Parental Beliefs and Learning

How Perceptions of the Process of Child Development Change

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Outline

Measuring Parental Beliefs

- The process of child development has recently received considerable attention in economics;
- The early years have been proven to be extremely important for their long term consequences.
  - Events that occur in the first 1000 days *since conception* have significant impacts on a variety of adult outcomes.
- The role played by parents is key in determining what happens in the first few years.
- It is therefore key to understand parental behavior.

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- In standard economic models, parents are often assumed to know the 'true' process of child development.
- .... and yet this assumption might be unrealistic.
- Individual choices are driven by beliefs, tastes and resources.
- It is possible that parents have misperceptions about the process of child development.
- Using only data on parental choices might be very hard to distinguish between the role played by tastes and beliefs.
- One possible research strategy is to elicit data from parents their vision of the process of child development.

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  - The (perceived) productivity of parental investment in the production function.
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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.
- The anthropologist Annette Lareau in her book *Unequal Childhoods* claims that in the US:
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Measuring beliefs: a motivation

- Recent studies have started to elicit data on individual beliefs.
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- In this presentation, I will first show some material from Attanasio, Cunha and Jervis (2020) in Colombia.
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How to elicit parental beliefs

- To elicit individual beliefs about the process of child development:
  - We present parents (typically mothers) with a scenario characterised 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:

$$\hat{H}_{k,a} = \hat{f}_a^i(H_{k.a-1}^q, X_i^q, \bar{Z}), \quad q = 1, 4$$

  We define such f as the *production function* of child development.

- We map four points of the domain of the production function into its outcomes.
  - As we will see 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.
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- As we cannot to consider all possible inputs, we assume that respondents *average* across Z_i and ϵ_i.

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

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

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

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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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How to build scenarios: parental investment

- A similar approach is used for parental investment.
- In this case we also use visual aids to describe the 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;
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Beliefs Elicitation Survey Instrument

To elicit subjective beliefs we use tablets...

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A digression: some Colombian results

- In the work with Cunha and Jervis, we looked at Colombian data collected within the evaluation of a stimulation intervention.
- The approach is similar with some methodological differences.
- In that paper we:
  - Present descriptive evidence on perceived returns under low and high initial conditions;
  - Relate actual parental investment to perceived returns;
  - Estimate objective and subjective production functions.
  - Asses whether individual beliefs under or over estimate the productivity of parental investment.

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Returns to parental investment under high and low initial conditions

- Using the data collected we can get some idea about returns to investment:

$$r_i\left(H^l_{a-1}\right) = E\left(H_{i,a} \middle| (H^l_{a-1}, X^h)\right) - E\left(H_{i,a} \middle| (H^l_{a-1}, X^l)\right)$$

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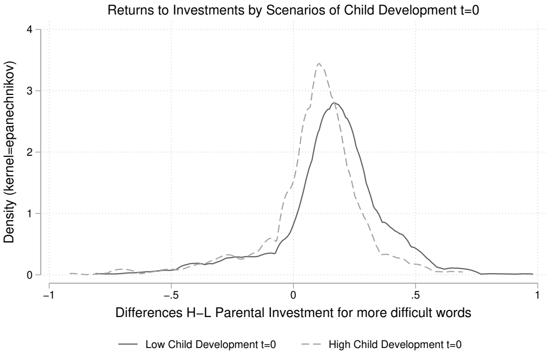

Parental investment and returns beliefs

Table: Parental Investment and Returns on Investment

VARIABLES	OLS	OLS[a]	OLS[b]	IV	IV[a]	IV[b]
Inv. Return: Low	-0.082	-0.045	-0.044	-0.086	-0.055	-0.057
Baseline Development	(0.059)	(0.056)	(0.056)	(0.070)	(0.068)	(0.067)
Inv. Return: High	0.126	0.014	0.088	0.404***	0.190 **	0.183 **
Baseline Development	(0.087)	(0.077)	(0.077)	(0.104)	(0.095)	(0.093)
Treatment Assignment			0.093*			0.092*
			(0.046)			(0.046)
Controls		yes	yes		yes	yes
R^2	0.003	0.095	0.016	0.050 .	0.087 .	0.096
F p-value	0.220	0.000	0.000	0.000	0.000	0.000
Observations	1112	1112	1112	1112	1112	1112

Regression controls: mother's age, education, gender, age of the child and wealth index .

