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DISCUSSION PAPER SERIES

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Warn N. Lekfuangfu
Chulalongkorn University, CEP and LSE

Grace Lordan
LSE and IZA

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Cross Cohort Evidence on Gendered Sorting Patterns in the UK: The Importance of Societal Movements versus Childhood Variables

We consider the extent to which societal shifts have been responsible for an increased tendency for females to sort into traditional male roles over time, versus childhood factors. Drawing on three cohort studies, which follow individuals born in the UK in 1958, 1970 and 2000, we compare the magnitude of the shift in the tendency of females in these cohorts to sort into traditionally male roles as compared to males, to the combined effect of a set of childhood variables. For all three cohorts we find strong evidence of sorting along gendered lines which has decreased substantively over time. We also find that there has been no erosion of the gender gap in the tendency to sort into occupations with the highest share of males. Within cohort, we find little evidence that childhood variables change the tendency for either the average or highest ability female to sort substantively differently. Our work underlines the importance of societal shifts, over and above childhood variables, in determining the sorting patterns we have seen over the last number of decades, and also those that remain today.

JEL Classification: J16, J4

Keywords: occupational choice, gender, societal change, childhood influences

Corresponding author:
Grace Lordan
London School of Economics and Political Science
Houghton Street
London WC2A 2AE
United Kingdom
E-mail: g.lordan@lse.ac.uk

"The first resistance to social change is to say it's not necessary". Gloria Steinman

I. BACKGROUND:

For decades economists have contributed to a literature that seeks to explain the gender wage gap[1]. A well accepted conclusion is that the lack of women in high paying, male dominated professions is one major cause of this gap (Bayard et al., 2003; Goldin, 2014 and Blau and Kahn, 2016). This has led to a search for the underlying causes of gender-based sorting. Explanations include differential human capital investments, (Altonji and Blank, 1999), discrimination (Becker, 1957), a lack of flexibility to combine a career and family in male dominated jobs (Goldin, 2014 and Bertrand, 2018) and differences in tastes and preferences (Lordan and Pischke, 2016 and Cortés and Pan 2017). In this work, we build on this literature, and consider the extent to which societal shifts have been responsible for an increased tendency for females to sort into traditional male roles over time, versus childhood factors that have already been shown by economists to shape the future successes of children in other life domains[2].

The importance of societal movements for gendered sorting is intuitive. A convincing narrative points to the fact that until the 1970's there were many more male dominated roles, than today. Between 1970 and 2018, a few stylised facts emerged. First, females sorted into many occupations that were traditionally male dominated. Examples include law, accountancy and pharmacy. Second, females failed to converge into other occupations. In white collar occupations examples mainly fall under the science, technology and engineering categories where the share of males in the UK, US and across the EU still exceed 80%[3]. Third, the revolution has been an asymmetric one, with males failing to sort into occupations that were traditionally female, such as social work, nursing and primary school teaching. These stylised facts are also visible in Figure 1, which plots the occupations of three cohorts born in 1958, 1970 and 2000 in the UK respectively[4]. There is a downward trend in the share of males in law over time, but no real change to engineering. The proportion of males in nursing is flat

[1] See Daymont and Andrisani (1984); Blau and Kahn (1997); Fortin (2008) and Blau and Kahn (2016).
[2] For example Akee et al (2013); Angrist and Lavy (1999); Black et al, (2007); Becker and Tomes (1986); Blau (1999); Datcher, (1982); Heckman et al (2013); Luo and Waite (2005); Van Den Berg et al (2006)
[3] Based on calculations from the quarterly Labour Force Survey in the UK (years 2015-2017 combined), the Current Population Survey in the US (years 2015-2017 combined) and the EU Labor Force Survey (2014-2016 combined).
[4] This cohort data is used in this paper and is subsequently described. For the 1958 and 1970 cohorts occupations are measured based on data collected when they were in their early 30's. For the cohort born in 2000 occupations are measured based on aspirations reported at age 12.

over the three periods, with the share of males planning to go into teaching decreasing to even lower levels for the most recent cohort. This highlights that the asymmetric gender revolution remains firmly in place.

Gendered sorting is intuitively influenced by social movements over time. Human capital investments, both of type and quantity, are affected by social norms. Systemic changes in attitudes over time can cause females to invest in different career paths if preferences are shaped by social norms. For example, the tolerance of discrimination has changed radically over the last five decades[5]. The current view among economists is that the remaining obstacle to more equal labor market outcomes between the sexes is a lack of flexibility to combine a career and family. Goldin (2014) argues this point most forcefully but it is also shared by Bertrand (2018). A systemic movement which causes males and females to share family responsibilities more equally removes constraints for females allowing them have a wider career choice. The influence of tastes and preferences on gendered sorting is also being explored (Lordan and Pischke, 2016 and Cortés and Pan 2017). While these papers do suggest that tastes and preferences have a role to play in occupational sorting, they may be socially constructed. This fits with the idea that individual decisions are influenced by the opinions of others of which ultimately shape identity (Akerlof and Kranton, 2000). A systemic change in the attitudes of society regarding what jobs fit each gender has the potential to change the career choices of females.

At a more local level gendered sorting has the potential to be influenced by childhood variables given that experiences in that period vary by gender. So why do experiences vary? First, some people may have preferences for a particular gender[6], or indeed have a preference for engaging children in different activities depending on whether they are a boy or a girl. Second, people may hold a belief[7] that boys and girls have different production functions, and because of this engage them in different activities. Third, there may be differential monetary

[5] Becker (1985), Katz and Murphy (1992) and Goldin (2006) have all suggested that the effects of gender discrimination are now much less relevant than other factors when it comes to explaining occupational segregation as compared to previous time periods.

[6] Suggestive evidence that father's strictly prefer sons can be found in Dahl and Moretti (2008) for the US and Kohler et al. (2005) for Denmark.

[7] We intentionally write "belief" given a recent meta-analyses highlights that, among both children and adults, females perform equally to males on math assessments, and the gender difference in verbal skills is small and varies depending on the type of skill assessed (Hyde 2016). Of course, there are other skills in which the sexes may differ, and the cause may be innate or psychosocial, regardless of whether these differences are real it is the belief among others in differences which drives how a child is treated.

and/or opportunity costs of engaging with boys over girls in specific activities. These three explanations are not mutually exclusive but together capture the underlying causes of why boys and girls are exposed to different experiences which ultimately may shape their futures.

Examples of differential treatment by gender abound in the literature[8]. Differential treatment has the potential to impact cognitive development, including soft skills and motor skills. We are interested in the extent these experiences, which vary *within cohorts,* change gendered sorting patterns as compared to systemic changes which occur *across cohorts*. Drawing on three British cohort studies, which follow children born in the UK 1958, 1970 and 2000 we compare the magnitude of the shift in the tendency of females in these cohorts to sort into traditionally male roles as compared to males, to the combined effect of a set of childhood variables which can be reasonably expected to be correlated with both gender and sorting patterns. These childhood variables capture cognitive, soft and motor skills, alongside socioeconomic variables, health status, parental influences and peer influences. We consider a number of proxies which capture the differential aspects of traditional male jobs. For those individuals born in 1958 and 1970, these proxies are based on their occupations in their early 30s. For the individuals born in 2000 the proxies are based on their aspirations for the future (when they turn 30 years old). These proxies range from the share of males in an occupation, to variables which capture an occupation's content.

A number of stylised facts emerge from our analyses. First, for all three cohorts we find strong evidence of sorting along gendered lines, regardless of the childhood variables we include in our regressions. Second, the tendency to sort along gendered lines has decreased substantively over time. That is, the gender gap has narrowed. Conversely, we find little evidence that childhood variables change the tendency within a cohort for the average female to sort substantively differently. Third, the same conclusions emerge if we focus only on individuals with the highest childhood cognitive ability. These are the individuals who we intuitively expect to subsequently sort into the top jobs. We view our work as underlining the importance of societal shifts, over and above childhood variables, in determining the sorting patterns we have seen over the last number of decades, and also those that remain today.

