Extrapolation of Treatment Effect Estimates Across Contexts and Policies: An Application to Cash Transfer Experiments

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Two extrapolation approaches

- Evidence-based policymaking is challenging
  - External validity not always guaranteed
  - From which evidence to extrapolate?

1. Extrapolation across contexts (within policies)
   - Policy A in context X $\Leftarrow$ Policy A in **context Y**
2. Extrapolation across policies (within contexts)
   - Policy A in context X $\Leftarrow$ **Policy B** in context X

- **Do two extrapolations result in different predictions?**
  - No theory & limited empirical evidence
  - Comparative analysis using **cash transfer experiments**

Cash transfer experiments

- Conditional cash transfers (CCTs) on school enrollment rates
  - Common version: conditional on regular school attendance
  - Popular anti-poverty policy (e.g. PROGRESA, Bolsa Familia, RPS)
  - Abundant empirical evidence showing **positive effects**
- Varying cost-effectiveness across programs
  - Heterogeneity in effect size Effect size by transfer amount
- Data: two RCTs in Malawi & Morocco
  - CCTs implemented in both RCTs
  - "Unconditional" cash transfers in Moroccan RCT

Overview

$$\text{Malawi CCTs} \quad \underbrace{\Rightarrow}_{\text{Across contexts}} \quad \text{Morocco CCTs} \quad \underbrace{\Leftarrow}_{\text{Across policies}} \quad \text{Morocco LCTs}$$

- Predict average effect of Moroccan CCTs on school enrollment rates
  - CCTs: cash transfers if school attendance $>$ threshold
  - LCTs: cash transfers $\perp\!\!\!\perp$ school attendance
- Compare predictions with actual treatment effect estimate
  - Predictions via **standard** method (Data-driven vs Structural)
  - Predictions via **same** method (Structural vs Structural)
- Identify source of prediction differences through structural model

Preview of findings

- Moroccan LCTs make more accurate predictions than Malawi CCTs
  - Estimated effect = 5.7 ppt: 5.9 ppt vs 21.2 ppt
  - Statistically significant difference only for across-contexts
  - Relative performance unchanged when using same method
- **(Perceived) returns to schooling** explain prediction differences
  - Key parameters in schooling decisions: cost today vs return tomorrow
  - Estimated cost of schooling: similar for same policy
  - Estimated returns to schooling: similar for same context
  - Discussion on varying perceived returns to schooling across contexts

Contributions to literature

- **Empirical investigation of out-of-sample predictions**
  - Pritchett and Sandefur (2015); Gechter et al. (2018)
  - Prediction performance of across-policies extrapolation
  - Comparative analysis of two extrapolation approaches
- Structural estimation with RCTs in development economics
  - Todd and Wolpin (2006); Attanasio et al. (2012)
  - Identification of flexible model about schooling
- New identification of dynamic discrete choice model
  - Scott (2014); Kalouptsidi et al. (2021)
  - No rational expectations assumption
  - First application to schooling decisions

Two cash transfer experiments

- Malawi (Baird et al., 2011)
  - Treatment: CCTs
  - Target: **girls at secondary school ages** (13 - 22 years old)
  - Teenage pregnancy & marriage as main driver of dropout

- Morocco (Benhassine et al., 2015)
  - Treatment: CCTs and LCTs (Labeled Cash Transfers)
  - Target: **boys and girls at primary school ages** (6 - 15 years old)
  - Various reasons to drop out: school quality, financially, domestic work
  - LCTs $\neq$ UCTs due to **endorsement effects**

▸ Summary statistics

Treatment effect estimates on school enrollment rates

	Malawi	Morocco	
	CCTs	CCTs	LCTs
Treatment	0.0369*	0.0567***	0.0726***
	(0.0200)	(0.0106)	(0.0107)
Control mean	0.896***	0.894***	0.893***
	(0.0154)	(0.00951)	(0.00833)
Obs.	1490	4982	3018

*** p<0.01 ** p<0.05 * p<0.1

- Estimated effects greater (not statistically)
  - for LCTs within contexts
  - for Morocco within policies

▸ Why LCTs more effective? ▸ Back

Across-context: linear projection

- Heterogeneous treatment effect approach
  1. Estimate linear regression with Malawi CCTs data

$$d_i = W_i' \beta^{\text{HTE}} + \beta_0^{\text{HTE}} \text{Treatment}_i + \sum_{k=1}^{K} \gamma_k^{\text{HTE}} \text{Treatment}_i \times w_{ik} + \omega_i$$