Colombia: Objective Technology of Skill Formation

$$H_{i,1} = \delta_0 + \delta_1 H_{i,0} + \delta_2 X_i + \delta_3 [H_{i,0} X_i] + \epsilon_i + \nu_i,$$

	First Stage	Second Stage	
		Cobb-Douglas	Translog
Intercept	-0.443 (0.289)	2.390 (0.066)	2.480 (0.081)
Log of Baseline Development	0.314 (0.099)	0.391 (0.027)	0.359 (0.032)
Log of Investment at Follow Up		0.154 (0.054)	-0.025 (0.107)
Log of Investment at Follow Up x Log of Baseline Development			0.064 (0.033)
Treatment Assignment (dummy)	0.161 (0.039)		
Control function		-0.123 (0.055)	-0.131 (0.055)

Note: Dependent Variable for the Fist Stage is the Log of Investments at Follow Up and the Dependent Variable for the Second Stage is the Log of Follow Up Development. The specifications control by mother's age, education, depression and IQ (standardised Raven's score) as well as gender and age of the child and wealth index (standardised). Observations: 1112.

Subjective production functions

Table 5: Estimation of Subjective Technology of Skill Formation

Dependent Variable: Expected Log of Follow Up Development				
	Cobb-Douglas	Fraction $\|t\| > 2$	Trans-log	Fraction $\|t\| > 2$
Intercept	2.519 (0.042)	93.80%	2.175 (0.056)	80.76%
Log of Baseline Development	0.350 (0.013)	73.29%	0.468 (0.018)	66.37%
Log of Investment at Follow Up	0.077 (0.005)	44.42%	0.692 (0.058)	23.47%
Log of Investment at Follow Up x Log of Baseline Development			-0.212 (0.019)	20.50%

Observations: 1112.

Perceived and true technology of skill formation

- Perceived technology of skill formation:

$$EH_{i,a} = \mu_{0,i} + \mu_{1,i}H_{i,a-1} + \mu_{2,i}X_i + \mu_{3,i}[(H_{i,a-1})(X)]$$

- 'True ' technology of skill formation:

$$EH_{i,a} = \delta_0 + \delta_1 H_{i,a-1} + \delta_2 X_i + \delta_3[H_{i,a-1}X_i] + \epsilon_i$$

- Cobb Douglas production function (δ_3 and $\mu_{3,i} = 0$):
  - On average, $\mu_{1,i}$ is similar to δ_1: (0.350 vs 0.314) .
  - On average, $\mu_{2,i}$ is much smaller than δ_2: (0.077 vs 0.154).
- Translog production function (δ_3 and $\mu_{3,i} \neq 0$)
  - The patterns of coefficients is very different.
  - $\mu_{1,i}, \mu_{2,i}$, and $\mu_{3,i}$ equal to $0.468, 0.692, -0.212$ on average;
  - δ_1, δ_2, and δ_3 equal to $0.359, -0.025, 0.064$

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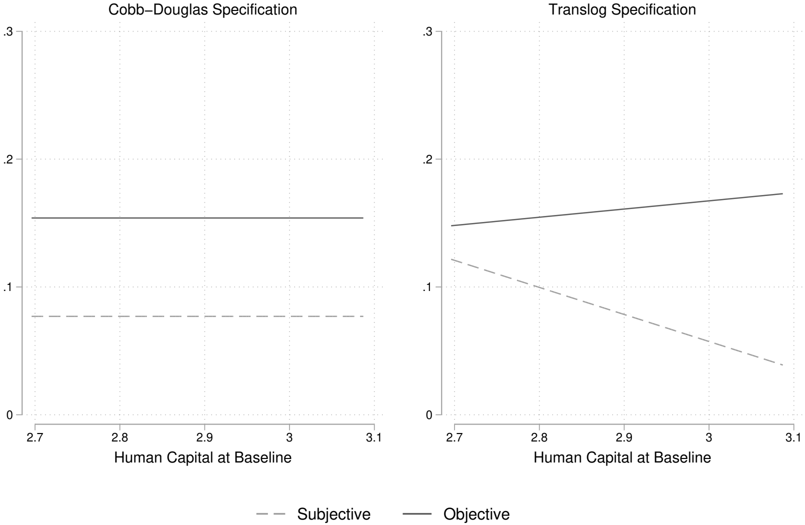
Subjective and Objective Marginal Products of Parental Investment