[8] See Lundberg (2005), Lundberg et al. (2007) and Yeung et al. (2001) work on parental time allocation; Aznar and Tenenbaum (2015) research on parental communications; Mondschein et al. (2000) work on parental assessments of ability and Dee's (2007) work on teach assignment.

II. ANALYTICAL FRAMEWORK AND EMPIRICAL DESIGN:

We are interested in the extent to which societal shifts have altered a female's tendency to pursue traditional male roles, versus childhood factors. The outcome variables considered in this study are proxies for aspects of work where we expect the sexes will bifurcate in sorting tendencies. These proxies cover income, hours, flexibility, job content and job competitiveness alongside the share of males. Drawing on individual level data for cohorts of individuals born in the UK in 1958, 1970 and 2000 we relate each proxy in turn to a female dummy variable, and sequentially add groups of childhood variables which we may expect to be correlated with both gender and the proxy. We take a holistic approach to specifying these childhood factors and examine demographic and socioeconomic variables from early childhood, alongside measures of cognitive and non-cognitive ability, childhood health, parental inputs and external influences. We are interested in the extent to which the coefficient on the female dummy is attenuated with the addition of these childhood factors. To the extent that the coefficient is attenuated substantively, we argue that it reveals that malleable factors at the individual level – many of which can be readily influenced by parents, schools and policy makers – play a large role in determining gendered sorting across generations for the average female. However, to the extent that the female coefficient is relatively stable, it is highly suggestive that the childhood factors that we usually view as important in determining adult outcomes matter little for explaining gendered sorting[9].

Specifically, our initial analysis relies on:

$$Y_{ij,adult} = \alpha_i + F_i\,\delta' + X_{i,child}\,\beta' + \varepsilon_{ij,\,adult} \qquad (1)$$

where Y is a proxy for a component of job j for respondent i in adulthood, and F is equal to 1 if individual i is female and 0 otherwise. $X_{i,child}$ is then a vector of individual control variables during childhood, which will be subseqently discussed. We run equation (1) separately for each cohort and obtain the estimate of δ', which indicates the extent of being a female influences occupational sorting across cohorts. We note here that we care most about how δ changes across cohorts, when we sequentially add childhood variables. We are not seeking to put structural interpretations on the coefficients of control variables (β'). However if F_i is

[9] The major threat to this argument is that all of our childhood variables are measured with error. This seems highly unlikely, given the quantity of variables that we do consider, but later we come back to this point.

attenuated by a particular $X_{i,child}$ we view this as evidence that something which is correlated with this same $X_{i,child}$ is driving sorting. Hence, childhood variables, in the general sense, matter in determine sorting.

It is also interesting to consider whether the same general patterns identified by equation (1), hold for the most intelligent children in the three cohorts. After all, these are the individuals we would expect to be most likely to reach the most prestigious jobs in society, where we may care more about having a better representation of women. To consider this, we follow the psychometric literature and use exploratory factor analysis to reduce the dimensionality of our proxies for childhood intelligence in each cohort study into one variable (Gorsuch, 1983; Thompson, 2004). A clear structure of one latent factor emerges in the first rotation (see Appendix A2). From this factor, we repeat the analysis documented above on individuals who are in the top quantile of this distribution only. We note that the female share in this decile is 51.9%, 49.4% and 49.12% for children born in 1958, 1970 and 2000 respectively.

An issue with estimating equation (1) is that there is a risk of overfitting, given we add a large number of childhood variables. We also estimate equation (1) applying LASSO regression analysis[10] and document the full results in Appendix D. We report only the coefficient, δ', on the female dummy from the LASSO regressions in the main text. LASSO is useful here given that many of the variables we sequentially add are highly correlated, so disentangling their true coefficient size given potential issues with multicollinearity is difficult. For our purposes LASSO is a useful as a check as to whether δ' remains non zero after the shrinkage process, emphasising that of all the variables included in the regression it is one of the most strongly associated with the outcome variable.

The first outcome we consider is the share of males in an individual's chosen occupation. This allows us to ask directly whether occupational segregation by gender has changed substantively for the three cohorts we are examining, and how these changes relate to the childhood variables we usually think of as determining a person's future. We complement

[10]LASSO is a shrinkage and variable selection method for linear regression models whose goal is to obtain the subset of predictors that minimizes prediction error for a quantitative response variable. The LASSO does this by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero. Variables with a regression coefficient equal to zero after the shrinkage process are excluded from the model. Variables with non-zero regression coefficients variables are most strongly associated with the response variable. Thus, the variables that are left over are the variables that most explain *Y*.

this with regressions that model the probability that a job with a share of males 80%+ is chosen, to allow us to quantify how this has changed over the three generations. We also consider an outcome that is equal to 1 if a female has opted out of the labour force and zero otherwise. This is our only outcome that is generated at the individual level, rather than the occupation level.

The next proxy we consider is average occupational income. For many years economists have contributed to a literature that seeks to explain just why there is a gender wage gap. It is now clear that the lack of women in high-paying, male dominated professions contributes significantly to this gap[11]. Therefore, considering average income of an individual's chosen occupation as an outcome in equation (1) allows us to examine directly whether females have been choosing jobs with significantly higher average income over time and how this is mediated by childhood variables.

We also consider the average hours in an individual's occupation as an outcome. Women who find it hard to juggle family and children – or indeed hard to imagine juggling in the future - may 'opt out' of occupations that make this more difficult. This suggests a constrained choice, with the constraints being potentially perceived and internalised as early as high school. Therefore, we re-estimate equation (1) with average hours as the dependent variable. δ' is then indicative of how important it is for females to be in occupations with lower average hours as compared to males. This fits with work that suggests that females 'opt elsewhere', choosing occupations that allow them to accommodate family responsibilities (Polachek 1981; Belkin 2003; and Stone 2007) or choose to work fewer hours to balance family responsibilities (Antecol 2010)[12].

We complement the average hours proxy with another variable which captures non-linear returns to hours worked. This follows, Goldin (2014) who presents evidence for full-time college graduate workers in 95 high paying occupations. Goldin's metric for the flexibility of

[11] See Blau (1977); Bielby and Baron (1984); Macpherson and Hirsch (1995); Carrington and Troske (1998); Bayard et al (2003) and Blau and Kahn (2016).

[12] We note that a number of other studies have also considered whether 'opt out' of the labour market occurs conditional on having children and do not find any differences by education level (Boushey (2005); Goldin (2006); Vere (2007); Cohany and Sok (2007); Fortin (2008) and Percheski (2008). For us, females do not necessarily opt out. Rather they may 'opt elsewhere' to allow them to better manage their current or expected family commitments, into occupations with lower average hours and enhanced flexibility. This is supported by Kie, Shauman and Preston (2003) who highlight that marriage and children move women from the male dominated fields of science and engineering towards other types of work.

an occupation is the elasticity of individual earnings with respect to hours worked: high elasticities imply a penalty for workers seeking short hours and indicate a lack of flexibility. Goldin (2014) demonstrates that less flexible occupations have a larger pay gap. By estimating equation (3) with the Goldin (2014) measure of flexibility as an outcome we can assess empirically, how the tendency to choose occupations with differential levels of flexibility has changed for females across the three cohorts, and how this is predicted by childhood characteristics.

