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An investigation of Social Class Inequalities in General Cognitive Ability in Two British Birth Cohorts[1]

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Abstract

The 'Flynn effect' describes the substantial and long-standing increase in average cognitive ability test scores, which has been observed in numerous psychological studies. Flynn makes an appeal for researchers to move beyond psychology's standard disciplinary boundaries and to consider sociological contexts, in order to develop a more comprehensive understanding of cognitive inequalities. In this article we respond to this appeal and investigate social class inequalities in general cognitive ability test scores over time. We analyse data from the National Child Development Study (1958) and the British Cohort Study (1970). These two British birth cohorts are suitable nationally representative large-scale data resources for studying inequalities in general cognitive ability.

We observe a large parental social class effect, net of parental education and gender in both cohorts. The overall finding is that large social class divisions in cognitive ability can be observed when children are still at primary school, and similar patterns are observed in each cohort. Notably, pupils with fathers at the lower end of the class structure are at a distinct disadvantage. This is a disturbing finding and it is especially important because cognitive ability is known to influence individuals later in the lifecourse.

Keywords: Social Class, Cognitive Ability, Longitudinal, Cohort Studies, Social Stratification, Inequality.

Introduction

The 'Flynn effect' describes the substantial and long-standing increase in average cognitive ability test scores, which has been observed in numerous psychological studies[2] (Flynn, 2012). Flynn makes an appeal for researchers to move beyond psychology's standard disciplinary boundaries and to consider sociological contexts, in order to develop a more comprehensive understanding of the influence of the social on cognitive inequalities. In this article we investigate social class inequalities in general cognitive ability through the examination of data from two British birth cohort studies.

The focus of this article is general cognitive ability in childhood, which is understood to be socially stratified from a very young age (Feinstein, 2003; Sullivan et al., 2013; Cunha and Heckman, 2009; Duncan et al., 1998; Gottfried et al., 2003). Childhood general cognitive ability is important because it is associated with later educational attainment, occupational attainment, and health and wellbeing across the lifecourse (Deary et al., 2007; Nettle, 2003; Vanhanen, 2011). Understanding social class inequalities in childhood cognitive test scores can therefore contribute to the wider sociological understanding of the reproduction of social inequalities.

Background

Neisser *et al.* (1995: 77) describes cognitive ability as the 'ability to understand complex ideas, to adapt effectively to the environment, to learn from experience, to engage in various forms of reasoning, to overcome obstacles by taking thought.' Cognitive ability tests are well validated measures of individual differences of cognitive capability (Deary et al., 2007; Sternberg et al., 2001). The association between parental social class and children's cognitive test performance has been consistently documented, and a wealth of empirical evidence

demonstrates that children from more advantaged families generally have better cognitive test scores (McCulloch and Joshi, 2001; Feinstein, 2003; Goodman and Gregg, 2010; Blanden et al., 2007; Schoon et al., 2011; Schoon et al., 2010; Dickerson and Popli, 2016; Sullivan et al., 2013). Shenkin et al. (2001) describe social class inequalities in the cognitive ability test performance of 11 year olds born in 1921. Lawlor et al. (2005) found that father's social class was an important predictor of cognitive ability test scores at ages 7, 9 and 11 for a cohort of children born between 1950 and 1956. Feinstein (2003) demonstrated socio-economic inequalities in cognitive skills at as young as 22 months for a cohort of children born in 1970. Similar inequalities were also found at ages 42 months, and at 5 and 10 years (Feinstein, 2003). Using data from the UK Millennium Cohort Study (MCS) a series of more recent investigations have shown that children from less advantaged social backgrounds perform worse on cognitive ability tests than their more advantaged peers throughout childhood (see Blanden and Machin, 2010; Blanden et al., 2007; Schoon et al., 2011; Schoon et al., 2010; Dickerson and Popli, 2012; Sullivan et al., 2013).

The overall motivation for this article is to directly respond to Flynn's appeal for researchers to move beyond psychology's standard disciplinary boundaries, and to consider sociological contexts with the aim of developing a more comprehensive understanding of cognitive inequalities. There has been a dearth of research investigating the extent to which social class inequalities in childhood cognitive test scores have changed between birth cohorts. This stands in stark contrast to the vast quantity of research that has investigated trends in inequalities in educational test scores, and the formal educational outcomes of children and young people (see for example Bradbury et al., 2015; Blanden and Gregg, 2004; Erikson et al., 2005).

The analyses within this article use data from two long running British birth cohort studies, the National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS). These

large-scale longitudinal surveys are ongoing and follow infants born in 1958 and 1970 respectively (Power and Elliott, 2006; Elliott and Shepherd, 2006). These two studies have proven to be invaluable sociological data resources. A sizable cannon of research regarding social mobility trends in the UK is based on comparisons between these two birth cohorts (e.g. Blanden and Machin, 2004; Blanden et al., 2005; Blanden et al., 2004; Machin and Vignoles, 2004; Goldthorpe and Jackson, 2007; Tampubolon and Savage, 2012; Blanden et al., 2013). A key concern in these projects is measuring changes between birth cohorts. For example studies have investigated changes in educational inequalities (Breen et al., 2010; Shavit and Blossfeld, 1991; Shavit et al., 2007), and changes in inequalities in access to advantaged occupational positions (Erikson and Goldthorpe, 1992; Breen, 2004). Building on the tradition of cross-cohort comparisons, this work compares social class inequalities in childhood cognitive ability test scores in these two cohorts.

