The Gender Wage Gap Among Those Born in 1958: A Matching Estimator Approach

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Project Overview

- Part of an ESRC funded project examining the GWG over the life course using birth cohort data
- The UCL team:
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- All information on the project can be found here: https://www.ucl.ac.uk/ioe/departments-and-centres/departments/social-science/gender-wage-gap-evidence-cohort-studies

Motivation

1. Drawbacks in parametric estimation of the gender wage gap (GWG)
    - Failure to compare ‘like’ men and women
2. Common to condition on potentially endogenous variables
    - Biases ‘true’ estimates of the GWG
3. Data from the National Child Development Survey (NCDS) provide good basis for tackling these issues:
    - Match men and women on a rich set of variables liable to impact wage formation over the life cycle which might conceivably differ by gender
    - Measured pre-labour market entry and thus less liable to be endogenous with respect to wage formation
        - Birth, 7, 11 and 16 years collected prospectively

Preview of Results

1. Large raw GWG rising until 40s then falls but remains sizeable to age 63
2. In contrast to findings in the literature in which the regression-adjusted GWG is considerably smaller than the raw gap, differences in log hourly mean earnings between men and women are of roughly similar size and, in some cases, wider than raw gaps conditioning on pre-labour market variables.
3. This is the case whether we use matching or linear estimation techniques.
4. However, the PSM estimated GWG is above the raw gap when cohort members are in their 40s, 50s and 60s.
5. The implication is that women have pre-labour market traits which reduce their earnings later in life relative to men.
   - Chief among these is occupational expectations
   - Not true for all traits

Previous Literature

1. Studies indicate inverted u-shape in the GWG over the life course
    - Small in early years, widening in 30s/40s, narrowing thereafter
2. Falls across cohorts
3. Raw gap tends to close by (roughly) one half when condition on other variables
    - Depends somewhat on data set and conditioning variables
4. Frequently treats education and fertility decisions as exogenous when, in fact, might be endogenous and partials out some of GWG
    - Same could be said of job traits
5. Some exceptions using structural estimation in an effort to tackle endogenous decision-making
    - Adda, Dustmann and Stevens 2017 "The Career Costs of Children", Journal of Political Economy

Value of Matching Estimators

1. Linear estimation (and decompositions on which most are based) based on unnecessarily restrictive assumptions regarding functional form
2. By ignoring common support, compare wages of women to men who may not be reasonable comparators
3. Matching may make a substantive difference to the estimation of the GWG
    - Strittmatter and Wunsch (2021) explain more of GWG when estimated with PSM
        - Substantial common support issue in their data
        - Combine exact matching on key wage determinants with PSM (radius) matching

PSM v OLS

1. Both assume relevant differences between treated and non-treated are captured by their observables (conditional independence assumption)
   - violated if analysis does not incorporate all factors affecting participation and outcome of interest
   - the assumption is not testable
2. Advantages of PSM relative to OLS
   - semi-parametric so does not require assumption of linearity in outcome equation
   - individual causal effect is completely unrestricted so heterogeneous treatment effects can be captured (no assumption of constant additive effects)
   - highlights problem of common support since women must have ‘like’ counterparts in male population. Thus, avoids extrapolating beyond CS but implications if many treated individuals remain ‘unmatched’

Data and Methods

1. National Child Development Study (NCDS)
2. Log hourly wages at ages 23, 33, 42, 50, 55, 61 and 63
    - Deflated to January 2000 prices
    - Rerun matching for each wage outcome
3. Propensity score matching (PSM) matching women to men on single index (the propensity score) derived from probit (0,1) if woman
4. Using pre- labour market covariates from mother, cohort member, teacher
    - Parental background; pregnancy/birth; ages 7, 11, 16
5. Theory driven as opposed to data driven (Machine Learning)
6. Plausibility of conditional independence assumption in this case
7. 5 nearest neighbours (Froelich) to recover ATT
    - enforces common support with 0.005 caliper
    - Bootstrapping (50 reps)

Covariates used in matching

Wave	Variables
Pre-birth/birth	White; country of birth; father's social class; mother smoked during pregnancy; birthweight (ounces); sibling birth order; mother smoking 4 months after birth
Age 7	Southgate reading test score; arithmetic problems; N Rutter symptoms; Score on Bristol Social Adjustment Guide; number of child illnesses
Age 11	Occupational expectations when aged 25; standardized reading score; standardized maths score
Age 16	In trouble with police; mother's assessment of over/underweight; disability; alcohol consumption; smoking behaviour