Our remaining proxies capture occupational content. This complements a recent emergence of explanations for occupational segregation which suggest that males and females have different tastes when it comes to the content of the work that they do. The psychologist Susan Pinker (2008) has pushed the idea that differences in the preferences of women and men are the main driver of gendered labour market choices. Pinker's (2008) work, based on qualitative research, highlights that women may not like the nature of male dominated jobs, preferring 'people' content over making 'things'. Lordan and Pischke (2016) provide quantitative evidence from three countries and a discrete choice experiment which backs up this claim. Overall their work suggests that females are more extrinsically motivated opting for jobs that are high in 'people' and 'brains' content, like medicine and law, over jobs that are relatively high in 'brawn content', like engineering. In contrast males care less about the job content. Cortes and Pan (2017) investigate the predictive power of a variety of occupational indexes in regressions that model the rate of females in an individual's occupation and show that social contribution and physical skill dominate. In other words, their research supports the thesis of Pinker, and the 'people' versus 'things' divide. Evidence is also provided by Grove, Hussey and Jetter (2011) who examine the pay gap of MBA graduates and find that female MBAs have a wage penalty owed to *choosing* occupations that contribute to society and have high ethical standards. Su, Rounds, and Armstrong (2009) also emphasis sex differences in occupations preferences in an overview of the psychology literature on this topic. Together, these results raise the question of whether on average women prefer jobs with a societal contribution. These differences in tastes by gender can be innate, evolutionary or socialised.

Evidence that females differentially select into work of different content, but with a pattern changing over time, point to a societal role in the formation of preferences. This we can model using equation (1). For example, if engineering and being a CEO are viewed as 'male roles', as argued by Akerlof and Kranton (2000), females may experience a loss of identity should they work in one of these occupations. We note that no change over time does not necessarily suggest innate tastes and preferences. This trend could equally be explained by sticky ideas in society about the type of work that is (and is not) done by women.

We create three proxies for job context, based on an approach introduced by Lordan and Pischke (2016) and drawing on O*NET activities and context data. Overall, these proxies represent 'People', 'Brains' and 'Brawn' context. That is, occupations with relatively high people content involve engaging with customers, clients or co-workers routinely (for example nurses, physicians, social workers and teachers). Occupations with relatively high brains content are economists, financial managers, aerospace engineers and CEOs. Finally, occupations that are relatively high on 'brawn' include explosives workers, mechanical engineers and surveyors. Given the empirical analysis of Lordan and Pischke (2016), we may expect females to choose jobs that are high in people and brains, and avoid jobs that are high in brawn context. If these preferences are socialised we should see attenuation in how the sexes bifurcate in choices over the cohorts if norms have also changed.

Experimental evidence has highlighted that females are more averse to competition as compared to males (Croson and Gneezy 2009). However, this evidence concerns small stake decisions where the avoidance of competition does not cost the participant significantly in the long run. This contrasts to an individual choosing to enter and stay in an occupation, which has a highly competitive environment where the stakes are high. Our last proxy, therefore is a measure of competitiveness at the occupational level from the O*NET database. We complement a large and influential experimental literature, which has shown that females avoid or do not perform as well as males if the environment is competitive[13]. We also build on Cortes and Pan (2016), who use the same measure of competiveness as we do here, and find that controlling for competitiveness there is a reduction in the magnitude of the observed correlation between the returns to working long hours and the gender pay gap. In more recent work, Cortes and Pan (2017) pin down competition against a variety of occupational indexes from the O*NET database, including social contribution, inflexibility of the job, interactional skills, cognitive skills and physical skills. Specifically, they find that competition and cognitive skills dominate in log wage regressions.

[13] For example see Dohmen and Falk (2011), Niederale and Vunderland (2008), Gneezy and Rusticini (2004) and Gneezy et al. (2003).

III. DATA:

We draw on the National Child Development Study (NCDS), a continuing study that follows the lives of 17,000 people living in Great Britain who were born in the week of March 3, 1958. The survey added about 700 children who were born in the same week and immigrated to Great Britain before their sixteenth birthday. Sweeps were carried out in in 1965 (age 7), 1969 (age 11), 1974 (age 16), 1981 (age 23), 1991 (age 33), 1999-2000 (age 41-42), 2004-2005 (age 46-47) and in 2008 (age 50). We use data from the survey at birth, and ages 7, 11 and 16. We measure the NCDS child's occupation variables at age 33.

We also draw on the 1970 British Cohort Study (BCS70). The BCS70 began by including more than 17,000 children born between April 5-11 in 1970. It is estimated that these births represent more than 95% of births over these days in England, Scotland, Wales and Northern Ireland. Currently data are available for eight major follow-up surveys: 1975, 1980, 1986, 1991, 1996, 2000, 2004 and 2008. Added to the three major childhood surveys (ages 5, 10 and 16) are any children who were born outside of the country during the week of April 5-11 and could be identified from school registers at later ages. We use the data from the survey at birth, and at ages 5, 10 and 16. We measure the BCS child's occupation variables at age 34[14].

In order to examine gender based occupational sorting for a cohort entering the workforce soon we draw on the Millennium Cohort Study (MCS). This group is now 17/18 years old and are about to make the decision on what to do after their schooling finishes. The MCS follows the lives of around 19,000 children born in the UK in 2000 and 2001. The sample was selected from a random sample of electoral wards using a stratified sampling strategy to ensure that the sample is over-represented of disadvantaged and ethnically diverse areas. We use the data from the survey at 9 months old (2001) and at ages 3 (2003/4), 5 (2005/6), 8 (2008/9) and 12 (2012/13). We draw on *aspired* occupation, reported by the cohort member in the 2012/13 sweep.

Outcome Variables:

For the NCDS and the BCS, the information on occupation is measured by four-digit socio-Economic Classification 2000 codes (SOC2000) at ages 33 and 34 respectively.

[14]There are two waves of the BCS that surveyed cohort members when they were in their 30s. We use the 2004 wave (aged 34) as the main source of occupation. We supplement missing occupation information in the 2004 wave with occupation reported in the 2000 wave (when cohort members were 30 years old).

For the MCS, the cohort members were asked in the 2012/13 sweep "*by the time you are 30, which of the following would you most likely to achieve?*" followed by a list of choices which follow the 4-digit UK Socio-Economic Classification 2010 (SOC2010). We convert SOC2010 to SOC2000 occupation coding using a cross walk provided by Lordan (2018).

Our occupation averages are calculated based on 1993-2012 Quarterly Labour Force Survey data (QLFS). So, the averages associated with each occupation are the same for the three cohorts, ensuring that *δ'* captures changing in sorting towards or away from particular occupation types rather than composition effects.

The QLFS is the main survey of individual economic activity in Britain, and provides the official measure of the national unemployment rate. It uses SOC90 codes from 1993 through 2000 and SOC00 from 2001. Thus, we first assign to each SOC90 code a SOC00 value based on a crosswalk from the British Household Panel Survey (BHPS)[15]. We calculate occupation averages- log of gross income, average hours and share of males - in a four-digit SOC00 occupation using the 1993-2012 Quarterly Labour Force Survey (QLFS), and match these directly to the NCDS, BCS and MCS's SOC00 codes.

We also create a variable to proxy the wage-hours elasticity used by Goldin (2014). Goldin interprets this occupation specific elasticity as capturing the wage penalty arising from working shorter hours: high elasticities imply a penalty for workers seeking short hours and indicate a lack of flexibility. Specifically, we create this variable by running a regression of the log of wages on log hours, occupation fixed effects, the interaction between log hours and the occupation fixed effects and a number of other controls[16] using the 1992-2012 QLFS and consistent British SOC00 codes. The proxy is then the coefficients on the interaction between occupation and log hours.

To complement the proxies constructed so far, we also consider a variable that is assigned equal to 1 if an individual is dis-employed and zero otherwise. For the MCS this is based on the child's response (asked at age 11/12) to a question on whether they expect to have a 'good' job by age 30. We interpret this as a proxy which is likely to be highly positively correlated

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[15]The QLFS uses British SOC90 codes from 1993 through 2000 and SOC00 from 2001. We first assign to each SOC90 code a SOC00 value based on a crosswalk created from the BHPS. This is possible because in the BHPS after the year 2000 every individual is assigned a SOC90 and SOC00 code simultaneously. This information allows for a consistent coding system in the QLFS based on SOC00.

