Essays in Applied Microeconomics

PhD Thesis defence

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Essays in Applied Microeconomics

Chapter 1: Does intelligence shield children from the effects of parental unemployment?

Chapter 2: Fertility choice and intelligence in developed countries
joint with Michele Boldrin and Aldo Rustichini

Chapter 3: From bad to worse: long-term effects of recession in adolescence

Chapter 4: Multiple imputation of university degree attainment
joint with Johanna Reuter

Chapter 1

Does intelligence shield children from the effects of parental unemployment?

Research question

Parental unemployment has negative effects on children in terms of

- education
  - Peter (2016), Pan and Ost (2014), Coelli (2011), and Rege, Telle, and Votruba (2011), etc.
- earnings and employment
  - Hilger (2016) and Page, Stevens, and Lindo (2009), etc.
- behaviour, beliefs and well-being
  - Angelini, Bertoni, and Corazzini (2018), Peter (2016), and Brand and Thomas (2014)

Does higher intelligence protect children from these effects?

This paper

- measures parental unemployment when children were 14 years old
- studies how the effects on children vary with their intelligence score
  - focuses on educational and labour-market outcomes
- examines causal interpretation within the difference-in-differences framework

Data: UK Household Longitudinal Study (UKHLS)

- Sample of $\approx 22,000$ individuals in wave 3 (2011-13)
- *Main variables*:
  - cognitive test results Relative stability
  - employment status of parents when respondents were 14 years old Recall bias
- *Education*: post-16 school, tertiary degree, university degree
- *Labour market*: work, labour earnings, occupational ranking, predicted life-cycle earnings

Empirical strategy

Difference-in-differences approach

$$Y_i = \beta_0 + \beta_1 UP_i + \beta_2 IQ_i + \boldsymbol{\beta_3} UP_i \times IQ_i + \beta_4 \mathbf{X}_i + \beta_5 \mathbf{P}_i + v_i$$

Y_i	outcome
UP_i	parent unemployed when child was 14
IQ_i	child's intelligence score
$\mathbf{X}_i$	child's pre-determined characteristics
$\mathbf{P}_i$	parents' pre-determined characteristics

Causal interpretation

$$Y_i = \beta_0 + \beta_1 UP_i + \beta_2 IQ_i + \boldsymbol{\beta_3} UP_i \times IQ_i + \beta_4 \mathbf{X}_i + \beta_5 \mathbf{P}_i + v_i$$

Necessary assumptions

1. **Modified parallel trends**: selection bias is proportional to parental employment

   Formula | Evidence in the BCS70

2. **Predetermined intelligence score**: $IQ_i^0 = IQ_i^1 = IQ_i$

   Evidence age 5 | Evidence age 16

$$\beta_3 = \frac{\partial}{\partial IQ} \mathbb{E}(Y^1 - Y^0 | UP = 1, IQ)$$

How intelligence changes the effect of parental unemployment

Results

- Education at higher IQ is more susceptible to parental unemployment See table
  - consistent with theory of dynamic complementarity (Cunha and Heckman 2010)
- The effect on first job ranking does not vary with IQ See table
- Higher IQ improves the effect on later labour-market outcomes See table
  - consistent with literature on employer learning (Farber and Gibbons 1996; Altonji and Pierret 2001; Arcidiacono, Bayer, and Hizmo 2010)

Next steps

- Examine mechanisms for educational effects:
  - non-cognitive skills
  - financial stress
  - preferences
- Examine mechanisms for labour-market outcomes:
  - Signalling vs human capital
- Use polygenic score of intelligence
- Study gender differences

Chapter 2

Fertility choice and intelligence in developed countries

joint with Michele Boldrin and Aldo Rustichini

Research question

- Intelligence has significant effects on a range of life outcomes

- Fertility is negatively associated with intelligence and education

How intelligence interacts with career aspirations to affect fertility choices?

