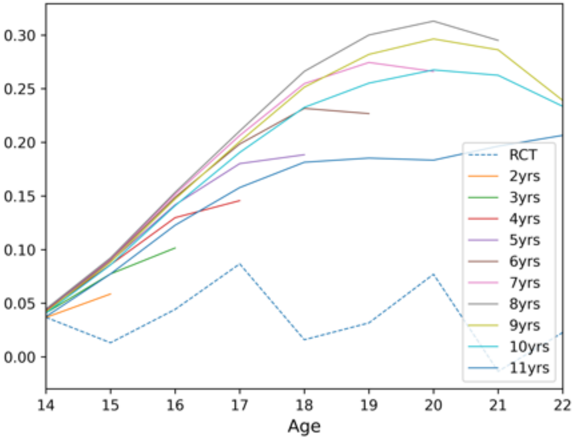
- Enrollment drops steeply

With Policy:

- Longer duration $\Rightarrow$ higher retention
- Full duration maintains >50% through age 21
- Effects largest at ages 17–22

Insight: Effects compound—sustained support during critical transition period (ages 16–20) yields disproportionate returns.

Policy vs. Experimental Treatment Effects



Striking Result:

- RCT effects: ~3–5 pp
- Policy effects: up to **30 pp**
- Gap largest at ages 17–22

Why the Gap?

1. **Dynamic selection**: RCT sample excludes low-preference girls
2. **Duration effect**: Forward-looking agents respond more to permanent policy

Main Takeaways

1. **Methodological Contribution**
   - Multi-arm RCT enables **dual role**: identification + validation
   - Structural model addresses SR and ER limitations of standard RCTs
   - Out-of-sample validation provides credibility for counterfactuals
2. **Substantive Findings**
   - Dynamic selection creates substantial bias in experimental estimates
   - Full-duration policy effects are **5–10$\times$ larger** than RCT estimates
   - Effects concentrate in ages 17–22 where selection is most severe
3. **Policy Implications**
   - Short-term evaluations *underestimate* long-term policy impacts
   - Sustained support through later adolescence yields largest returns
   - RCT estimates alone may mislead cost-benefit analyses

Conclusion

Summary

We combine structural modeling with a multi-arm RCT to:

- Correct for dynamic selection in experimental recruitment
- Account for forward-looking behavior under finite-horizon interventions
- Recover *long-duration* policy treatment effects for the *full population*

Broader Applicability

- Any RCT with eligibility criteria
- Short-duration interventions
- Forward-looking agents

Thank You!

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Backup Slides

Backup: Utility Function Specification

Per-Period Utility:

$$u_a = \underbrace{\frac{\alpha_{02}}{\alpha_{00}} \left(c_a(1 + \alpha_{01} m_a)\right)^{\alpha_{00}}}_{\text{Consumption utility}} + \underbrace{(\alpha_1^{k} + \alpha_2 a) s_a}_{\text{Schooling (age-varying)}} + \underbrace{(\alpha_3 + \alpha_4 a) m_a}_{\text{Marriage (age-varying)}}$$

$$+ \alpha_5 sp_a + \underbrace{\alpha_6 e_a + \alpha_7 e_a^2}_{\text{Education stock}} + \underbrace{\alpha_8 n_a + \alpha_9 n_a (1 - ms_a)}_{\text{Pregnancy (marital status)}}$$

$$+ \alpha_{10} X_a + \alpha_{11} ms_a + \underbrace{(\alpha_{12} + \alpha_{13} a)(1 - s_{a-1}) s_a}_{\text{School re-entry cost}}$$

$$+ m_a \varepsilon_a^m + s_a \varepsilon_a^s + sp_a \varepsilon_a^{sp}$$

Terminal Value at Age 25:

$$V_{25}(\Omega_{25}) = \beta_1 e_{25} + \beta_2 n_{25} + \beta_3 ms_{25}$$

Back to Model

Backup: Income Equations (Estimated Exogenously)

1. **Parental Income**

$$y_a = \exp\left(\phi_0^y + \phi_1^y X_a + \varepsilon_a^y\right)$$

2. **Girl's Income from Sexual Partner** (conditional on $sp_a = 1$)

$$g_a = \exp\left(\phi_0^g + \phi_1^g a + \phi_2^g a^2 + \phi_3^g s_a + \phi_4^g e_a + \phi_5^g n_a + \phi_6^g X_a + \varepsilon_a^g\right)$$

3. **Budget Constraint**

$$c_a = y_a + sp_a \cdot g_a + \tau \cdot \mathbf{1}\{Z = \text{UCT}\} + \tau \cdot s_a \cdot \mathbf{1}\{Z = \text{CCT}\}$$

Data Source

Monthly household expenditure $\approx$ 9,000 MK ($\approx$ \$9 USD)

Parental income inferred: $y_a = c_a - sp_a \cdot g_a$

Back to Model

Backup: State Transitions

Birth Probability (flow):

$$\Pr(b_a = 1) = \Lambda\left(\lambda_0 + \lambda_1 a + \lambda_2 a^2 + \lambda_3 ms_a + \lambda_4 s_a + \lambda_5 sp_a + \lambda_6 \log(y_a^{total})\right)$$

where $\Lambda(x) = [1 + \exp(-x)]^{-1}$ and total family income includes transfers:

$$y_a^{total} = y_a + \tau^{uct} \cdot \mathbf{1}\{Z = \text{UCT}\} + \tau^{cct} \cdot \mathbf{1}\{Z = \text{CCT}\} \cdot s_a$$

Ever-Pregnant State (stock): $n_{a+1} = \max(n_a, b_a)$

Flow b_a (birth event) updates stock n_a (ever-pregnant). The max operator ensures n is absorbing.