Note: Other variables we have experimented with include: mum's social class; breast fed; region; housing tenure; household size; verbale and non-verbale test scores aged 11; female teacher; teacher rating of child aged 11 and 16; child's expectations on schooling; mum's and dad's interest in education of child; financial hardship and FSMs aged 7 and 11

Occupational Expectations At Age 25 Asked at Age 11

	Male	Female
Professional	9	4
Other non-manual, scientific	6	4
Typist, clerical	2	11
Shop assistant	1	7
Junior non-managerial	3	1
Personal services	1	9
Foreman, manual	<1	<1
Skilled manual	18	1
Semi-skilled manual	3	<2
Unskilled manual	<1	<1
Self-employed	1	1
Farm worker	2	2
HM Forces	7	<1
Sports man/woman	9	<1
Student	<1	<1
Teacher/nurse	2	20
Unclassifiable	34	38

Match Bias

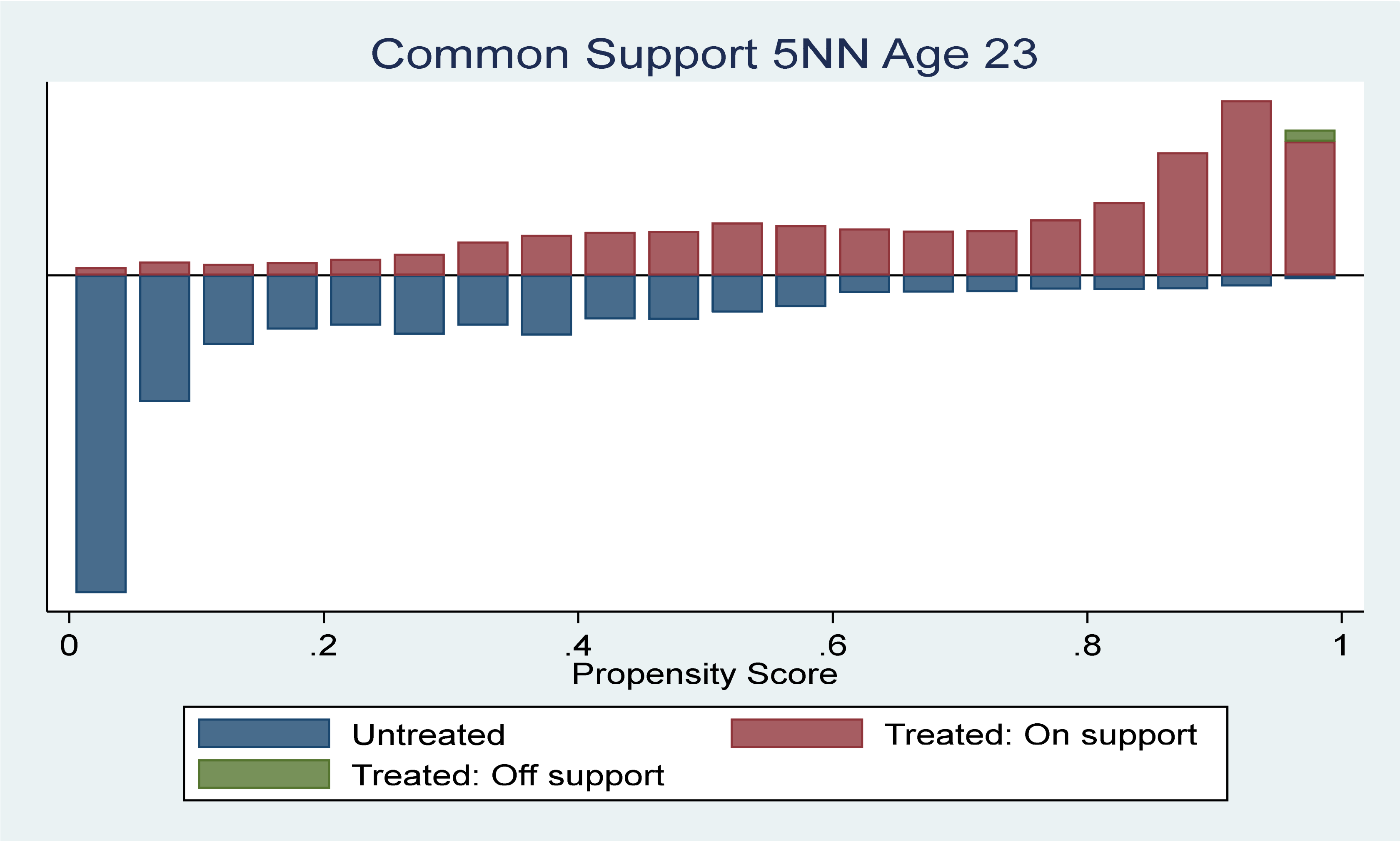
	23	33	42	50	55	61	63
Pseudo r-sq:							
Unmatched	0.398	0.390	0.380	0.384	0.395	0.408	0.408
Matched	0.010	0.015	0.014	0.018	0.030	0.062	0.062
Rubin's B	23.1	29.2*	27.5*	31.5*	40.2*	58.9*	58.9*
Rubin's R	1.04	1.07	0.95	1.07	1.08	1.34	1.34