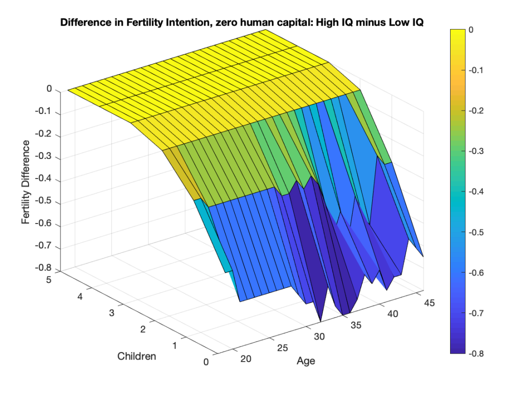
This paper

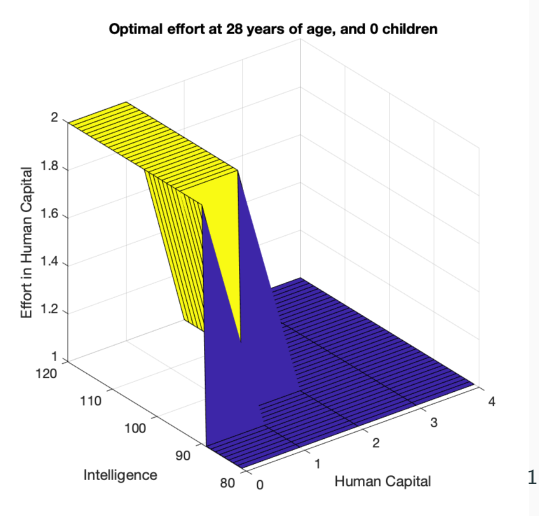
- Builds a dynamic model where career and fertility choices are made jointly
- Studies how intelligence interacts with effort to acquire human capital
- Tests the predictions in a large survey data using various measures of fertility

Model

- Dynamic model of fertility and career choices
- Women derive utility from wage, number of children and leisure
- States: age (n), intelligence (θ), human capital (h) and number of children (c)
- Each period women choose work/school effort (s) and fertility intention (b)
  - given s, human capital changes by ξ with probability $\Pr(\xi|\theta, s) = \boldsymbol{\pi(\theta s)}$
  - given $b = 1$, number of children changes by ζ with probability $\Pr(\zeta|n)$

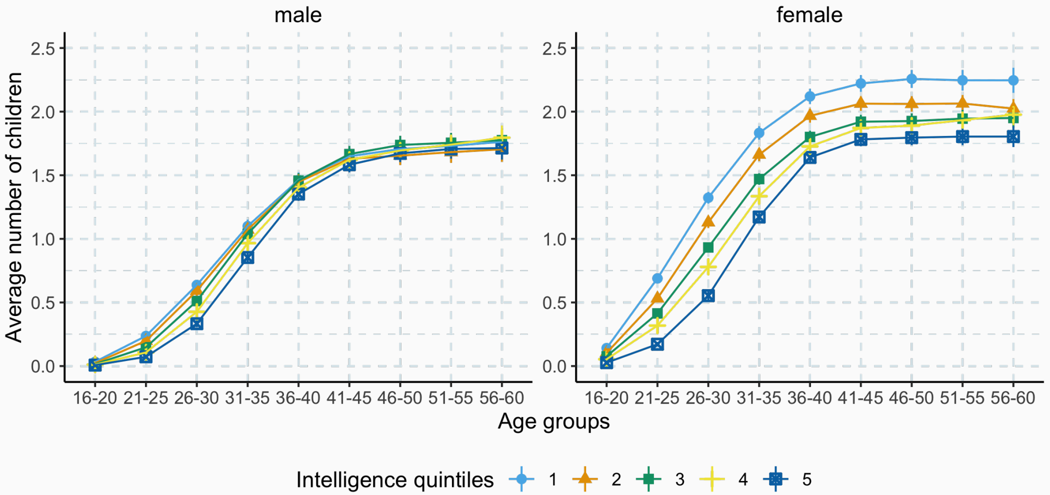
More intelligent women prioritise career over fertility





Data (UK Household Longitudinal Study)

More intelligent women have fewer children and have them later in life



Results

- Cross-sectional analysis
  - Higher IQ is associated with fewer children and later age at first birth
  - The effects are mediated through degree attainment and earnings
- Longitudinal analysis
  - With higher IQ, birth probabilities $\downarrow$ at early ages and $\uparrow$ at later ages
  - The effects are stronger among women who earn a degree See table

Higher IQ makes all women postpone and those with a degree - reduce total fertility

Conclusions

- Intelligence affects fertility through career aspirations of women

- Complementarity between intelligence and effort is key

Next step:

- Test using data from other advanced countries

Chapter 3

From bad to worse: long-term effects of recession in adolescence

Research question

- "Scarring" effects of entering the labour market during recession
  - summarised in von Wachter (2020)
- Especially among workers with low educational attainment

How local economic conditions affect education and subsequent earnings?

