Parental Beliefs, Learning and Networks

How Perceptions of the Process of Child Development Change

Orazio P. Attanasio[1], Flavio Cunha[2], Pamela Jervis[3], Alessandro Toppeta[4]

*E*xpectations and Learning in Dynamic Structural Models

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[1]Yale, and NBER
[2]Rice University
[3]Universidad de Chile
[4]SOFI

Outline

1. Introduction

2. Parental beliefs

3. Networks and their measures

4. Learning

5. Conclusions

Introduction

- In the process of child development, the early years have been proven to be extremely important for their long-term consequences.
- The role played by parents is key;
- In most models, parental investment in children will depend on:
  - Parental resources;
  - Parental preferences;
  - The (perceived) productivity of parental investment in the production function.
- Parents are often assumed to know the 'true' process of child development.
- .... and yet this assumption might be unrealistic.
- Using only data on parental choices might be very hard to distinguish between the role played by tastes and beliefs.

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Differences in parental beliefs

- There is some evidence that parents in disadvantaged situations may have distorted beliefs about the process of child development.
- Parents might be *investing little* not because they don't love their children but because they might think it is not particularly useful.
- It is also possible that parents *learn* about the process of child development.
- Distortions and biases can arise as an equilibrium outcome.
  - see Bellue (2024)
- Understanding how parents learn can therefore be very important.

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- In this paper, we:

1. Propose measures of parental beliefs about the process of child development;
   We develop previous work (Cunha et al, 2023, and Attanasio, Cunha and Jervis, 2022).
2. Implement these measures longitudinally and validate them relating them to investment behavior;
3. We document how beliefs evolve and model parental learning.
   - We play particular attention to the role of local networks in the process.

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Measuring beliefs: a motivation

- Recent studies have started to elicit data on individual beliefs.
  - Cunha et al (2023)
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- In this project we use as a starting point the measures developed Attanasio, Cunha and Jervis (2022) in Colombia.
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How to elicit parental beliefs

- To elicit individual beliefs about the process of child development, we assume that child development from age $a-1$ to age a depends on:
  - The level of development at age a, which we label as *initial conditions*;
  - Parental investment
  - Other variables.

$$H_{i,a} = f_a(H^q_{i,a-1}, X^q_i, \bar{Z}), \quad q = 1, 4$$

- We define such f as the *production function* of child development.
- We assume parents use a similar model but not necessarily with the 'right' parameters.

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- We present parents (typically mothers) with a scenario characterized by a level of investment and a level of initial development...

  ... and ask how they expect a hypothetical child would develop under this scenario.

- We build different scenarios by varying the level of investment and initial conditions;

  - We consider two investment and two initial condition scenarios:

- We map four points of the domain of the production function into its outcomes.
- As we will see, for each scenario, we ask several questions about various outcomes.
- We explicitly ask about a hypothetical child of a certain age and not their own child or any other specific child.
  - We want to avoid self justification and other types of biases.
  - More importantly we want to allow for the possibility that several other variables, for which we do not construct scenarios, are determinants of child development.
  - The assumption is that, when referring to a hypothetical child, parents average the other variables.

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- As we cannot to consider all possible inputs, we assume that respondents *average* across Z_i and ϵ_i.

$$\hat{H}^i_{i,a} = \hat{f}^i_a(H^s_{i,a-1}, X^r_i, \bar{Z}), \quad s, r = l, h$$

- The four scenarios we consider correspond to:
  'low' and 'high' values of investment and initial conditions.
- We can then compute expected returns to investment:

$$Ret^{i,h} = \hat{f}^i_a(H^h_{i,a-1}, X^h_i, \bar{Z}) - \hat{f}^i_a(H^h_{i,a-1}, X^l_i, \bar{Z}), \text{ return for high initial condition}$$

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Challenges

- There are a number of challenges:
  1. How to design scenarios;
  2. How to deal with measurement error in beliefs;
  3. How to obtain beliefs in a metric that can be compared to the actual data on development;

How to build scenarios: initial conditions

- To design scenarios for initial conditions, we use our data to estimate a factor model (IRT) for language and cognitive development for 12 month old children;

$$m^*_{i,k,t-1} = \alpha^k + \beta^k y_{i,t-1} + \epsilon_{i,k};$$

  - Dichotomous variables $m_{i,k,t-1} \in \{0,1\}$: $Prob\{m_{i,k,t-1} = 1\} = Pr\{m^*_{i,k,t-1} \geq 0\}$;
  - Polytomous variables $m_{i,k,t-1} \in \{1,2,...,L\}$: $Prob\{m_{i,k,t-1} = l\} = Pr\{c_{l-1} \leq m_{i,k,t-1} \leq c_l\}$, where $c_0 = -\infty$;
  - Continuous variables: $m_{i,k,t-1} = m^*_{i,k,t-1}$;

- The estimates of this factor model are used to identify a number of words that seem to be particularly salient as a marker of cognitive development;
- The assumption is that respondents use the same measurement system to assess children development;
- Given the estimated parameters, we can translate a scenarios in some of the $m_{i,k,t-2}$ into an estimate of $y_{i,t-1}$.

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Measurement tools

- The interviewers first 'trains' respondents in the use of the tablets we use for elicitation.
- In particular we want to elicit measure of child development as probability statements relative to certain outcomes.

  training

- The interviewers then move on to a different example closer to the questions that will be asked

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- Finally there are questions about child development

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How to build scenarios: parental investment

- We use visual aids to describe the investment scenario.

Low investment

High investment

Final outcomes, measurement error, and metric

- For final outcomes, we use a similar approach: measurement system and identification of items with particular salience.
- To deal with measurement error we ask about the ability of a child to perform different tasks for each scenario.
  - These different measures allow us to deal with measurement error.
- We want to design the questions so that the implied latent factors can be measured in the same metric as the data used to estimate the objective production function.
- In this respect, we used different approaches in Colombia and India:
  - In Colombia, we ask the age at which a child is able say certain words for each scenarios;
  - In India, we elicit the probability that the child will say certain words for each scenario.
  - The second approach is easier to deal with to get a comparable metric.

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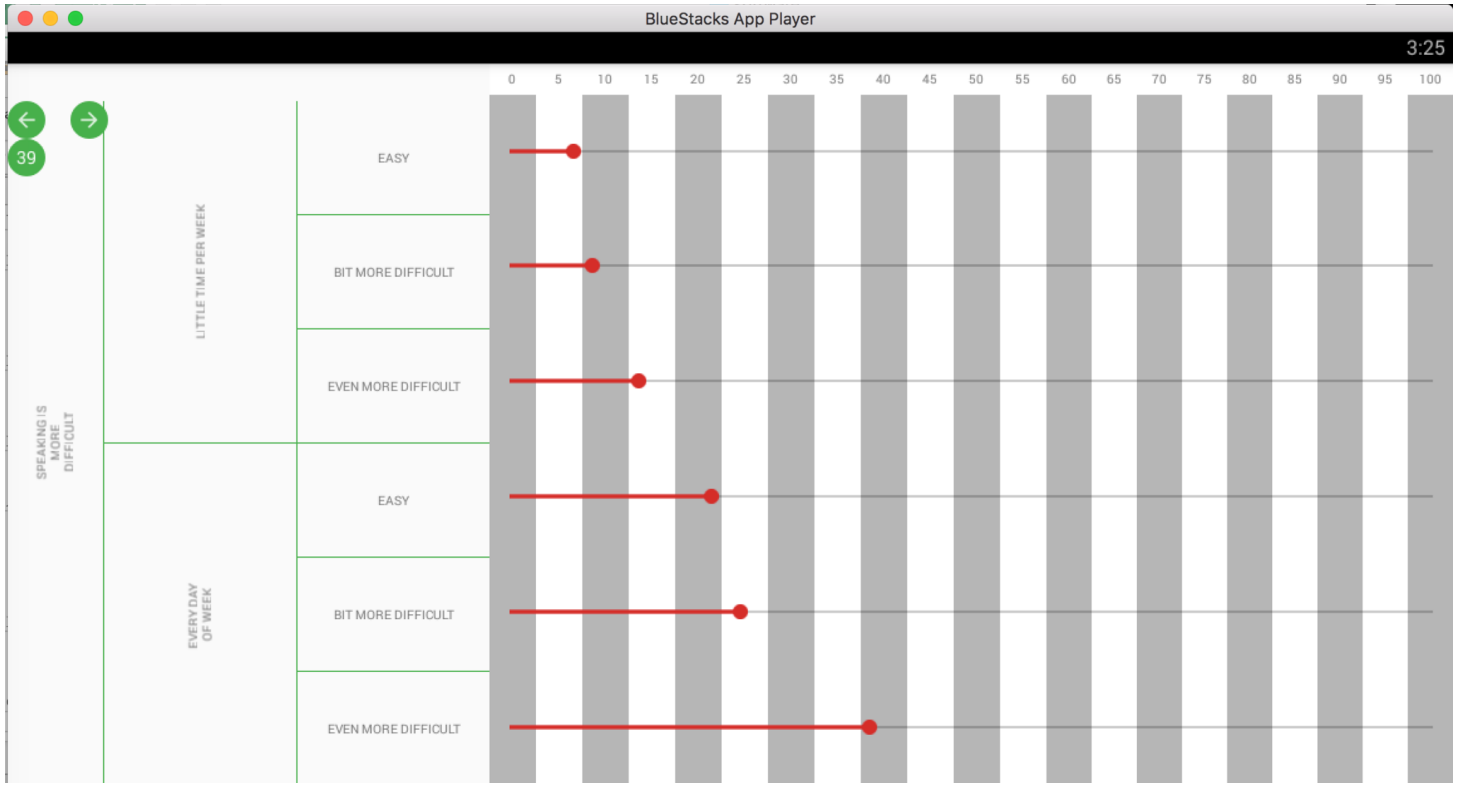
Measuring beliefs

