Education and Earnings: Insights from the NCDS

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based on joint work with
Jack Light (UCL)
and Barbara Sianesi (IFS)
ESRC Research Centre (CPP) at IFS

NCDS Conference - Celebrating 60 Years!

Centre for Longitudinal Studies (CLS)
UCL Institute of Education

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Insights from the NCDS

Contributions and innovations - an economist's perspective.

A remarkable research design, ahead of its time.

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   - early years parental investments, attitudes and behaviour
   - BSAG internalising and externalising behaviours
   - comprehensive test scores and teacher assessments

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4. Cross-cohort behaviour - across the cohort studies
   - NCDS, BCS & MCS; LYSPE

Brought new insights across a range of areas, including

1. Understanding socio-economic mobility through intergenerational linkages and behaviours.
2. Long-run effects of early test scores, non-cognitive abilities, parental behaviours and SES on wages and employment.
3. The lasting impact of childhood health and circumstance on adult economic outcomes.
4. The scarring effects on wages from youth unemployment.
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- what can we learn from the extensive early years and background variables and the data through to age 55?

- But first, to set the scene, use these six contributions to draw out some of the key features of NCDS, and the other cohort studies.

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  - drawing on detailed family background measures and cross-cohort comparisons.
- They compare the intergenerational transmission of home ownership for individuals in the 1958 and 1970 British birth cohorts,
  - finding that home ownership for 42 year olds from the 1970 birth cohorts shrunk disproportionately among those whose parents did not own their own home when they were children.
- Given housing is the key component of wealth for most people, their results reinforce a picture of falling social mobility in Britain.

2. Long run effects of early measures on adult wages and employment.

- Again picking one key study, this time by Janet Currie and Duncan Thomas,
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- Find that children of lower SES have both lower age 16 test scores and higher returns to these test scores in terms of age 33 wages and employment probabilities than high-SES children.
- They then examine determinants of age 16 scores,
  - conditional on having had the same age 7 mathematics scores, high-SES children go on to achieve higher age 16 mathematics scores than children of low or middle-SES.
- These differences are greatly reduced when observable measures of *school quality* are added to the model.

3. The lasting impact of childhood health and circumstance on adult economic outcomes.

- A key study by Anne Case, Angela Fertig and Chris Paxson,
  - drawing on early health measures.
- Using the NCDS they examine the effects of childhood health and circumstance on education and employment.
- They find find strong associations between fetal conditions and children's educational attainment,
  - children born at low birthweight pass significantly fewer O-level exams on average.
- Finally they establish that chronic health conditions in childhood are significantly associated with labour market outcomes in adulthood.
- See also the influential study by Goodman, Joyce and Smith, PNAS, 2011.

4. Wage scar effects from youth unemployment..

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  - drawing on the unfolding life-cycle sequence of detailed measures.

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  - drawing on the unfolding life-cycle sequence of detailed measures.
- Find that individuals with a relatively short spell of unemployment of around 1-2 months can recover and earn on average a similar wage to those with no youth unemployment,
  - longer spells of youth unemployment carry a wage scar which is evident up to 20 years later.
- Part of the wage scar comes from the individual with youth unemployment experiencing further unemployment in subsequent decades, but even after controlling for this the scar at age 42 remains high at 10 per cent for 13+ months of youth unemployment..

5. The effect of different kinds of training on earnings and employment..

- Again picking one key study, this time by Lorraine Dearden, Alissa Goodman, Howard Reed and me!
  - drawing on the sequential nature of the NCDS and the detailed family background and test score measures to control for bias due to unobserved heterogeneity.
- Document the cumulation of qualification based training during adult working life (see also Andrew Jenkins, CLS WP 2013),
  - find strong complementarities with earlier education investments.
- Largest returns for employer-provided qualification based training
  - these labour market impact are maintained even controlling for detailed background variables,
  - this is a key issue we should return too using the cohort studies.

6. The "causal" effect of education on earnings

- Pick on my own work with Lorraine Dearden and Barbara Sianesi,

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- Show significant bias from ignoring background heterogeneity.
- Explicitly consider treatment heterogeneity in a multiple-treatment framework distinguishing between discrete levels of educational qualifications.
- But that work started nearly 20 years ago.... when the 1991 study was the most recent wave available.
- Now we are 60, well actually 55!

  - the life-cycle of the 1958 cohort moves on.... and we have learned a little more too....