This paper

- Measures unemployment rate in the county of birth/school at age 14
- Estimates the effect of local economic conditions on
  - years of education and degree attainment
  - predicted life-cycle earnings
- Using IV approach, computes the effect of lost education on predicted earnings

Results

Higher local unemployment rate at age 14

- decreases (↓) educational attainment See table
  - among children aiming at lower qualifications
- decreases (↓) wages permanently throughout career See figure
- decreases (↓) wages by 8% per year of education lost at ages 26-30 See figure

Next steps

- Interaction with intelligence score
- General-equilibrium effects
- Late enrolment decisions
- Asymetric response to boom vs recession

Chapter 4

Multiple imputation of university degree attainment

joint with Johanna Reuter

Research question

- Universities in the UK: traditional (pre-1992) and new (post-1992)
- Type of higher education institutions matters
- Common surveys offer limited information

Differentiate higher education institution types using multiple imputation

This paper

- Uses the BHPS (1991-2008) to impute in the UKHLS (2009-)
- Uses multiple imputation (Rubin 1987) Intuition
- Examines the validity of inferences using simulations See figure
- Compares with the external benchmark on graduation rates See figure

Next step:

- Compare with true types released in wave 11 (November 2021)

Thank you!

Appendices

Chapter 1: relative stability of intelligence score (BCS70)

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Chapter 1: recall bias

Chapter 1: modified parallel trends (continuous IQ)

Potential outcomes

- Y^0 when not treated
- Y^1 when treated

Parental unemployment

- $UP = 0$ employed
- $UP = 1$ unemployed

Modified parallel trends implies

$$\underbrace{\frac{\partial}{\partial IQ} \ln \left[\mathbb{E}(Y^0|UP = 1, IQ) - \mathbb{E}(Y^0|IQ)\right]}_{\text{\% change in selection bias}} = \underbrace{\frac{\partial}{\partial IQ} \ln \left[1 - \Pr(UP = 1|IQ)\right]}_{\text{\% change in parental employment probability}}$$

Selection bias across IQ is proportional to parental employment probabilities

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Chapter 1: modified parallel trends (binary IQ)

Potential outcomes

- Y^0 when not treated
- Y^1 when treated

Parental unemployment

- $UP = 0$ employed
- $UP = 1$ unemployed

Binary intelligence

- $IQ = 0$ low
- $IQ = 1$ high

Modified parallel trends implies

$$\underbrace{\frac{\mathbb{E}(Y^0|UP=1, IQ=1) - \mathbb{E}(Y^0|IQ=1)}{\mathbb{E}(Y^0|UP=1, IQ=0) - \mathbb{E}(Y^0|IQ=0)}}_{\text{relative selection bias}} = \underbrace{\frac{1-\Pr(UP=1|IQ=1)}{1-\Pr(UP=1|IQ=0)}}_{\text{relative parental employment probabilities}}$$

Selection bias across IQ is proportional to parental employment probabilities

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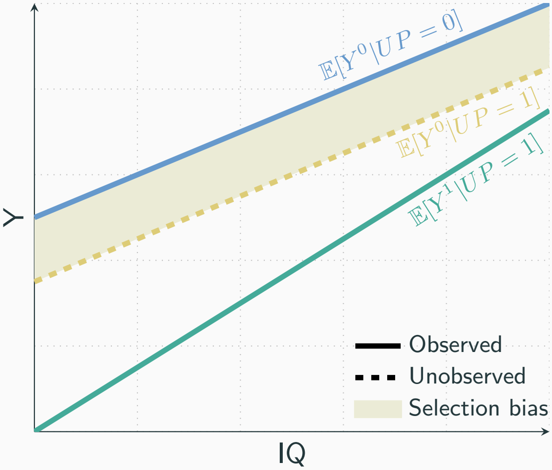
Chapter 1: modified parallel trends (special case)