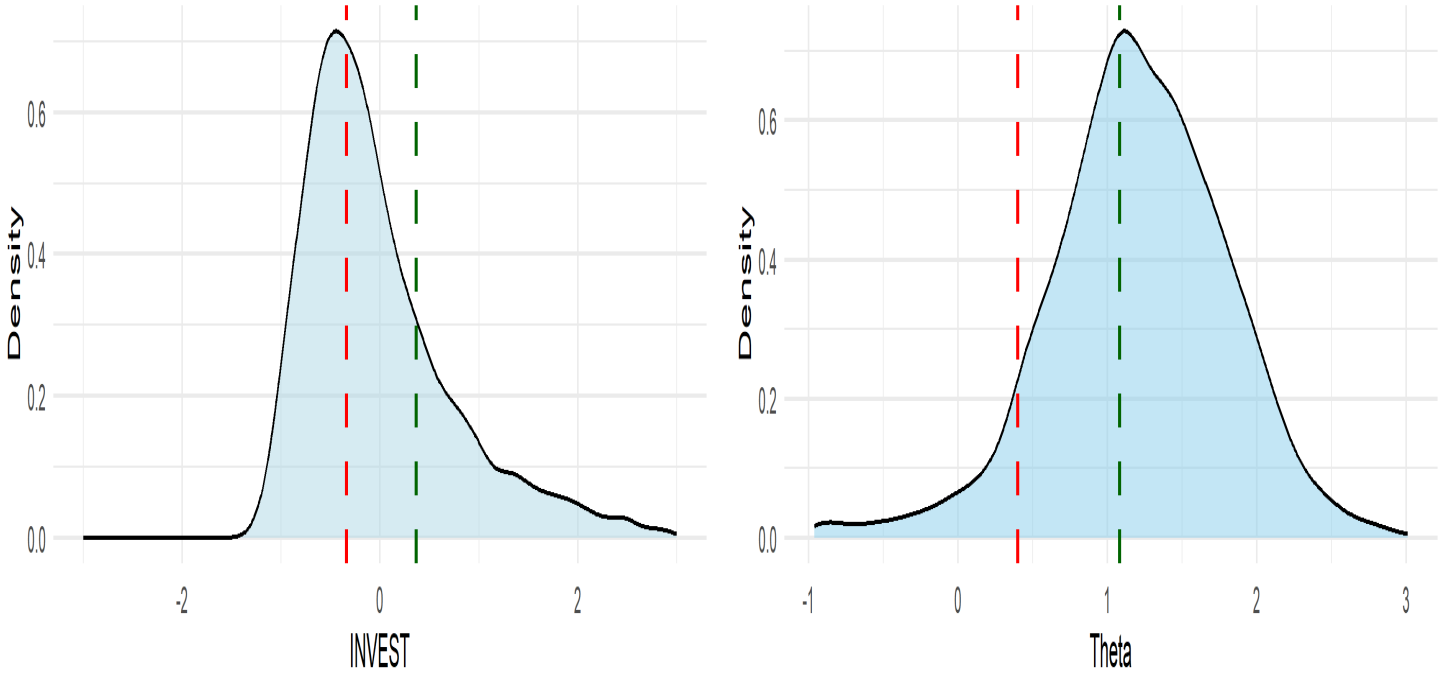
- In the end we will have something like



- This is repeated with different initial conditions

Constructing Hypothetical Scenarios

- The estimates of the IRT model and the definitions of the scenarios can be used to establish what part of the relevant domains are spanned by the scenarios.



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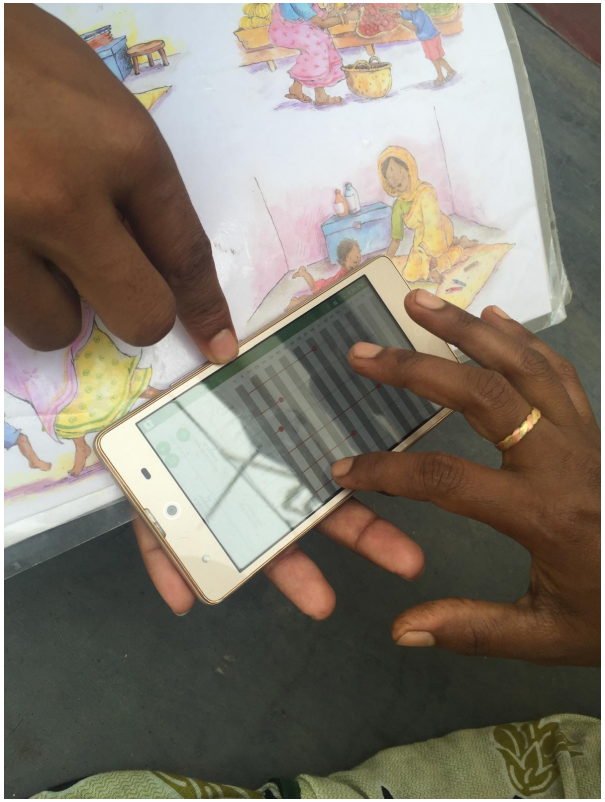

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Measuring beliefs in rural India

- We collected data around an RCT to evaluate a parenting intervention in India.
- The data has a *longitudinal dimension* as it was collected at baseline and at midline, 12 months later.
- The RCT was conducted in 3 districts in Odisha; 192 (small) villages randomised into:
  - a control group;
  - a nutritional education intervention;
  - a parenting intervention delivered through home visits;
  - a parenting intervention delivered through group visits.

- In each villages we have a sample of 12 children and their principal caregivers (PC);

- We observe the connections within each group;

- In one of the arms, the sample PC meet once a week with their children to discuss and practice the parenting curriculum.

- This structure gives a unique opportunity to analyse the role of (small) networks in learning

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Parenting interventions and their impacts: a summary

- The two parenting interventions have been shown to have an impact on cognitive development of children aged about 12 months at baseline;
- The results, published in Grantham-McGregor (2020), show an impact of about 0.3SD for both arms.
- No impact in the nutritional education arm

Beliefs and the intervention

- As we collect data on beliefs we:
- ... describe the distribution of the subjective probability obtained for each of the four scenarios;
  - .... consider the distribution of the average probabilities, between hard, medium and easy words.
- ... relate subjective beliefs to parental investment.
- ... explore the longitudinal dimension and check how beliefs change over time.

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  - .... consider the distribution of the average probabilities, between hard, medium and easy words.
- ... relate subjective beliefs to parental investment.
- ... explore the longitudinal dimension and check how beliefs change over time.

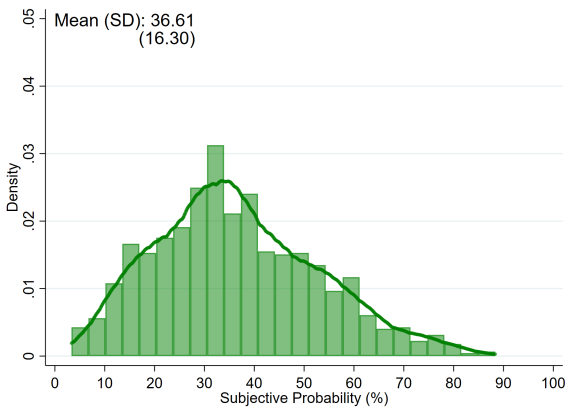
Beliefs and the intervention

- As we collect data on beliefs we:
- ... describe the distribution of the subjective probability obtained for each of the four scenarios;
  - .... consider the distribution of the average probabilities, between hard, medium and easy words.
- ... relate subjective beliefs to parental investment.
- ... explore the longitudinal dimension and check how beliefs change over time.

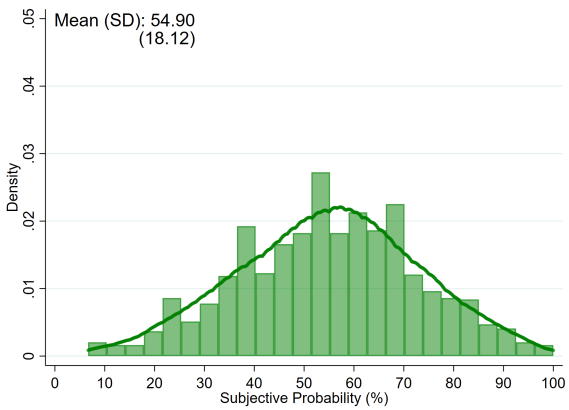
Beliefs (average subjective prob) at baseline

- We can now look at the data on subjective beliefs, starting from the distribution of probabilities under different scenarios.

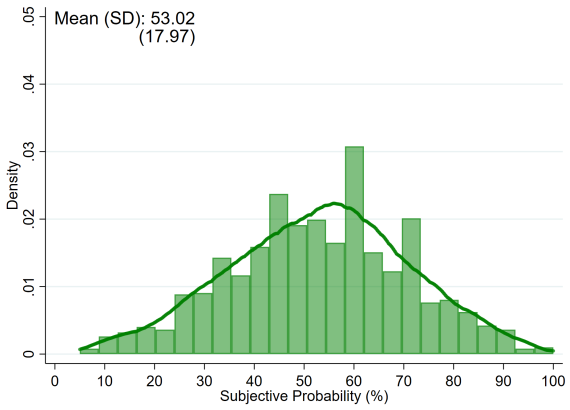
Low development, Low investment



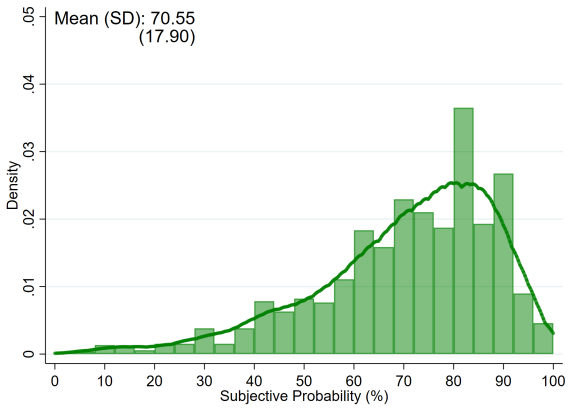
Low development, High investment



High development, Low investment

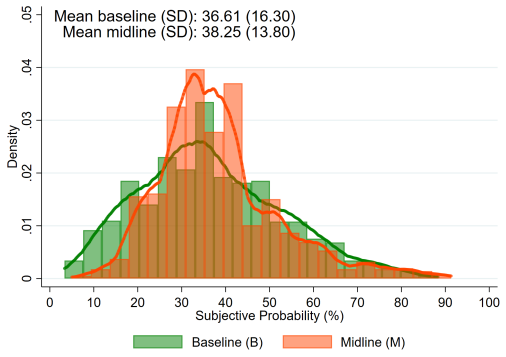


High development, High investment

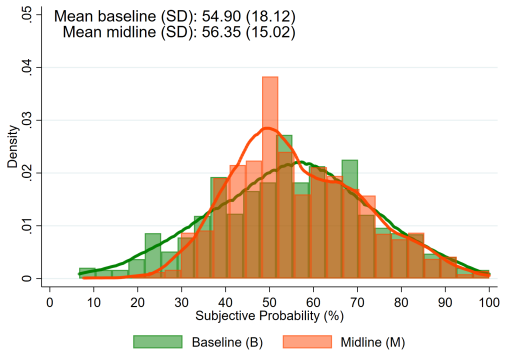


Beliefs (average subjective prob) at midline

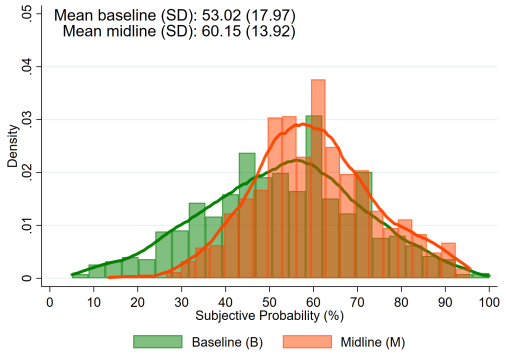
Low development, Low investment



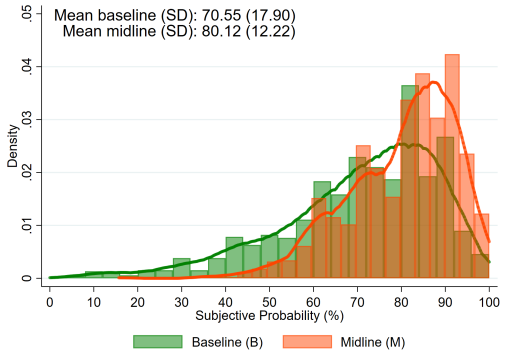
Low development, High investment



High development, Low investment



High development, High investment



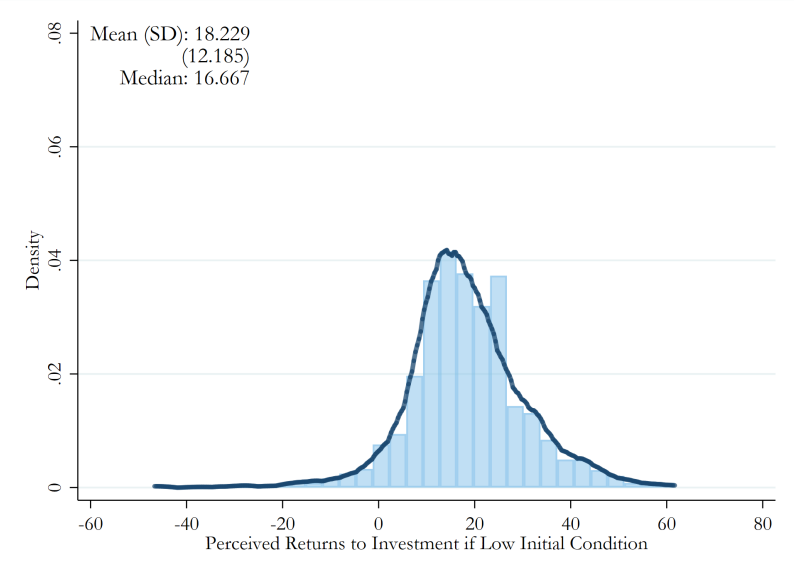
Returns to investment

- The data on probabilities can be used very simply to compute returns to investment.
- We can compute returns to investment when the initial conditions are low and high