Earnings and Higher Education in the NCDS

Key Questions:

- How has the earnings premium/private gross return for higher education changed over the working life?
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Approach:

- For the application here we use a broad single definition of Higher Education close to the "Dearden" definition used in the JRSS paper,
  - University or CNNA first degree or higher degree,
  - Higher vocational including HNC and HND, ...(any NVQ4 or above)
- Leave heterogeneity and multiple treatment for a detailed analysis.
- Focus on highest qualification at age 23,
  - but note the importance of the cumulation of higher education qualifications post age 23.

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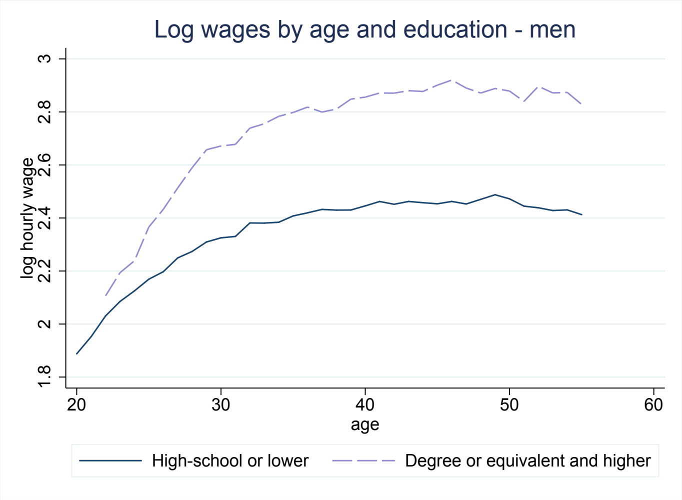
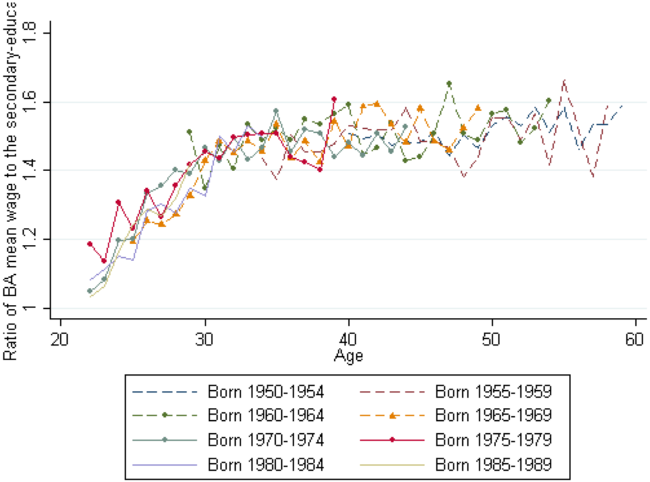
- Focus on highest qualification at age 23,
  - but note the importance of the cumulation of higher education qualifications post age 23.
- What does the raw wage premium look like? First, in the BHPS and LFS?

Log hourly wage profiles by education by age in the BHPS



Notes: Men in the BHPS 1991-2008. Source: Blundell, Costa-Dias and Meghir(2017).

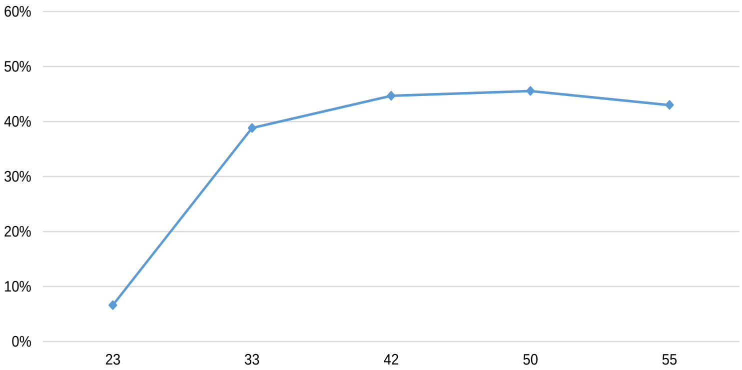
Graduate wage premium by cohort in the LFS



Notes: Men in the LFS. Source: Blundell, Green and Jin (2017).

