

Examining the size of the gender wage gap within and across birth cohorts: some reflections on methodological challenges

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Alex Bryson
UCL

Life course analysis: data and methodological challenges
ISER, University of Essex

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Project Overview

- Three years (September 2019-September 2022)
- Analyses birth cohort data to explore the gender wage gap across cohorts and over the life-course
- Providing a comprehensive analysis of the GWG across individuals' lives, up to the age of 60 in the case of the 1958 cohort, and across generations
- The UCL team:
 - Alex Bryson (PI)
 - Heather Joshi (co-investigator)
 - David Wilkinson (co-investigator)
 - Francesca Foliano (Research Fellow)
 - Bozena Wielgoszewska (Research Fellow)
- All information on the project, including news and updates, is on the website: <https://www.ucl.ac.uk/ioe/departments-and-centres/departments/social-science/gender-wage-gap-evidence-cohort-studies>

Research Questions

1. What does the GWG look like ***over the life course and across birth cohorts?***
2. How much of the GWG is accounted for by differences in ***human capital accumulation*** over the life course?
3. What roles do family formation and ***care responsibilities*** play in the emergence of, and persistence in, the GWG?
4. How much of the gender wage gap is attributable to the ***sorts of jobs*** undertaken by men and women, particularly in relation to full-time/part-time status and occupation?
5. What role do ***early childhood attributes and experiences*** play in determining the subsequent wage gap between men and women and do childhood influences still matter having accounted for early adulthood experiences?

Data

National Child Development Survey (NCDS): a cohort of over 17,000 individuals born in one week in 1958. They have been surveyed nine times to the age of 55 and, given the length of the proposed project, we will be able to follow them through to age 61 (Sweep 10).

The **British Cohort Survey (BCS):** a cohort of over 17,000 individuals born in one week in 1970. They have been surveyed 10 times to the age of 47.

Next Steps, (previously the Longitudinal Study of Young People in England) which, in 2004, started surveying all young people in Year 9 who attended state and independent schools in England (around 16,000 individuals born in 1989/90). They were surveyed every year until 2010 and were last surveyed in 2015/16 for Sweep 8 at age 25.

National Survey of Health and Development: 1946 Birth Cohort

Millennium Cohort Study (MCS): a cohort of 19,000 individuals born in 2000-2002. Now aged 20.

All participated in the **COVID-19 Survey:** 3 waves (May 2020, Sept/Oct 2020, Feb/Mar 2021) <https://cls.ucl.ac.uk/covid-19-survey/>

Pseudo birth cohorts: LFS, ASHE, Understanding Society, BHPS

Why Birth Cohort Data?

1. Different cohorts are exposed to different labour market and policy conditions during their lifetimes.
2. For instance, the 1958 cohort left school when the Equal Pay Act was first being implemented whereas the Act had been in place for a decade when the 1970 cohort left compulsory education.
3. The education gap between men and women has disappeared and even reversed, such that the returns to employment will have shifted markedly between men and women across the generations.
4. Attitudes to women's labour market participation and men's household production have shifted. These changes in social norms, together with attendant changes in public policy, have created opportunities for men and women to combine paid and unpaid work and leisure in ways not hitherto possible, with uncertain consequences for the life choices and earnings patterns of men and women across the life-course.

Methods

By analysing nationally representative birth cohort data for people born in 1958, 1970 and 1989/90 this study addresses the topic from three angles:

1. We consider the evolution of the GWG over the whole life-course. This is important because factors governing both selection into employment and wage determination vary for men and women well into later life.
2. Because we track people from birth, we obtain a picture of the links between childhood circumstances, skills and experiences and subsequent earnings for men and women - and thus the size of the wage gap.
3. We distinguish between the effects of ageing and birth cohort, something that is only possible with data tracking multiple birth cohorts.

Methodological Challenges

Selection into employment: over the life course and across cohorts

Panel attrition

Imputation to tackle data missingness/item non-response

Consistency in dependent variable

Consistency in independent variables

Common support problems

Cross cohort comparison

Selection into Employment

Selection into employment may vary over time and by age group, imparting different biases to a GWG based solely on those in employment.

This can occur simply because the participation rate varies over time, or else because different types of women/men refrain from the labour market.

When interpreting trends in the GWG one needs to account for the changing composition of women (and men) in and out of employment.