Data

The UK data portfolio is well endowed with large-scale nationally representative birth cohort datasets. The National Child Development Study (NCDS) follows the lives of babies born in England, Scotland and Wales from the 3rd to the 9th of March 1958 (see Power and Elliott, 2006). The British Cohort Study (BCS) follows babies born in England, Scotland and Wales from the 5th to the 11th of April 1970[3] (see Elliott and Shepherd, 2006). Childhood data were collected at birth, age 7 and age 11 in the NCDS (SN5565, University of London, 2014), and at birth, age 5 and age 10 in the BCS (SN2666, SN2699, SN3723, University of London, 2013; University of London, 2016a; University of London, 2016b).

The UK also has a more recent nationally representative birth cohort, the Millennium Cohort Study (MCS) (see Connelly and Platt, 2014). The overall design, the selection strategy, and the content of the MCS differs substantially from the previous British birth cohorts. The MCS 5th

sweep (age 11) only contains one subtest of the British Ability Scales, the Verbal Similarities Test. This single test would not be sufficient to compute an overall general ability test score that is suitably comparable with the tests included in the NCDS and BCS. The MCS 5th sweep (age 11) also contains two cognitive tests drawn from the Cambridge Neuropsychological Test Automated Battery, however these tests are very different in nature to the tests completed in the NCDS and BCS (see Atkinson, 2015).

Goisis et al. (2017) undertook a comparative analysis of the effects of low birth weight in the NCDS, BCS and MCS. They operationalised a cognitive measure by using only the verbal test scores within the NCDS and the BCS, and then compared them with the single Verbal Similarities Test in the MCS. We do not adopt this strategy because psychometricians have warned against the use of isolated subtests for the measurement of general cognitive ability (McDermott et al., 1990). Ensuring the comparability of cognitive tests is challenging, especially when studying test scores over time (see Must et al., 2009). Flynn (2012) highlights that performances on different cognitive ability subtests have improved at different rates. In particular, the similarities subtest has shown some of the largest increases. Therefore, the use of the similarities subtest from the MCS cohort in isolation is likely to result in misleading comparisons.

General Ability Test Scores

In the NCDS and the BCS cohort members completed general ability tests at age 11 and 10 respectively. The general ability test in the NCDS comprised of 40 verbal and 40 non-verbal items (see Shepherd, 2012). The general ability test in the BCS comprised of four sub-scales from the British Ability Scales, word definition, word similarities, recall of digits and matrices (see Parsons, 2014).

We computed an overall cognitive ability test score using the summated test scores. This is the method used in previous studies which examine the role of cognitive ability in educational and occupational attainment (e.g. Breen and Goldthorpe, 2001). Alternatively principal components analysis (PCA) could be used to summarise the relationship between the cognitive ability subtests in order to produce an estimate of general ability 'g'. This method has also been deployed in previous studies using the cognitive ability test scores in the NCDS and BCS (e.g. Schoon, 2010). We have computed scores using the two alternative methods, and we find that the total scores and the PCA scores are almost perfectly correlated (NCDS: $r = 0.999$, $p < 0.001$; BCS: $r = 0.997$, $p < 0.001$). Therefore, we conclude that either approach would be suitable for this analysis, but we have chosen the total score measure because of their direct comparability with previous studies in this field.

The general ability test in the NCDS is comparable with the test in the BCS (see Elliott et al., 1978; Shepherd, 2012). However, it is not possible to directly assess the Flynn Effect using the general ability test measures in the NCDS and the BCS. This is because the tests include a different number of items and have different total scores. The two measures are suitable for the current analysis because our focus is on relative social class inequalities within each of the two cohorts. In order operationalise the analyses we construct a cross-cohort measure using arithmetic standardisation, which has been used in previous studies (see Schoon, 2010). The summary statistics for the cognitive ability tests are provided in table 1.

Table 1: Descriptive statistics for general ability test scores in the NCDS and BCS.

Cohort	Age at Test	Mean	Std. Dev.	Min	Max	n
NCDS 1958	11	100.87	14.71	60.10	133.50	9,617
BCS 1970	10	100.84	14.77	45.38	151.19	8,099

Note: Figures are based on the complete records analysis.

Parental Social Class

The central analytical focus of this article is an investigation of the effects of parental social class on filial general cognitive ability test scores. Social class schemes are widely used in sociological research and are regarded as socio-economic measures that divide the population into unequally rewarded categories (Crompton, 2008). We employ an occupation-based socio-economic measure because it provides a robust and parsimonious indicator of parental social positions (see Connelly et al., 2016b). Occupation based socio-economic measures do not simply act as a proxy where income data are unavailable, they are sociological measures designed to better understand fundamental forms of social relations and inequalities to which income is merely epiphenomenal (Rose and Pevalin, 2003). In this analysis we employ the United Kingdom National Statistics Socio-Economic Classification (NS-SEC) (see Rose and Pevalin, 2005) which is widely used in sociological analyses and in official statistics.

Gregg (2012) coded and deposited UK standard occupational classification codes (SOC2000) for the job titles of NCDS fathers collected in the age 11 survey, and BCS mothers and fathers collected in the age 10 survey (SN7023, Gregg, 2012). These detailed occupational codes are an invaluable resource, and we use them to compute NS-SEC in both cohorts. As detailed occupational information (i.e. SOC codes) is only available for fathers in the NCDS[4] we only use father's information in the BCS (see table 2).

Further Explanatory Variables

In previous research gender differences in childhood cognitive ability test scores have been observed (see Van der Sluis et al., 2006; Strand et al., 2006; Sullivan et al., 2013). Parental education is measured using mother's and father's years of education completed after the compulsory school leaving age. We categorise these variables in a similar manner to previous

research using these data (see Cheung and Egerton, 2007). We are cautious not to attribute titles to these categories because in British samples years of education do not neatly map on to an individual's educational experiences and attainments (see Connelly et al., 2016a). We use the highest level of education of the cohort member's parents to represent the parental level of education (see table 2). Parental education is included as a control variable which may measure an additional dimension of a family's socio-economic position.