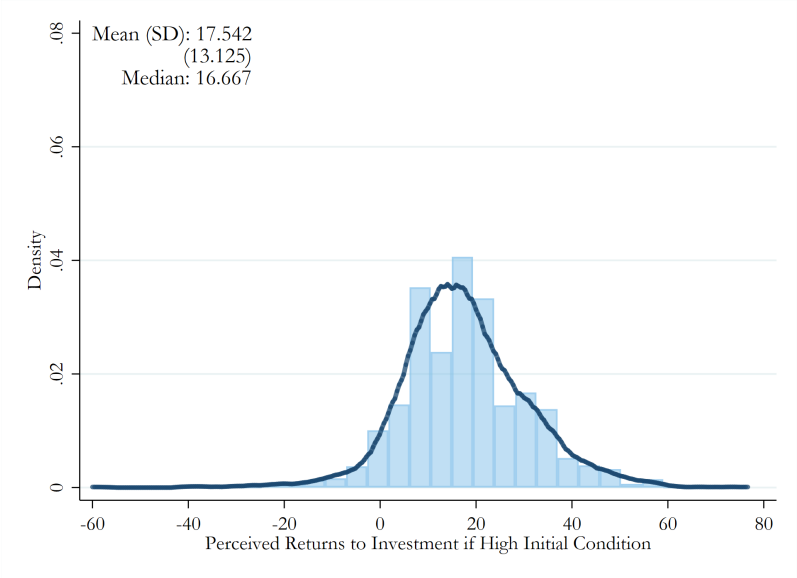
Perceived returns to investment at baseline

Perceived returns to investment at baseline

Low initial condition



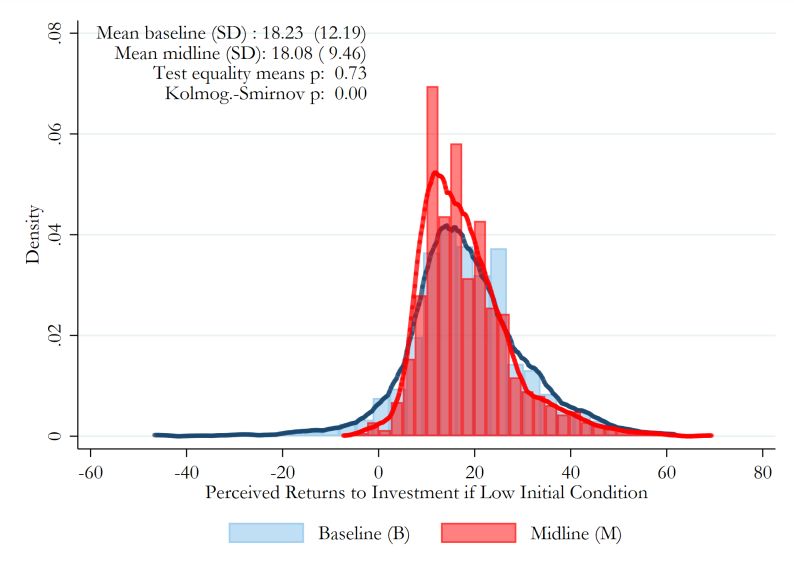
High initial condition



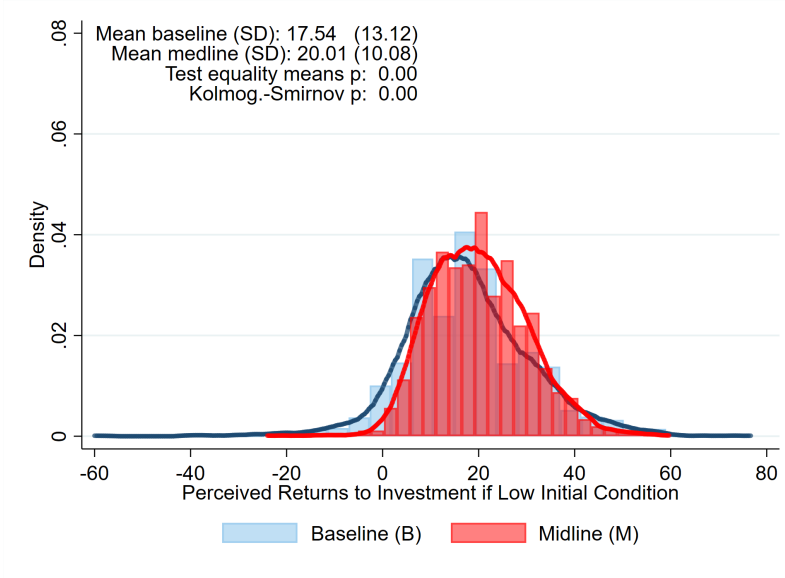
Perceived returns at baseline vs midline

Perceived returns to investment at baseline vs midline

Low initial condition



High initial condition



Do perceived returns to investment predict investment at endline?

Dependent variable:	Material Investment (endline)					
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)	(5) (OLS)	(6) (IV)
Perceived returns (*medium* words) if High Dev. (midline)			0.059**	0.117***	0.056**	0.107***
			(0.029)	(0.040)	(0.028)	(0.038)
Perceived returns (*medium* words) if Low Dev. (midline)	0.025	0.068*			0.011	0.037
	(0.028)	(0.040)			(0.027)	(0.037)
Observations	1251	1251	1251	1251	1251	1251
Kleibergen-Paap F-stat (first stage)		619.510		545.432		458.964
Controls	Yes	Yes	Yes	Yes	Yes	Yes

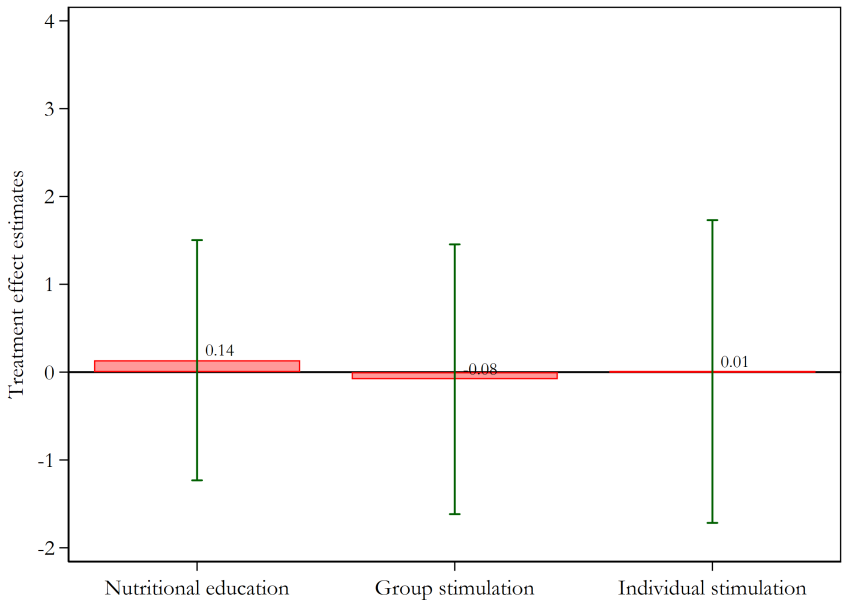
Dependent variable:	Time Investment (endline)					
	(1) (OLS)	(2) (IV)	(3) (OLS)	(4) (IV)	(5) (OLS)	(6) (IV)
Perceived returns (*medium* words) if High Dev. (midline)			0.080***	0.092***	0.071**	0.081**
			(0.028)	(0.034)	(0.028)	(0.035)
Perceived returns (*medium* words) if Low Dev. (midline)	0.055**	0.065**			0.037	0.041
	(0.025)	(0.033)			(0.025)	(0.033)
Observations	1251	1251	1251	1251	1251	1251
Kleibergen-Paap F-stat (first stage)		619.510		545.432		458.964
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note. The variables have been standardized to have mean 0 and standard deviation 1. The perceived returns to investment (saying *medium* words) at midline are instrumented by the perceived returns to investment (saying *hard* word) at midline. Time investment is measured by the FCI questionnaire, while material investment is measured through the HOME questionnaire. The additional controls are a dummy variable equal to 1 if the child is the first born, the gender of the target child, the number of siblings in the household, the mother's education and Raven score. Standard errors in parentheses are clustered at the village level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

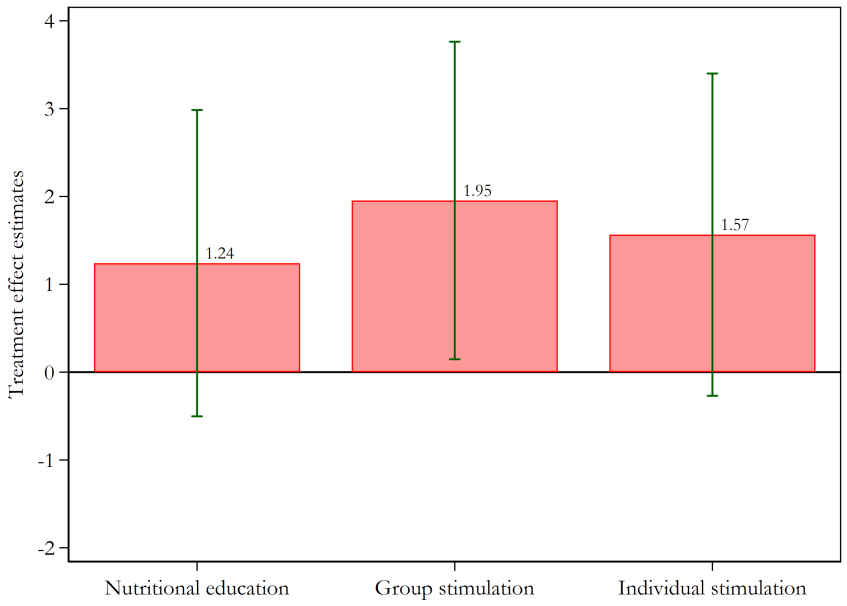
Treatment effect on perceived beliefs

- Having looked at the impact of the interventions on various outcomes, we look at their impacts on beliefs.