  2. Predict d_i in Moroccan CCTs data using estimated linear model
  3. Estimate treatment effect via OLS

$$\hat{d}_i = \alpha_0^{\text{HTE}} + \alpha_1^{\text{HTE}} \text{Treatment}_i + \text{Stratum}_i + \nu_i^{\text{HTE}}$$

- W_i = (age, education, per-capita income, school costs, transfer amount)

- Key assumption: **cond. on W_i, potential outcomes $\perp\!\!\!\perp$ contexts**

▸ Propensity score weighting

Across-policies: dynamic model of schooling

- Child i makes binary schooling decisions over finite time horizon
  - Schooling ($d_i = 1$): pay school costs (s_i), add 1 year of education
  - Non-schooling ($d_i = 0$): consume (per-capita) income (y_i)
  - Flow utility function: $u(c) = \theta \ln(c_i)$

- At terminal period T, child receives lump-sum returns
  - Returns are a function of education: $R_i = R(e_{i,T}) = R\left(e_{i,t} + \sum_{\tau=t}^{T-1} d_{i,\tau}\right)$

- Cash transfers (z_i) relax budget constraints exogenously
  - Budget constraint: $c_i = y_i - d_i \times s_i$
  - CCTs lower school costs: $s_i = s_i - z_i$ if i in treatment group
  - LCTs increase income: $y_i = y_i + z_i$ if i in treatment group

Formal representation

Prediction with θ & $R\left(e_{i,T}\right)$

- Predict prob. of schooling under Moroccan CCTs

$$\hat{P}\left(d=1|e_{i,2},y_{i,2},s_{i,2}\right)=\frac{\exp\left(\hat{\theta}\ln\left(\frac{y_{i,2}-s_{i,2}}{y_{i,2}}\right)+\beta\widehat{\Delta R}\left(e_{i,2}\right)\right)}{1+\exp\left(\hat{\theta}\ln\left(\frac{y_{i,2}-s_{i,2}}{y_{i,2}}\right)+\beta\widehat{\Delta R}\left(e_{i,2}\right)\right)}$$

- Estimate treatment effect via OLS

$$\hat{P}\left(d=1|e_{i,2},y_{i,2},s_{i,2}\right)=\delta_1+\delta_2\text{Treatment}_i+\text{Stratum}_i+\nu_i$$

Structural estimation: sketch

1. Compute probability of schooling in all possible state values
   - Frequency estimator or **parametric to smooth across states**

2. Consider two hypothetical paths for each individual
   - (Baseline, Midline) = (Schooling, Non-schooling), (Non-schooling, Schooling)
   - Same years of education in next period after Midline
   - **Continuation values after Midline fixed**

3. Compare changes in probability of schooling across these paths
   - Differences only in flow utilities between Baseline and Midline
   - **Δ in prob $\Leftrightarrow$ Δ in flow utility, shifted by cash transfers**
   - Size of Δ in flow utility different across CCTs and LCTs

▸ Formal derivation

Identification of θ using cash transfers

$$\underbrace{\ln \frac{P_{it}^{1}}{1-P_{it}^{1}} - \beta \ln \frac{P_{i,t+1}^{2}}{1-P_{i,t+1}^{3}}}_{\text{Change in prob. of schooling across paths}} = {\color{red}\theta} \underbrace{\left\{ \ln \left(\frac{y_{it}-s_{it}}{y_{it}} \right) - \beta \ln \left(\frac{y_{i,t+1}-s_{i,t+1}}{y_{i,t+1}} \right) \right\}}_{\text{Change in flow utility of schooling across paths}}$$

$$+ \underbrace{\beta \left(\eta_{it}(1) - \eta_{it}(0) \right)}_{\text{Expectation errors at baseline (Unobservable)}}$$

- Endogeneity: **expectation errors correlated with income levels**
  - e.g.) information friction, ability to forecast

- **Treatment assignment** as an IV
  - Relevance: cash transfers (only) shift school costs (↓) or income (↑)
  - Exclusion: assignment $\perp\!\!\!\perp$ baseline expectation

Identification of $R(e;x)$

- Identification of terminal payoffs depends on time horizon

- Set terminal period at one period after Midline ($T = 3$)