[16] The controls follow Goldin (2014). These are gender, age, age squared, age to the power of three, age to the power of four, education, ethnicity and year dummies.

with labor market attachment. We assign a variable equal to 1 if a good job is expected and zero otherwise.

Our analysis also utlises three variables which capture what a job is about. These variables are created following the approach described by Lordan and Pischke (2016). Specifically, we retrieve from O*NET version 5 items relating to the activities and context of an individual's work. These items on activities and context are linked to US Standard Occupation Codes (SOC) 2000. These 79 items report the level at which an occupation has a particular characteristic from 1 to 7. For example, in activities, an item might describe to which degree an occupation involves 'assisting and caring for others,' 'analysing data or information,' or the 'repairing and maintaining of mechanical equipment.' Examples for context are the level of 'contact with others,' 'the importance of being exact or accurate,' and 'being exposed to hazardous conditions.' We match the US SOC00 codes in the O*NET data directly to the British SOC00 using a crosswalk provided by Anna Salomons. We then match the O*NET items to the QLFS using the British SOC00 codes. Three latent factors 'people,' 'brains,' and 'brawn' (PBB) are calculated using this data. We match these three factors for each occupation to the NCDS, BCS and MCS data using the British SOC00 codes.

We turn to the O*NET database version 15 for our measure of occupation competiveness. Specifically, incumbents are asked: *"To what extent does this job require the worker to compete or to be aware of competitive pressures?"* with response options of 'not at all competitive' 'slightly competitive' 'moderately competitive' 'highly competitive' and 'extremely competitive'. We standardise this variable to have a mean of zero and a standard deviation of 1, and match to the NCDS, BCS, and MCS in the same manner described for the PBB factors.

NCDS, BCS and MCS control variables:

Our aim is to consider a holistic set of controls that capture as many of possible of the childhood variables that are simultaneously correlated with gender and the outcomes we consider. Across all three surveys efforts are made for these controls to be measured at similar ages and have relatively consistent definitions. Fuller details of all controls, along with the relevant means and standard deviations can be found in Appendix A. All covariates described below are standardised to have a mean of 0 and standard deviation of 1. We run all our specifications using robust standard errors to allow for heteroscedasticity of an unknown form. The regression samples contains the same individuals across all specifications. Our estimation approach to equation (1) is sequential. We first estimate equation (1) with the female dummy variable and no other controls. Subsequently we add the following variables:

i) Demographics and Socio-Economic Variables ($fam_{i,child}$)

Childhood demographics and the socio-economic status variables are elicited as close to birth as possible (for exact timing see Appendix A). These variables are: mother's age, father's age, social status, a set of marital status dummies indicating whether the child's parents were together or not in each wave, a dummy variable indicating whether the child's mother stayed in school beyond the minimum required age, household income, household tenure, a dummy indicating whether or not the child's mother worked, a dummy variable indicating low birthweight, a dummy variable indicating whether the cohort child was the first-born, a dummy indicating whether the cohort child was breastfed, region of residence and a dummy variable indicating if the cohort child is White and zero otherwise.

(ii) Cognitive ability scores (verbal and math/science) ($cog_{i,child}$),

We draw on all available measures of the child's cognitive ability in the three surveys[17]. Each of the measures considered is standardised to have a mean of zero and standard deviation of 1, unless it is represented by a set of dummy variables where no change is made. These measures essentially capture the child's verbal and math/science abilities.

In the NCDS, at age 7 the child completed the Southgate Reading Test, a 35 Item Reading Comprehension Test and the General Ability Test. At ages 11 and 16 they completed the 35 Item Reading Comprehension Test. These five proxies of verbal ability are included in our regressions.

The composite verbal ability score in the BCS is derived from tests conducted at ages 5 and 10. Specifically, at age 5, the 50-item Reading Test score, which is modified from the Schonell Reading Test was administered. At age 10, the 21-item Word Similarity subscale of the British Ability Scale was administered. We also draw on the 67-item Shortened Edinburgh reading test, which assesses vocabulary, syntax, sequencing, comprehension and retention at age 10.

[17] See Shepherd (2012) for NCDS, Parsons (2014) for BCS and Johnson et al (2015) for the MCS.

For the MCS, the composite verbal ability score is derived from instruments administered at ages 3, 5, 7 and 11. The British Ability Scale (BAS) was administered at ages 3 and 5, the Pattern Similarity and the Pattern Construction subscale of the BAS at ages 5 and 7, the 900-item Word Reading of the BAS at age 7 and the Verbal Similarity subscale of the BAS at age 11.

The Math-and-science proxies for the NCDS include three tests measured at ages 7, 11 and 16, as well as teacher ratings for math and science. Specifically, these tests are the Problem Arithmetic Test score at age 7, a 40-item Arithmetic/Mathematic Test at age 11 and a 31-item Mathematics test at age 16. We also include the teacher's ratings which reflect their perception of the child's ability in maths and science. These rating scores equal 3, 2, 1 and 0 if the teacher thinks the child's ability is equivalent to A-level, high-graded GCSE, low-graded GCSE and below GCSE, respectively[18].

For the BCS we draw on tests administered at ages 10 and 16[19]. These are the Friendly Maths Test and the Recall of Digit subscale of the BAS administered at age 10, and the actual raw GCSE scores for Maths and four science subjects (science, chemistry, physics and biology) reported at age 16.

Finally, for the MCS we draw on tests administered at age 7 and 11. The NFER Number Skills test was taken at age 7. We also include the teacher's evaluation of the MCS member's ability at age 11 in maths, science and technology. These scores equal to 5, 4, 3, 2 and 1 respectively, when the teacher evaluated the MCS member to be: well-below average, below average, average, above average and well-above average.

(iii) Motor skills (gross motor and fine motor) ($gross_{i,child}$, $fine_{i,child}$),

We consider instruments related to both gross motor and fine motor skills, captured across childhood as our proxies for motor skills. Specifically, gross motor skills are those which require whole body movement and involve the core stabilising muscles of the body to perform everyday functions, such as standing, walking, running, and sitting upright. It also includes

[18] Students completing A-levels stay in school until roughly 18 years and generally aim for third level education. A certificate of secondary education (CSE), O-levels or a general certificate of secondary education (GCSE) represent a low-level secondary school qualification that is usually achieved when the student is aged 15.

[19]These are the Friendly Maths Test and the Recall of Digit subscale of the BAS administered at age 10, and the actual raw GCSE scores for Maths and four science subjects (science, chemistry, physics and biology) reported at age 16.

eye-hand coordination skills such as ball skills. Fine motor skills are smaller movements. They include clothing fastenings, cleaning teeth, using cutlery drawing, writing and colouring, as well as cutting and pasting.

For the NCDS we draw on teacher assessed measures of gross motor skills at ages 7 and 11 that follow definitions by Sigurdsson *et al* (2002)[20]. This definition is consistent in the BCS with measurements taken at age 10. In the MCS, gross motor skills are estimated using a subset of the Denver Developmental screening test (see Frankenburg and Dodds, 1967), and are assessed at age 1 by the child's parent.

We have two measures of fine motor skills in the NCDS. These are based on the teacher assessment of the Human Figure Drawing test (taken at age 7) and the Copying-Design test (taken at ages 7 and 11). The same measures of fine motor ability are available in the BCS (measured at age 10). For the MCS, we again draw on relevant sub components of the Denver Developmental screening test, assessed at age 1 by the primary carer.

(iv) Non-cognitive skills (externalising and internalising behaviour) ($\boldsymbol{behav_{i,child}}$),

We construct two separate measures of non-cognitive skills in childhood which proxy externalising behaviour and internalising behaviour respectively. For all three surveys, we choose assessments provided by teachers over parents. In the NCDS, the behaviour scores are calculated from relevant items taken from the Bristol Social Adjustment Guide (BSAG) at age 7 and 11. Essentially we separate the questions into proxies that represent internalising and externalising behaviour. For the BCS, we utilize the Rutter's Behavioural Scale, from age 10 (Rutter, 1967) in the same way. Finally, measures of internalising and externalising behaviour in the MCS are constructed from the Strength and Difficulty Questionnaire (SDQ) at age 7.

