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The Intergenerational Elasticity of Earnings: Exploring the Mechanisms

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Why do high income parents have high income children?

Potential explanations: Children of high income families ...

... attain more years of schooling

... have higher cognitive skills

... receive more investments: parental time & school quality

... face different family environment: more educated parents, fewer siblings

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⇒ We quantify the importance of these explanations

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Literature: Mechanisms

How can we explain intergenerational earnings persistence?

1. Human Capital:
   - Schooling: Carneiro & Heckman (2002), Caucutt & Lochner (2020), Blanden et al. (2007)
   - Cognitive and non-cognitive skills: Dahl & Lochner (2012), Agostinelli & Sorrenti (2018), Kautz et al. (2014)
   - Parental Investments: Cunha & Heckman (2008), Cunha et al. (2010), Attanasio et al. (2020), Dearden et. al (2002)
   - Family background: Meghir & Palme (2005), Heckman & Karapakula (2019), Bhalotra & Clarke (2020)
2. Alternative Explanations
   - Personal connections, aspirations, correlation of preferences for work, etc.

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Our contribution

- Understand how these channels operate and interact ("Structural Modeling" from sociology)
- Mediation/path analysis: Allows for a large amount of flexibility
- Large number of direct and indirect effects of each channel on lifetime income:
  - School quality → lifetime income
  - School quality → schooling → lifetime income
  - School quality → cognition → schooling → lifetime income
- Solving this would be very difficult with an economics structural model (just think of the number of states you'd have to keep track of....)
- Use of data that links early life circumstances to outcomes across the lifecycle for the same sample of individuals

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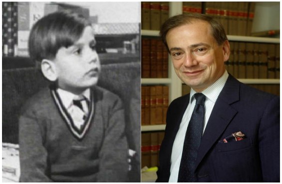
Outline

Data - National Child Development Study (NCDS)

John



Tony

- Population born in one week in Britain in 1958
- Followed at ages 0, 7, 11, 16, 23, 26, 33, 37, 42, 49, 55
- Data on:
  - Parental income measured when child is 16
  - Individual's earnings over the lifecycle
  - Potential drivers of the Intergenerational Elasticity of Earnings (IGE)

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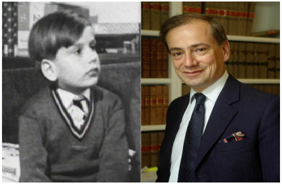

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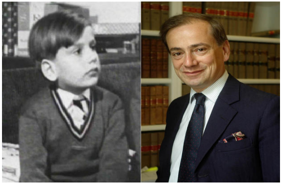

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Key Facts: Children from high income families ...

1. ... grow up in a different family environment: Details
   - More educated parents, fewer siblings
2. ... receive more time investments: Details
   - e.g. reading to child, outings with child, interest in child's education
3. ... go to better quality schools: Details
   - e.g. student-teacher ratios, PTA, fraction that continues education
4. ... have better cognitive skills at age 16: Details
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Time investments differ by parental income

	Parental Income Tertile:			
	Bottom	Middle	Top	P-val
Time investment				
% of fathers go on outings w child 7	65.2	72.5	71.5	0.00
% of parents want child to go to uni 11	81.2	82.8	85.2	0.08
% of mothers very interested at age 16	31.5	32.8	35.6	0.19
School quality				
% whose PTA holds meetings 7	56.8	57.6	58.7	0.71
Student-teacher ratio 11	24.8	24.7	24.3	0.06
% from child's class studying for GCEs 16	44.0	44.4	50.5	0.00

School quality investments differ by parental income

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	Bottom	Middle	Top	P-val
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Cognition differs by parental income

	Parental Income Tertile			
	Bottom	Middle	Top	P-values
Cognition				
Reading at age 16	-0.11	0.01	0.10	0.00
Math at age 16	-0.08	-0.02	0.10	0.00
Education				
Age left education	17.9	17.9	18.1	0.02

Outline

Summary of our approach

1. Estimate dynamic model of human capital investments and earnings correcting for measurement error

2. Decompose IGE into multiple channels, allowing for increasing degrees of mediation

Lifetime earnings

$$\begin{aligned}\ln Y \;=\; & \alpha_0 + \alpha_1 S + \alpha_2 \ln\theta_C + \alpha_3 S \times \ln\theta_C + \alpha_4 \ln\theta_N + \alpha_5 S \times \ln\theta_N \\ & + \alpha_6 \mathbf{F} + \alpha_7 \mathbf{I} + \alpha_8 \ln Y_{Parent} + u^Y\end{aligned}$$

where $E[u^Y | S, \ln\theta_C, \ln\theta_N, \mathbf{F}, \mathbf{I}, \ln Y_{Parent}] = 0.$