- Expand prob. of schooling at Midline ($t = 2$)

$$\underbrace{\ln \frac{P^1_{i,2}}{1 - P^1_{i,2}}}_{\text{Odds of schooling}} = \underbrace{\theta \ln \left(\frac{y_{i,2} - s_{i,2}}{y_{i,2}} \right)}_{\text{Flow utility of schooling}} + \beta \underbrace{\left(R(e_{i,2} + 1; x_{i,2}) - R(e_{i,2}; x_{i,2}) \right)}_{\equiv \Delta R(e_{i,2}; x_{i,2})}$$

- $\Delta R(e_{i,2}; x_{i,2})$: Perceived relative returns to schooling
  - **Schooling unexplained by contemporaneous effects of cash transfers**
  - Consequences of schooling decisions after RCTs
  - Heterogenous across state values

Across-contexts (reduced-form) vs Across-policies (structural)

	Target	Across-contexts	Across-policies
Treatment	0.0567***	0.212***	0.0590***
	(0.0106)	(0.00442)	(0.00545)
Control mean	0.894***	1.127***	0.941***
	(0.00951)	(0.00373)	(0.00531)
Obs.	4982	4982	4982
= Target TE		0.000	0.674
= Target control mean		0.000	0.000

Note: *** $p<0.01$ ** $p<0.05$ * $p<0.1$

- Across-contexts: significantly overpredict
- Across-policies: numerically and statistically accurate

▸ Linear vs Reweighting

Across-contexts (structural) vs Across-policies (structural)

	Target	Across-contexts	Across-policies
Treatment	0.0567***	0.0431***	0.0590***
	(0.0106)	(0.00465)	(0.00545)
Control mean	0.894***	0.702***	0.941***
	(0.00951)	(0.00390)	(0.00531)
Obs.	4982	4982	4982
= Target TE		0.004	0.674
= Target control mean		0.000	0.000

Note: *** p<0.01 ** p<0.05 * p<0.1

- Across-contexts: slightly but statistically significantly underpredict

How to extrapolate $\Delta R(e; x)$ Why improvement via structural method?

Comparison of θ and $\Delta R(e; x)$

- Comparative analysis at model parameter level
  - Structural model estimated for each intervention (including Moroccan CCTs)
  - Comparison of parameter estimates across interventions
  - Identification of varying DGP if model is true Check model fit

- Two parameters that determine schooling decisions
  - Flow utility cost of schooling: $\theta \ln(y - d \times s)$
  - Perceived relative returns to schooling: $\Delta R(e; x)$

Comparison of θ

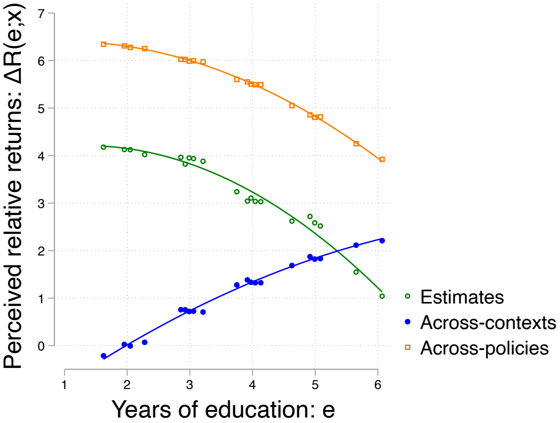
	Malawi	Morocco	
	CCTs	CCTs	LCTs
θ	1.008***	2.670***	38.90***
	(0.256)	(0.454)	(11.30)
Obs.	1479	4981	3016
1st stage F statistics	113.011	3843.510	25.483
= target θ	0.000		0.001

Note: I report the Kleiberge-Paap F statistics for weak identification. *** p<0.01 ** p<0.05 * p<0.1

- Numerically closer estimates if same policy

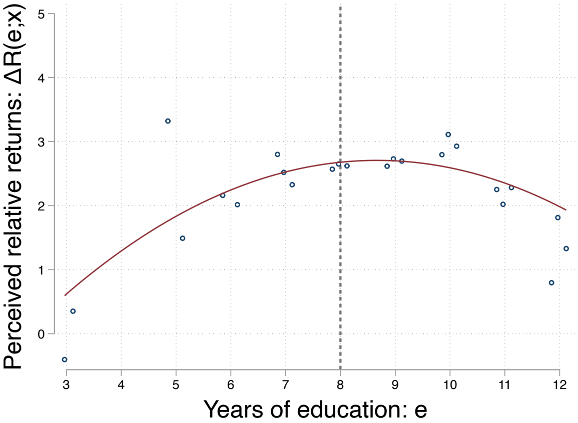
Compare elasticity
Replace with estimated values

Comparison of $\Delta R(e;x)$



- Estimate of $\Delta R(e;x)$: downward sloping due to increasing opportunity costs
- $\Delta R(e;x)$ from Moroccan LCTs: parallel to target values
- $\Delta R(e;x)$ from Malawi CCTs: opposite direction

Why extrapolation of $\Delta R(e;x)$ from Malawi CCTs wrong?