Table 2: Descriptive statistics of the gender and parental education variables in the NCDS and BCS.

Variable		NCDS %	BCS %
Gender	Male	51	51
	Female	49	49
Parent's Highest Education	Compulsory School Only	72	51
	Compulsory School + 1 to 3 Years	22	34
	Compulsory School + 4 to 5 Years	1	6
	Compulsory School + 6 or more Years	4	8
Father's NS-SEC	1.1 Large Employers and Higher Managerial	3	5
	1.2 Higher Professional	5	6
	2 Lower Managerial and Professional	12	15
	3 Intermediate	9	9
	4 Small Employers and Own Account Workers	12	13
	5 Lower Supervisory and Technical	17	18
	6 Semi-Routine	18	15
	7 Routine	24	20
n		9,617	8,099

Note: Figures are based on the complete records analysis.

Missing Data

Longitudinal studies typically have missing data (see Hawkes and Plewis, 2006; Plewis et al., 2004; Mostafa and Wiggins, 2014; Mostafa and Wiggins, 2015). In the current analyses we use information from across multiple sweeps of the studies. The size of the longitudinal sample

with complete records is reduced due to attrition (i.e. drop out), wave non-response (i.e. not being present in one or more of the surveys), and item non-response (i.e. not fully responding to a survey item). Missing data in the cohort studies has the potential to induce bias into estimation within some analyses. As Carpenter and Kenward (2012) strongly advise we first conduct a complete records analysis, followed by a series of principled approaches to handling missing data. We have undertaken sensitivity analyses of several different approaches to handling missing data. Our results below use multiple imputation and inverse probability weights in combination in order to provide improved adjustments in the presence of missing data (see Little and Rubin, 2014; Seaman et al., 2012). Full details of the complete multiple imputation process and sensitivity analyses are provided in the online supplement.

Reproducibility

Concern about the lack of the reproducibility of research persists across a range of academic disciplines (Nature [Editorial], 2016). There is a general appeal for extra materials to be routinely provided alongside research publications which include sufficient information for a third party to reproduce results without any additional information from the authors (Diggle, 2015; King, 1995; King, 2003). An innovative aspect of this work is that we go beyond providing the usual supplementary material and make the complete workflow openly available. We take the trailblazing step of rendering the complete workflow accessible and reproducible within a Jupyter notebook[5] (Kluyver et al., 2016). Jupyter notebooks are an open source web-based application that enable researchers to author documents that include live code[6] (e.g. Stata or R code), alongside data analysis outputs (e.g. modelling results, plots etc.), and documentation (e.g. narrative text describing and detailing the workflow). Jupyter notebooks have been used in Nobel Prize winning high-profile big science applications[7] but are rarely used in Sociology.

Descriptive Results

The relationship between father's social class (NS-SEC) and children's cognitive ability test scores is reported in table 3. There is very clear evidence of a social class effect and, on average, children with more occupationally advantaged fathers have higher cognitive ability test scores in both cohorts. The difference between the children with the most advantaged fathers (NS-SEC 1.1, e.g. a chief executive officer) and the least advantaged fathers (NS-SEC 7, e.g. a construction labourer) is on average 13 points for those in the NCDS cohort, and 11 points for those in the BCS cohort. The greatest differences are observed between children with fathers in NS-SEC 1.2 (e.g. university professors) and children with fathers in NS-SEC 7 (e.g. a construction labourer). These differences are on average 14 points in the NCDS and 15 points in the BCS, which is approximately one standard deviation for both cohorts.

Table 3: Mean and Standard Deviation of ability test scores by father's NS-SEC.

Variable			NCDS Mean (SD)	BCS Mean (SD)
Father's NS-SEC	1.1	Large Employers and Higher Managerial	109 (13)	106 (14)
	1.2	Higher Professional	110 (12)	110 (13)
	2	Lower Managerial and Professional	108 (13)	106 (14)
	3	Intermediate	105 (14)	105 (13)
	4	Small Employers and Own Account Workers	100 (14)	99 (14)
	5	Lower Supervisory and Technical	100 (15)	100 (14)
	6	Semi-Routine	99 (14)	98 (14)
	7	Routine	96 (14)	95 (14)
n			9,617	8,099

Note: Figures are based on the complete records analysis.

Modelling Results

The models reported in table 4 are ordinary least squares (OLS) linear regression analyses of the cognitive ability test scores. The data from the two cohorts have been pooled, and the models include a dummy variable indicating cohort membership. Table 4, model 1 shows that boys have marginally lower cognitive ability test scores. Children of parents who have spent a longer period of time in education on average have higher cognitive ability test scores. There is also a large social class effect that is significant, net of parental education and gender[8].

Children from the least advantaged social class NS-SEC 7 (e.g. the daughter of a construction labourer) score on average score 7 points lower than children from social class NS-SEC 3 (e.g. the daughter of a police officer). By contrast children from social class NS-SEC 1.2 (e.g. the daughter of a university lecturer) on average score 2 points higher than counterparts in NS-SEC 3. Similar socio-economic inequalities in cognitive test scores have previously been reported (see Shenkin et al., 2001; Lawlor et al., 2005; Feinstein, 2003; Sullivan et al., 2013).

In model 2 (table 4) we include an interaction term representing father's NS-SEC and cohort, to investigate changes between the cohorts. Including the interaction term in the model does not improve the proportion of variance explained overall. We do not find either systematically increasing or decreasing differences in the coefficients for NS-SEC between the two cohorts.

Table 4: Regression analysis (OLS) of general ability test scores pooled NCDS and BCS data, with adjustments for missing data.