Rubin's B: absolute standardised differences of means of linear index of propensity score in treated and match non-treated groups (B<25 is ok)

Rubin's R: ratio of treated to matched non-treated variances of propensity score index (R between 0.5 and 2 is deemed balanced)

- means falls outside tolerable balance limits

Common Support



40 cases off common support. Zero at other ages

GWG At Different Ages using PSM

Age:	23	33	42	50	55	61	63
Fem	1.536	1.843	1.908	2.080	2.022	2.611	2.635
Male Unmatched	1.704	2.209	2.354	2.435	2.359	2.890	2.913
Male Matched	1.693	2.206	2.378	2.460	2.369	2.950	2.950
Raw difference	-.168 (21.41)	-.367 (25.91)	-.446 (25.38)	-.355 (21.81)	-.337 (17.35)	-.279 (10.89)	-.278 (11.08)
Matched difference	-.156 (7.95)	-.363 (10.82)	-.471 (10.98)	-.381 (8.88)	-.347 (7.19)	-.339 (4.75)	-.315 (4.33)
N	8011	6881	7175	6031	4992	1668	1668

GWG follows an inverted-U shape over the life course, peaking when women are in their 40s

Raw gap is very substantial, ranging from around .17 log points when cohort members are in their early 20s to .45 log points in their 40s

The PSM estimated GWG is similar to the raw gap when cohort members are in their 20s and 30s. However, the PSM estimated gap is above the raw gap when they are in their 40s, 50s and 60s

The implication is that women have pre-labour market traits which reduce their earnings later in life relative to men

GWG from Log Hourly Wage Regressions

Age:	23	33	42	50	55	61	63
OLS	-.176 (17.37)	-.350 (19.91)	-.438 (19.79)	-.352 (17.49)	-.375 (15.25)	-.331 (10.27)	-.332 (10.52)
OLS with PSM weights	-.150 (10.58)	-.343 (14.59)	-.457 (12.86)	-.356 (12.77)	-.348 (10.54)	-.336 (7.98)	-.308 (7.38)
OLS with entropy weights	-.162 (11.57)	-.342 (15.03)	-.460 (13.37)	-.340 (12.91)	-.372 (10.46)	-.325 (6.98)	-.293 (6.56)
N	8011	6881	7175	6031	4992	1668	1668

OLS regression adjusted gaps are similar to raw gaps until age 55 and later when the regression-adjusted estimates are larger than the raw gap.

Unweighted OLS regression adjusted gaps are larger than the OLS estimates with PSM weights entropy weights.

No systematic difference in the size of the GWG as indicated by the matched difference in last slide and regression adjusted estimates here: the matched difference is larger at ages 33, 42, and 50 whereas the OLS estimate is larger at ages 23 and 63

Summary

1. Large raw GWG rising until 40s then falls but remains sizeable to age 63
2. In contrast to findings in the literature in which the regression-adjusted GWG is considerably smaller than the raw gap, differences in log hourly mean earnings between men and women are of roughly similar size and, in some cases, wider than raw gaps conditioning on pre-labour market variables.
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What Next?

1. Specification for probit
   - Have we got the right covariates?
   - More flexible specification
2. Whether to ‘hard match’ on occupational expectations?
3. Alternative matching estimators
   - NN, kernel; combine exact matching with PSM; entropy balancing
4. Tackline participation decision
   - Bringing in the zeros results in a much larger GWG
   - Using matching estimates to impute earnings to non-participants
   - Is this the right thing to do?
5. Attrition