- Increase during primary education
- Start decreasing at which school dropout becomes more realistic
- Naive extrapolation: use increasing part to predict in target context

What explains variation in perceived returns across contexts?

- Perceived relative returns to schooling are key for prediction accuracy
  - Negative correlation bet. estimates and extrapolation across contexts
- To what extent differences in $\Delta R(e;x)$ explained by observables?
  1. Normalize years of education of Malawi sample
  2. Restrict sample by age and sex

Normalization of years of education

	Target	Across-contexts		
Treatment	0.0567***	0.0431***	0.0150***	0.0147***
	(0.0106)	(0.00465)	(0.000788)	(0.00265)
Control mean	0.894***	0.702***	0.903***	0.875***
	(0.00951)	(0.00390)	(0.000674)	(0.00221)
Obs.	4982	4982	4982	4982
Normalization			✓	✓
Sample restriction				✓
= Target TE		0.004	0.000	0.000
= Target control mean		0.000	0.000	0.000

Note: *** p<0.01 ** p<0.05 * p<0.1

- Extrapolation using decreasing part of $\Delta R(e;x)$
- Treatment effect still underpredicted (while overall prediction improved)

▸ RF with normalization

Heterogeneity by sex of Moroccan sample

	Target		Across-contexts	
	Boys	Girls	Boys	Girls
Treatment	0.0479***	0.0681***	0.0151***	0.0148***
	(0.0130)	(0.0144)	(0.00109)	(0.00129)
Control mean	0.912***	0.871***	0.902***	0.903***
	(0.0115)	(0.0129)	(0.000913)	(0.00112)
Obs.	2666	2313	2666	2313
= Target TE			0.000	0.000
= Target control mean			0.000	0.000

Note: *** p<0.01 ** p<0.05 * p<0.1

- Prediction separately by sex of Moroccan sample
- No additional improvement

Heterogeneity by age for Malawi Sample

	Target		Across-contexts	
	Boys	Girls	Boys	Girls
Treatment	0.0479***	0.0681***	0.00376***	0.00402***
	(0.0130)	(0.0144)	(0.000254)	(0.000318)
Control mean	0.912***	0.871***	0.980***	0.980***
	(0.0115)	(0.0129)	(0.000211)	(0.000270)
Obs.	2666	2313	2666	2313
= Target TE			0.000	0.000
= Target control mean			0.000	0.000

Note: *** p<0.01 ** p<0.05 * p<0.1

- Prediction based on young Malawi sample (age < 17)
- No additional improvement

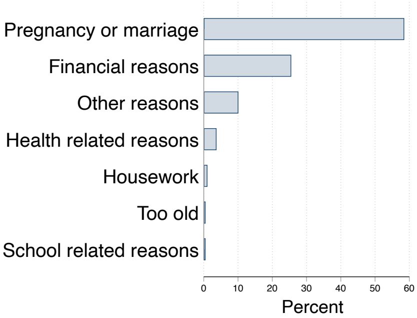
Plausible explanations for no improvement

1. Two Moroccan cash transfers are more alike than two CCTs ATE estimates
   - **Endorsement effects** Within-intervention variation
   - Confusion about conditionality of Moroccan CCTs Under perfect knowledge

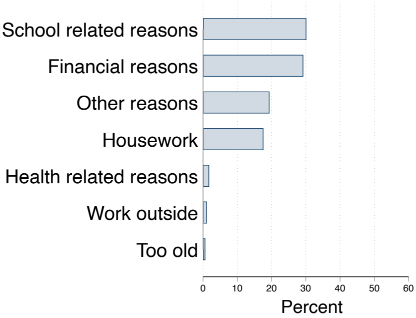
2. **Outside options are different across contexts**
   - $\Delta R(e; x)$ represents returns relative to outside options
   - Suggestive evidence by looking at primary reasons for school dropout

Varying outside options across contexts

Malawi CCTs



Moroccan CCTs



- Primary reasons for dropout differ across contexts
- Differential consequences of non-schooling