	Model 1 (MI+IPW)			Model 2 (MI+IPW)		
	Coef.		SE	Coef.		SE
Gender						
Female	Ref.			Ref.		
Male	-0.55	**	(0.18)	-0.56	**	(0.18)
Parent's Highest Education						
Compulsory School Only	Ref.			Ref.		
Compulsory School + 1 to 3 Years	5.87	***	(0.24)	5.87	***	(0.24)
Compulsory School + 4 to 5 Years	8.30	***	(0.54)	8.31	***	(0.53)
Compulsory School + 6 or more Years	10.63	***	(0.46)	10.65	***	(0.46)
Father's NS-SEC						
NS-SEC1.1	1.79	**	(0.58)			
NS-SEC1.2	2.28	***	(0.59)			
NS-SEC2	1.19	**	(0.43)			
NS-SEC3	Ref.					
NS-SEC4	-3.53	***	(0.43)			
NS-SEC5	-3.31	***	(0.41)			
NS-SEC6	-4.80	***	(0.43)			
NS-SEC7	-7.17	***	(0.41)			
Cohort						
NCDS (1958)	Ref.					
BCS (1970)	-2.09	***	(0.18)			
Father's NS-SEC x Cohort Interaction						
NS-SEC1.1 x NCDS				2.82	**	(0.86)
NS-SEC1.1 x BCS				-0.64		(0.78)
NS-SEC1.2 x NCDS				1.85	*	(0.77)
NS-SEC1.2 x BCS				0.96		(0.77)
NS-SEC2 x NCDS				1.71	**	(0.62)
NS-SEC2 x BCS				-0.90		(0.59)
NS-SEC3 x NCDS				Ref.		
NS-SEC3 x BCS				-1.59	*	(0.68)
NS-SEC4 x NCDS				-3.24	***	(0.63)
NS-SEC4 x BCS				-5.42	***	(0.62)
NS-SEC5 x NCDS				-2.94	***	(0.59)
NS-SEC5 x BCS				-5.29	***	(0.57)
NS-SEC6 x NCDS				-4.48	***	(0.60)
NS-SEC6 x BCS				-6.75	***	(0.59)
NS-SEC7 x NCDS				-7.12	***	(0.56)
NS-SEC7 x BCS				-8.78	***	(0.56)
Constant	104.06	***	(0.43)	101.74	***	(0.49)
n	28,331			28,331		
Adjusted R^2	0.14			0.14		

Note: IPW = Inverse Probability Weights; MI = Multiple Imputation. AIC and Log likelihood cannot be calculated for models using Multiple Imputation. The sample size for models 1 and 2 is all non-deceased cohort members who were present in the third survey. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Despite the overall lack of improvement in model fit when the interaction is included, we observe that there are some small statistically significant differences between the cohorts (table 4, model 2). To aid in the interpretation a plot of the regression coefficients for father's NS-SEC and 95 per cent quasi-variance comparison intervals[9] is provided (figure 1). Overall, in figure 1 there is no clear pattern of either increasing or decreasing social class inequalities between the two cohorts.

BCS members have marginally lower test scores, across all social class groups. We emphasise that the cognitive ability tests in the NCDS and the BCS are not identical, however the two measures are suitable for the current analysis because our focus is on relative social class inequalities within the two cohorts. The outcome variable in this model is constructed using arithmetic standardisation. The difference between the scores in the NCDS and the BCS in this analysis should not therefore be understood as a direct assessment of the Flynn Effect. We conclude that the more parsimonous model that does not include the interaction is more appropriate.

Figure 1: Coefficients and Quasi-Variance Comparison Intervals for the interaction.

Predictions of General Ability Test Score by Father's Social Class
OLS Regression Coefficients and 95% Quasi-Variance Comparison Intervals
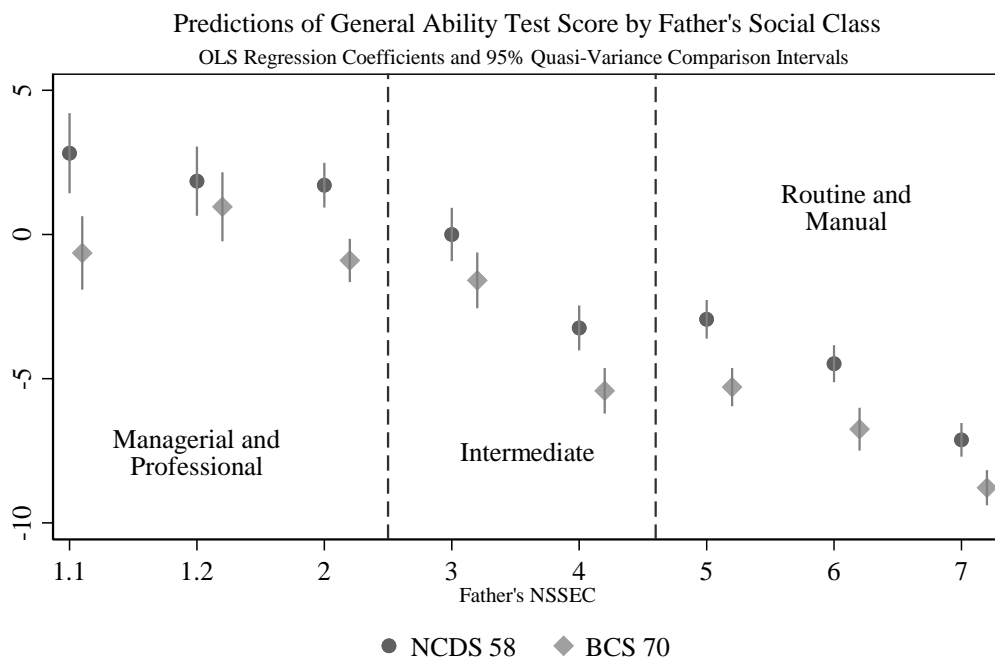
Data: 1958 National Child Development Study and 1970 British Cohort Study.
Note: Estimates are taken from table 4, model 2. Model also contains Gender and Parent's Highest Education.