S = years of schooling

θ_C, θ_N = (latent) age 16 cognitive, non-cognitive skills

$\boldsymbol{I} = [\ln ti_7, \ln ti_{11}, \ln ti_{16}, \ln sq_7, \ln sq_{11}, \ln sq_{16}]$

$\ln ti_t, \ln sq_t$=(latent) parental time, school quality investments

$\boldsymbol{F} = [ed_m, ed_f, sib]$=ed. of mother, father, siblings

Y_{Parent}=parent's lifetime income

$\Rightarrow$ Can test restrictions, e.g. $\alpha_{sq_7} = \alpha_{sq_{11}} = \alpha_{sq_{16}} = 0$

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Skills

$$\theta_{k,t+1} = [\gamma_{t,k,1}\theta_{C,t}^{\phi_{t,k}} + \gamma_{t,k,2}\theta_{N,t}^{\phi_{t,k}} + \gamma_{t,k,3}\mathbf{I}_t^{\phi_{t,k}} + \gamma_{t,k,4}ed_m^{\phi_{t,k}} + \gamma_{t,k,5}ed_f^{\phi_{t,k}}]^{\frac{1}{\phi_{t,k}}}(A_{k,t+1}),$$

$$A_{k,t+1} = \exp(\gamma_{t,k,6} + \gamma_{t,k,7}sib + \gamma_{t,k,8}\ln Y_{Parent} + u_{t+1}^k)$$

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Schooling and investments

Determinants of years of schooling:

$$S = \gamma_{0,S} + \gamma_{1,S} \ln \theta_{C,t} + \gamma_{2,S} \ln \theta_{NC,t} + \gamma_{3,S} \mathbf{F} + \gamma_{4,S} \mathbf{I} + \gamma_{5,S} \ln Y_{Parent} + u^S$$

Parental time investments

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Latent Factors and Measurement Error

- We do not directly observe cognitive $\ln\theta_{Ct}$ and non-cognitive $\ln\theta_{Ct}$ skills, time investments $\ln ti_t$, and school quality $\ln sq_t$
- Instead: Multiple noisy measures for each $\omega = \theta_{Ct}, \theta_{Nt} ti_t, sq_t$

$$\underbrace{Z_{\omega,m}}_{\text{Measure}} = \underbrace{\lambda_{\omega,m}}_{\substack{\text{Loading}\\\text{Parameter}}} \underbrace{\omega}_{\substack{\text{Latent}\\\text{factor}}} + \underbrace{\epsilon_{\omega,m}}_{\substack{\text{Measurement}\\\text{error}}}$$

- Key assumptions: $\epsilon_{\omega,m} \perp$ all other variables
- Note: Exploiting multiple measures and correcting for measurement error matters! We will see later....

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  1. Select measures using exploratory factor analysis
  2. Estimate measurement system parameters (e.g., $\lambda_{\omega,m}$s)
     More Details 1

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Identification of measurement parameters

$$\boxed{Z_{\theta_C,i,m} = \lambda_{\theta_C,m} \ln \theta_{C,i} + \epsilon_{\theta_C i,m}}$$

Scaling parameter λ:

- $\epsilon_{\theta_C,i,m}$ assumed independent across individuals and measures
- For example 3: Reading score, maths score, teacher rated ability
- We normalized $Var(\ln \theta_C) = 1$
- Then: $Cov(Z_{read}, Z_{maths}) = \lambda_{read}\lambda_{maths} Var(\ln \theta_C)$
  $Cov(Z_{read}, Z_{teacher}) = \lambda_{read}\lambda_{teacher} Var(\ln \theta_C)$
  $Cov(Z_{teacher}, Z_{maths}) = \lambda_{teacher}\lambda_{maths} Var(\ln \theta_C)$

$\Rightarrow$ 3 equations, 3 unknowns $\lambda_{read}, \lambda_{maths}, \lambda_{teacher}$