If the attributes of those in employment have changed over time, gender differences in these changing attributes may disguise the underlying rate of change in the GWG.

Part of GWG may reflect non-random selection into employment based on earnings potential but the nature of potential bias is uncertain a priori

Previous literature on Selection

Various methods for dealing with selection

- Imputation of wages to non-employed (assumes selection captured by observed data)
- Sample selection adjustment (requires instrument but exclusion restriction problems (Adda et al, 2017))
- Bounding (Blundell et al., 2007)
- Sub-group analysis where men and women similar eg FT

No consensus in the literature as to trends in selection into employment (see [Table A2 of Bryson et al. 2020 supplementary appendix](#))

In the UK

- reduction in positive female selection into employment in last few decades due to big rise in overall female participation rates
- Fall in participation among older men has meant positive selection in recent years
- Female selection into employment in the early post-war period was likely to have been different (negative)

Impute Earnings of the Non-Employed

Various options

- use panel nature of the data where individuals are intermittently employed eg. Olivetti and Petrongolo (2008)
- Predict with Mincerian wage equation
- Match non-employed to 'like' earners (Neuburger et al 2011)

We do the last of these

Run matching estimators for various subgroups

- Employees without wage; self-employed; unemployed; non-participants
- Within sweep and within gender
- Using nearest neighbour PSM to identify those with nearest employment probability
- Enforce with common support

Mechanics of Matching to Impute Earnings of the Non-Employed

Probits for probability of employment separately by sex and cohort sweep

Covariates to be used in the matching process

- Fortunate in the case of the birth cohorts due to richness of data from birth

Enforce common support by dropping cases whose propensity for waged employment falls below the lowest probability for the waged employee sample at that sweep

Median imputed wages for non-employed by sex and sweep presented in

Appendix Figures [A1a-A2b](#)

- Shows imputed earnings tend to be lower for non-employed than employed in case of men and women
- However, varies a lot by age
- And in some cases (eg self-employed women) imputed wage is above that for employed women



Adjusting for Panel Attrition

Lose substantial part of the sample by the time NCDS reach age 55

We adjust for sample attrition by weighting the separate male and female wage equations by the inverse probability of responding to each sweep

For each sweep the response variable takes the value 1 when the outcome of the interview was productive for the given person; and 0 if the interview was productive at age 10/11, but not the given sweep.

Cohort members who died or emigrated were not included in the target sample for that sweep. When there was missing data for covariates, missing dummies were included. For continuous variables, the values of covariates were assigned the mean of known values for each sweep and gender. For each model the values of weights which were below the 1st percentile and above 99th percentile, were replaced to the 1st and 99th percentile respectively.

See [Appendix Tables A7a and A7b](#) for covariates used in NCDS and BCS

Derivation of the GWG

We calculate unadjusted and covariate-adjusted gender wage gaps by estimating a quantile regression model at the median by gender for each sweep.