Perceived returns
if low development



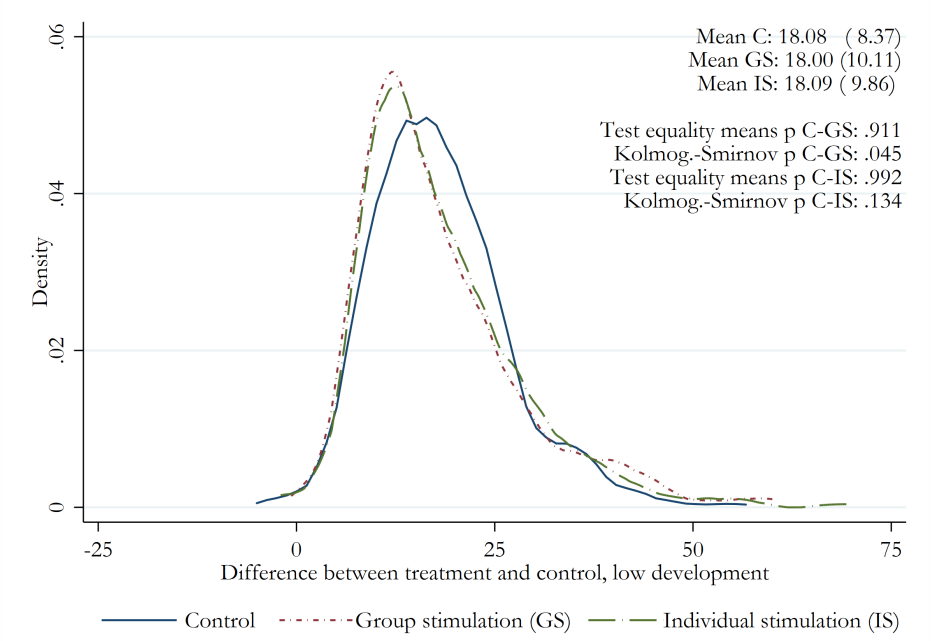
Perceived returns
if high development



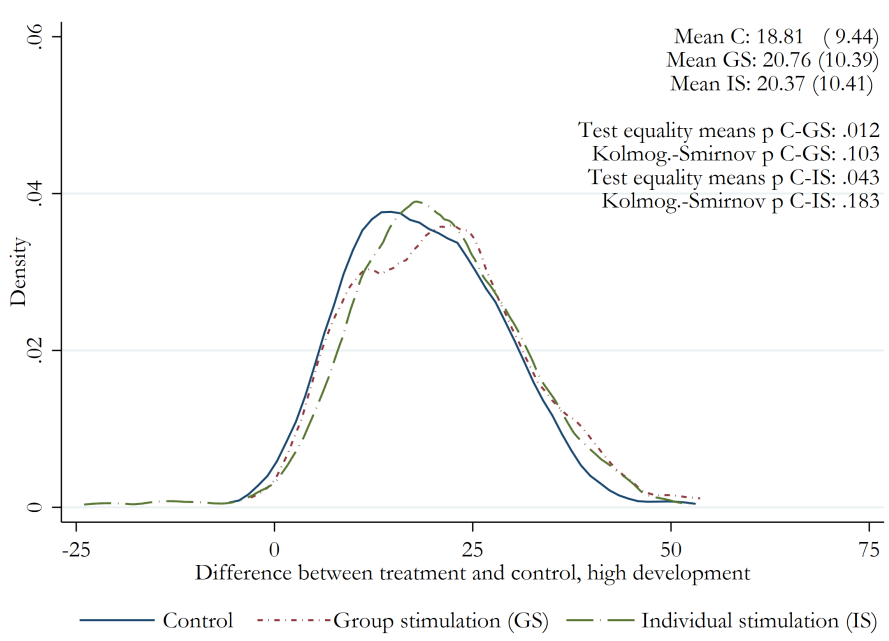
Note. 95% confidence intervals in green

Density plots by treatment status

Perceived returns
if low development



Perceived returns
if high development



Estimating production functions

- The next step is to use the beliefs data to estimate subjective production functions.
- We start with the assumption that individuals:
  - have the right *functional form assumption*
  - but could have the *wrong parameters*.
- We assume the PF is Cobb-Douglas, which is not a bad approximation.

$$lny_{i,t} = \psi_1 lny_{i,t-1} + \psi_2 lnX_{i,t} + v_{i,t}$$

where $lny_{i,t}$, and $lnX_{i,t}$ are latent factors for child development and investment respectively.

- To get estimates of these latent factors we use the same measurement system we used to design the *scenarios*.

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Estimating production functions

- The subjective PF will be given by:

$$lny_{it} = \mu_{1,it} lny_{i,t-1} + \mu_{2,it} lnX_{it} + \varepsilon_{it}$$

- This approach and the use of the right normalizations guarantees that the same metric is used in the objective and subjective production functions, so that the estimated parameters are comparable.
- For each individual respondent, we have 4xn observations to estimate the production function:
  - 4 scenarios;
  - n outcomes.
- We use a OLS estimator to estimate these coefficients.

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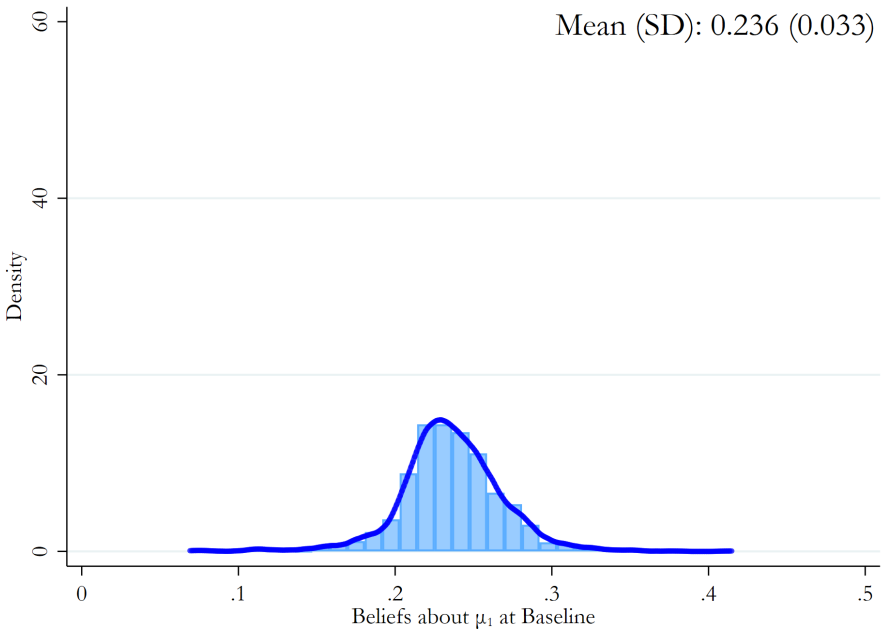
Objective production function

Outcome	Input	Estimate	Standard Error	P-value
Ln Human Capital	Ln Human capital (baseline)	0.343***	0.111	0.002
	Ln Parental investment	0.377**	0.191	0.049
	Raven score (mother)	-0.027	0.020	0.173
	Mother's Education	-0.077	0.066	0.241
	Child firstborn	-0.027	0.041	0.516
	Child's gender	0.035*	0.020	0.089
	Number of siblings	0.038*	0.021	0.065
Ln Parental Investment	Treatment indicator	0.177***	0.054	0.001
	Ln Human capital (baseline)	0.329***	0.115	0.004
	Raven score (mother)	0.094***	0.023	0.000
	Mother's Education	0.355***	0.051	0.000
	Child firstborn	0.121**	0.059	0.040
	Child's gender	-0.023	0.041	0.569
	Number of siblings	-0.093***	0.030	0.002

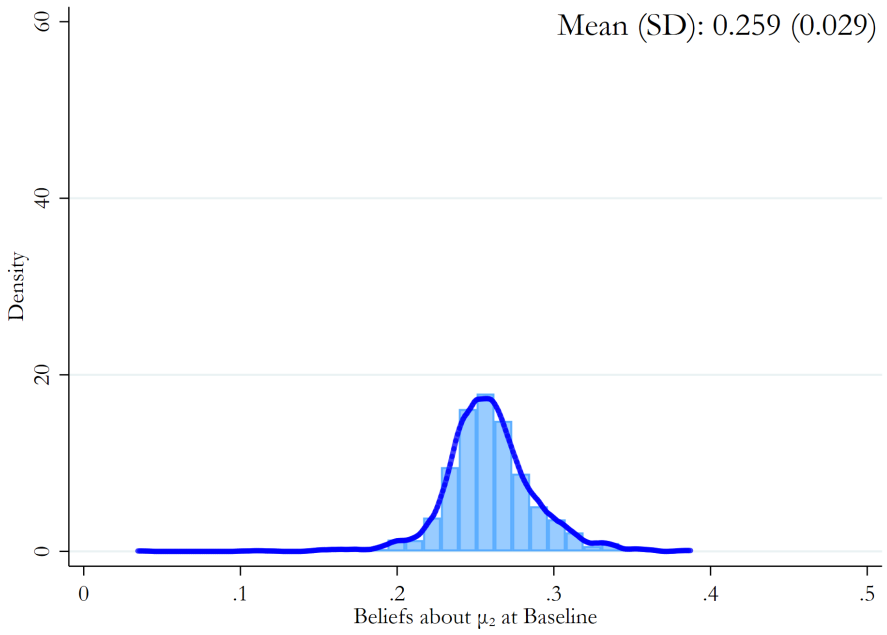
Note. Sample: N=1222. The measurement system and the production function are estimated jointly with the estimation method developed by Muthen (1984). Standard errors in parentheses computed based on inverting information matrix (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Beliefs on Cobb-Douglas at baseline