Special case

- constant $\Pr(UP=1|IQ)$

Potential outcomes

- Y^0 when not treated
- Y^1 when treated

Treatment status

- $UP=0$ not treated
- $UP=1$ treated

Constant selection bias

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Chapter 1: characteristics at birth in the BCS70

	Regressors				
Variable	Parent unemp	IQ	Parent unemp × IQ	Obs.	Mean variable
Birthweight, g	-40.227	60.880***	-7.167	4,890	3,282
	(28.969)	(10.369)	(26.475)		
Age of mother	0.641**	0.357***	0.315	4,894	26.21
	(0.267)	(0.084)	(0.265)		
Age of father	1.843***	0.435***	0.317	4,303	29.05
	(0.345)	(0.104)	(0.319)		
Height of mother, cm	-0.570*	0.369***	0.003	4,860	161
	(0.315)	(0.115)	(0.278)		
Mother married	0.003	0.001	-0.006	4,894	0.95
	(0.012)	(0.004)	(0.01)		
Age of mother at first birth	-0.522***	0.471***	0.026	4,874	21.68
	(0.176)	(0.063)	(0.178)		

$^{\dagger}q < 0.1; ^{\dagger\dagger}q < 0.05; ^{\dagger\dagger\dagger}q < 0.01$

$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

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Chapter 1: cognitive test results at age 5 in the BCS70

Variable	Parent unemp	IQ	Parent unemp × IQ	Obs.	Mean variable
	Regressors				
Composite score (PC1)	-0.124*	0.263***	-0.040	2,076	-0.05
	(0.064)	(0.04)	(0.066)		
Age at test, days	-3.674**	-0.492	0.033	4,366	1,853
	(1.437)	(0.992)	(1.345)		
Reading score	-0.791***	1.447***	-0.801	2,157	3.09
	(0.272)	(0.183)	(0.299)		
English picture vocabulary score	-0.230***	0.373***	0.037	4,453	-0.35
	(0.073)	(0.026)	(0.071)		
Copying designs score	-0.057	0.393***	0.072	4,453	-0.10
	(0.051)	(0.017)	(0.048)		
Draw-a-man score	-0.029	0.286***	0.094	4,453	-0.17
	(0.063)	(0.021)	(0.064)		
Complete-a-profile score	-0.419*	0.493***	-0.328	4,304	6.85
	(0.216)	(0.075)	(0.22)		

$^{\dagger}q < 0.1; ^{\dagger\dagger}q < 0.05; ^{\dagger\dagger\dagger}q < 0.01$

$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

Go back

Chapter 1: cognitive test results at age 16 in the BCS70

	Regressors				
Variable	Parent unemp	IQ	Parent unemp × IQ	Obs.	Mean variable
Composite score (PC1)	-0.125*	0.585***	0.005	1,259	-0.07
	(0.073)	(0.027)	(0.075)		
Reading score	-1.865*	7.403***	0.778	1,336	53.55
	(1.004)	(0.369)	(1.01)		
Spelling score	1.169	14.626***	2.550	4,894	73.90
	(3.936)	(1.418)	(3.566)		
Vocabulary score	0.538	6.079***	-0.425	4,894	19.57
	(1.078)	(0.395)	(0.993)		
Math score	-1.112	6.102***	-0.519	1,591	36.10
	(0.901)	(0.298)	(0.864)		
Complete-matrix score	-0.203	0.579***	-0.038	1,368	8.81
	(0.132)	(0.052)	(0.149)		

$^{\dagger}q < 0.1;^{\dagger\dagger} q < 0.05;^{\dagger\dagger\dagger} q < 0.01$

$^{*}p < 0.1;^{**} p < 0.05;^{***} p < 0.01$

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Chapter 1: education results

	Regressors			
Depedent variable	Parent unemp	IQ	Parent unemp × IQ	Obs.
Post-16 school	-0.053***	0.138***	-0.035††	20,420
	(0.014)	(0.003)	(0.012)	20,420
Degree	-0.026*	0.134***	-0.022††	20,420
	(0.014)	(0.003)	(0.011)	20,420
Uni degree	-0.017	0.102***	-0.023†	20,420
	(0.014)	(0.005)	(0.012)	20,420