Conclusion

- When across-contexts extrapolation does not work, what can we do?
  - Status-quo approach in out-of-sample predictions
  - Empirical evidence on limitation of across-contexts extrapolation
- This paper sheds light on potentials of across-policies extrapolation
  - Similar policy that resembles how target policy works
  - Cash transfers w/o regular school attendance for CCTs
  - Proof-of-concept analysis but relevant beyond CCTs
- Across-policies dominates across-contexts due to perceived returns to schooling
  - Perceived returns to schooling more context-dependent
  - Suggestive explanations: endorsement effects & outside options

Extensions

1. Can we generalize empirical findings in this paper?
   - Three ways to generalize: contexts, policies, and methods
   - Conditions for better predictions via across-policies extrapolation

2. What features are must-have for accurate predictions?
   - WTP for precise estimates of policy effects (e.g. Hjort et al. 2021)
   - Policy designs useful for future predictions
   - Any unintended consequences of such designs?

3. Can we aggregate evidence from multiple policies?
   - Recent development on aggregation for same policies (Meager, 2019, 2022)
   - e.g.) Better predictions by using Malawi CCTs and Moroccan LCTs?

Thank you very much! Feel free to email your comments!

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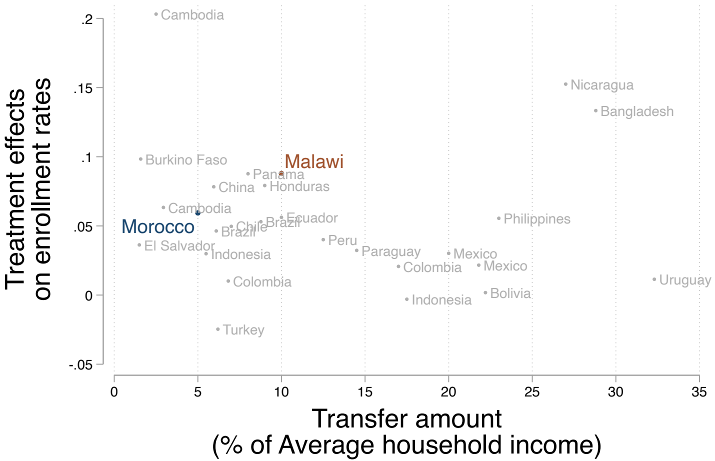
Collection of CCTs effect estimates



Source: Baird et al. (2014)

Back

Summary statistics at baseline

	Malawi		Morocco		
	Control	CCTs	Control	CCTs	LCTs
= 1 if enrollment	1.000	1.000	0.909	0.921	0.920*
Years of education	8.046	7.960	2.755	2.776*	2.764
Per-capita income (in 100 USD)	1.173	1.571	5.368	5.335	5.345
School costs (in 100 USD)	0.123	0.124	0.213	0.212	0.212
Cash transfers (in 100 USD)	NA	1.006	NA	1.054	1.057
=1 if girls	1.000	1.000	0.448	0.471*	0.486**
Age	14.964	14.740	9.889	9.910	9.912
Obs.	1145	412	1276	3706	1740
Joint F-test		0.153		0.250	0.106

Back

Discussion on LCTs vs CCTs in Morocco

- Why LCTs and CCTs comparable?
  1. Endorsement effect driving cash transfer effects
  2. CCTs misperceived as unconditional

- Why LCTs more effective than CCTs?
  - LCTs compliers: children not confident about regular school attendance

- Do Moroccan CCTs differ from Malawi CCTs?
  - Endorsement effect attached to Malawi CCTs
  - Conditionality correctly understood in Malawi CCTs

Back

Across-context: Reweighting

- Propensity score weighting (Stuart et al., 2011)
  1. Pool Malawi and Moroccan data
  2. Estimate propensity score of being in Malawi data via logit

$$\mathbf{1}\{i \in \text{Malawi CCTs}\} = W_i'\beta^{\text{PSW}} + \beta_0^{\text{PSW}}\text{Treatment}_i + u_i$$

  3. Estimate ATE with Malawi data reweighted by inverse of propensity score

$$d_i = \alpha_0^{\text{PSW}} + \alpha_1^{\text{PSW}}\text{Treatment}_i + \text{Stratum}_i + \nu_i^{\text{PSW}}.$$

- W_i = (age, education, per-capita income, school costs, transfer amount)

- Key assumption: **cond. on W_i, potential outcomes $\perp\!\!\!\perp$ contexts**