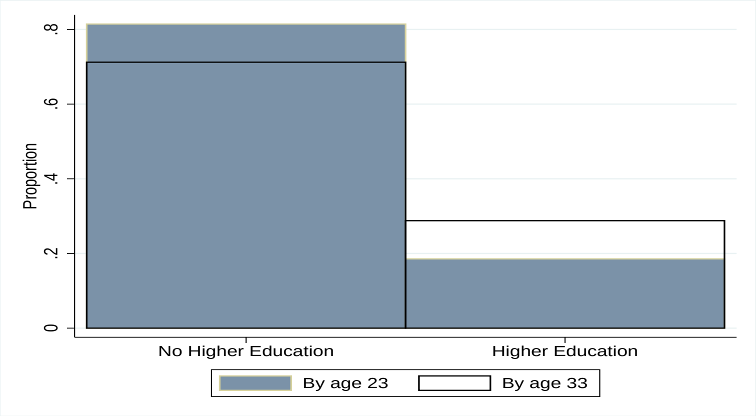
The raw wage premium for higher education in the NCDS

The raw wage premium for men by age for higher education (23)



Notes: Minimal controls. Higher education qualification by age 23

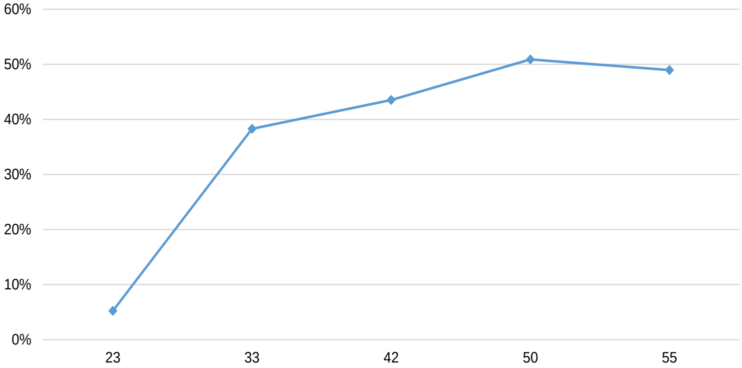
Higher education at age 23 and 33



Notes: Men in the NCDS; stronger growth for women.

The raw wage premium for higher education

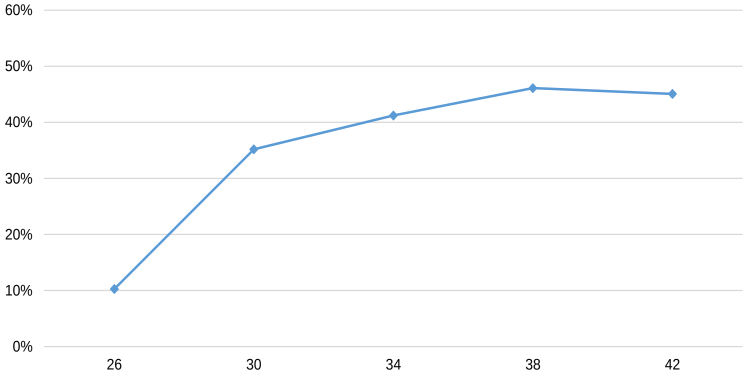
The raw wage premium for men by age for higher education (33)



Notes: Minimal controls. Higher education qualification by age 33

The raw wage premium for higher education in the BCS

The raw wage premium for men by age for higher education (26)



Notes: Higher education qualification by age 26

Education and Earnings: Heterogeneity Bias and the Beauty of the NCDS

Economists (and econometricians) obsess about unobserved heterogeneity, why?

- Three key forms in examining private returns to education and training.
  1. Heterogeneity in "ability" and family background,
  2. Heterogeneity in "returns" across people and over the life-cycle,
  3. Heterogeneity/measurement error in "treatment".
- 'Alternative' solutions to 2. and 3.
  - measurement and matching,
  - instrumental variables and control functions.
- NCDS is ideally suited for making use of **both**!
  - and detailed qualification measurement to overcome 3.

Formalising the role of heterogeneity

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$$\begin{array}{ll} y_{ia}^1 = \beta_{ia} + u_{ia} & \text{if } S_i = 1 \\ y_{ia}^0 = u_{ia} & \text{if } S_i = 0 \end{array} \tag{1}$$

so that

$$y_{ia} = S_i y_{ia}^1 + (1 - S_i)\, y_{ia}^0. \tag{2}$$

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  where, β_{ia} is the heterogeneous return (or treatment effect) for individual i at age a and u_{ia} is the remaining component of earnings.
- Typically u_{ia} will be made up of an individual 'fixed' effect α_i, representing pre-treatment heterogeneity, and an age varying component ε_{ia},

$$u_{ia} = \alpha_i + \varepsilon_{ia}.$$

Correcting for bias in estimated returns

The observable outcome for earnings (log hourly wage) is then

$$y_{ia} = \beta_{ia} S_i + \alpha_i + \varepsilon_{ia}. \tag{3}$$

- The issue is that α_i is typically not fully observed
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- When S_i and α_i are correlated then the estimate of the effect of S_i on earnings at age a (ATT, ATE and ATNT) will be biased;
  - bias remains even when β_{ia} is constant over i,
  - when S_i and β_{ia} are correlated ATE and ATNT are biased even when S_i and α_i are independent.