Discussion of the Social Class Effect on General Cognitive Ability

There is a clear and observable negative social class gradient that is net of gender and parental education. Overall children from more occupationally advantaged social classes perform better on the general cognitive ability test. The negative social class gradient, and the differences between social class categories, may reflect the instability, and the economic and social strain that results from belonging to the more disadvantaged social class groups (Layte, 2017; Elder, 1994; Conger and Conger, 2002). These differences may also reflect other characteristics of parents jobs, such as complexity (see Parcel and Menaghan, 1994).

At the apex of the social class hierarchy are fathers in the 'Managerial and Professional' class. These include fathers in NS-SEC 1.1 (Large Employers, Higher Managerial and Administrative Occupations), along with fathers in NS-SEC 1.2 (Higher Professional Occupations) and fathers in NS-SEC 2 (Lower Managerial, Administrative and Professional Occupations). The 'Managerial and Professional' class comprises more complex and higher skilled occupations, and employees usually enjoy a high degree of job security, and have a regular, and known, monthly income (Goldthorpe and McKnight, 2006). Fathers in the 'Managerial and Professional' class can have realistic expectations of salary increases, for example via incremental pay scales, and they can realistically expect to be promoted within their occupations up to the age of 50 and even beyond. These advantages are likely to make substantial economic, social, and cultural contributions to the households in which children grow up.

At the base of the social class hierarchy are the 'Routine and Manual Occupations' (NS-SEC 5, 6 and 7). In both cohorts children born into families in 'Routine and Manual Occupations' have markedly lower cognitive ability test scores than children from families with 'Managerial and Professional Occupations' (NS-SEC 1.1, 1.2 and 2). The fathers in NS-SEC 6 and NS-SEC

7 comprise a group of wage-workers in lower skilled jobs that are usually of a routine nature. The economic lives of the fathers in these classes are characterised by a relatively high risk of job loss, recurrent and often long-term unemployment, and lower earnings. Occupations in NS-SEC 6 and NS-SEC 7 are often rewarded on a weekly rather than an annual basis, and pay can vary as a result of the availability of overtime, piece-rates or shift work premia (Goldthorpe, 2016). The advent of negative events such as job loss and unemployment are likely to have immediate impacts on a household's economic and social circumstances. We speculate that the precarious nature of the employment conditions that are experienced by employees in routine and manual occupations hangs like a sword of Damocles over these families. The lack of economic security and the lower material rewards associated with jobs in NS-SEC 6 and NS-SEC 7 may contribute to the impoverished cognitive ability of children with fathers in these classes.

Occupations in NS-SEC 5 (Lower Supervisory and Technical) usually require specific skills and organisational knowledge. Occupations in this class generally provide more stable employment and include some of the conditions of employment, for example an annual salary, typical in the Managerial and Professional class. The additional occupational complexity, along with the improved economic security and benefits associated with occupations in NS-SEC 5 may contribute to the improved cognitive ability of children with fathers in this class.

Between the 'Managerial and Professional Occupations' (NS-SEC 1.1, 1.2 and 2) and the 'Routine and Manual Occupations' (NS-SEC 5, 6 and 7) rests the 'Intermediate Occupations' (NS-SEC 3 and 4). Despite being distinctive the 'Intermediate Occupations' are not organised into a hierarchical order. NS-SEC 4 (Small Employers and Own Account Workers) theoretically stands apart from NS-SEC 3 (Intermediate) because it is composed of self-employed workers and small employers. NS-SEC 4 comprises both those who are engaged in

largely manual work along with others who are engaged in non-manual work. In contrast to fathers in NS-SEC 1.1 (Large Employers and Higher Managerial Occupations), the fathers in NS-SEC 4 carry out the majority of the entrepreneurial and managerial functions within their enterprise. The children with fathers in NS-SEC 4 have cognitive test scores that are more similar to counterparts in NS-SEC 5 than to other children with fathers in NS-SEC 3. The better performance of children with fathers in NS-SEC 3 may be a reflection of their father's being engaged in intermediate occupations that can reasonably be described as being 'white collar'. Being engaged in white collar occupations generally leads to better employment conditions and economic rewards.

In the discussion above we have focussed on the employment characteristics and conditions associated with the NS-SEC categories. The observable negative gradient leads to the plausible conclusion that class differences are the result of the substantial differences in the economic, social and cultural milieus within households. We speculate that social class differences in cultural values, parenting styles and family activities may also play a role in reproducing inequalities (see Bourdieu and Passeron, 1977; Ermisch, 2008; Kiernan and Mensah, 2011; Lareau, 2011; Washbrook, 2011; Vincent and Ball, 2007; Sullivan et al., 2013). Researchers in fields such as psychology have pointed to the heritability of general cognitive ability (see for example Tucker-Drob et al., 2013; Hill et al., 2014; Deary et al., 2006), which might be another potentially plausible dimension contributing to the social class gradient.

Conclusions

Overall, this article provides persuasive evidence that whilst there are sociologically important and informative differences between social classes, there has not been a notable change in the relative ordering of social class inequalities in childhood general cognitive ability test scores between these two birth cohorts. These analyses detect that gender, parental education and

social class have structuring effects on general cognitive ability in childhood. This underlines the benefits of moving beyond psychology's standard disciplinary boundaries in order to develop a more comprehensive understanding of social influences on cognitive inequalities (Flynn, 2012).