▸ Back

$$\max_{\{d_{i\tau}\}_{\tau=t}^{T-1}} E\left[\sum_{\tau=t}^{T-1} \beta^{\tau-t}\left\{\theta \ln\left(c_{i\tau}\right)+\varepsilon_{i\tau}\left(d_{i\tau}\right)\right\}+\beta^{T-t} R\left(e_{i,T}; x_{i,T}\right) \middle| \Omega_{i\tau}\right]$$

$$\text{s.t. } c_{i\tau} = y_{i\tau} - d_{i\tau} s_{i\tau}$$

$$e_{i\tau} = e_{i,\tau-1} + d_{i,\tau-1}$$

- State variables How to construct
  - e_{it} : Years of education
  - y_{it} : Per-capita income
  - s_{it} : School costs
  - ε_{it} : Preference shocks
  - $\Omega = \{e, y, s, \varepsilon\}$

- Parametric assumptions
  - Discount factor: $\beta = 0.95$
  - Preference shocks: $\varepsilon \sim$ Type 1 extreme value, i.i.d across (t, i, d)

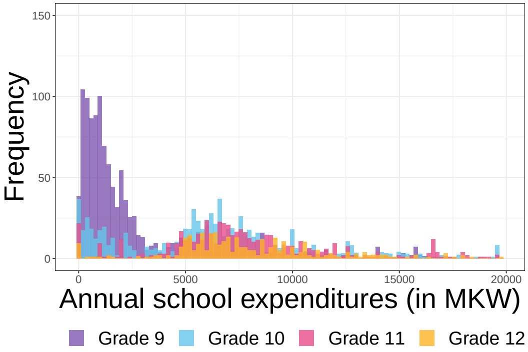
Back

Variables construction

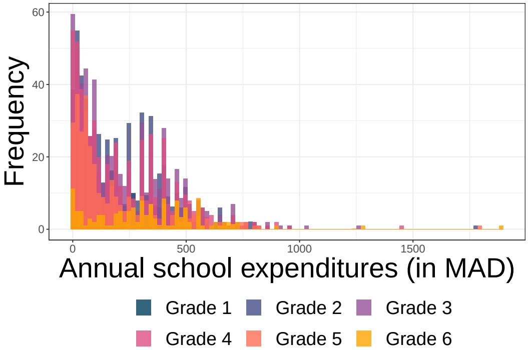
- Directly observe in data: (e_{it}, d_{it}, z_{it})
- Per-capita income: y_{it}
  - Income is unobserved or measured with errors
  - Use annual household expenditures
  - Divide by household size adjusted by OECD equivalence scale
  - If in LCTs, add cash transfer amount
- School costs: s_{it}
  - School costs that parents have to pay upfront
  - Use annual expenditures on school related stuff
  - Take median for schooling children in control group for each grade
  - If in CCTs, subtract cash transfer amount

Distribution of school costs

Malawi: secondary school



Morocco: primary school



Structural estimation: HM inversion

- Rewrite choice prob. at baseline using HM inversion ▸ How to estimate CCP

$$\underbrace{\ln \frac{P\left(d=1|e_{it},x_{it}\right)}{P\left(d=0|e_{it},x_{it}\right)}}_{\text{Odds of schooling}} = \underbrace{v\left(e_{it},x_{it},1\right)-v\left(e_{it},x_{it},0\right)}_{\text{Differences in conditional value functions}}$$

- Expand continuation values at baseline (Scott, 2014; Kalouptsidi et al., 2021)

$$\begin{aligned} v\left(e_{it},x_{it},d\right) &= \theta \ln\left(y_{it}-d\times s_{it}\right)+\beta E_x\left[\overline{V}\left(e_{i,t+1},x_{i,t+1}:\theta\right)|e_{it},x_{it},d\right] \\ &= \underbrace{\theta \ln\left(y_{it}-d\times s_{it}\right)}_{\text{Flow utility}}+\beta\left(\underbrace{\overline{V}\left(e_{i,t+1},x_{i,t+1}:\theta\right)}_{\text{Realized value function}}+\underbrace{\eta_{it}\left(d\right)}_{\text{Expectation errors}}\right) \end{aligned}$$

Structural estimation: finite dependence

- Specify decisions after intervention to have $e_{i,t+2} = e_{i,t} + 1$ for everyone

$$\overline{V}\left(e_{i,t+1}, x_{i,t+1} : \theta\right) = \begin{cases} v\left(e_{it}+1, x_{i,t+1}, 0\right) + \gamma - \ln P\left(d=0 | e_{it}+1, x_{i,t+1}\right) & \text{if } d_{it} = 1 \\ v\left(e_{it}, x_{i,t+1}, 1\right) + \gamma - \ln P\left(d=1 | e_{it}, x_{i,t+1}\right) & \text{if } d_{it} = 0 \end{cases}$$