(v) Health conditions (childhood physical health issues, psychological health issues) ($\boldsymbol{phy_{i,child}}$, $\boldsymbol{psy_{i,child}}$):

We follow Goodman et al (2011) when constructing the measures of psychological and physical health in childhood and classify physical health issues into (a) major physical health

[20] Because of the absence of direct and positive measures of gross motor skills in the NCDS and BCS, Sigurdsson et al (2002) exploit the five measures of gross motor impairment (rated by class teacher) and calculate for the average score of gross motor deficiency. Smaller scores indicates more positive gross motor development. In the MCS, we can use Denver Developmental Scale to directly measure gross motor skills at early ages.

and (b) minor physical health issues. For the NCDS, medical assessments were conducted at ages 7 and 16. At age 11, the information came from the parent's report. In the BCS, the medical assessment was administrated at ages 5, 10 and 16. For the MCS, we use parental reports on the child's medical conditions at age 3, 5, 7 and 11.

The psychological health measures in the NCDS are calculated from medical examinations capturing emotional maladjustment at ages 7 and 16, as well as parental reports of the child's mental health support visits for ages 11 and 16. In the BCS, we follow similar classifications to the NCDS, drawing on data from parent reports of mental health support visits at ages 10 and 16. At age 16, the child also went through a number of medical assessments, capturing aspects of emotional maladjustment. Finally, for the MCS, psychological maladjustment is captured by teacher and parent reports of mental illness at ages11/12, and reports of adolescent mental health services utilisation at school.

(vi) Parental investments ($invest_{i,child}$)

We add measures of parental inputs, which mainly capture time inputs. For the NCDS, we draw on parent reported frequencies at age 7 of how often the mother and father reads to their child ; teacher-rated levels of parental interest in their child's education at age 7 years and parental reports of engaging in various activities with their child at ages 7 and 11 (see Appendix A). For the BCS, we use information on parental-assessed frequency of how often the mother and father reads to their child measured at age 5, teacher-rated levels of mother and father interest in their child's education at age 10 years and parental reports of engaging in various activities with their child at ages 5 and 10. For the MCS, we draw on frequency of reading, and parent-assessed frequency reports at ages 3 and 5 of whether the parents i) reads to the child ii) tells stories to the child iii) paints with the child and iv) plays music with the child. We also draw on teacher-rated levels of parental interest in the child's education when aged 11 years, and a set of variables on frequencies parent visited various places with child at ages 3 and 5 (see Appendix A).

(vi) Parental Aspirations ($invest_{i,child}$)

We also consider measures of parental aspirations. For the NCDS, we draw on parent reports at age 16 that are equal to 1 if a parent wishes their child leave school at age 15 years, and 0 otherwise. We consider additional measures of aspirations, measured at age 16, which correspond to how long the parent wishes their NCDS child stay in education (16 years, 18 years, beyond 18 years or uncertain).

In the BCS, we draw on parent reports measured at age 16. We create a dummy variable that is equal to 1 if a parent advises their child to leave full-time education immediately after age 16, and 0 otherwise. We also consider additional measures of aspirations, measured at age 16, which correspond to how long the parent wishes the BCS child to stay in education (leaves at 16, finishes A-levels, goes to university, uncertain).

In the MCS, we draw on parent reports when the child is aged 11 on their perception on whether their child will attend university. Specifically, parents are asked to estimate the likelihood they think the child will attend university: very likely, fairly likely, not very likely and not at all. The responses are then added to the regression as a set of dummy variables.

(vii) External Influences ($external_{i,child}$).

Finally, we try and capture aspects of the child's external environment. Given the data available the variables we consider mainly capture the school environment. For the NCDS, we include a set of dummy variables that capture whether the child's teacher perceives they would benefit from further education (measured when the NCDS child is 16. We also include a separate set of dummy variables which capture the teacher's expectation of the highest level of education the child the child is likely to attain (university, lower college, advanced course, certificate, other further education, part-time professional qualification, other part-time education, and no other qualification). Similarly for the BCS, we include a set of dummy variables which capture the BCS child's teacher report on whether further education will benefit the BCS child. A further set of indicator variables are constructed from the teacher's expectation of whether the child would attend further education after age 16. For the MCS, we also add similar measures. These measures indicate the teacher's perception of whether the MCS child would (a) stay in full-time education after age 16, and (b) attend university. These variables were measured at when the MCS child was 11 years.

For the NCDS and BCS we also capture some characteristics of the child's classmates. For the NCDS and the BCS these variables are measured at age 16 and relate to the school wide: i) share of fathers from non-manual occupations, (ii) share of students staying on at school last year, (iii) share of girls obtaining at least two pass grades of GCSE or equivalent, (iv) share of 15-year old girls studying GCSE or equivalent only, (v) share of boys obtaining

2 passes of GCSE or equivalent, and (vi) share of 15-year old boy studying GCSE or equivalent.

Inclusion criteria:

We begin with the total observations from the first sweep of each cohort survey (NCDS = 18,558, BCS = 18,752, MCS = 19,518). From the full sample, we drop observations with missing values on gender (NCDS = 4, BCS=326, MCS =700). We then drop observations with missing values on realised occupation around age 33/34 years old (the NCDS and the BCS)[21]. For the MCS, we drop observations with missing values on aspired occupation in the fifth sweep (age 11). The exclusions up to this stage reduce the NCDS, the BCS and the MCS samples to 11,469, 10,234 and 11,200 observations respectively. We then match the occupation around age 33/34 to the associated occupation averages, generated from the Labour Force Survey and O*NET. We are then left with the samples of 9,722, 8,973 and 11,200 observations for NCDS, BCS and MCS respectively. (See Appendix Table B1).

An issue when working with cohort data, with this many variables and waves, is that there are many missing values. To address this problem we apply mean imputation with missing indicator variables (the so-called Missing Indicator method) to the control variables described in (.i) through (vii) above. When a variable is missing, we replace it with the average value from the non-missing sample. In the finalised sample, the share of female is 49.5%, 48.4% and 51.3% in the NCDS, the BCS and the MCS respectively. (See Table B1 in the Appendix.)

IV. RESULTS:

Figure 2 plots the propensity for females to choose occupations with high share of males for each cohort. As we move from left to right from (i) to (ix) we are exploring richer variants of each model. Three things are worth noting. First, over time females have become more likely to choose jobs with higher shares of males as compared to their male peers. Specifically, the gap observed in the share of males between males and females is attenuated by about 5% across cohorts. Recall for children born in 2000 our outcome is based on aspirations, so this

[21] There are two survey waves on life outcomes around age 30s for the BCS cohort (ages 30 and 34). In this analysis, we prioritise the responses given at the 34-year survey (1984). To maintain the size of observations of the BCS sample, we supplement any missing values of our variables at age 34 with the information given at age 30 to the exact questions. This strategy increases the final BCS sample from 6870 to 8973 observations. Running the models only with the 6870 observations does not change the results.

difference may tend towards earlier cohorts once the true constraints of jobs with high shares of males are realised by female workers[22]. Still, it is a clear and significant trend towards less gendered sorting over time. Second, even with this convergence, aspirations of females in the most recent cohort are still markedly different from their male peers in terms of share of males. Specifically, the share of males in jobs aspired to by females is about 35% lower as compared to their male peers. Third, the gradient in Figure 2 is flat. This tells us that childhood variables have little explanatory power with respect to changing the tendency to sort along gendered lines for the average female. In other words, the influence of being female on occupation choice is independent of the childhood variables we consider.