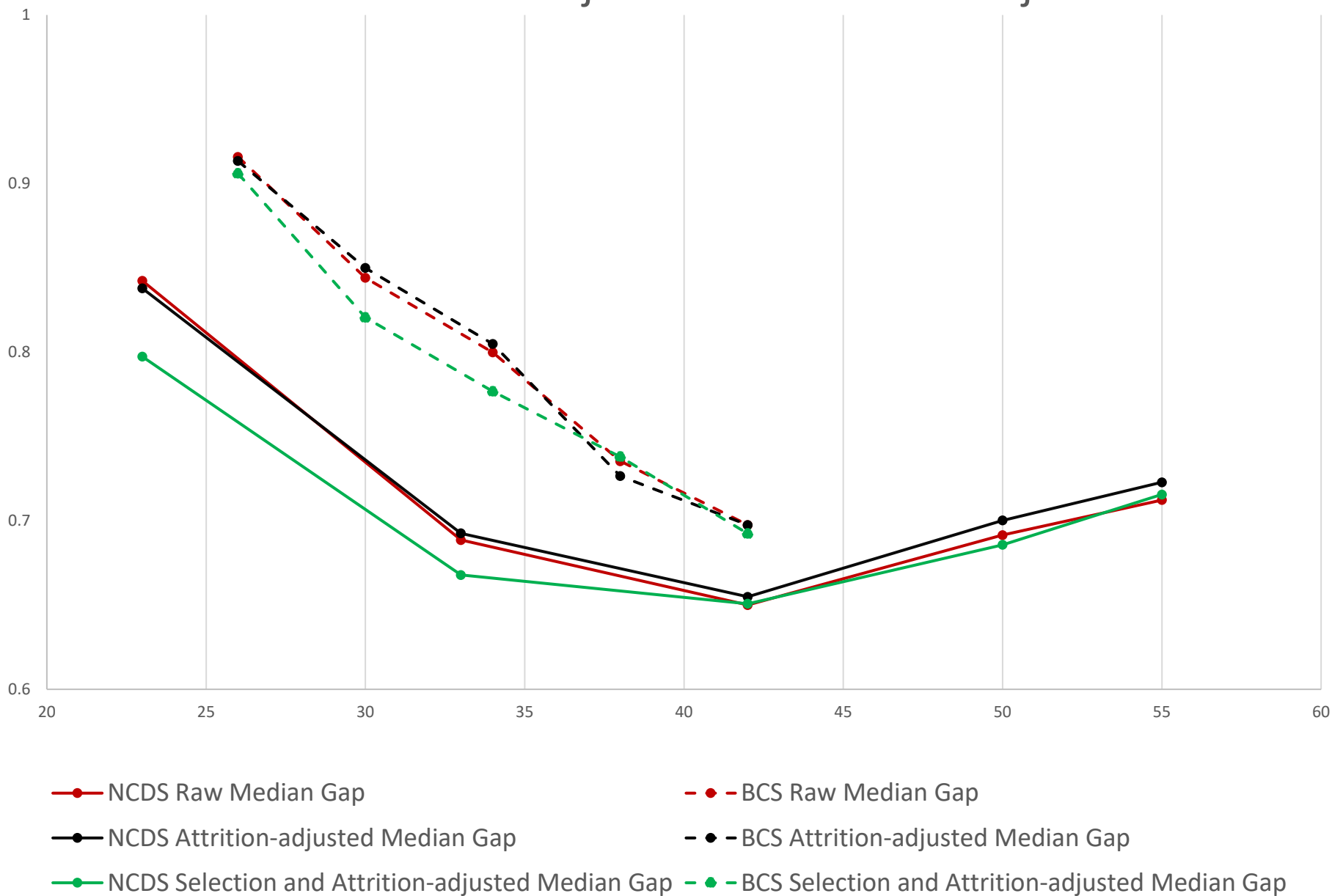
We then recover predicted wages for the sample of females, based on their characteristics, under a female-only model and under the male-only model.

We express the gap between these two predictions as a ratio of the median wages obtained under female-only model, relative to the median wages obtained under the male-only model.

To account for selection into employment we perform the same exercise, but this time combining both observed and imputed wages.