In Britain since the end of the Second World War there have been ongoing concerns about social inequality in education. Despite numerous new educational policies and initiatives the structure and organisation of primary schools remained relatively unchanged in the second half of the twentieth century. Primary schools in the post-war period might reasonably be described as being in a state of 'constant flux'. The children of the NCDS began primary school in the early 1960s, and the children of the BCS entered primary school twelve years later. Nevertheless, the evidence from analysing these two British birth cohorts is that social class inequalities in childhood cognitive ability test scores were notable and persistent. The extent to which parental social class inequalities in general cognitive ability test scores have changed in more recent cohorts is a question for further empirical investigation. Unfortunately, at the current time we are not aware of any nationally representative UK datasets that contain suitable general cognitive ability test measures to effectively examine more recent cohorts.

Children's cognitive ability test scores summarize their capability to understand complex ideas, to engage in various forms of reasoning, to learn from experience and to effectively adapt to their environment. The overall finding, that social class divisions in cognitive ability can be observed when children are still at primary school, and that these inequalities are persistent, is a disturbing result. Pupils with fathers in 'routine and manual occupations' are at a distinct disadvantage. These pupils arrived at secondary school already weighed down with stones in their satchels. This is an important finding to emphasise because cognitive ability is known to

influence individuals throughout their lives (see Deary et al., 2007; Nettle, 2003; Vanhanen, 2011; Schoon, 2010).

There is an increasing desire and requirement to make sociological research more transparent, and to actively render it reproducible. In addition to the substantive findings, this article makes a ground breaking methodological contribution by using Jupyter notebooks which are an internationally recognised open source research platform. Publishing the Jupyter notebook allows third parties to fully reproduce the complete workflow behind the production of the article, and to duplicate the empirical results. In addition to increasing transparency, this approach enables the possibility for other researchers to extend the work, for example with different measures, additional data or alternative techniques. Improving transparency is an attractive feature and is highly likely to make a major contribution to quantitative sociology.

In developing an open and published workflow we have drawn upon ideas advanced in computer science especially the concept 'literate computing', which is the weaving of a narrative directly into live computation, interleaving text with code and results in order to construct a complete piece that achieves the goals of communicating results[10] (Knuth, 1992). A further innovation within this work has been the adoption of 'pair programming' which is a technique from software development in which two programmers work together in the development of code. In addition we have also used 'code peer review', and each author has run the complete workflow independently using a different computer and software set-up. This has enabled us to undertake an in-depth test of the reproducibility of the work. These practices are new to sociological research but will bring great benefits to the discipline.

Notes

[1] We are indebted to the National Child Development Study and 1970 British Cohort Study participants. We are grateful to The Centre for Longitudinal Studies, UCL Institute of Education for the use of these data and to the UK Data Archive and Economic and Social Data Service for making them available. These organizations bear no responsibility for the analysis or interpretation of these data. This work was funded by the Economic and Social Research Council [Grant Number: ES/N011783/1].

[2] Although there is some evidence that these increases may have slowed, or even stopped, in recent years (Teasdale and Owen, 2008).

[3] The 1970 British Cohort Study included babies born in Northern Ireland in the first interview (at birth) but these babies were dropped from all subsequent sweeps of data collection within the study.

[4] A measure of mother's occupation before pregnancy was collected in the NCDS birth survey, variable n539. However more than half of mothers in our sample have no occupational information and the information available is only provided as a small number of categories based on the General Registrar Office 1951 coding system (e.g. 'bank clerks etc.', 'Textile-labourer', 'Clerks, typists'). Information on mother's occupation is also provided in the age 11 NCDS survey dataset, variable n1225. This variable indicates that over half of mothers in our sample have no occupational information and also does not include detailed occupational information. Mother's Registrar General Social Class (n2393) and Socio-Economic Group (n2394) are available from the age 16 NCDS survey, however more than half mothers in our sample have no occupational information. We chose not to use the available mother's occupational information because of the large number of mothers with no occupational information. The classification of occupations would not enable us to produce comparable socio-economic measures in a suitably standardised manner. We do not use the mother's occupational information from the age 16 sweep of the survey as it is collected 5 years after the outcome of interest and it would not allow us to produce NS-SEC in a standardised manner, we therefore consider that it is not an appropriate measure for the present analysis.

[5] The Jupyter Notebook is available here: https://github.com/RoxanneConnelly/Social-Class-Inequalities-in-General-Cognitive-Ability-in-Two-British-Birth-Cohorts.

[6] We utilise Jupyter Notebooks in combination with the Stata Kernel designed by J.R. Fiedler. See here: https://github.com/jrfiedler/stata-dta-in-python.

[7] For example see: https://losc.ligo.org/s/events/GW150914/GW150914_tutorial.html.

[8] There is a significant relationship between parental education and father's social class ($\chi^2 = 4700$; $p < 0.001$ @ 21 d.f.). The association between parental education and father's social class is relatively weak ($V = 0.30$). The average variance inflation from the complete records model was 1.70. Following conventional methodological advice we conclude that multicollinearity is not a concern in this model (see Menard, 2002).

[9] Quasi-variance comparison intervals allow comparisons to be made between all categories whereas conventional confidence intervals are restricted to comparisons with the reference category (see Firth, 2003; Gayle and Lambert, 2007). The quasi-variance estimation approach is based on an approximation (see Firth, 2003).

[10] See also: http://blog.fperez.org/.

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<div align="center">**Online Supplement**</div>

Missing Data

Missing data in the cohort studies has the potential to induce bias into estimation within some analyses. The sample sizes and unit missingness for the two cohorts are shown in table S1, and table S2 shows the patterns of item missingness.

Table S1: Patterns of unit missingness for the NCDS and BCS.

	Present at First Survey (Birth) n	Deceased (Age 10/11) n	Missing 'Other' (Age 10/11) n	Present at Third Survey (Age 10/11) n (% original sample)
NCDS	17,415	840	2,001	14,574 (84)
BCS	16,568[†]	595	2,216	13,757 (83)
Total	33,983	1,435	4,217	28,331 (83)

Note: [†]Excludes babies born in Northern Ireland. In addition to the datasets cited above information on response rates are derived from the NCDS and BCS response datasets (SN5560 (NCDS) and SN5641 (BCS), University of London, 2015b; University of London, 2015a).