- Eliminate continuation values after intervention

$$\begin{aligned} v\left(e_{it}+1, x_{i,t+1}, 0\right) &= \theta \ln\left(y_{i,t+1}\right) + \beta E_x\left[\overline{V}\left(e_{it}+1, x_{i,t+2} : \theta\right) | x_{i,t+1}\right] \\ v\left(e_{it}, x_{i,t+1}, 1\right) &= \theta \ln\left(y_{i,t+1} - s_{i,t+1}\right) + \beta E_x\left[\overline{V}\left(e_{it}+1, x_{i,t+2} : \theta\right) | x_{i,t+1}\right]. \end{aligned}$$

- Substitute back to HM inversion

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CCP estimation

- Estimate probability of schooling at each state value
  - Needed to construct dependent variable in 2SLS regression
- Smooth probabilities across states by using a flexible logit
  - Ideally frequency estimates for each state
  - Practically no variation for some states
- Choose MLE or GMM to replicate treatment effects at this stage

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Robustness to how to extrapolate across contexts

		Across-contexts	
	Target	HTE	PSW
Treatment	0.0567***	0.212***	0.00660
	(0.0106)	(0.00442)	(0.0184)
Control mean	0.894***	1.127***	0.895***
	(0.00951)	(0.00373)	(0.0128)
Obs.	4982	4982	1490
= Target TE		0.000	0.007
= Target control mean		0.000	0.927

Note: *** p<0.01 ** p<0.05 * p<0.1

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Robustness to how to extrapolate $\Delta R(e;x)$

		Across-contexts		Across-policies	
	Target	Linear	RF	Linear	RF
Treatment	0.0567***	0.0431***	0.0412***	0.0590***	0.0577***
	(0.0106)	(0.00465)	(0.00644)	(0.00545)	(0.00542)
Control mean	0.894***	0.702***	0.676***	0.941***	0.942***
	(0.00951)	(0.00390)	(0.00556)	(0.00531)	(0.00529)
Obs.	4982	4982	4982	4982	4982
= Target TE		0.004	0.016	0.674	0.863
= Target control mean		0.000	0.000	0.000	0.000

Note: *** p<0.01 ** p<0.05 * p<0.1

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Comparison of extrapolation methods

	Target	Across-contexts			
		HTE		PSW	
Treatment	0.0567***	0.212***	0.0308***	0.00660	-0.0459**
	(0.0106)	(0.00442)	(0.00421)	(0.0184)	(0.0202)
Control mean	0.894***	1.127***	1.111***	0.895***	1.000***
	(0.00951)	(0.00373)	(0.00367)	(0.0128)	(0.00221)
Obs.	4982	4982	4982	1490	1490
= Target TE		0.000	0.000	0.007	0.000
= Target control mean		0.000	0.000	0.927	0.000
Normalization of s, y, z			✓		✓

Note: *** p<0.01 ** p<0.05 * p<0.1

- Structural: school costs & cash transfers **relative to per-capita income**
- Across-contexts using relative values in reduced-form not improved

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Estimates of elasticity of schooling

	Malawi	Morocco	
	CCTs	CCTs	LCTs
$E\left[\frac{\partial P^1_{i,2}}{\partial z_{i,2}} \frac{z_{i,2}}{P^1_{i,2}}\right]$	0.185	0.332	0.142

- $E\left[\frac{\partial P^1_{i,2}}{\partial z_{i,2}} \frac{z_{i,2}}{P^1_{i,2}}\right]$: average elasticity of schooling w.r.t cash transfers
- Across-contexts: difference in effective size of cash transfer
- Across-policies: substitution effects

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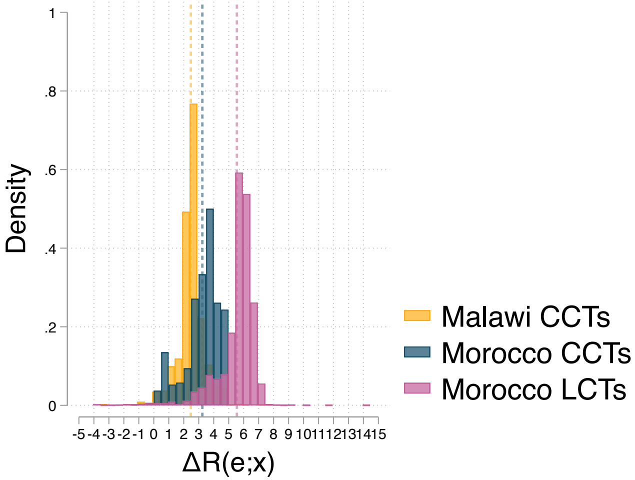
Estimates of $\Delta R_i(e;x)$