Household Size Transition:

$$\Pr(HS_{a+1} - HS_a = 1) = \Lambda\left(\psi_0^X + \psi_1^X a + \psi_2^X a^2 + \psi_3^X HS_a\right)$$

Back to Model

Backup: Shock Distributions

Joint Distribution of Shocks:

$$\begin{pmatrix} \varepsilon^m \\ \varepsilon^s \\ \varepsilon^{sp} \\ \varepsilon^y \\ \varepsilon^g \end{pmatrix} \sim N(\mathbf{0}, \Sigma), \quad \Sigma = \Gamma\Gamma'$$

where Γ is lower-triangular Cholesky factor.

- ε^m: shock to marriage preference
- ε^s: shock to schooling preference
- ε^{sp}: shock to sex partner preference
- ε^y: shock to parental income
- ε^g: shock to income from sex partner

Back to Model

Backup: Auxiliary Regressions for Indirect Inference

We match OLS coefficients from auxiliary regressions (Control & UCT groups):

1. Marriage Probability (LPM)

$$\Pr(ms_{i,a+1} = 1) = \kappa_0^m + \kappa_1^m a + \kappa_2^m a^2 + \kappa_3^m e_{i,a} + \kappa_4^m n_{i,a} + \kappa_5^m HS_{i,a} + \kappa_6^m \log(y_{i,a})$$

2. School Enrollment Probability (LPM)

$$\Pr(s_{i,a} = 1) = \kappa_0^s + \kappa_1^s a + \kappa_2^s a^2 + \kappa_3^s e_{i,a} + \kappa_4^s n_{i,a} + \kappa_5^s HS_{i,a} + \kappa_6^s \log(y_{i,a})$$

3. Sex Partner Probability (LPM) (if unmarried: $ms_{i,a} = 0$, $m_{i,a} = 0$)

$$\begin{aligned}\Pr(sp_{i,a} = 1) = \kappa_0^{sp} &+ \kappa_1^{sp} a + \kappa_2^{sp} a^2 + \kappa_3^{sp} e_{i,a} + \kappa_4^{sp} n_{i,a} \\ &+ \kappa_5^{sp} HS_{i,a} + \kappa_6^{sp} s_{i,a} + \kappa_7^{sp} \log(y_{i,a})\end{aligned}$$

Back to Estimation

Backup: Auxiliary Regressions (Continued)

4. Ever-Pregnant Probability (LPM)

$$\begin{aligned} \Pr(n_{i,a+1}=1) = \kappa_0^n + \kappa_1^n a + \kappa_2^n a^2 + \kappa_3^n e_{i,a} + \kappa_4^n n_{i,a} + \kappa_5^n ms_{i,a} \\ + \kappa_6^n HS_{i,a} + \kappa_7^n m_{i,a} + \kappa_8^n s_{i,a} + \kappa_9^n sp_{i,a} + \kappa_{10}^n \log(y_{i,a}^{total}) \end{aligned}$$

Exogenously Estimated (Outside Model)

- Log parental income: $\log(y_{i,a}) = \phi_0^y + \phi_1^y HS_{i,a} + \varepsilon_{i,a}^y$
- Log income from sex partner: $\log(g_{i,a}) = \phi_0^g + \phi_1^g a + \phi_2^g a^2 + \ldots + \varepsilon_{i,a}^g$
- Variance of residuals and covariances

Identification

33 structural parameters matched to moments (direct + indirect inference)

Back to Estimation

Backup: Targeted Moments Summary

Direct Moments

- School attendance rates (2008–2010)
- Ever-married rates (2009–2010)
- Ever-pregnant rates (2009–2010)
- School re-entry rates by age
- Age-specific schooling ratios

Indirect Inference

- 4 auxiliary regressions (LPM)
  - Marriage
  - Schooling
  - Sex partner
  - Ever-pregnant
- Matched for Control & UCT

School Re-entry Rates (2007)

	Rate	Std. Error
Age ≤ 16	0.106	0.038
Age > 16	0.027	0.014

Back to Estimation

Backup: Parameter Groups

Estimated within Model

- Preference parameters (16)
  - Consumption utility (CRRA)
  - Schooling (age-varying)
  - Marriage (age-varying)
  - Sex partner
  - Education stock
  - Pregnancy
  - Household characteristics
  - School re-entry cost
- Terminal value parameters (3)
- Birth probability parameters (7)
- Unobserved type probabilities (4)
- Variance of sex partner shock (1)

Estimated Exogenously

- Parental income process
  - Coefficients
  - Variance of shocks
- Income from sex partner process
  - Coefficients
  - Variance of shocks
- Covariance of income shocks
- Household size transition

Total: 33 structural parameters estimated via SMM

Back to Results

Backup: Cohort Structure

Sample: Girls born 1986–1995, aged 13–22 in 2008

	R1 (Baseline) 2007–2008	R2 2008–2009	R3 2010	R4 2012
Born 1995	Age 13	Age 14	Age 15	Age 17
Born 1994	Age 14	Age 15	Age 16	Age 18
Born 1993	Age 15	Age 16	Age 17	Age 19
⋮	⋮	⋮	⋮	⋮
Born 1986	Age 22	Age 23	Age 24	Age 26

Sample Sizes:

- Baseline: 3,796 girls (2,907 schoolgirls + 889 dropouts)
- Randomized: 2,284 participants across Control, CCT, UCT

Back to Data