Turning to Table 1, we can examine these patterns more precisely. Specifically, Table 1 details the coefficient on the female dummy with its associated standard error, alongside the adjusted R squared for each model. As we move through the rows from (i) to (ix) in each panel we are estimating richer variants of equation (1). It is again striking that while there are significant differences in the female coefficient across all three cohorts, the coefficient is not attenuated greatly when childhood variables are added. For example, from panel A (i), a female born in 1958 chooses an occupation where the share of males are 45% lower on average as compared to their male peers. This compares to 41% for females born in 1970, and 34% for females born in 2000. Overall, this suggests that over time UK females have been more often choosing occupations with higher share of males, however the gap between the aspirations of females and males in the most recent cohort is still marked.

Turning to Table 1 Panel B, there is no difference in the probability that females born in 1958 or 1970 will choose a job that has a share of males of 80% or higher as compared to their male peers. The coefficient on female for those born in 2000 is slightly reduced, implying that females in this cohort are 46% less likely to choose occupations with the highest share of males as compared to comparable males. This emphasises that females still shy away from occupations with the highest shares of males[23]. Across all three cohorts the female coefficient

[22] Recent work by Lekfuangfu and Odermatt (2018) looks at occupational aspirations of the NCDS 1958 cohorts when they were 11 and 16 years old. They find that gender sorting is highly prevalent. For instance, out of 500 children wishing to become a nurse, only one is a boy. In contrast, among children who wished to work in skilled manual jobs, only 10 percent was female. They also show that gender-biased occupational choices are also observed in parents and teachers of the NCDS cohorts.

[23] This is consistent with a literature which highlights that females are less likely to finish STEM majors (Arcidiacono, Aucejo, and Hotz, (2016) and Ost (2010) and another which highlights that females may underestimate the gains from 'male-dominated' fields (see Zafar (2011), Zafar (2013) and Arcidiacono, Hotz and Kang (2012).

is not markedly attenuated with the addition of childhood variables, and the R squared remains flat.

Table 1 panel C focuses on the probability a female is dis-employed (or in the case of the MCS children aspires to have a job that is not 'good'). For the NCDS, being female is associated with a 21% increase in the probability of being dis-employed as compared to male peers. This compares to 9% for the BCS. The female coefficient for the MCS is not significantly different from zero, emphasising that for the most recent cohort there is no difference in aspirations between males and females in their tendency to expect a 'good' job by age 30. The addition of the childhood variables does not attenuate the female coefficient significantly for any of the cohorts, nor change the R squared notably.

Table 2 panel A highlights that the BCS cohort have occupations with a smaller wage gap, as compared to females in the NCDS cohort. However, the aspirations of the MCS cohort, if fulfilled, would cause a greater gender pay gap than those born in 1970 and 1958. Specifically, MCS girls are aspiring to do jobs that are paid 31% lower than males. The childhood variables do not attenuate the female coefficient significantly for any of the cohorts, and the R squared is flat. For the BCS cohorts, adding the childhood variables actually increases the female coefficient, with the addition of cognitive skills having the greatest impacts.

Table 2 panel B highlights that the propensity for females to sort into jobs with lower average hours, as compared to male peers, has declined significantly and substantively over the three cohorts. However, the difference between female aspirations and their male peers is still substantive for those born in 2000 (with females aspiring to work in jobs that have 3 hours less on average). The addition of the childhood variables gives modest attenuation across the three cohorts, but these additions do increase the R squared for the 1958 cohort (from 11% in the most basic model to 14% for the fullest model). For the other two cohorts the R squared is relatively flat.

Table 2 panel C documents the results for the flexibility regressions. Overtime, the gap between males and females in terms of sorting into flexible jobs has narrowed. Notably, the coefficient for the aspirations of the 2000 cohort is roughly one third of that for the NCDS children. For all three cohorts, the addition of the childhood variables does little to attenuate the female coefficient and the R squared is flat. This suggests that changing patterns over time determined the movement away from flexibility, over and above childhood factors.

Table 3 documents the estimates from our models which consider job content. A few stylised facts emerge. First, over time females have moved more towards jobs that are high in brains as compared to their male peers, with the MCS girls being substantively more likely than the MCS boys to choose jobs with high brain content. Females across all three cohorts choose jobs with higher people content and lower brawn content, as compared to male peers. However, for the MCS cohorts the coefficients are about the half the size. This suggests that females in this cohort are still choosing job content along gender lines, but it is not as marked as it was for older cohorts. Only time will tell whether these aspirations translate into realised sorting. Finally, across all three cohort studies there is a gender gap in the propensity to choose jobs that are highly competitive, with males choosing work with higher competitive content. Markedly, there is no attenuation in this trend over time, with the MCS girls being substantively *less* likely to aspire to work in jobs that are competitive as compared to MCS males. Second, while there a couple of exceptions (brains for NCDS and brawn for BCS), in general the addition of the childhood variables does not attenuate the female coefficient in the job content regressions. Third, across the three cohorts there are substantive changes to the R squared when we add the childhood variables for the brains and brawn regressions (in both cases the addition of the cognitive proxies is the most important). In contrast, the R squared is flat with these additions for the people and competitiveness content regressions.

Tables 4 through 6 document estimates from equation (1) for children who are in the top 20% of the cognitive distribution. There has always been less of a difference between high skilled females and their male peers in their tendency to sort into jobs with high shares of males. While the gradient of the coefficient decreases across the three cohorts, it is much flatter as compared to the average female regressions. Notably, females with high cognitive ability born in 2000 are still aspiring to enter occupations with 27% lower male shares, as compared to males. Panel B, highlights that that high ability females have become *less* likely than their male peers to sort (or aspire in the case of those born in 2000) into jobs with the highest shares of males. Given that these regressions pertain to the highest skilled females only it seems that that the trend of females sorting into science, technology and engineering are not improving across the three cohorts.

Consistent with the results for the average female, the gender gap in occupational hours (Table 5, panel B), flexibility (Table 5, panel C) and the potential to be dis-employed (Table 4, Panel C) has narrowed over time. High ability females have a lower occupation level average pay gap, if we compare the 1970 cohort to the 1958 cohort. However females born in 2000 are choosing jobs that have significantly *lower* average pay, as compared to their male peers. Together, these results suggest that females born in 2000 plan to have higher levels of labour force attachment as compared to females in earlier cohorts, but are less extrinsically motivated as compared to their current male peers.

Turning to Table 6, stylised facts consistent with table 3 emerge. First, the gap between males and females in terms of job brains content has grown over time, with females choosing jobs with higher brain content as compared to their peers. Second, females across all three cohorts choose jobs with higher people content, but lower brawn and competiveness content as compared to their male peers. Notably, for the MCS cohort the difference between males and females in brawn content is lower than for the NCDS and BCS females, but he competiveness gap is the larger.

Across Tables 4 through 6 childhood variables do little to attenuate the coefficient on the female dummy. However, the addition of the childhood variables does explain significant proportions of the variation for a number of outcomes (log of average occupational income, brains content and brawn content for all three cohorts).

Table 7 documents the LASSO estimates from the fullest model (see Appendix D for the full Lasso results). First note that in no case is the coefficient on female shrunk to zero leading to the conclusion that gender has been, and is now, a key factor in determining how individual's sort. The narrative from the OLS models remains. Overtime females (both average and high ability) have sorted more regularly into male traditionally male dominated jobs, have decreased their propensity of being dis-employed as compared to male peers and the gender gap has narrowed in terms of flexibility and hours. However, for both average and high ability children born in the year 2000 there is a larger greater gender gap in the propensity to pursue jobs that are 80%+ share of males, in average occupational income and occupational competiveness. Over time, all females have preferred jobs with higher brains and brawn content, as compared to their male peers. The average female also has been choosing jobs with less people content over time, as compared to their male peer. However, for females with high ability the preference of the 2000 cohort is for jobs that are *higher* in people content as compared to those born in 1970.