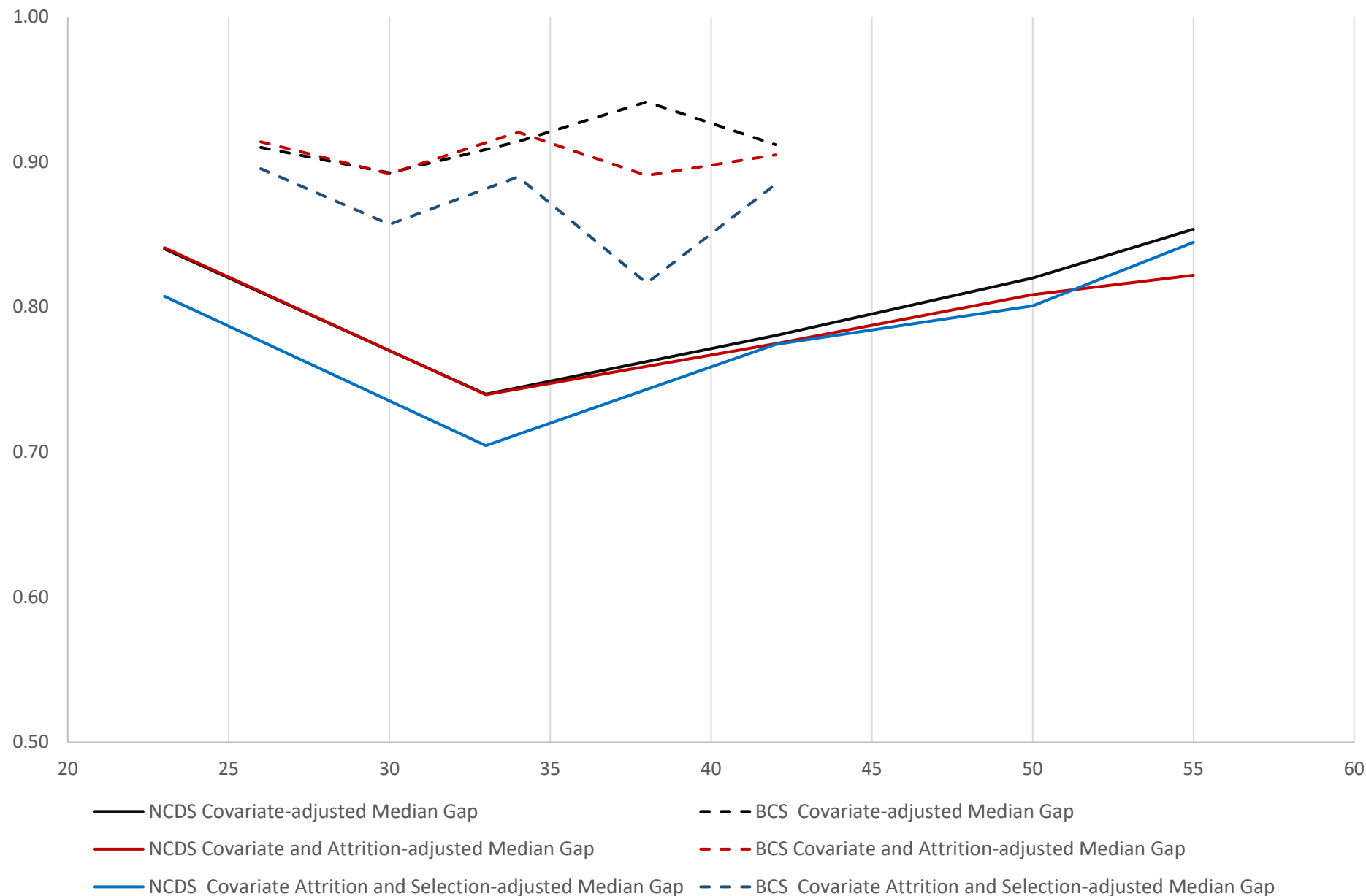
Raw female-to-male ratios of median pay, by survey attrition adjusted and selection adjusted



Findings for Raw GWG

1. The GWG grows until mid-age then falls
2. The GWG is smaller across the life-cycle in BCS v NCDS
 - Raw, attrition adjusted and selection adjusted
3. Results are not particularly sensitive to attrition adjustment
 - The black lines track the red lines
 - Attrition adjustment closes the GWG a little later in life in NCDS
4. Adjusting for selection into employment plays a small, albeit significant, role in the size of the GWG over the life-cycle
 - Adjusting for selection into employment increases the size of the GWG in early life in both NCDS and BCS

Female-to-male ratios of median covariate,
attrition, and selection adjusted pay, by survey



Findings for covar-adjusted GWG

1. NCDS

- Life-course pattern of GWG similar to that for raw gap, but gap begins to close in 30s not 40s
- Gap is less pronounced than raw gap due to human capital differences in 30s and 40s
- Accounting for attrition gap is larger later in life
- Selection-adjustment means gap is larger until 40s

2. BCS

- GWG much flatter between 20s and 40s when covariate adjust due to human capital differences
- GWG always smaller than in case of NCDS
- GWG smaller with selection-adjustment