Indian beliefs

Back to the Indian data

- 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 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 village a sample of 8 children of the relevant age and their households and 4 additional households nearby with children just out of the target age were included in the study.
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Parenting interventions and their impacts

- 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.
- We collect data on beliefs using a methodology not too different from the one used in Colombia.
- We can then look at the impact of the interventions on parental beliefs.
- We describe the distribution of the subjective probability obtained for each of the four scenarios;
- We consider the distribution of the average probabilities, between hard, medium and easy words.
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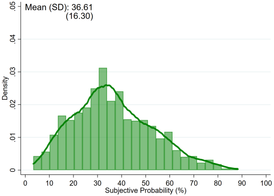
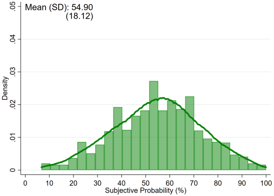
Beliefs (average subjective prob) at baseline

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

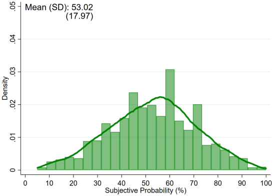
Low development, Low investment



Low development, High investment



High development, Low investment



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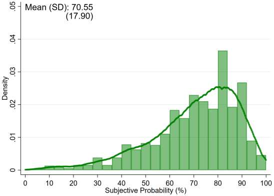
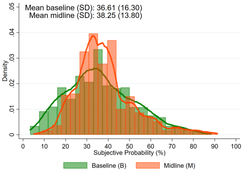


Beliefs (average subjective prob) at midline

Low development, Low investment



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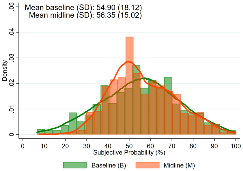

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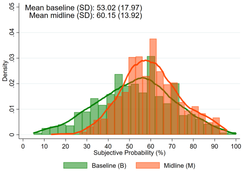

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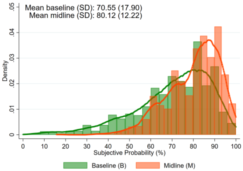
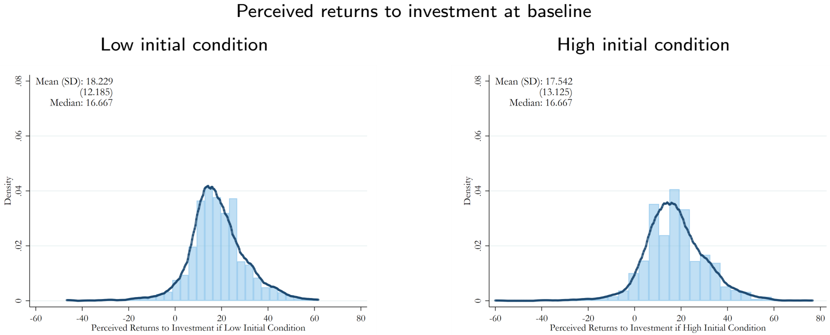


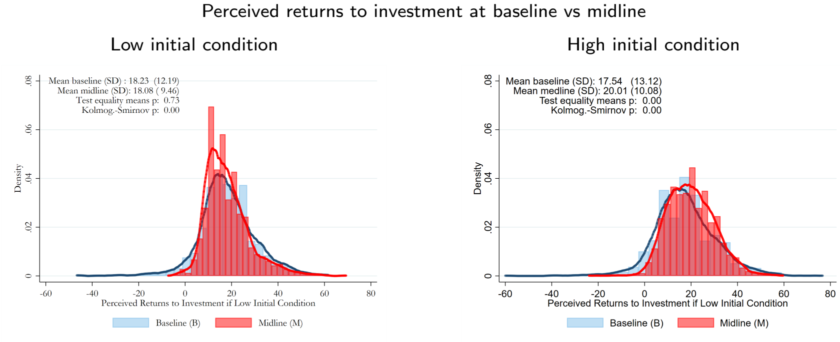
Returns to investment

- 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 at baseline vs midline



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)
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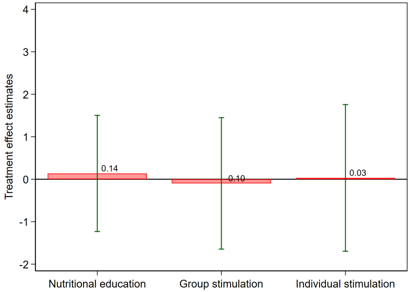
Controls	Yes	Yes	Yes	Yes	Yes	Yes