Standard errors in parentheses

$^{\dagger}q < 0.1; ^{\dagger\dagger}q < 0.05; ^{\dagger\dagger\dagger}q < 0.01$ (sharpened q-value Anderson 2008)

$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

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Chapter 1: occupational ranking results

	Regressors			
Depedent variable	Parent unemp	IQ	Parent unemp × IQ	Obs.
First job	-0.031**	0.024***	0.012	17,315
	(0.013)	(0.003)	(0.012)	17,315
Current job	-1.097***	0.915***	0.546††	20,420
	(0.219)	(0.056)	(0.215)	20,420

Standard errors in parentheses

$^{\dagger}q < 0.1; ^{\dagger\dagger}q < 0.05; ^{\dagger\dagger\dagger}q < 0.01$ (sharpened q-value Anderson 2008)

$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

Go back

Chapter 1: labour-market results

	Regressors			
Depedent variable	Parent unemp	IQ	Parent unemp × IQ	Obs.
Work	-0.058***	0.055***	0.032††	20,420
	(0.013)	(0.003)	(0.013)	20,420
%Δ earnings	-22.822***	30.344***	7.467†	20,420
	(4.298)	(1.280)	(4.525)	20,420
Earn > 0	-0.057***	0.057***	0.032††	20,420
	(0.013)	(0.003)	(0.013)	20,420
Current job	-1.097***	0.915***	0.546††	20,420
	(0.219)	(0.056)	(0.215)	20,420

Standard errors in parentheses

$^{\dagger}q < 0.1;^{\dagger\dagger}q < 0.05;^{\dagger\dagger\dagger}q < 0.01$ (sharpened q-value Anderson 2008)

$^{*}p < 0.1;^{**}p < 0.05;^{***}p < 0.01$

Go back

Chapter 2: longitudinal results among women

Dependent variable: birth probabilites by age

		Relative to ages 16-20				
	Ages 16-20	21-25	26-30	31-35	36-40	41-45
Constant	-2.737***	0.647***	0.867***	0.639***	-0.274***	-1.985***
	(0.048)	(0.053)	(0.054)	(0.058)	(0.075)	(0.163)
Degree	-1.609***	0.735***	1.416***	1.799***	1.938***	1.907***
	(0.080)	(0.088)	(0.085)	(0.086)	(0.094)	(0.158)
IQ	-0.196***	0.096**	0.202***	0.287***	0.262***	0.383***
	(0.025)	(0.030)	(0.030)	(0.032)	(0.040)	(0.083)
Degree $\times$ IQ	-0.239***	0.031	0.165*	0.218**	0.240**	0.282*
	(0.068)	(0.079)	(0.074)	(0.075)	(0.083)	(0.142)

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Chapter 3: education results

	Dependent variable			
	Years of edu	Degree	Traditional uni degree	Other HE
Panel A: Average effect				
L. unemp at 14	-0.102**	-0.014*	-0.001	-0.010**
	(0.044)	(0.007)	(0.010)	(0.005)
Panel B: Interacted by gender				
L. unemp at 14	-0.103**	-0.014*	-0.001	-0.009*
	(0.044)	(0.007)	(0.011)	(0.005)
Female	0.008	0.013	0.020	0.041**
	(0.134)	(0.022)	(0.039)	(0.017)
L. unemp at 14 $\times$ Female	0.003	0.001	0.000	-0.003
	(0.015)	(0.002)	(0.003)	(0.002)
Obs.	15,147	15,136	10,009	15,136
F statistic	5.407	3.544	0.004	4.273