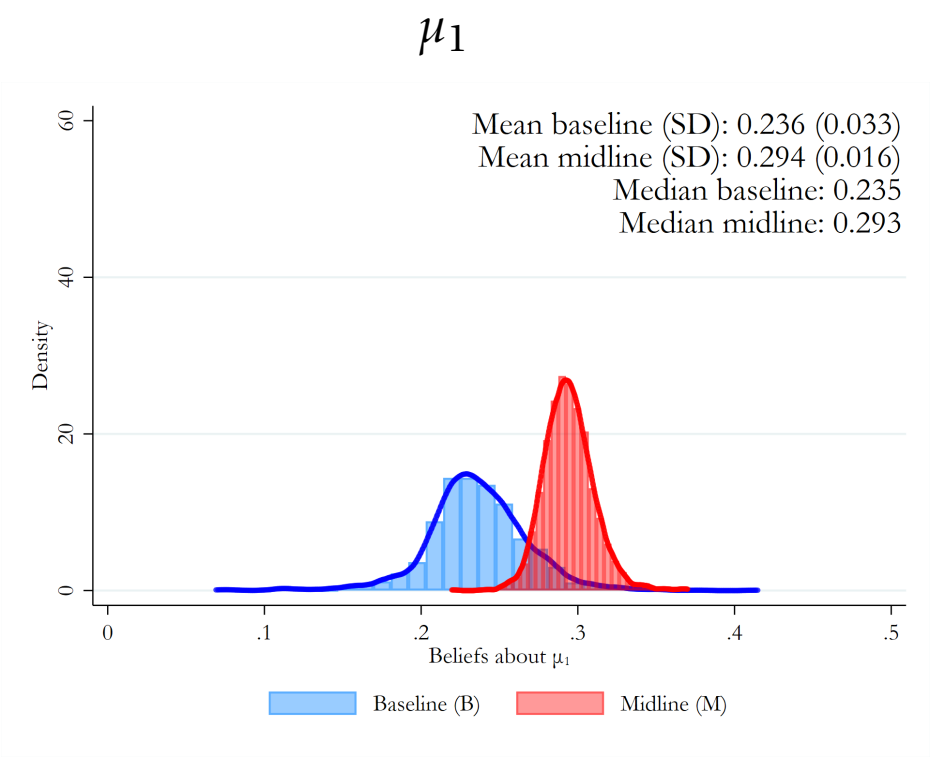
μ_1 at baseline

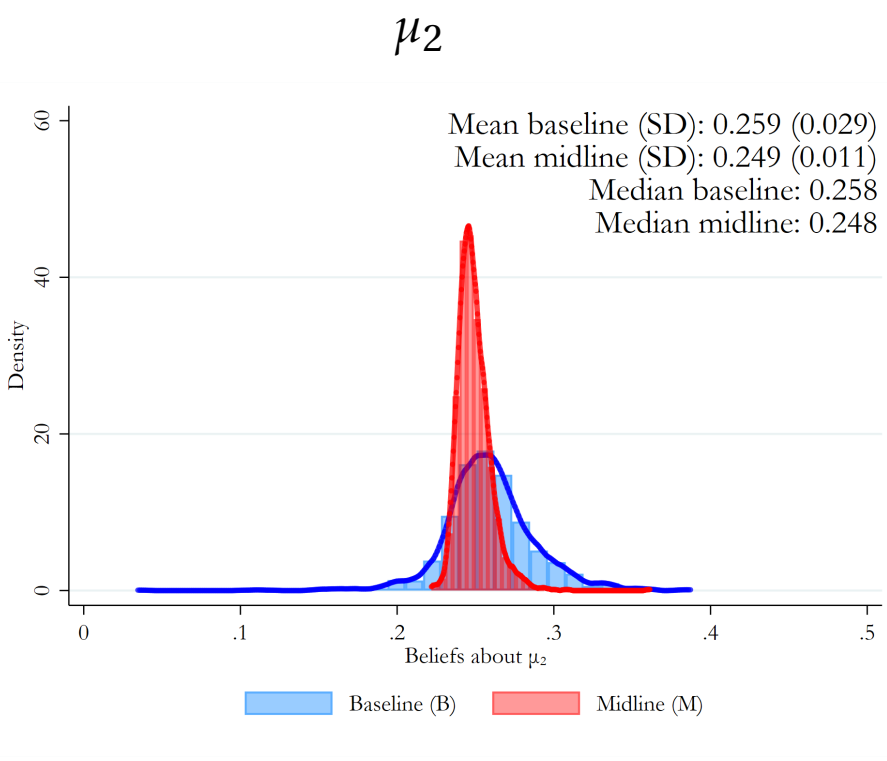


μ_2 at baseline

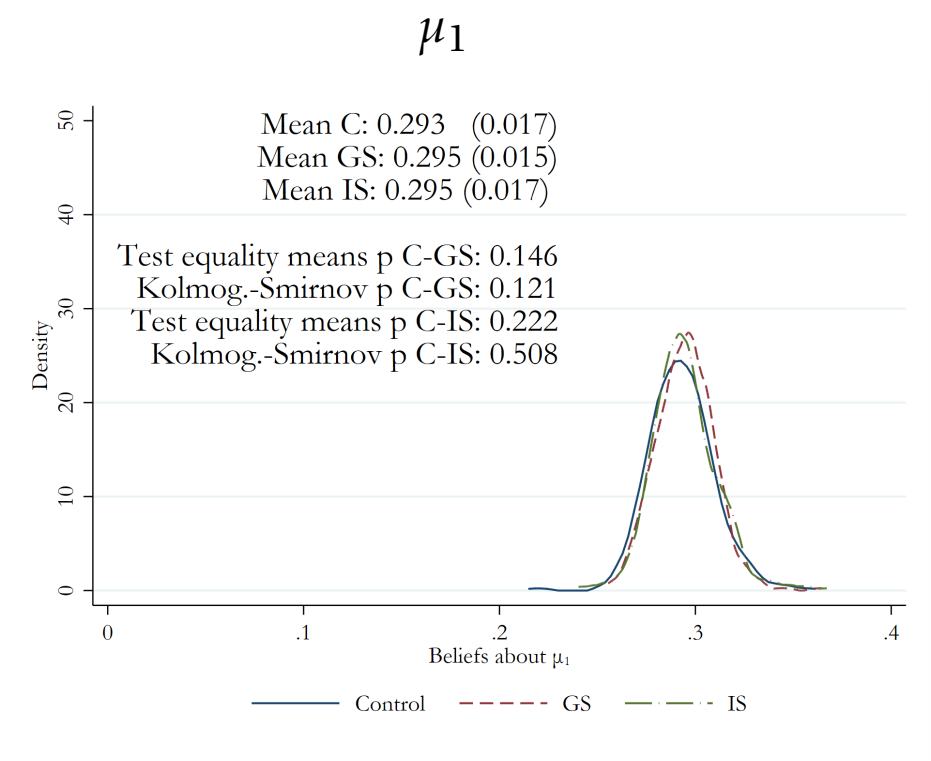


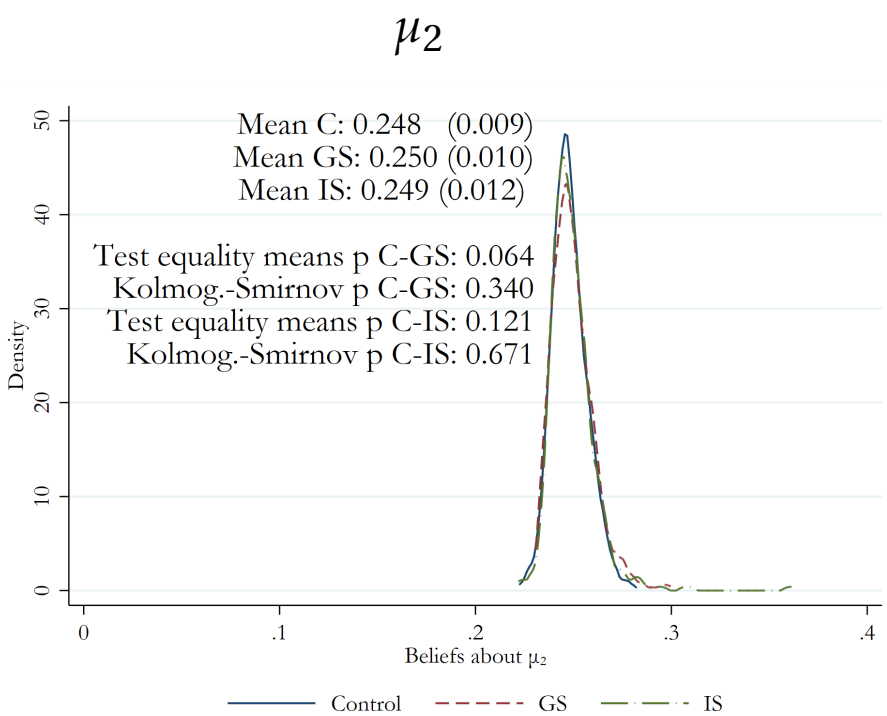
Beliefs on Cobb-Douglas at baseline vs. midline





Treatment status of beliefs: midline evidence





Outline

1. Introduction

2. Parental beliefs

3. Networks and their measures

4. Learning

5. Conclusions

Measuring networks' structure

- The data longitudinal dimension leads us to study learning and changes in beliefs.

- A big advantage of the in each survey wave, we collected detailed data on the social network among study participants.
- In each village, we have 12 households in the sample.
- Each respondent was asked 'Do you know [NAME]?', for each other survey member in their village.
  - If a respondent answered affirmatively to knowing another participant, we asked a series of follow-up questions relating to the intensity of their relationship.

- These data provide a detailed picture of not only who knows whom, but also how well they know each other.

Network measures

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- These data provide a detailed picture of not only who knows whom, but also how well they know each other.

Network measures

Measuring the architecture of the network

- The nature of our data and the information we have on the connectedness within each group (village) allows us to compute measures of the quality of the connections using adjacency matrices for each.
- In particular, given an adjacency matrix, w_{ij} we compute:

$$C_{out}(i) = \sum_{j}^{N} w_{ij} \; ; \qquad C_{in}(j) = \sum_{i}^{N} w_{ij} \; ;$$

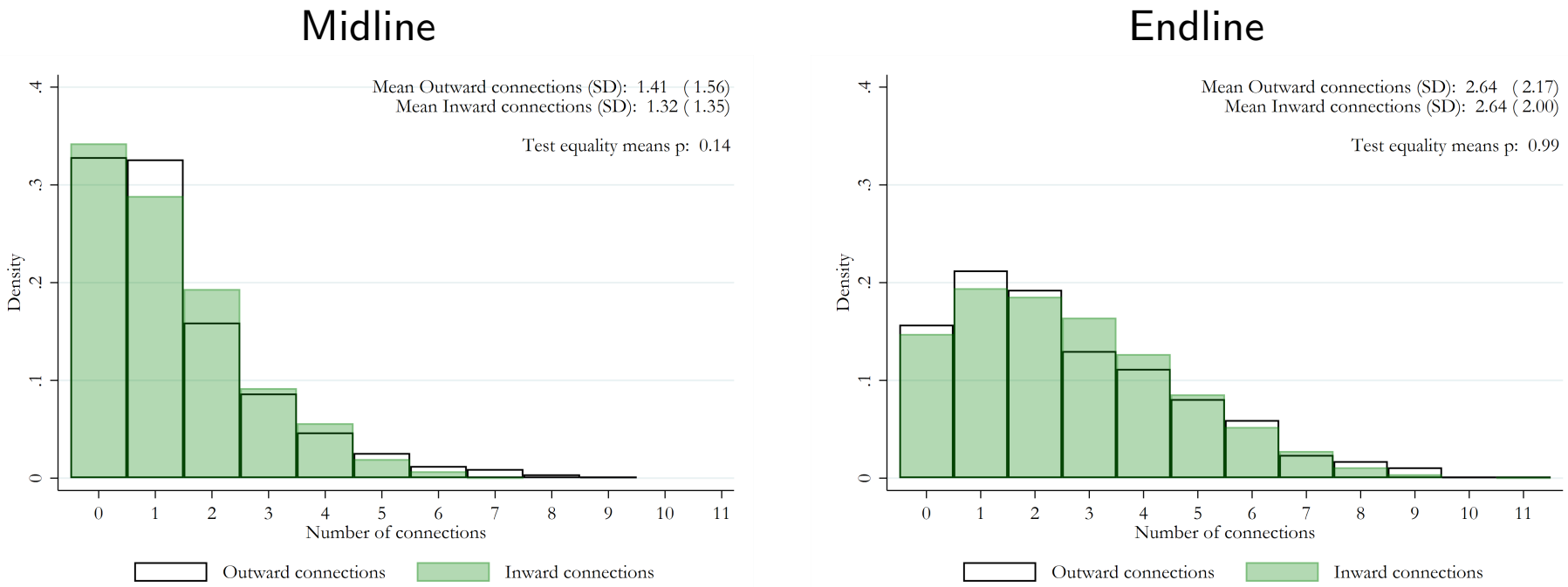
where $C_{out}(i)$ and $C_{in}(i)$ our out-degree and in-degree centrality ;
w_{ij} is either:

- 1 if i knows j
- a factor valued from 0 and 1, measuring how well i know j, obtained from an IRT model on the available measures

quality of links

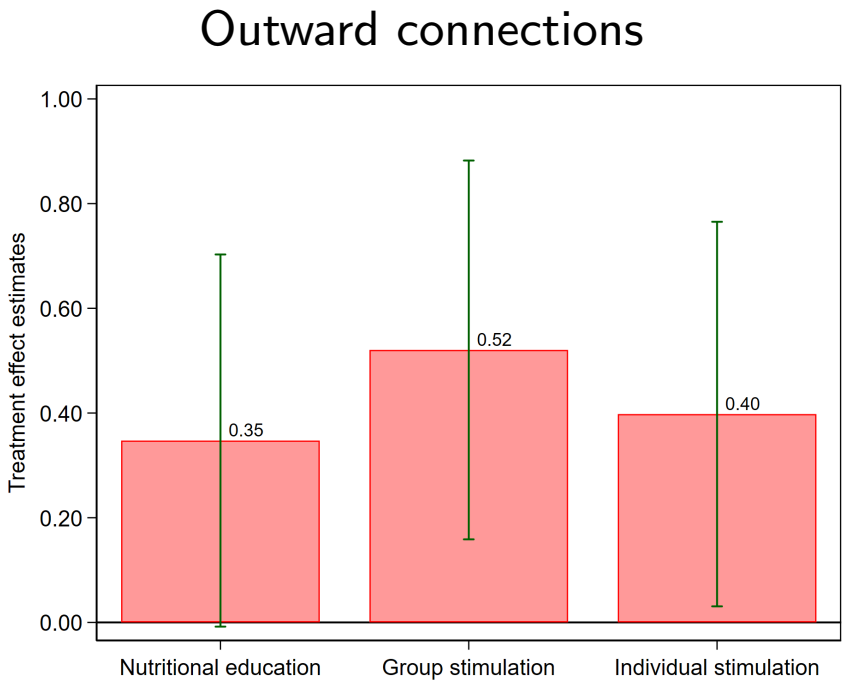
High isolation in the sample

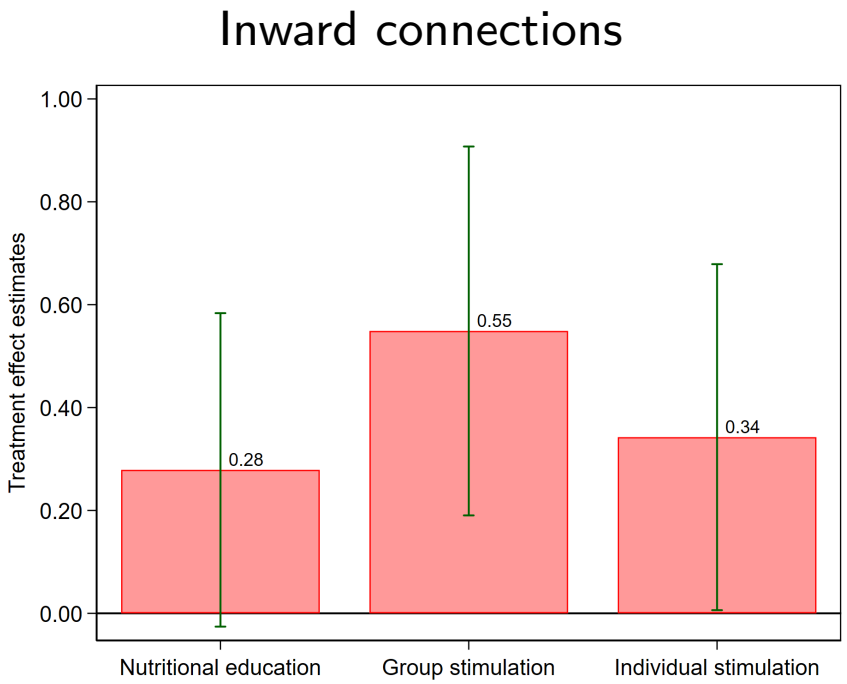
- Our sample is characterised by very few connections.



Note. The Figure presents the histograms of the distribution of connections at midline and endline. Inward connections: people that report to know you. Outward connections: people you know. The figures report the mean and the standard deviation of the distribution in parentheses. We report the p-value of a t tests on the equality of means between the two groups assuming unequal variances.

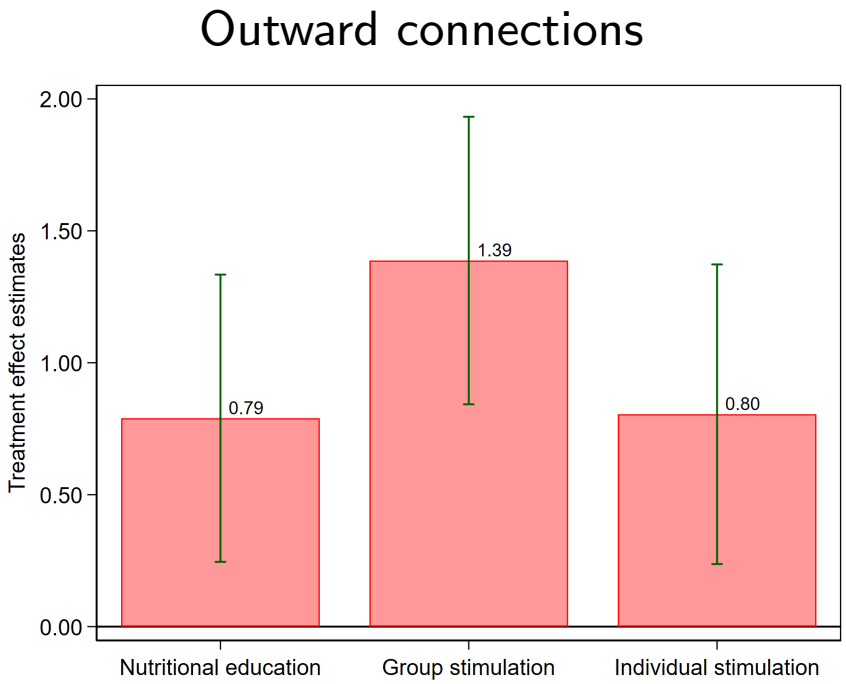
The (group) intervention improves connections at midline

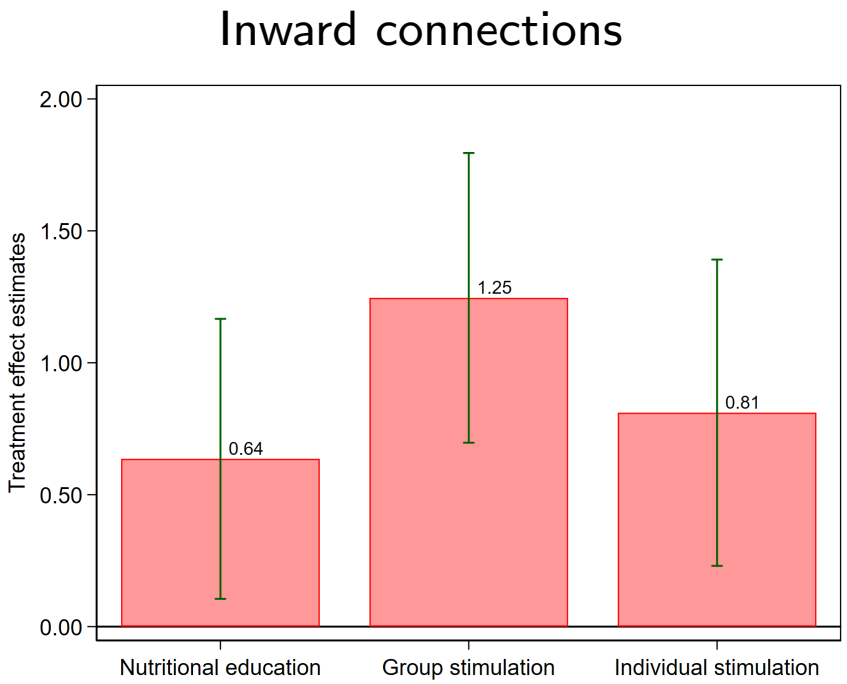




Note. 95% confidence intervals in green.

The (group) intervention improves connections at midline and endline





Note. 95% confidence intervals in green.

The (group) intervention improves connections

Panel A: Midline Dependent variable:	Outward connections (1)	Inward connections (2)	Quality outward connections (3)	Quality inward connections (4)
Group stimulation (GS)	0.521***	0.549***	0.326***	0.261***
	(0.183)	(0.182)	(0.120)	(0.097)
Individual stimulation (IS)	0.398**	0.342**	0.260**	0.165*
	(0.186)	(0.170)	(0.124)	(0.093)
Nutritional education (NE)	0.347*	0.279*	0.187	0.057
	(0.180)	(0.154)	(0.114)	(0.082)
Observations	1282	1282	1282	1278
P-val GS=NE	0.343	0.131	0.254	0.040
P-val GS=IS	0.516	0.284	0.616	0.377
P-val IS=NE	0.785	0.703	0.558	0.251
Panel B: Endline Dependent variable:	Outward connections (1)	Inward connections (2)	Quality outward connections (3)	Quality inward connections (4)
Group stimulation (GS)	1.388***	1.246***	0.882***	0.352***
	(0.276)	(0.278)	(0.183)	(0.119)
Individual stimulation (IS)	0.805***	0.811***	0.587***	0.303**
	(0.288)	(0.294)	(0.196)	(0.131)
Nutritional education (NE)	0.790***	0.636**	0.481**	0.140
	(0.276)	(0.269)	(0.187)	(0.113)
Observations	1261	1261	1261	1261
P-val GS=NE	0.037	0.031	0.045	0.100
P-val GS=IS	0.050	0.156	0.157	0.735
P-val IS=NE	0.959	0.557	0.617	0.242

Note. The table presents the estimates from the impact of the treatment on the number of outward and inward connections at midline and endline. Standard errors in parentheses are clustered at the village level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

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Modeling learning

- The next step is to model how people's beliefs change over time.
- The longitudinal dimension of the data allows us to study how perception changes over time.
- Time $t+1$ perception depends on time t perceptions and a *signal*
- We perform the exercise looking at:
  - Changes in expected returns to parental investment:
    - Low initial conditions
    - High initial conditions
  - Putting more structure on the beliefs:
    - How the parameters of the subjective production function change.
- We use as signals:
  - Rate of growth of own child and children in the village;
  - 'Surprises' in the same, given subjective production function;
  - OLS estimates of the production function on the village children.
  - Other individuals parameters.
- The intervention affects connections and therefore can change the mechanics of learning.

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- We use as signals:
  - Rate of growth of own child and children in the village;
  - 'Surprises' in the same, given subjective production function;
  - OLS estimates of the production function on the village children.
  - Other individuals parameters.
- The intervention affects connections and therefore can change the mechanics of learning.