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 village level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

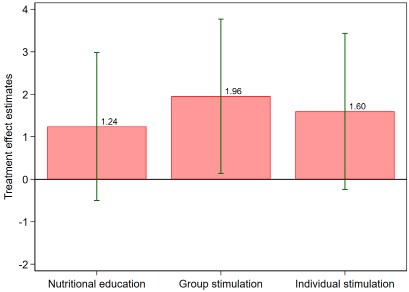
Treatment effect on perceived beliefs

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

Perceived returns
if low development

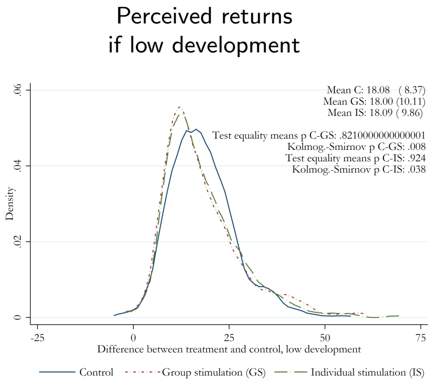


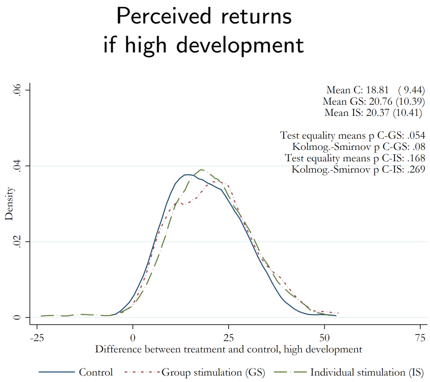
Perceived returns
if high development



Note. 95% confidence intervals in green

Density plots by treatment status





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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- 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:
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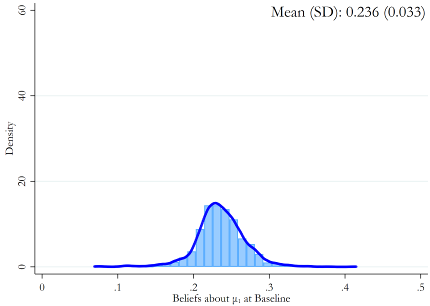
Objective production function

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

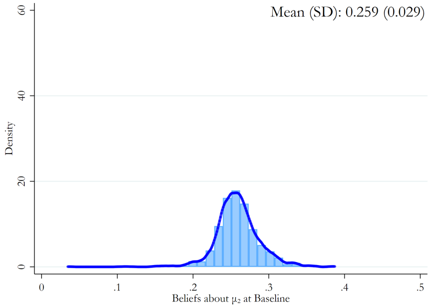
Note. Sample: N=1222. The measurement system and the production function are estimated jointly with the estimation method developed by Muthen (1984). Standard errors in parentheses computed based on inverting information matrix (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Beliefs on Cobb-Douglas at baseline

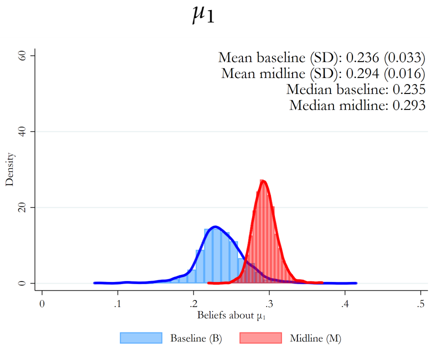
μ_1 at baseline

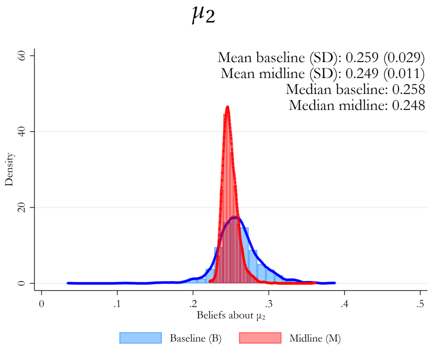


μ_2 at baseline



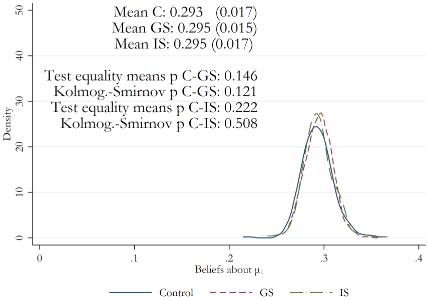
Beliefs on Cobb-Douglas at baseline vs. midline