Back

Signal-to-Noise Ratios

$$Z_{\omega,i,m} = \lambda_{\omega,m}\omega_i + \epsilon_{\omega,i,m}$$

$$s_{\omega,m} = \frac{(\lambda^2_{\omega,m})Var(\omega)}{(\lambda^2_{\omega,m})Var(\omega) + Var(\epsilon_{\omega,m})}$$

Cognition at 16		**Time Inv 16**		**School Quality 16**	
Reading Score	0.56	P:Supportive	0.32	School Type	0.08
Math Score	0.62	M:Interest in ed	0.90	%Cnt School	0.35
Teacher: Math	0.80	F: Interest in ed	0.75	%FT degree	0.82
Teacher: English	0.72			%Passed A-levels	0.93
				%Studying towards A-levels	0.45
				Teacher Student Ratio	0.20

Back

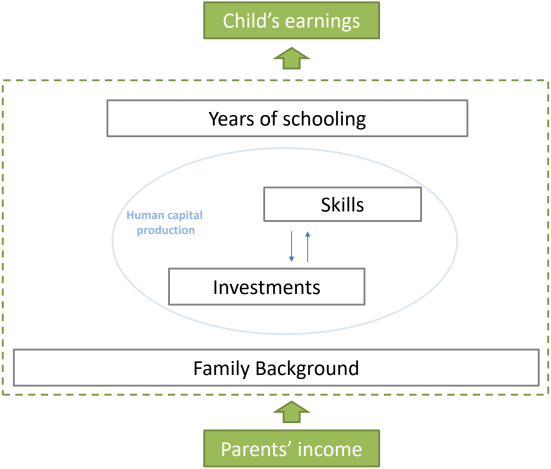
Estimation approach (Attanasio Meghir Nix (2020))

1. Approximate joint distribution of all variables in the data (including latent factors) as mixtures of normals
2. Simulate measurement error free data
3. Estimate production functions and other equations using NLLS

Decomposition approach

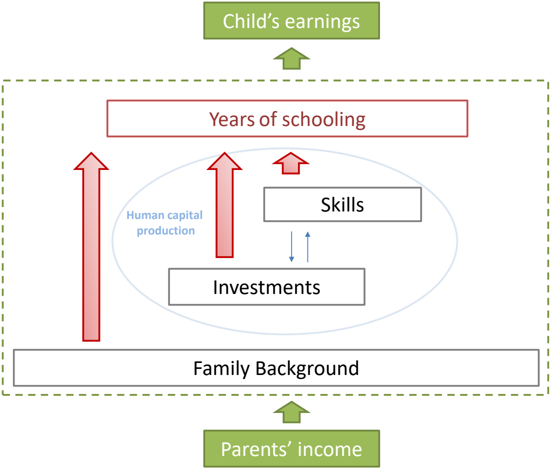
1. Use estimated model to simulate life histories, including lifetime earnings, calculate variance of lifetime earnings, covariance with parent's income, calculate IGE
2. Set one channel equal to sample means, re-simulate model, re-calculate variance of lifetime earnings, covariance with parent's income, calculate IGE

Baseline - Decomposition of IGE



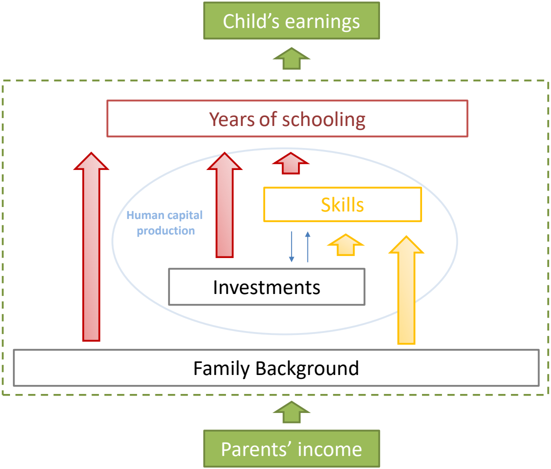
Equalize variables (e.g., investments) only in the earnings equation