Modeling learning

- The next step is to model how people's beliefs change over time.
- The longitudinal dimension of the data allows us to study how perception changes over time.
- Time $t+1$ perception depends on time t perceptions and a *signal*
- We perform the exercise looking at:
  - Changes in expected returns to parental investment:
    - Low initial conditions
    - High initial conditions
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Learning subjective returns on low initial conditions

Table: Learning: perceived returns if low initial conditions

Dependent variable:	Perceived returns if low initial conditions						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perceived returns if low development - baseline	0.066**	0.070*	0.063**	0.063**	0.061*	0.065	0.031
	(0.032)	(0.041)	(0.031)	(0.032)	(0.032)	(0.041)	(0.043)
Average returns if low dev. (village)		-0.000				0.000	-0.001
		(0.003)				(0.003)	(0.003)
Average *perceived* returns if low dev. (village)			0.190***			0.155*	0.152*
			(0.068)			(0.089)	(0.086)
Change in child dev. (midline-baseline)				0.000		-0.029	-0.052
				(0.138)		(0.164)	(0.160)
Average change in child dev. (village)					0.180	0.169	0.164
					(0.261)	(0.274)	(0.264)
Observations	1303	936	1303	1269	1269	914	912
Controls	No	No	No	No	No	No	Yes

Note. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at the village level (*** p<0.01, ** p<0.05, * p<0.1).

Learning subjective returns on high initial conditions

Table: Learning: perceived returns if high initial conditions

Dependent variable:	Perceived returns if high initial conditions						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Perceived returns if high development - baseline	0.042	0.033	0.052*	0.039	0.040	0.038	0.047
	(0.030)	(0.035)	(0.029)	(0.030)	(0.030)	(0.034)	(0.033)
Average returns if high dev. (village)		-0.007*				-0.005*	-0.005*
		(0.004)				(0.003)	(0.003)
Average *perceived* returns if high dev. (village)			0.301***			0.329***	0.335***
			(0.075)			(0.090)	(0.090)
Change in child dev. (midline-baseline)				0.033		0.021	0.022
				(0.128)		(0.160)	(0.159)
Average change in child dev. (village)					-0.308	-0.082	-0.134
					(0.256)	(0.292)	(0.315)
Observations	1303	930	1303	1269	1269	909	907
Controls	No	No	No	No	No	No	Yes

Note. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at the village level (*** p<0.01, ** p<0.05, * p<0.1).

Learning the production function

Table: Learning: μ_1

Dependent variable:				μ_1			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
μ_1 (baseline)	-0.028	-0.057*	-0.033	-0.032	-0.035	-0.047	-0.030
	(0.030)	(0.032)	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)
Average perceived μ_{1t} village	0.183***					0.161***	0.158***
	(0.031)					(0.032)	(0.032)
Signal own child		-0.077**				-0.064**	-0.046
		(0.032)				(0.032)	(0.032)
Signal of network (average)			0.027			0.040	0.053
			(0.029)			(0.059)	(0.058)
Signal of *connected* network (weighted average)				0.025		-0.027	-0.040
				(0.030)		(0.062)	(0.060)
OLS μ_{1t} village					0.089***	0.060***	0.055***
					(0.022)	(0.018)	(0.016)
Observations	1303	1250	1281	1281	1303	1250	1248
Controls	No	No	No	No	No	No	Yes

Note. Vars have been standardized to have mean 0 and std 1. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at the village level (*** p<0.01, ** p<0.05, * p<0.1).

Learning the production function

Table: Learning: μ_2

Dependent variable:				μ_2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
μ_2 (baseline)	0.114**	0.111**	0.110**	0.110**	0.113**	0.110**	0.101**
	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.046)	(0.045)
Average perceived μ_{2t} village	0.012					0.010	0.011
	(0.033)					(0.034)	(0.034)
Signal own child		0.007				0.007	-0.000
		(0.030)				(0.030)	(0.030)
Signal of network (average)			0.013			0.018	0.010
			(0.028)			(0.060)	(0.060)
Signal of *connected* network (weighted average)				0.007		-0.019	-0.013
				(0.029)		(0.063)	(0.063)
OLS μ_{2t} village					0.011	0.011	0.011
					(0.031)	(0.030)	(0.035)
Observations	1303	1250	1281	1281	1303	1250	1248
Controls	No	No	No	No	No	No	Yes

Note. Vars have been standardized to have mean 0 and std 1. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at the village level (*** p<0.01, ** p<0.05, * p<0.1).

heterogeneous learning

Outline

1. Introduction

2. Parental beliefs

3. Networks and their measures

4. Learning

5. Conclusions

Conclusions

- In this talk, I have shown:
  - How to design questions about subjective beliefs and how to validate them.
  - How to use these data to estimate the parameters of a *subjective production function* to be compared to an objective one.
  - Our first attempt to model learning and how beliefs evolve.
- This specific example is indicative of a wider agenda which has been looking at the construction, validation and use of new measures.
- Would be grateful for any feedback.

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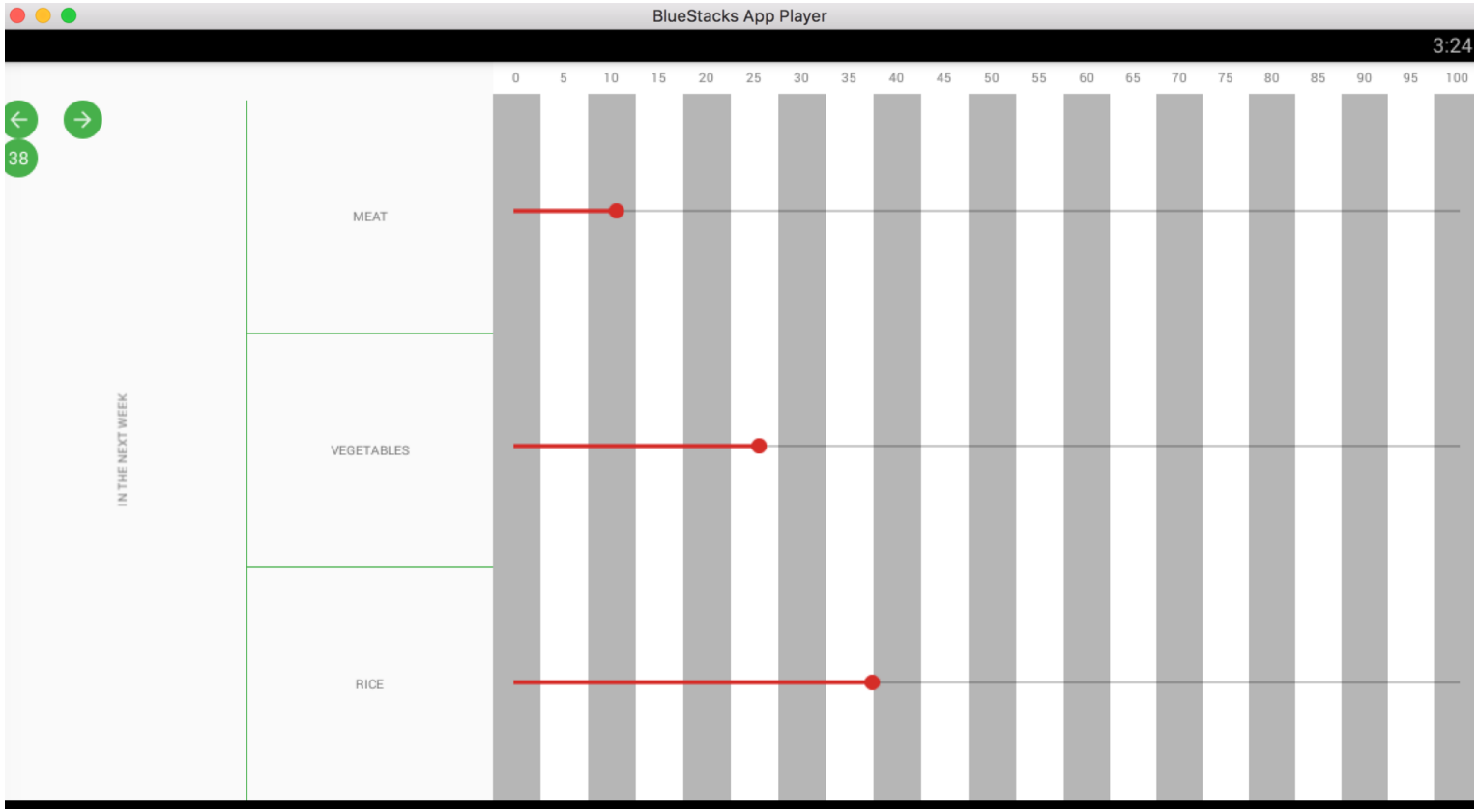
Measurement tools

- INTERVIEWER:
  - Out of the 100 families in your village, how many do you think will eat MEAT at dinner in the next week?
  - Out of the 100 families in your village, how many do you think will eat VEGETABLES at dinner in the next week? Â
  - Out of the 100 families in your village, how many do you think will eat RICE at dinner in the next week?
- If the respondent provides decreasing numbers of families (number of families in 2 smaller than in 1 and/or number of families in 3 smaller than in 2), please explain again the idea of the board as described above before going to the next questions.

Measurement tools



Back

Measurement tools: health exercise

- INTERVIEWER I will now ask you some questions about when children start to walk. Not particularly your child (or children in this village), but children in general. As before, you can move these beads to answer my questions and you will be able to modify your answers at any time of the game. This is the same board that we used before but now we will have number of children instead of number of families. But it is again from 0 to 100!
- So if my answer is 60 out of 100 for example (meaning that out of 100 children like the one we are considering, 60 of them will achieve the task) I will put the bead here. You get it? Notice, that the numbers at this side (0) means less children and at this other side (100) means more children.
- Let's start with our story- Suppose that there are 100 9-month-old children that are already crawling and they are healthy, which means they are fed well with a diversified diet, and have no illness:
  - Out of these 100 children, how many will be able to WALK by the age of 12-months-old?
  - and how many of them will be able to WALK by the age of 15-months-old?
- INTERVIEWER: If the respondent provides decreasing numbers of children (number of children in b smaller than in a), please explain again the idea of the board as described above before going to the next questions.