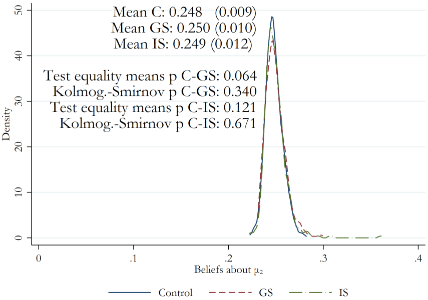


Treatment status of beliefs: midline evidence

μ_1



μ_2



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.

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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]?

Measuring the architecture of the network

- The nature of our data and the fact that 'groups' are defined more or less by distance, allows us to compute measures of network connections.
- We compute the following measures:
    - Number of Outward Connections

$$Outward \;\; Connections_i = \sum_j^N \mathbb{1}(i \; knows = j)$$

    - Number of Inward Connections

$$Inward \;\; Connections_i = \sum_j^N \mathbb{1}(j \; knows = i)$$

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:

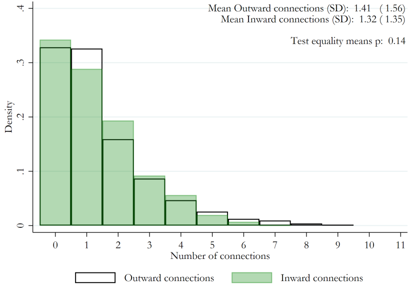
$$Z_{ijk} = \frac{exp(a_k \theta_{ij} + b_k)}{1 + exp(a_k \theta_{ij} + b_k)} \tag{1}$$

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

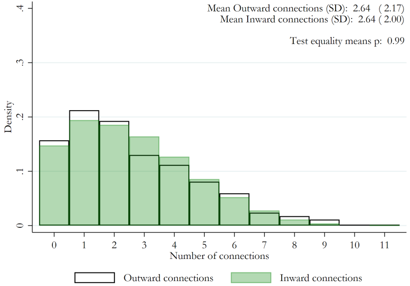
High isolation in the sample

- Our sample is characterised by very few connections.

Midline

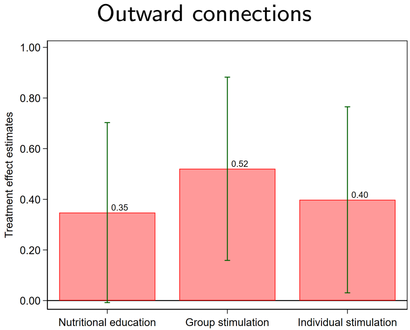


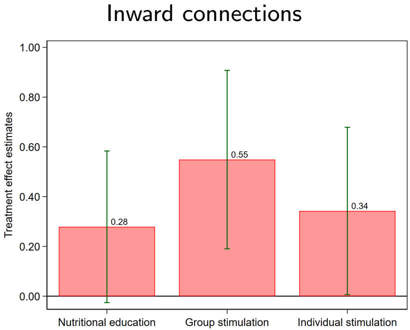
Endline



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.

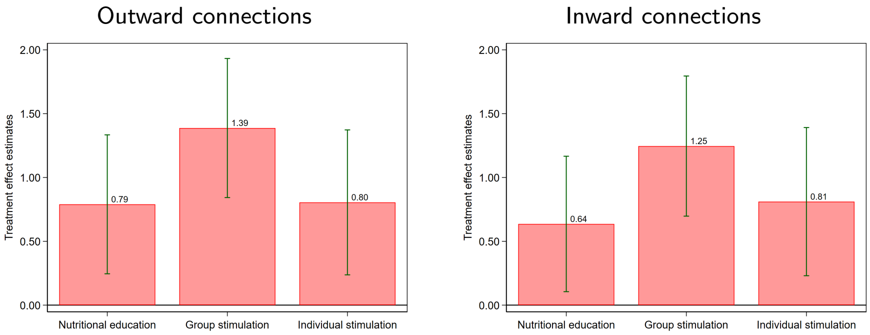
The (group) intervention improves connections at midline