Level 2 - Indirect effects via years of schooling



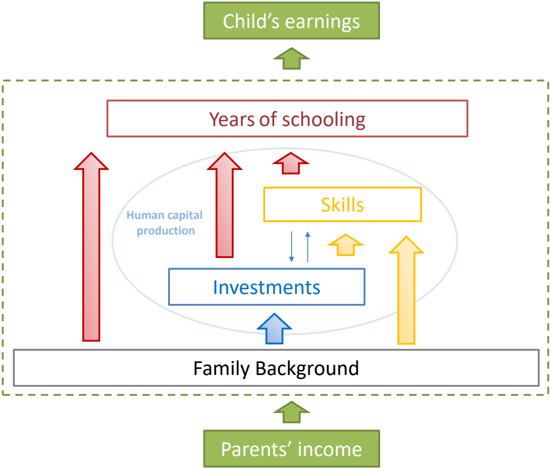
Equalize variables (e.g., investments) in the earnings and schooling equations

Level 3 - Indirect effects via skills



Equalize variables (e.g., investments) in the earnings, schooling, and skills equations equation

Level 4- Indirect effects via investments



Equalize variables (e.g., parental education) in the earnings, schooling, skills, and investments equations

Outline

Introduction

Data & Key Facts

Approach

Results

IGE Estimates with Measurement Error Corrections

$$\ln Y_i = \rho \ln Y_{Parent,i} + u_i$$

where $\rho =$ Intergenerational Elasticity of Earnings (IGE)

	Male model	Male corrected	Male uncorrected	Female model	Female corrected	Female uncorrected
IGE	0.332	0.339	0.160	0.211	0.213	0.103
		(0.097)	(0.045)		(0.101)	(0.048)

- **Problem:** we measure parents income at age 16 (when parent on avg. age 42), not lifetime income
- **Solution:** errors in variables approach
  - Calculate reliability ratios for the children (for whom we observe lifetime income, and age 42 income)
  - Assume reliability ratio is same for the parent

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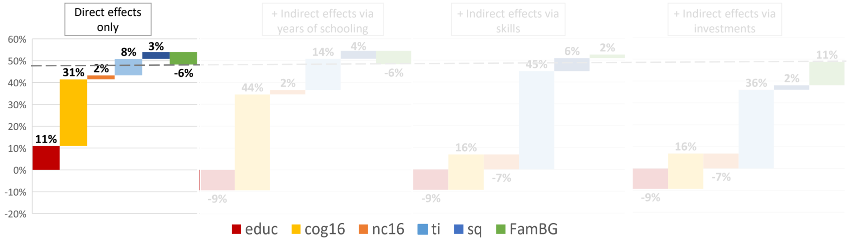
Results: Mediation Analysis - Level 1



⇒ 54% of IGE is explained by our channels

⇒ Cognitive skills and schooling significantly affect IGE

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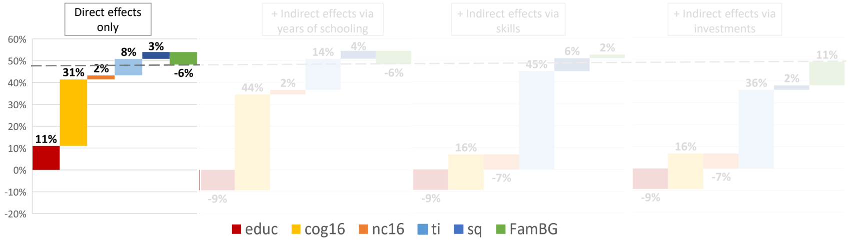

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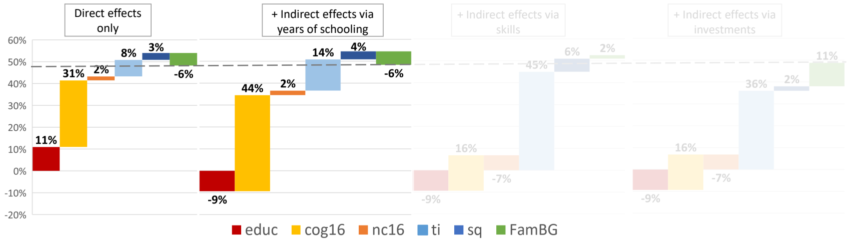
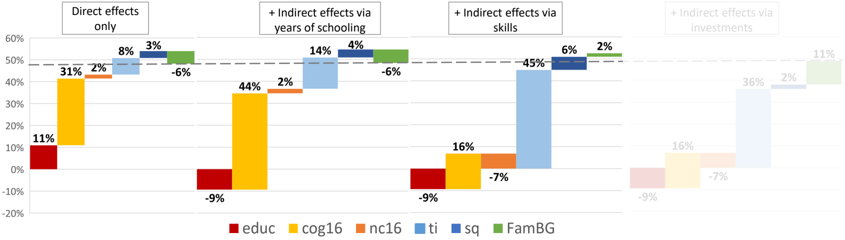
Results: Mediation Analysis - Level 2