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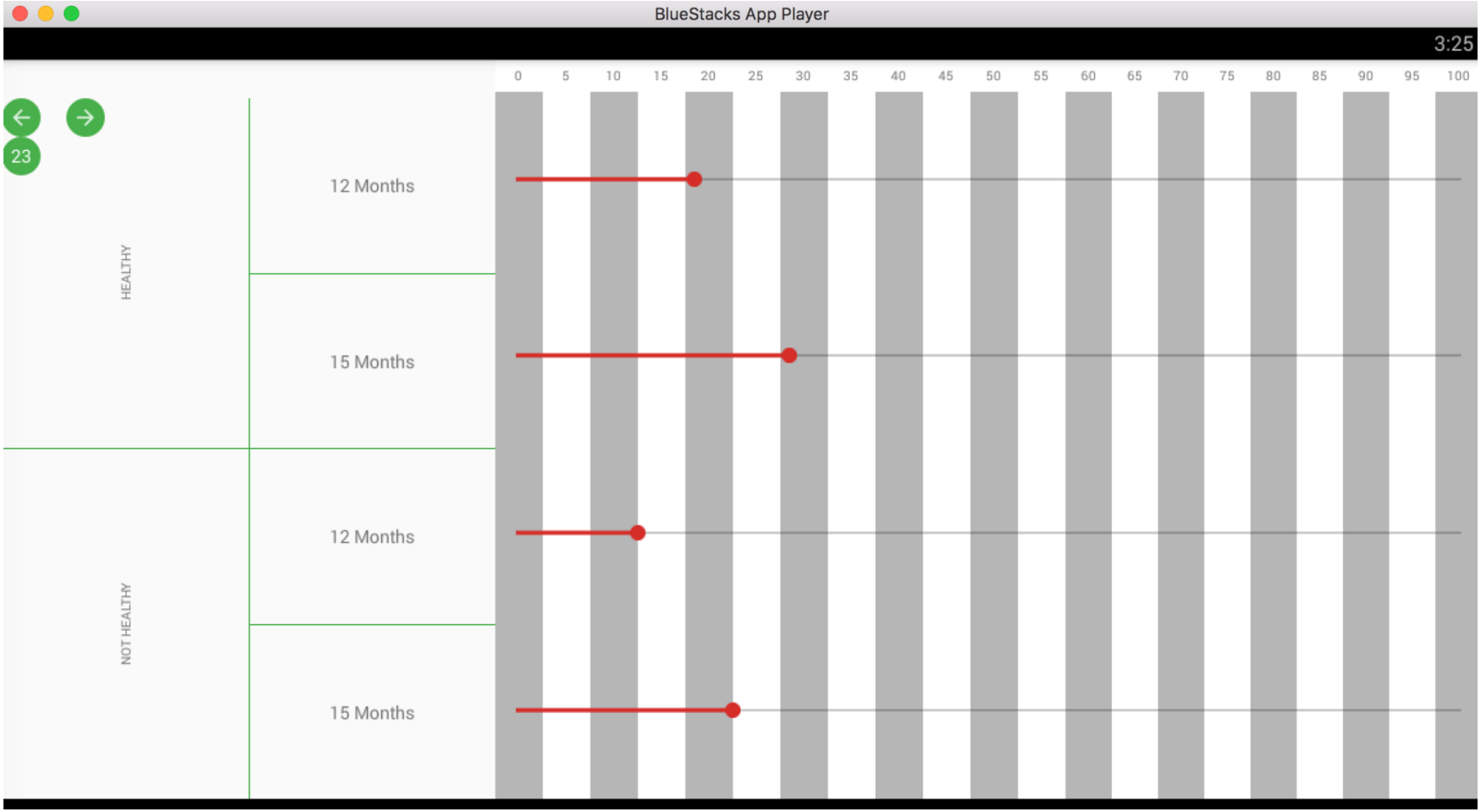
Back

Measurement tools

- INTERVIEWER: Let's change the story a bit:
  - Now, we will consider another 100 9-month-old children that are already crawling, but now they are unhealthy, which means that they are fed poorly – only with rice:
    - Out of these 100 children, how many of them will be able to WALK by the age of 12-months-old if you told me that the number of healthy children were XXX (show bead from line 1)?
    - and how many of them will be able to WALK by the age of 15-months-old if you told me that the number of healthy children were XXX (show bead from line 2)?
- INTERVIEWER: If the respondent provides decreasing numbers of children (number of children in b smaller than in a), please explain again the idea of the board as described above before going to the next questions.

Measurement tools



Measurement tools

- INTERVIEWER: Now we'll talk about how children learn to speak. Please notice that we still will talk about children in general not about your own children.
- INTERVIEWER Let's imagine that we have now 2 TYPES of 12 months old children one type that speak easily and another type that find it harder.
- INTERVIEWER: (INTRODUCE ILLUSTRATIONS) We also have 2 TYPES of families.

  In the first type of family, the mother spends little time with her child, so, for instance, the child is left alone with only one picture children book, when she goes to the market the child is left alone, when she cooks or cleans the house she does not talk much to the child so the child is also left on her own to play or to draw with only one pencil and one paper sheet.

  In the other type of family, the mother, every day, spends much more time with the child: she tells stories to her child meanwhile they look several picture children books together, they do the shopping together in the market, they play together and they draw together with several colouring book, paper sheets and pencils.
- INTERVIEWER: (EXPLAIN TABLET WITH NUMBER OF CHILDREN AGAIN) This is the same board that we used before. You can move these beads to answer my questions and you will be able to modify your answers at any time of the game (take away board 2). Notice, that the numbers at this side (0) means less children and at this other side (100) means more children.
- INTERVIEWER: Before we start with this story, let me remind you that the children first start to say easy words, then a bit more difficult words and then even more difficult words!

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- INTERVIEWER: Before we start with this story, let me remind you that the children first start to say easy words, then a bit more difficult words and then even more difficult words!

Maternal Beliefs on Involvement/Stimulation

- Suppose that there are 100 12-month-old children for whom speaking is more difficult. They are able to say easy words as water, bye bye or milk but they still are not able to say more difficult words as table, train or pitcher,

  If the mother of these children spends little time per week with her child:
  - Out of these 100 children, how many of them will be able to say easy words like: nose, bread or eye by the age of 36 months?
  - And out of these 100 children, how many of them will be able to say a bit more difficult words like: inside, lace or carrot by the age of 36 months?
  - And out of these 100 children, how many of them will be able to say even more difficult words like: dirty, clean or garden by the age of 36 months?

  For the same 100 children, if their mother spends much time with them every day:
  - Out of these 100 children, how many of them will be able to say easy words like: nose, bread or eye by the age of 36 months?
  - And out of these 100 children, how many of them will be able to say a bit more difficult words like: inside, lace or carrot by the age of 36 months?
  - And out of these 100 children, how many of them will be able to say even more difficult words like: dirty, clean or garden by the age of 36 months?

Back

Measuring the quality of connections

If a respondent answered affirmatively to knowing another participant, the respondent is asked about the quality of the connections:

1. Do you know [NAME]?
2. How long have you known [Name]?
3. How many years/months/days ago was the last time you spoke to [Name]?
4. How many times have you visited [Name]'s house in the past 15 days?
5. Do you talk about recipes with [Name]?
6. Do you wash clothes or fetch water with [Name]?
7. Do you talk about your young children (for example their health, nutrition, parenting techniques or play) with [Name]?
8. If you wanted to talk to someone about something personal or private (for instance, if you had something on your mind [...]) would you talk to [Name]?
9. Would [Name] lend you food, kerosene or money if you needed it?
10. Do you often have fun and relax with [Name]?

Back

Measuring the quality of connections

- We also compute a measure of 'connectedness' in the network to measure how well you know the people in the village.
- We used the follow-up questions relating to relationship intensity.
- We estimate a two parameters IRT model for 'connectedness', conditional on a connection existing between i and j;
- The connection between i and j as measured by indicator Z_{ijk} $k = (1, ..., 8)$ is modelled as:

$$Z_{ijk} = \frac{exp(a_k \theta_{ij} + b_k)}{1 + exp(a_k \theta_{ij} + b_k)} \tag{1}$$

where θ_{ij} is the 'connectedness' index (distributed normally with mean 0 and standard deviation 1). Back

Heterogeneous learning

Table: Learning: heterogeneity by SES

Dependent variable:	μ_1		μ_2	
Mother's education	Below secondary	Above secondary	Below secondary	Above secondary
	(1)	(2)	(3)	(4)
μ_1 (baseline)	-0.072	-0.000		
	(0.047)	(0.038)		
μ_2(baseline)			0.028	0.152**
			(0.036)	(0.073)
Average perceived μ_{1t}	0.196***	0.144***		
(in village)	(0.051)	(0.035)		
Average perceived μ_{2t}			0.041	-0.006
(in village)			(0.043)	(0.040)
Signal own child	0.007	-0.096**	0.011	-0.013
	(0.049)	(0.040)	(0.036)	(0.042)
Signal of network	0.019	0.085	-0.074	0.086
(average)	(0.087)	(0.072)	(0.076)	(0.086)
Signal of *connected* network	0.057	-0.111	0.137	-0.129
(weighted average)	(0.086)	(0.074)	(0.084)	(0.089)
OLS μ_{1t} village	-0.071*	0.099***		
	(0.041)	(0.034)		
OLS μ_{2t} village			-0.023	0.087***
			(0.027)	(0.032)
Observations	477	771	477	771
Controls	Yes	Yes	Yes	Yes

Note. Vars have been standardized to have mean 0 and std 1. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

Heterogeneous learning: heterogeneity by Raven

Dependent variable:	μ_1		μ_2	
Raven	Below median	Above median	Below median	Above median
	(1)	(2)	(3)	(4)
μ_1 (baseline)	-0.032	-0.047		
	(0.036)	(0.056)		
μ_2 (baseline)			0.044	0.197*
			(0.029)	(0.109)
Average perceived μ_{1t} village	0.139***	0.186***		
	(0.039)	(0.046)		
Average perceived μ_{2t} village			0.007	0.013
			(0.039)	(0.050)
Signal own child	-0.045	-0.052	0.040	-0.074*
	(0.041)	(0.056)	(0.036)	(0.045)
Signal of network (average)	0.087	0.009	0.021	0.012
	(0.089)	(0.077)	(0.083)	(0.097)
Signal of *connected* network (weighted average)	-0.035	-0.047	-0.015	-0.031
	(0.094)	(0.078)	(0.085)	(0.101)
OLS μ_{1t} village	0.024	0.070***		
	(0.036)	(0.018)		
OLS μ_{2t} village			-0.008	0.070*
			(0.028)	(0.037)
Observations	724	524	724	524
Controls	Yes	Yes	Yes	Yes

Note. Vars have been standardized to have mean 0 and std 1. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

Heterogenous learning: by baseline beliefs

Dependent variable:		μ_1			μ_2	
Baseline belief	Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)
μ_1 (baseline)	-0.046	0.009	-0.056			
	(0.045)	(0.058)	(0.066)			
μ_2 (baseline)				0.059	-0.044	0.320*
				(0.050)	(0.238)	(0.184)
Average perceived μ_{1t} village	0.130***	0.168***	0.197***			
	(0.047)	(0.054)	(0.051)			
Average perceived μ_{2t} village				0.018	0.007	-0.012
				(0.046)	(0.042)	(0.054)
Signal own child	-0.039	-0.068	-0.055	0.002	0.022	-0.045
	(0.048)	(0.059)	(0.057)	(0.042)	(0.050)	(0.057)
Signal of network (average)	-0.055	0.026	0.150	-0.165**	0.053	0.147
	(0.074)	(0.105)	(0.107)	(0.075)	(0.122)	(0.110)
Signal of *connected* network	0.016	0.052	-0.150	0.133	-0.040	-0.158
(weighted average)	(0.085)	(0.111)	(0.104)	(0.082)	(0.121)	(0.126)
OLS μ_{1t} village	-0.019	0.083**	0.108***			
	(0.023)	(0.038)	(0.031)			
OLS μ_{2t} village				-0.010	-0.030	0.233**
				(0.036)	(0.026)	(0.115)
Observations	412	414	422	412	414	422
Mean	0.222	0.238	0.248	0.231	0.257	0.288
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note. Vars have been standardized to have mean 0 and std 1. Controls: Mother's education, Raven score, first born, child's gender, number of siblings. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

Back

ITT on networks (other measures)

Dependent variable:	Closeness	Betweeness
	(1)	(2)
Group stimulation (GS)	0.008**	0.061
	(0.004)	(0.050)
Individual stimulation (IS)	0.002	0.006
	(0.004)	(0.049)
Nutritional education (NE)	0.001	0.052
	(0.004)	(0.052)
Constant	0.018***	0.357***
	(0.003)	(0.043)
Observations	1355	1355
P-val GS=NE		
P-val GS=IS		
P-val IS=NE		

Note. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).