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	Inward connections	Connectedness index
	(1)	(2)	(3)
Group stimulation (GS)	0.521***	0.549***	0.326***
	(0.183)	(0.182)	(0.120)
Individual stimulation (IS)	0.398**	0.342**	0.260**
	(0.186)	(0.170)	(0.124)
Nutritional education (NE)	0.347*	0.279*	0.187
	(0.180)	(0.154)	(0.114)
Constant	1.088***	1.028***	0.617***
	(0.128)	(0.112)	(0.079)
Observations	1282	1282	1282
P-val GS=NE	0.343	0.131	0.254
P-val GS=IS	0.516	0.284	0.616
P-val IS=NE	0.785	0.703	0.558
Panel B: Endline			
Dependent variable:	Outward connections	Inward connections	Connectedness index
	(1)	(2)	(3)
Group stimulation (GS)	1.388***	1.246***	0.866***
	(0.276)	(0.278)	(0.180)
Individual stimulation (IS)	0.805***	0.811***	0.580***
	(0.288)	(0.294)	(0.195)
Nutritional education (NE)	0.790***	0.636**	0.474**
	(0.276)	(0.269)	(0.185)
Constant	1.886***	1.958***	1.106***
	(0.189)	(0.188)	(0.118)
Observations	1261	1261	1261
P-val GS=NE	0.037	0.031	0.048
P-val GS=IS	0.050	0.156	0.166
P-val IS=NE	0.959	0.557	0.615

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 village level (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Outline

Modeling learning

- The next step is to model how people's beliefs change over time.
- For this, we will look at a parametric version of the beliefs data: individual answers are reflection of an underlying production function.
- If the production function is a Cobb Douglas:

$$y_{ivt} = \mu_{1,ivt-1} y_{i,vt-1} + \mu_{2,ivt-1} X_{ivt} + v_{ivt}$$

  - y_{it} is child development at t, X_{it} is parental investment in village v
- We assume parents have some ideas about its parameters μ.
- These initial μ's are those inferred from beliefs at baseline.
- After baseline they observe other children, their development and parental behaviour.
- As we observe several children per village, we assume that parents use that information (and their own child) to compute new estimates of the μ's.

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Modelling learning: using a private signal

- The expected child development is the following:

$$\hat{y}_{ivt} = \hat{\mu}_{1,ivt-1} y_{iv,t-1} + \hat{\mu}_{2,ivt-1} X_{ivt}$$

- Define signal as the difference between the realized child development and the expected child development:

$$s_{ivt} = y_{ivt} - \hat{\mu}_{1,ivt-1} y_{iv,t-1} - \hat{\mu}_{2,ivt-1} X_{ivt}$$

- Parents then modify their initial beliefs with this new estimates.

$$\hat{\mu}_{k,ivt} = \delta_1 \hat{\mu}_{k,ivt-1} + \delta_2 s_{ivt} \quad \forall k = 1, 2$$

where:

- δ_1 is the weight given to the initial belief;
- δ_2 is the weight given to the new evidence.

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Social Learning

- Mothers may learn about child development comparing their child to others;
- The intervention affects connections and therefore can change the mechanics of learning.
- Not only the signal from their own child might matter to change beliefs.
  - The average development in the network might matter;
  - The observed development of the 'best' kids' might matter;
  - This information might be weighted by the quality of the connections.

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Signals from the network

Recall that the signal from own child is measured as the difference between the realized child development and the expected child development:

$$s_{ivt} = y_{ivt} - \hat{\mu}_{1,ivt-1} y_{iv,t-1} - \hat{\mu}_{2,ivt-1} X_{ivt}$$

- The signal of the network in village v:

$$s^V_{ivt} = \frac{\sum_j \mathbb{1}(i\ knows{=}j) y_{jvt}}{N} - \hat{\mu}_{1,ivt-1} \frac{\sum_j \mathbb{1}(i\ knows{=}j) y_{jv,t-1}}{N} - \hat{\mu}_{2,ivt-1} \frac{\sum_j \mathbb{1}(i\ knows{=}j) X_{jvt}}{N}$$

- The signal of the connected network where θ_{ij} is the connectedness index from IRT:

$$s^W_{ivt} = \frac{\sum_j \mathbb{1}(i\ knows{=}j)\theta_{ij} y_{jvt}}{N} - \hat{\mu}_{1,ivt-1} \frac{\sum_j \mathbb{1}(i\ knows{=}j)\theta_{ij} y_{jv,t-1}}{N} - \hat{\mu}_{2,ivt-1} \frac{\sum_j \mathbb{1}(i\ knows{=}j)\theta_{ij} X_{jvt}}{N}$$