Imputation for Data Missingness

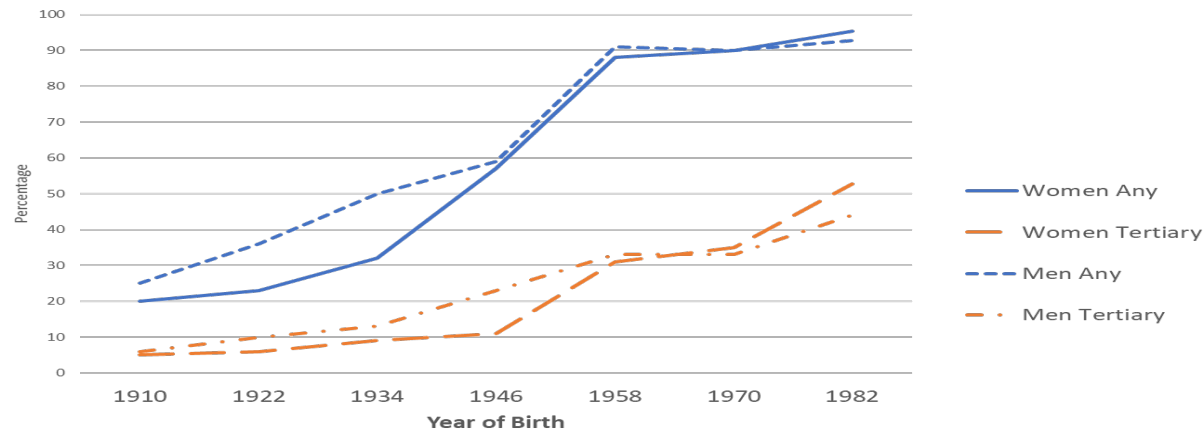
1. So far have adopted standard approach in economics
 - Imputation at mean and additional imputation dummy
 - Inclusion of missing category where categorical
 - Check against complete (non-missing) estimates
2. Be clear about assumptions regarding missingness at random
3. In on-going work we are adopting multiple imputation techniques more commonly used by our CLS colleagues
4. Likely to adopt Schafer's data augmentation approach (Schafer, 1997) under the assumption of 'missing at random' (MAR). Implies that our estimates are valid if missingness is due to variables included in our models (Mostafa et al., 2020; Silverwood et al., 2020).

Consistency in Dependent Variable

1. Want consistency but not always apparent
2. Which earnings? Gross v net
3. Which hours? With or without overtime etc.
4. How were they requested?
 - Interviewer v self-completion; question ordering; contemporaneous v earlier jobs
5. What to do when not consistent?
 - Ways to convert net into gross earnings
 - We also cross-referred to data containing both for similar years (the FES)
 - How do your gross hourly earnings compare to measures used in other studies?
 - Which earnings/hours; median v mean; log v not
 - Outliers and trimming

Consistency in Independent Variables

1. Some are particularly problematic
2. Occupational classifications
 - Cross-walks
 - Programmes taking verbatim data and recoding
 - But occupations really do change
3. Qualifications
 - Really tough to code consistently over life course
 - Derived from Census, GHS, birth cohort studies and LFS



The Common Support Problem

1. When men and women are so different
2. Part-time employment a big issue for women but early on very few men in PT employment making it difficult to compare due to low N problem and potential for collinearity with female and PT
3. Can run analyses for FT workers only
4. But we are able to recover estimates which condition on PT status in our case. And becomes easier with increasing N male PT in recent years

Cross-cohort Comparisons

1. Be clear why you are doing it

- Might be external validity in testing a theory you expect to hold across cohorts
- Or might expect differences, e.g. theory guiding expectations on selection into employment
 - Cf no selection issue in MCS

2. Interpretation of similarity/difference can be tricky without theory

3. Construct validity across cohorts

- Testing to see whether respondents/parents in cohorts interpreted a question in a conceptually similar manner by checking for measurement invariance
- Scalar and metric invariance
- Not relevant to hourly wage but to other things e.g. conduct problems

Lessons I'm trying to Learn

1. How robust are results to doing things differently?
 - E.g. methods for addressing selection into employment
2. Potential benefits of multiple imputation
 - how different are the results?
3. Tension between innovation and consistency in data collection
 - How a data item is gathered
 - Ensuring same set of key data items available
4. Grappling with alternative estimation methods (Strittmatter and Wunsch, 2021)
 - Assumptions behind various decomposition methods: Gelbach, JMP and how they relate to one another
 - Value of semi-parametric approaches

Detail on Some of the Issues Discussed

[Bryson, A., Joshi, H., Wielgoszewska, B. and Wilkinson, D. \(2020\) "A Short History of the Gender Wage Gap in Britain", *Oxford Review of Economic Policy*, 36, 4: 836-854](#)

[Supplementary Appendix to Bryson et al 2020](#)

[Joshi, H., Bryson, A., Ward, K. and Wilkinson, D. \(2021\) "The Gender Gap in Wages over the Life Course: Evidence from a British Cohort Born in 1958", *Gender, Work & Organization*, 28: 397-415](#)