$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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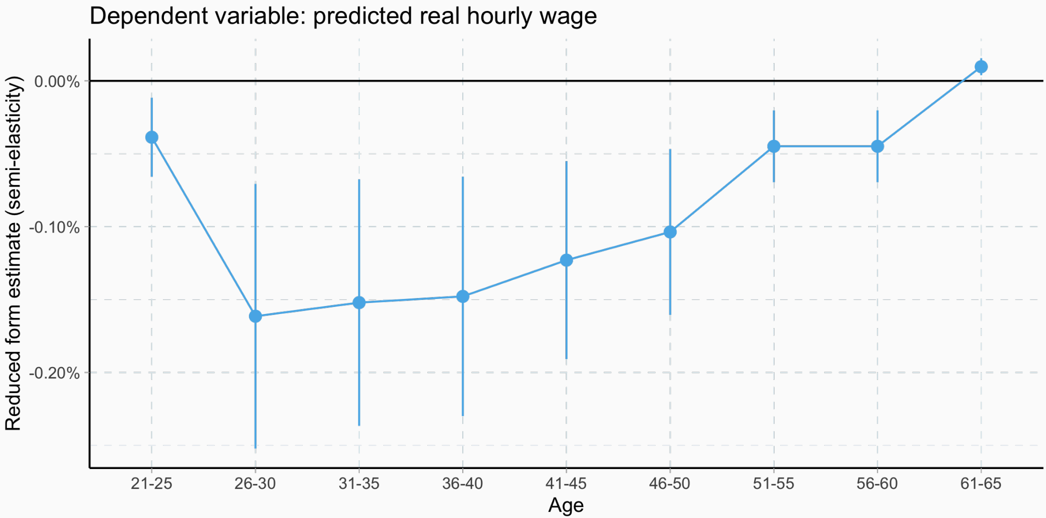
Chapter 3: labour-market results



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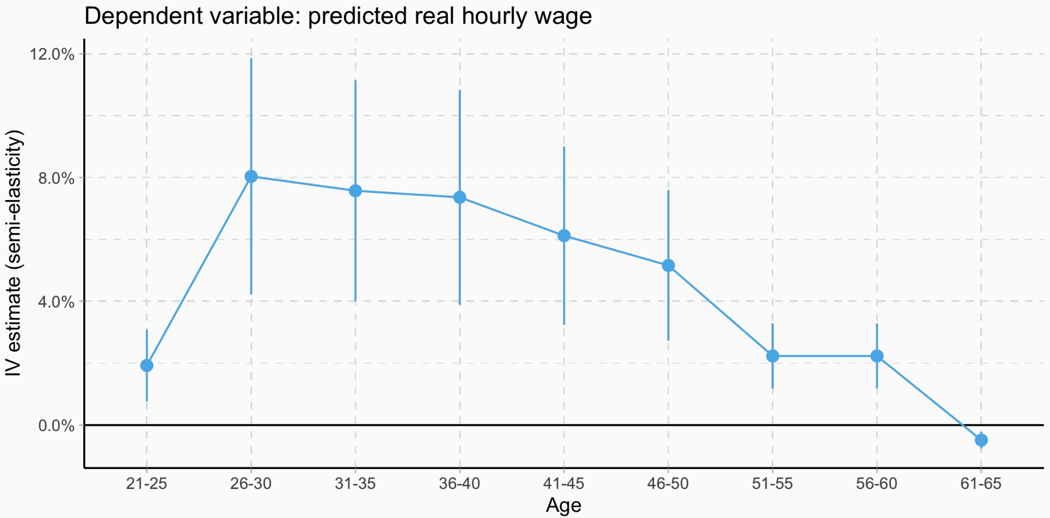
Chapter 3: IV estimates



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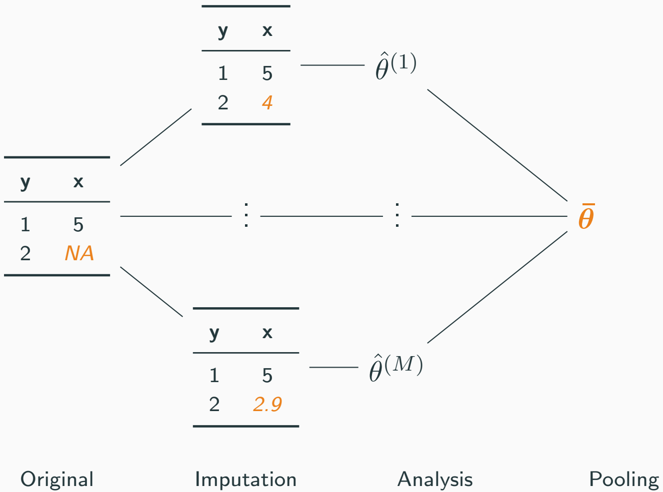
Chapter 4: intuition behind multiple imputation