Table S2: Patterns of item missingness for the NCDS and BCS data pooled.

Variable	Missingness Patterns								
Ability Test Score	✓	✓	x	x	x	✓	✓	x	x
Gender	✓	✓	✓	✓	✓	✓	✓	✓	x
Parent's Highest Education	✓	✓	x	✓	✓	x	x	x	x
Father's NS-SEC	✓	x	x	x	✓	✓	x	✓	x
n	17716	4908	3690	2814	2340	1433	771	302	9

Note: ✓ indicates that the value for the variable is non-missing (i.e. present), x indicates that the value for the variable is missing.

As Carpenter and Kenward (2012) advise we first conduct a complete records analysis (see table S4), followed by a series of principled approaches to handling missing data.

1. We construct inverse probability weights (IPW) in an attempt to reduce bias in the complete records analysis due to attrition (see table S5, model 1).

2. We also undertake multiple imputation by chained equations (see table S5, model 2).

3. We use multiple imputation and inverse probability weights in combination (results shown in main paper).

The substantive conclusions of the models using these different missing data strategies are largely consistent but this could not have been known *a priori*. We focus our discussion in the main article on the more sophisticated models, which use multiple imputation and inverse probability weights to provide improved adjustments in the presence of missing data. Missing data techniques are at the cutting edge of statistical methods. It is highly likely that as statistical theory develops, the techniques and approaches that are currently prescribed may be modified. We also envisage that facilities within data analysis software will inevitably change. Therefore, we argue that there are obvious benefits to providing clearly documented information about the processes relating to handling missing data in order to enable the work to be reproducible at some point in the future.

Inverse Probability Weights

We constructed inverse probability weights (IPW) in an attempt to reduce bias in the complete records analysis due to attrition (see Höfler et al., 2005). To produce the inverse probability weights we first model whether a cohort member is present at the age 11 (NCDS) or the age 10 (BCS) sweep of the survey. We selected variables to predict this outcome based on their use in previous models of missingness in the cohort studies (see Plewis et al., 2004; Mostafa and

Wiggins, 2015), and also the degree of missingness on these variables themselves. The variables used in these models are shown in table S3.

A very small per cent of variance in missingness at age 11/10 is accounted for by our models (less than 1 per cent in the NCDS, and 3 per cent in the BCS). This indicates that the predictive power of our models is weak and our attrition weights are unlikely to have a major impact on the results. We have made a best attempt however, with the available information, to construct suitable inverse probability weights. Including additional variables in the models of missingness at age 10/11 did not lead to large increases in pseudo R^2 and led to a reduction in the number of observations included in the model due to item missingness. Mostafa and Wiggins (2015) argue that the use of metadata, such as interviewer characteristics and conditions surrounding the collection of the data, could account for more of the variance in unit missingness in the cohort studies. These metadata variables are currently not available in the deposited NCDS or BCS datasets available to researchers.

Table S3: Variables used to produce the Inverse Probability Weights.

NCDS		BCS	
Variable	Original Name	Variable	Original Name
Mother's Age (Age 0 Survey)	n553	Mother's Age (Age 0 Survey)	BD1MAGE
Parity (Age 0 Survey)	n504	Parity (Age 0 Survey)	a0166
Mother's Marital Status (Age 0 Survey)	n545	Mother's Marital Status (Age 0 Survey)	BD1MAGM
Cohort Member's Gender	n622	Cohort Member's Gender	SEX
Region (Age 0 Survey)	n0region	Region (Age 0 Survey)	BD1REGN

Following the models of missingness at age 10/11, we calculated predicted probabilities of observing the cohort member at age 10/11. The weight is the inverse of these predicted probabilities (Höfler et al., 2005). For 235 cases there was missing information that prevented the calculation of the probability of inclusion. In these cases a weight of 1 was allocated to

ensure that these cases were included in the models and that the overall sample sizes would remain consistent.

Multiple Imputation

We implemented Multiple Imputation using the mi commands in Stata SE 14.1. In multiple imputation a number of plausible values are computed that better represent the uncertainty around the missing value. This method imputes multiple values for each missing variable from a cycle of regression models. These datasets are then pooled when analyses are undertaken using 'Rubin's rules' (see Little and Rubin, 2014). Our missing data model included all of the variables in the explanatory model of interest as well as parity and mother's marital status (see table S3 for details of these additional variables). We imputed missing values on both our explanatory and dependent variables. There has been some debate concerning the imputation of missing values for dependent variables (see Von Hippel, 2007). Recent methodological research recommends that imputed values on the dependent variable should not be deleted prior to analysis, and this is the approach we have taken in this article (see Sullivan et al., 2015). We carried out multiple imputation on the missing data from all cohort members present at the first sweep of the studies, and we deleted deceased cohort members before the substantive analysis.

When computing the interaction term in our models (father's NS-SEC x cohort) we have a scenario where there is missing data on the father's NS-SEC variable but no missing data on the cohort variable. Because cohort is not missing and has only two levels (NCDS or BCS) we carried out multiple imputation separately for each cohort (see Enders, 2010: 267-268; Carpenter and Kenward, 2012: 148-150). We then created the interaction term following the multiple imputation.