- The signal from the best child (signal of network MAX):

$$s^{MAX}_{ivt} = y^{MAX}_{jvt} - \hat{\mu}_{1,ivt-1} y^{MAX}_{jv,t-1} - \hat{\mu}_{2,ivt-1} X^{MAX}_{jvt}$$

- The signal from the worst child (signal of network MIN):

$$s^{MIN}_{ivt} = y^{MIN}_{jvt} - \hat{\mu}_{1,ivt-1} y^{MIN}_{jv,t-1} - \hat{\mu}_{2,ivt-1} X^{MIN}_{jvt}$$

Social learning estimates: $\Delta\mu_1$

Dependent variable:	Δ Perceived returns to investment (μ_1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Signal own child	0.145***		0.138***	0.139***		0.137***	0.138***
	(0.028)		(0.027)	(0.028)		(0.027)	(0.028)
Signal of network (average)		0.067**	0.052*	0.035			
		(0.031)	(0.031)	(0.040)			
Signal of network (MAX)				0.027			
				(0.039)			
Signal of *connected* network (weighted average)					0.071**	0.055*	0.031
					(0.030)	(0.030)	(0.041)
Signal of *connected* network (weighted MAX)							0.034
							(0.040)
Observations	1239	1261	1231	1220	1261	1231	1221

Note. The Table presents the estimates from the learning model estimates for μ_1. Variables have been standardized to have mean 0 and standard deviation 1. Signal is the difference in realized and perceived child development. Signal of network (average) is the average signal in the village, while connected is weighted to consider how well the household knows the people in the village. MAX is the signal from the best child in the village, while MIN is the signal from the worst child in the network. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

Social learning estimates: $\Delta\mu_2$

Table: Learning model estimates: change in perceived returns to human capital and investment (medium words).

Dependent variable:	Δ Perceived returns to investment (μ_2)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Signal own child	0.233***		0.216***	0.227***		0.217***	0.228***
	(0.033)		(0.032)	(0.031)		(0.032)	(0.031)
Signal of network (average)		0.131***	0.110***				
		(0.036)	(0.037)				
Signal of network (MAX)				0.035			
				(0.039)			
Signal of *connected* network (weighted average)					0.120***	0.097***	0.059
					(0.036)	(0.036)	(0.043)
Signal of *connected* network (weighted MAX)							0.060
							(0.041)
Observations	1239	1261	1231	1220	1261	1231	1221

Note. The Table presents the estimates from the learning model estimates for μ_2. Variables have been standardized to have mean 0 and standard deviation 1. Signal is the difference in realized and perceived child development. Signal of network (average) is the average signal in the village, while connected is weighted to consider how well the household knows the people in the village. MAX is the signal from the best child in the village, while MIN is the signal from the worst child in the network. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

Learning from the village: μ_1 and μ_2

Another approach:

- each participant can 're-estimate' μ_1 and μ_2 from the children in their villages.
- current μ's will then depend on own lagged μ and village's μ.

Dependent variable:	μ_1 at midline		μ_2 at midline	
	(1)	(2)	(3)	(4)
μ_1 (baseline)	-0.034	-0.026		
	(0.031)	(0.030)		
μ_1 village at t	-0.006	-0.007		
	(0.029)	(0.029)		
μ_2 (baseline)			0.115**	0.107**
			(0.045)	(0.045)
μ_2 village at t			-0.042*	-0.044*
			(0.025)	(0.025)
Observations	1308	1306	1308	1306
Other controls	No	Yes	No	Yes

Note. The Table presents the estimates from the learning model estimates: perceived returns to human capital and investment. Variables have been standarized to have mean 0 and standard deviation 1. Other controls are the mother's education, number of siblings in the household, gender of the target child and a dummy equal to 1 if the target child is the first born. Standard errors in parentheses are clustered at village level (*** p<0.01, ** p<0.05, * p<0.1).

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Learning from the village μ's

Another approach:

- Maybe communication with the other mothers affects individual $\mu's$;
- One can then think that current μ's will then depend on past μ's and village's μ's.

$$\mu_{k,i,t} = f(\mu_{k,i,t-1}, E_{j \neq i}[\mu_{k,j,t-1}]); \quad k = 1, 2.$$

  where the average can be weighted by the connections.
- Or one can think that the new μ's depend both on other individual μ's and the signals from the children.

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  - 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.
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