Key assumptions:

- ignorable non-response
- congruence with analysis model
- consistency of $\hat{\theta}$ in true dataset



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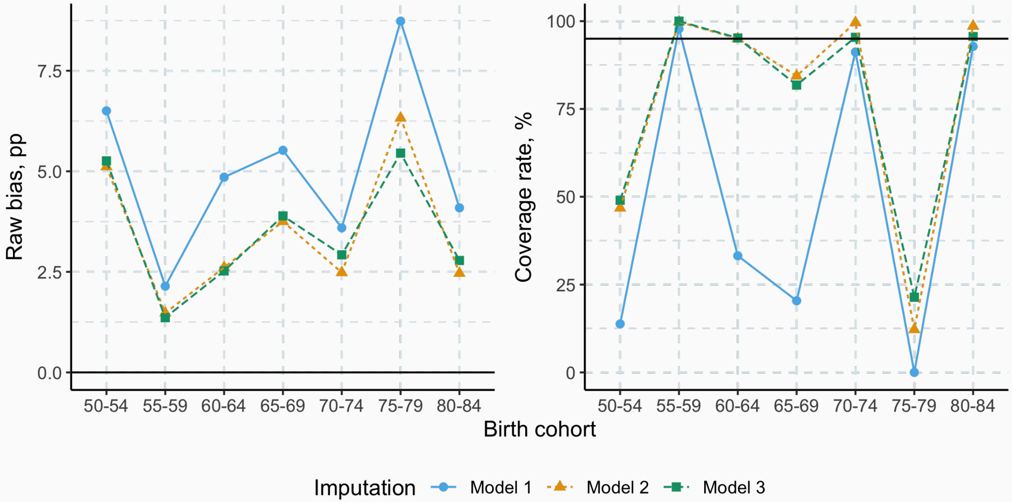
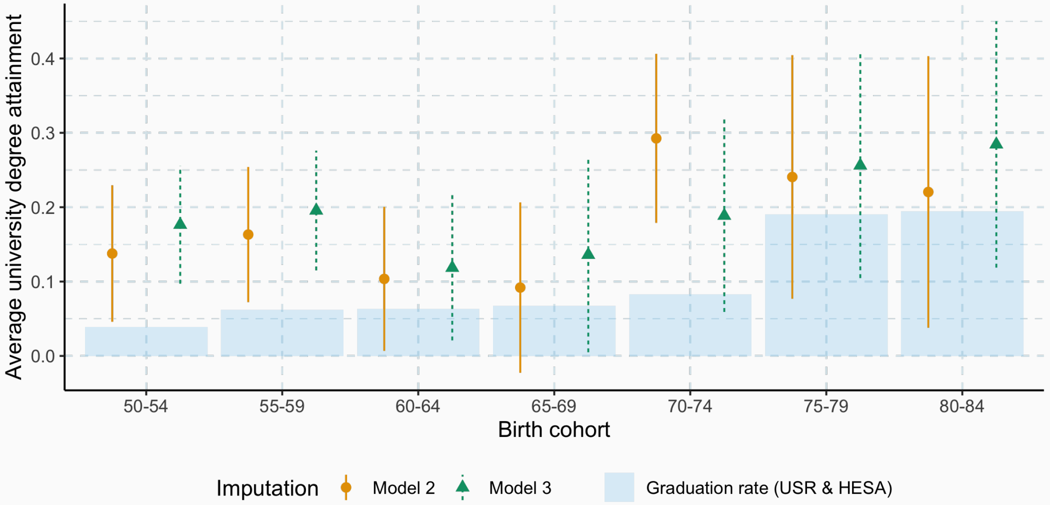

Raw bias, pp
0.0
2.5
5.0
7.5
Coverage rate, %
0
25
50
75
100
50-54
55-59
60-64
65-69
70-74
75-79
80-84
Birth cohort
Imputation
Model 1
Model 2
Model 3

Go back

Chapter 4: comparison with graduation rates from USR and HESA



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