- Dashed lines indicate $E[\Delta R(e;x)]$ under each experiment

Model fit

	Malawi	Morocco	
	CCTs	CCTs	LCTs
Treatment	0.0317***	0.0554***	0.0539***
	(0.00495)	(0.00777)	(0.00954)
Control mean	0.895***	0.894***	0.900***
	(0.00241)	(0.00747)	(0.00889)
Obs.	1490	4982	3018
= Target TE	0.290	0.869	0.051
= Target control mean	0.721	0.981	0.476

Note: *** p<0.01 ** p<0.05 * p<0.1

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Extrapolation from Malawi CCTs with true θ or $\Delta R(e;x)$

	Target	Across-contexts		
Treatment	0.0567***	0.0431***	0.0953***	0.0367***
	(0.0106)	(0.00465)	(0.00486)	(0.00721)
Control mean	0.894***	0.702***	0.688***	0.901***
	(0.00951)	(0.00390)	(0.00411)	(0.00689)
Obs.	4982	4982	4982	4982
Replace θ			✓	
Replace $\Delta R(e;x)$				✓
= Target TE		0.004	0.000	0.006
= Target control mean		0.000	0.000	0.276

Note: *** p<0.01 ** p<0.05 * p<0.1

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Within-intervention variation of $\Delta R(e;x)$

	$E[\theta \ln(y - s/y)]$		$E[\beta \Delta R(e;x)]$	
	Control	Treatment	Control	Treatment
Malawi CCTs	-0.292	0.594***	2.526	2.373*
Morocco CCTs	-0.117	0.409***	3.045	3.085
Morocco LCTs	-1.706	-1.390***	5.109	5.383***

*** p<0.01 ** p<0.05 * p<0.1 for difference across groups in each intervention.

- Within-intervention variation affects prediction of treatment effect
- Malawi CCTs: $\Delta R(e;x)$ smaller for treatment group
  - Children with lower perceived returns to choose schooling
- Moroccan CCTs: $\Delta R(e;x)$ larger for treatment group (if anything)
  - Same pattern for Moroccan LCTs

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Reduced-form extrapolation with normalization

	Target	Across-contexts		
		Structural	HTE	PSW
Treatment	0.0567***	0.0150***	0.0352***	0.0655***
	(0.0106)	(0.000788)	(0.00346)	(0.0140)
Control mean	0.894***	0.903***	0.894***	0.920***
	(0.00951)	(0.000674)	(0.00302)	(0.0112)
Obs.	4982	4982	4982	1490
= Target TE		0.000	0.000	0.534
= Target control mean		0.000	0.833	0.022

Note: *** p<0.01 ** p<0.05 * p<0.1

- HTE & PSW: $s/y, z/y$ & standardized e and age

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Confusion about conditionality of Moroccan CCTs

- Moroccan CCTs sample largely misunderstood conditionality
  - 11% understood conditionality correctly
  - 14% thought CCTs were tied to school enrollment
  - More similar to Moroccan LCTs than Malawi CCTs

- If perfect understanding, across-contexts extrapolation more accurate?

- Compute counterfactual effect of Moroccan CCTs with no confusion
  - Estimate model under Moroccan CCTs with degree of confusion
  - Simulate model by assuming perfect knowledge

	Estimation		Across-contexts	Across-policies
	Original	Counterfactual	Linear	Linear
Treatment	0.0567***	0.122***	0.0431***	0.0590***
	(0.0106)	(0.00836)	(0.00465)	(0.00545)
Control mean	0.894***	0.868***	0.702***	0.941***
	(0.00951)	(0.00814)	(0.00390)	(0.00531)
Obs.	4982	4982	4982	4982
= Target TE			0.000	0.000
= Target control mean			0.000	0.000

Note: *** $p<0.01$ ** $p<0.05$ * $p<0.1$

- Treatment effect becomes bigger under perfect knowledge
- Both extrapolations are statistically different from estimate

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