V. ROBUSTNESS CHECKS:

Measurement errors in childhood variables

The childhood variables we consider do not explain a significant proportion of the variation in any of our outcomes over and above what is explained the gender dummy. So, we conclude that the variables we usually think about as being important during childhood do not explain sorting, but gender is still a notable and independent determining factor. An obvious conclusion is perhaps the childhood variables we consider are simply measured with error. An easy way to explore this is to look at other outcomes that we think as important in adulthood, and look to see how our childhood variables relate to them. We are specifically interested in gauging their impact on the R squared. Table 8 documents estimates from this exercise. We document for a number of adult outcomes in the NCDS and BCS (we do not yet observe adult outcomes for MCS children) the coefficient on the female dummy and its associated standard error, along with the R squared when we estimate regressions with the female dummy only and our fullest specification. We note that for most of these outcomes adding the full set of the childhood variables explains a significant amount of the variation in our outcome. For example, when we add the childhood variables to regressions that seek to explain log of net earnings in adulthood the R squared increases by 8% for both the NCDS and BCS regressions. The increase in R squared for the regressions that consider the likelihood the child attends university increases by about 30% for both cohorts. When we consider the regressions that model cognitive ability in adulthood, R squared increases by 15% and 37% for the NCDS and BCS cohorts respectively. In addition, for many of our adult outcomes, the female coefficient does change substantively with the addition of the childhood variables. See for example, the regressions that relate to general health status, attitudes towards racial issues, smoking behaviour in adulthood and the probability of attending university. Overall, we are therefore confident that the variables do measure something meaningful about childhood, but that these variables are just not important determinants of occupational sorting nor are they correlated with gender.

Shifting occupational preferences:

It is interesting to consider whether it is changes in the preferences of males versus females that drives the conclusions found in this work. Table 9 documents the average and standard deviation of our outcomes for each cohort, alongside the overall change occurred between 1958-2000. Table 9 highlights that for the most recent cohort, it is males' increased propensity of pursuing high income and competitive work that is causing us to conclude that the sorting trends of the most recent cohort in these domains is less comparable to male peers as compared to the previous two cohorts. When we look at Table 9 we can see that over time females have sorted into occupations that were higher income and more competitive over time, but for the most recent cohort not to the same extent of males. Males have also more regularly pursued jobs with high people content over time, however for all three cohorts females more regularly choose jobs that are high in people content. In contrast, females have more regularly pursued jobs with high brawn content over time, however for all three cohort males more regularly choose jobs that are high in brawn. Across cohorts, males have remained in occupations with similar average weekly work hours (approximately 46 hours), whereas females have more regularly chosen occupations with higher average hours. British women in the recent cohorts have chosen occupations with *less* job flexibility, whilst men's jobs have remains highly inflexible over time. Overall, the comparison between the changes across cohorts suggests that the shifts in sorting patterns across cohorts are more marked for females as compared to males, with the exception of changes in aspirations for high income competitive work by males in the most recent cohort.

VI. CONCLUSIONS:

This study work considers the extent to which societal shifts have been responsible for an increased tendency for females to sort into traditional male roles over time, versus individual level childhood factors. In other words, we are interested in the extent that childhood factors which vary *within cohorts,* influence gendered sorting patterns as compared to societal changes which occur *across cohorts*. Overall we find that societal changes had a far greater influence on gendered sorting patterns in the UK over and above the childhood variables that we consider for children born in 1958, 1970 and 2000. We are aware that our childhood variables do not adequately capture every childhood factor that could potentially mediate gendered sorting. However, we would expect that most of the relevant omitted factors would be correlated with the variables that we do include so their signal should be picked up in our regressions. So, we are confident in our conclusion that societal shifts have done the heavy lifting with respect to influencing gendered sorting pattern. This holds true for average ability and high skilled groups.

Our analyses has also revealed several interesting stylised facts regarding gendered sorting over time. First, for all three cohorts we find strong evidence of sorting along gendered lines but this tendency has decreased substantively over time. That is, the gender gap has narrowed. Our analyses also reveals persistent gender gaps in the tendency to sort into occupations with the highest shares of males (80%) that have not changed over time. These jobs are often the golden pathway to C Suite positions and positions of power, and encapsulate science, technology and engineering posts as well as front office trading roles and politics. It may be tempting to conclude that the flatness in the gender gap in the tendency to sort into occupations with the highest share of males, particularly for children with the highest academic ability, reflects innate preferences. However, we note that over time both genders have significantly changed their tendency to sort into occupations that are high on people, brains and competitiveness content (see Table 9)[24]. Some of this will be determined by labour markets (i.e. it is unsurprising that both genders sort towards jobs that are high in people, given the growth in services and jobs that require interpersonal skills), but we also view these changes as highly suggestive that preferences are socialised, rather than representing innate differences by gender.

While all eyes are normally on the tendency for females to change their preferences, our analysis reveals that the changing preferences of males are contributing to stubborn gender gaps in traditionally male dominated positions. Noteworthy, is that males in the most recent cohort are aspiring to work in occupations with significantly higher levels of competitiveness and larger incomes as compared to previous cohorts and their current female peers. Therefore, even though the females born in 2000 have nearly closed the gender gap in terms of the hours and flexibility they are demanding, the type of work they are aspiring to sort into suggests that the gender pay gap may prevail unless the rewards given to different occupations change, or indeed preferences change for even younger cohorts. These conclusions hold if we focus only on children with the highest academic ability.

This study raises questions on what can really be achieved by individuals at a local level, by parents to move the needle on gendered sorting in the absence of a more general societal movement or a tipping phenomenon. For example, if a mother encourages their daughter to be an astrophysicist, but the society she is growing up in sends different messages the efforts may be lost on the average girl. It is possible that these messages may be dominated by, for example, STEM toys being mainly targeted to boys[25], the media covering females and males

[24] Females have also changed their tendency to sort into jobs with high brawn content
[25] Institution of Engineering and Technology (2016)

at the height of their careers differently[26], a child's schooling experiences varying by their gender and the images society has for its leaders still being male. Overall, we view our work as underlying the importance of the role of societal shifts, over and above childhood variables, in determining the sorting patterns we have seen over the last number of decades in the UK, and also those that remain today.

[26] See Fu et al (2016) for evidence of gender bias when covering sports heroes, Fowler and Lawless (2009) and Meeks (2012) for evidence of differential coverage by gender of politicians

REFERENCES

Akee, Randall, Emilia Simeonova, William Copeland, Adrian Angold, and Jane Costello. 2013. "Young adult obesity and household income: Effects of unconditional cash transfers." *American Economic Journal: Applied Economics* 5(2): 1-28.

Akerlof, George, and Rachel E. Kranton. 2000. "Economics and Identity." *The Quarterly Journal of Economics* 115(3): 715–753.

Altonji, Joseph G, and Rebecca M Blank. 1999. "Race and Gender in the Labor Market." Essay. In *Handbook of Labor Economics*, 3C:3143–3259. Amsterdam: Elsevier.

Angrist, Joshua, and Victor Lavy. 1999. "Using Maimonides Rule to Estimate the Effect of Class Size on Student Achievement." *The Quarterly Journal Of Economics* 114 (2): 533–75.

Antecol, Heather. 2010. "The Opt-Out Revolution: A Descriptive Analysis." IZA Discussion Paper 5089.

Arcidiacono, Peter, Joseph V Hotz, and Songman Kang. 2012. "Modeling college major choices using elicited measures of expectations and counterfactuals." *Journal of Econometrics* 166(1): 3-16.

Arcidiacono, Peter, Esteban M Aucejo, and Joseph V Hotz. 2016. "University differences in the graduation of minorities in STEM fields: Evidence from California." *American Economic Review* 106(3): 525-62.

Aznar, Ana, and Harriet R Tenenbaum. 2015. "Gender and age differences in parent–child emotion talk." *British Journal of Development Psychology* 33: 148–155.