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  - but instruments have to strongly affect S_i while not depend on u_{ia},
  - typically therefore, very hard to find. Financial stress in family at 16?
- Matching seeks observable measures for α_i and β_{ia} that can fully account for selection on the unoberservables and on the returns.
  - need priors on what are likely to be important - the NCDS design!

CIA and Matching

The solution advanced by matching is based on the following assumption:

Conditional on the set of observables X, the "non-treated" outcomes are independent of the HE status,

$$y_{ia}^{0} \perp S_i \mid X_i$$

which is equivalent to the unobservable in the non-treated outcome equation being independent of the participation status conditional on X_i.

- This means that, conditional on X, HE and non-HE individuals are comparable with respect to the non-HE outcome
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- Of course, we also need a common support assumption to hold too, perhaps less problematic for the ATT.
- IV (and CF) are based on a different independence assumption and can be used to check for further selection on unobservables.

Control function and instrumental variables

Briefly back to the model for log hourly wage at age a

$$y_{ia} = \beta_{ia} S_i + u_{ia}. \tag{4}$$

Suppose, the binary response model for S_i

$$S_i = 1[\pi_{zi} Z_i + \pi_{xi} X_i + \nu_i > 0]. \tag{5}$$

- where the Z_i are instrumental variables, X_i are the other controls.

If $S_i \perp u_{ia} \mid \nu_i, X_i$ then, estimating the $\pi's$ and adding the control function

$$\lambda(\hat{\pi}_{zi} Z_i + \hat{\pi}_{xi} X_i) \tag{6}$$

to estimation *while also saturating the model with all the X_i controls* will generate a consistent estimator of the ATT.

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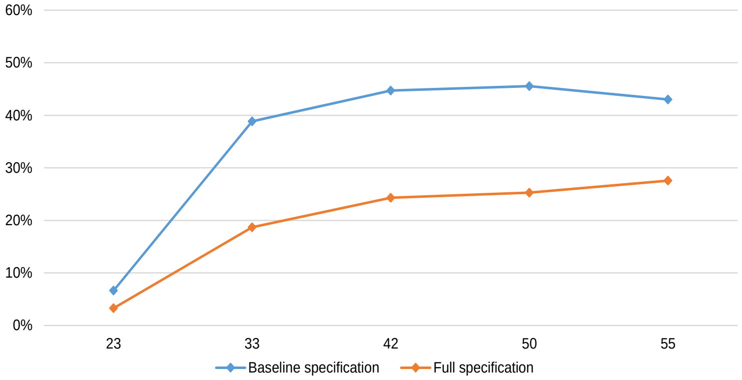
Combining approaches is strategy we first developed in the JRSS paper - works a treat with NCDS data because of the breadth of early ability measures and family background measures through adolescence.

Table: Controls included in each specification

Model	Controls
(i) Basic controls	Ethnicity, region at 16
(ii) Family controls	Class of mother/father, whether mother works, number of siblings
(iii) Test scores etc	Test scores at 7 (maths, copying, drawing and reading), test scores at 11 (general ability, reading, maths and copying), whether deemed outstanding at 11, whether deemed creative at 7
(iv) Parental investments	Mother/father reads to child (age 7), mother/father interested in child's education, mother/father outings with child (age 7), mother/father takes child on trips to public parks, recreation ground, swimming pool, play centre, cinema, library or walks (all at age 11), is mother/father member of a library (age 11)
(v) Externalising BSAG	Hostility towards children, hostility towards adults, inconsequential behaviour, restlessness, anxiety for acceptance by adults and anxiety for acceptance by children (all at ages 7 and 11)
(vi) Internalising BSAG	Depression, withdrawal, unforthcomingness and writing off adults and adults standards (all at ages 7 and 11)

Correcting the higher education wage premium

The wage premium for men by age for higher education (23)



Notes: Higher education qualification by age 23. Full specification includes test scores (7 & 11), family background, investments and BSAG.