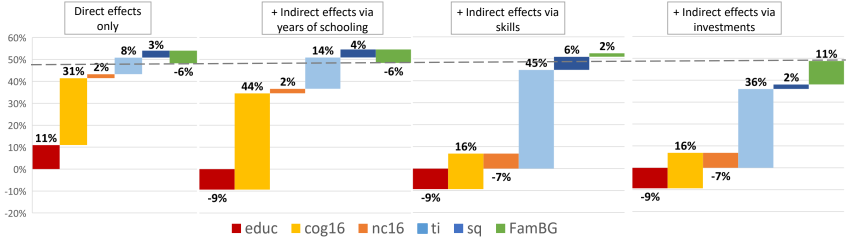
⇒ Effect of schooling is completely mediated by cognitive skills

Results: Mediation Analysis - Level 3



⇒ Most differences in cognition are explained by differences in time investments and school quality

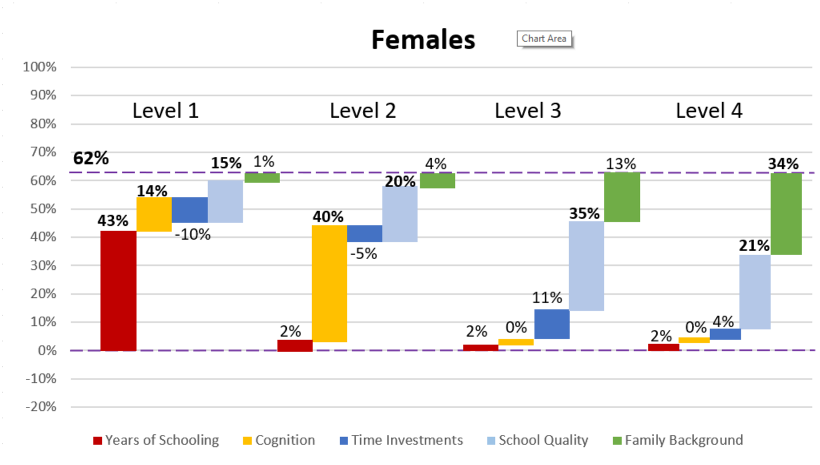
Results: Mediation Analysis - Level 4



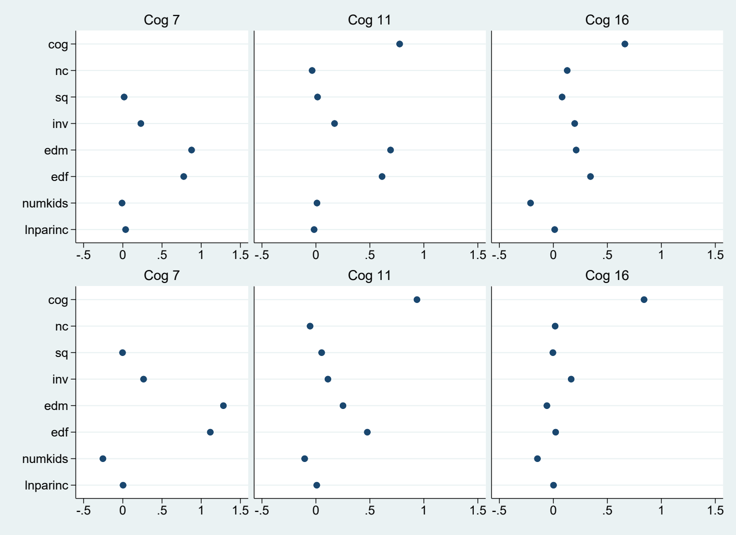
⇒ Family background-related differences explain 19% of IGE.

⇒ Even if we control for family background, the income gradient in investments persists

Results: Mediation Analysis - Females



Production functions: Effect of 1 unit increase in input



Key Results - Summary

For both, men and women:

- Years of schooling and cognition explain the large shares of the IGE
- But: Effect of years of schooling is entirely mediated by cognition ...

  ... and cognition is largely mediated by investments

⇒ Differences in investments between rich and poor families really matter for the IGE...

... and not all of them can be explained by family background

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