We also use multiple imputation and inverse probability weights in combination (see Seaman et al., 2012). These models are presented in the main article. This is carried out by imputing the data as described above, then deleting those cases who were not present in the age 10/11 surveys. In the analytical model we combine the imputed datasets, as described above, and adjust the analyses using the inverse probability weights. Seaman et al. (2012) note that whilst combining multiple imputation and inverse probability weights will generally have no advantages if the imputation models are correctly specified, the combination of multiple imputation and inverse probability weights can act as a robustness check. The strategy of combining multiple imputation and inverse probability weights has been used previously in the analysis of the National Child Development Study (Caldwell et al., 2008; Stansfeld et al., 2008), however we do not have access to the inverse probability weights used in these previous studies.

Table S4: Regression analysis of general ability test scores, pooled NCDS and BCS data.

	Model 1 (CR)			Model 2 (CR)		
	Coef.		SE	Coef.		SE
Gender						
Female	Ref.			Ref.		
Male	-0.66	**	(0.21)	-0.67	**	(0.21)
Parent's Highest Education						
Compulsory School Only	Ref.			Ref.		
Compulsory School + 1 to 3 Years	5.63	***	(0.25)	5.64	***	(0.25)
Compulsory School + 4 to 5 Years	7.87	***	(0.59)	7.90	***	(0.59)
Compulsory School + 6 or more Years	10.24	***	(0.49)	10.28	***	(0.49)
Father's NS-SEC						
NS-SEC1.1	1.56	*	(0.63)			
NS-SEC1.2	2.08	***	(0.59)			
NS-SEC2	1.15	**	(0.45)			
NS-SEC3	Ref.					
NS-SEC4	-3.44	***	(0.45)			
NS-SEC5	-3.26	***	(0.42)			
NS-SEC6	-4.66	***	(0.43)			
NS-SEC7	-6.98	***	(0.41)			
Cohort						
NCDS (1958)	Ref.					
BCS (1970)	-2.00	***	(0.21)			
Father's NS-SEC x Cohort Interaction						
NS-SEC1.1 x NCDS				2.41	**	(0.92)
NS-SEC1.1 x BCS				-1.04		(0.85)
NS-SEC1.2 x NCDS				1.43		(0.81)
NS-SEC1.2 x BCS				0.73		(0.80)
NS-SEC2 x NCDS				1.51	*	(0.62)
NS-SEC2 x BCS				-1.10		(0.61)
NS-SEC3 x NCDS				Ref.		
NS-SEC3 x BCS				-1.90	**	(0.69)
NS-SEC4 x NCDS				-3.40	***	(0.61)
NS-SEC4 x BCS				-5.37	***	(0.63)
NS-SEC5 x NCDS				-3.03	***	(0.58)
NS-SEC5 x BCS				-5.40	***	(0.58)
NS-SEC6 x NCDS				-4.57	***	(0.57)
NS-SEC6 x BCS				-6.68	***	(0.61)
NS-SEC7 x NCDS				-7.16	***	(0.54)
NS-SEC7 x BCS				-8.58	***	(0.57)
Constant	102.65	***	(0.39)	102.61	***	(0.48)
n	17,716			17,716		
Adjusted R^2	0.13			0.13		
AIC	8.08			8.08		
Log likelihood	-71529			-71526		

Notes: CR = Complete Records. * p<0.05, ** p<0.01, *** p<0.001

Table S5: Regression analysis (OLS) of general ability test scores with adjustments for missing data, pooled NCDS and BCS data.

	Model 1 (IPW)			Model 2 (MI)		
	Coef.		SE	Coef.		SE
Gender						
Female	Ref.			Ref.		
Male	-0.66	**	(0.21)	-0.58	**	(0.18)
Parent's Highest Education						
Compulsory School Only	Ref.			Ref.		
Compulsory School + 1 to 3 Years	5.66	***	(0.26)	5.84	***	(0.23)
Compulsory School + 4 to 5 Years	7.96	***	(0.58)	8.22	***	(0.56)
Compulsory School + 6 or more Years	10.29	***	(0.47)	10.64	***	(0.47)
Father's NS-SEC x Cohort Interaction						
NS-SEC1.1 x NCDS	2.39	**	(0.87)	2.91	**	(0.91)
NS-SEC1.1 x BCS	-0.99		(0.83)	-0.65		(0.79)
NS-SEC1.2 x NCDS	1.42		(0.74)	1.86	*	(0.82)
NS-SEC1.2 x BCS	0.70		(0.74)	0.97		(0.80)
NS-SEC2 x NCDS	1.50	*	(0.58)	1.71	**	(0.64)
NS-SEC2 x BCS	-1.14		(0.60)	-0.90		(0.59)
NS-SEC3 x NCDS	Ref.			Ref.		
NS-SEC3 x BCS	-1.85	**	(0.66)	-1.64	*	(0.70)
NS-SEC4 x NCDS	-3.41	***	(0.61)	-3.26	***	(0.63)
NS-SEC4 x BCS	-5.40	***	(0.62)	-5.42	***	(0.61)
NS-SEC5 x NCDS	-3.03	***	(0.58)	-2.93	***	(0.59)
NS-SEC5 x BCS	-5.44	***	(0.58)	-5.31	***	(0.58)
NS-SEC6 x NCDS	-4.56	***	(0.57)	-4.49	***	(0.61)
NS-SEC6 x BCS	-6.74	***	(0.61)	-6.73	***	(0.59)
NS-SEC7 x NCDS	-7.16	***	(0.54)	-7.09	***	(0.58)
NS-SEC7 x BCS	-8.60	***	(0.57)	-8.76	***	(0.56)
Constant	102.60	***	(0.47)	101.76	***	(0.49)
n	17,716			32,548		
Adjusted R^2	0.13			0.14		
AIC	8.08					
Log likelihood	-71527					

Note: IPW = Inverse probability weights. MI = Multiple Imputation. AIC and Log likelihood cannot be calculated for models using Multiple Imputation. The sample size for model 2 is all cohort members present in the first survey minus those who are deceased by the third survey. * p<0.05, ** p<0.01, *** p<0.001.

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