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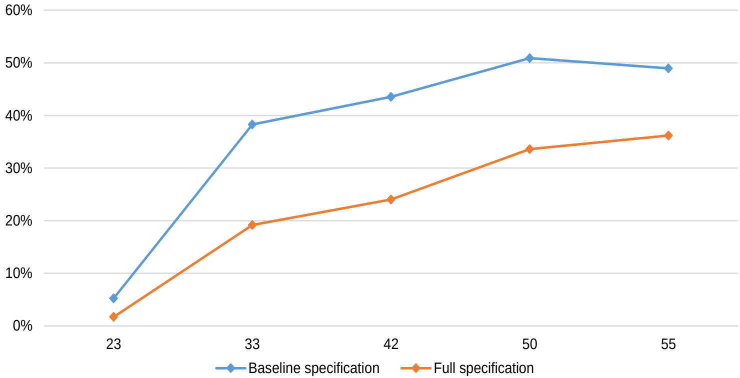

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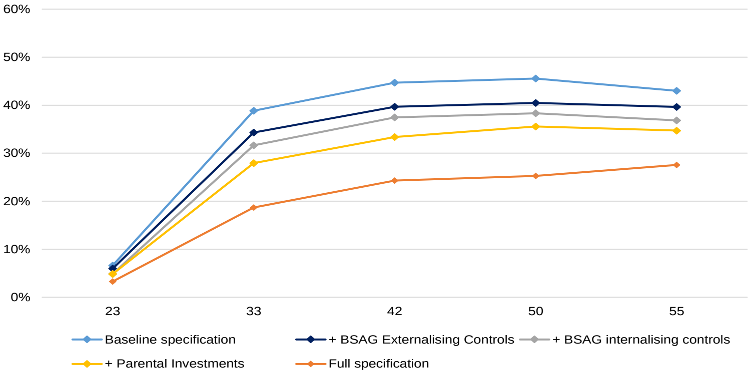

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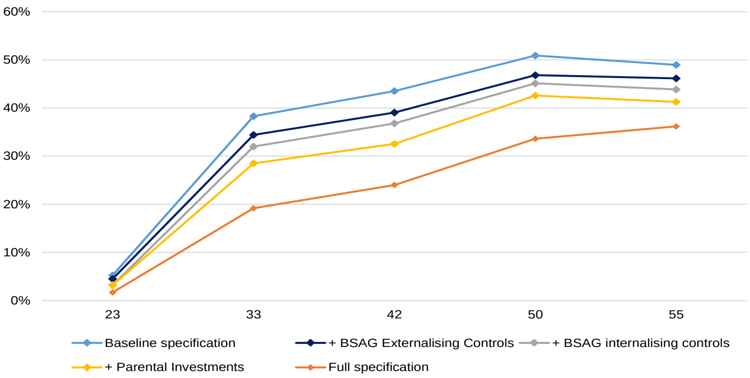

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Results and Implications

- Bias from selection on family background, etc
  - large bias in "standard" data analysis, early test scores help a lot but family background and BSAG are also key, even at age 55,
  - no evidence of remaining selection on unobservables (from CF results using JRSS instruments at age 16).
- Once extensive NCDS early life controls are included, estimated wage returns continue to increase but at a decreasing rate - a la Mincer.
  - impact of early life bias correction falls with age.
- Stronger growth in returns once HE is updated at age 33.
  - corrected series show strong growth through to 55,
  - but caution: non-treated group has changed and the controls may not be sufficient to correct for biases when HE by age 33 is used,
  - may need more recent instruments and could include controls for similar histories.
- This is just wages and just men...

Women, Work Experience and Family Income

- Employment and hours of work:

  - employment and hours at each age are likely to be endogenous,
  - need some form of exclusion restrictions to construct control functions or instruments.

  Note: In other work on panel data (BHPS and PSID) we use tax credit and welfare benefit changes as instruments for female employment and hours, conditional on early years controls where available.
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- Women's earnings and past work experience:
  - need measure of work history, the NCDS retrospective data ask economic activity with month and year start and end for each spell,
  - link with NI and tax records? ..... Plenty more to be done!

Opportunities and Challenges

A remarkable research design, ahead of its time

1. Measuring "unobserved" heterogeneity - breadth/width of the study.
2. Building a full life-cycle - length of the cohort study 60,....
3. Detailed measurement of key adolescent and adult outcomes.
4. Cross-cohort behaviour - across the cohort studies.

Data record linkages are a key future challenge and opportunity:

- link to HMRC and DWP administrative data,
- health records,
- NPD data, ...

Working with ELSA:

- nurses visits and other objective health measurements,
- detailed measurement of pension incentives, as in NCDS60.

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Working with ELSA:

- nurses visits and other objective health measurements,
- detailed measurement of pension incentives, as in NCDS60.

Methods:

- More could be done exploiting the width of the data, using machine learning and complementary data methods.

Thank you NCDS!

Looking forward to following you into a happy and productive retirement!

Happy 60th Birthday!

Richard Blundell (UCL and IFS)