Bayard, Kimberly, Judith Hellerstein, David Neumark, and Kenneth Troske. 2003. "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data." *Journal of Labor Economics* 21(4): 887-922.

Becker, Gary Stanley. 1957. *The Economics of Discrimination*. 2nd ed. Chicago: Univ. of Chicago Press.

Becker, Gary Stanley. 1985, "Human Capital, Effort, and the Sexual Division of Labor." *Journal of Labor Economics* 3(1): S33-S80.

Becker, Gary Stanley, and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal Of Labor Economics* 4(3): 1-39.

Belkin, Lisa. 2003. "The Opt-Out Revolution." *The New York Times Magazine* 43-86.

Bertrand, Marianne. 2018. "Coase Lecture – The Glass Ceiling." *Economica* 85(338): 205–231.

Black, Sandra, Paul J Devereux, and Kjell G. Salvanes. 2007. "From the cradle to the labor market? The effect of birth weight on adult outcomes." *The Quarterly Journal Of Economics* 122(1): 409-439.

Blau, David. 1999. “The effect of income on child development.” *Review Of Economics And Statistics* 81(2): 261-276.

Blau, Francine, and Lawrence M Kahn. 1997. “Swimming Upstream: trends in the Gender Wage Differential in the 1980s.” *Journal of Labor Economics* 15:1-42.

Blau, Francine, and Lawrence M Kahn. 2016. “The Gender Wage Gap: Extent, Trends, and Explanations.” NBER Working Paper No. 21913.

Booth, Alison, and Patrick Nolen. 2012. “Gender differences in risk behavior: does nurture matter?” *The Economic Journal* 122(558): F56-F78.

Cortés, Patricia, and Jessica Pan. 2016. “Prevalence of Long Hours and Skilled Women’s Occupational Choices.” IZA Discussion Paper 10225.

Cortés, Patricia, and Jessica Pan. 2017. “Occupation and Gender.” IZA Discussion Paper 10672.

Croson, Rachel, and Uri Gneezy. 2009. "Gender Differences in Preferences." *Journal of Economic Literature*, 47 (2): 448-74.

Dahl, Gordon, and Enrico Moretti. 2008. “The Demand for Sons.” *The Review of Economic Studies* 75(4): 1085–1120.

Datcher, Linda. 1982. “Effects of community and family background on achievement.” *The Review Of Economics And Statistics*: 32-41.

Daymont, Thomas. and Paul J Andrisani. 1984. “Job Preferences, College Major, and the Gender Gap in Earnings.” *Journal of Human Resources* 19:408-428.

Dee, Thomas S. 2007. “Teachers and the gender gaps in student achievement.” *Journal of Human Resources* 42(3): 528-554.

Dohmen, Thomas, and Armin Falk. 2011. "Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender." *American Economic Review*, 101 (2): 556-90.

Fowler Linda L, and Jennifer L Lawless. 2009. “Looking for Sex in All the Wrong Places: Press Coverage and the Electoral Fortunes of Gubernatorial Candidates.” *Perspectives on Politics* 7:519 -536.

Fu, Liye, Cristian Danescu-Niculescu-Mizil, and Lillian Lee. 2016. “Tie-breaker: Using language models to quantify gender bias in sports journalism.” *Proceedings of the IJCAI workshop on NLP meets journalism.*

Frankenburg WK, Dodds JB. 1967. The Denver developmental screening test. *J of Pediatrics.* Aug;71(2):181–191

Gneezy Uro and Niederle Muriel. 2003. Performance in Competitive Environments: Gender Differences. *The Quarterly Journal of Economics.* 118 (3): 1049-1074.

Gneezy, Uri, and Aldo Rustichini. 2004. "Gender and Competition at a Young Age." *American Economic Review*,94 (2): 377-381.

Goldin, Claudia. 2006. "The Quiet Revolution That Transformed Women's Employment, Education, and Family."*American Economic Review* 96(2):1-21.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104(4):1091-1119.

Gorsuch, Richard L. 1983. *Factor Analysis*. 2nd ed. Hillsdale: Lawrence Erlbaum Associates.

Grissmer, David, Kevin J. Grimm, Sophie M. Aiyer, William M. Murrah, and Joel S. Steele. 2010. "Fine motor skills and early comprehension of the world: two new school readiness indicators." *Developmental psychology* 46(5):1008.

Grove, W, Hussey, A and Jetter, M, (2011), The Gender Pay Gap Beyond Human Capital: Heterogeneity in Noncognitive Skills and in Labor Market Tastes, Journal of Human Resources, 46 (4).

Heckman, James, Rodrigo Pinto, and Peter Savelyev. 2013. "Understanding the Mechanisms through Which an Influential Early Childhood Program Boosted Adult Outcomes." *American Economic Review* 103(6): 2052-86.

Hyde, Jane. 2014. "Gender Similarities and Differences" *Annual Review of Psychology* 65(3): 373-398.

Johnson, Jon, Mark Atkinson, and Rachel Rosenberg. 2015. "Millennium Cohort Study: psychological, developmental and health inventories." *Centre for Longitudinal Studies, London*.

Katz, Lawrence, and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *The Quarterly Journal of Economics* 107(1):35-78.

Kohler, Hans-Peter, Jere R Behrman, and Axel Skytthe. 2005. "Partner + children = happiness? An assessment of the effect of fertility and partnerships on subjective well-being in Danish twins." *Population and Development Review* 31(3): 407–445.

Lekfuangfu. Warn and Odermatt Reto (2018) Raising aspirations to raise intergenerational mobility? The role of aspirations of children, parents and teachers, mimeo.

Lordan, Grace and Jorn-Steffen Pischke 2016. Does Rosie like riveting? Male and female occupational choices. *NBER working paper,* 22495. National Bureau of Economic Research, Cambridge, USA.

Lundberg, Shelly. 2005. "The Division of Labor by New Parents: Does Child Gender Matter?" IZA Discussion Paper 1787.

Lundberg, Shelly, Sabrina Pabilonia. 2007. "Time Allocation of Parents and

Investments in Sons and Daughters." Working paper. Department of Economics, University of Washington.

Luo, Ye, and Linda J Waite. 2005. "The impact of childhood and adult SES on physical, mental, and cognitive well-being in later life." *The Journals Of Gerontology Series B: Psychological Sciences And Social Sciences* 60(2): 93-101.

Meeks, Lindsey. 2012. "Is She 'Man Enough'? Women Candidates, Executive Political Offices, and News Coverage." *Journal of Communication* 62(17): 5-93.

Mondschein, Emily, Karen E Adolph, Catherine S Tamis-LeMonda. 2000. "Gender Bias in Mothers' Expectations about Infant Crawling." *J Exp Child Psychol* 77:304–16.

Nielderle M and Vesterlund L . 2008. Gender Differences in Competition. *Negotiation Journal.*

Ost, Ben. 2010. "The Role of Peers and Grades in Determining Major Persistence in the Sciences." *Economics of Education Review* 29(6): 923-934.

Parsons, Samantha. 2014. "Childhood cognition in the 1970 British cohort study." *CLS Data Note*.

Polachek, Solomon. 1981. "Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure." *The Review of Economics and Statistics* 63(1): 60-69.

Shepherd, Peter. 2012. "Measures of ability at ages 7 to 16." *National Child Development Study User Guide.*

Stone, Pamela. 2007. *Opting Out? Why Women Really Quit Careers and Head Home.* 1st ed. University of California press.

Su, Rong, James Rounds, and Patrick Ian Armstrong (2009). "Men and Things, Women and People: A Meta-Analysis of Sex Differences in Interests." *Psychological Bulletin*, 135(6): 859-884.

Thompson, Bruce. 2004. *Exploratory and confirmatory factor analysis: Understanding concepts and applications.* Washington, DC, US: American Psychological Association.

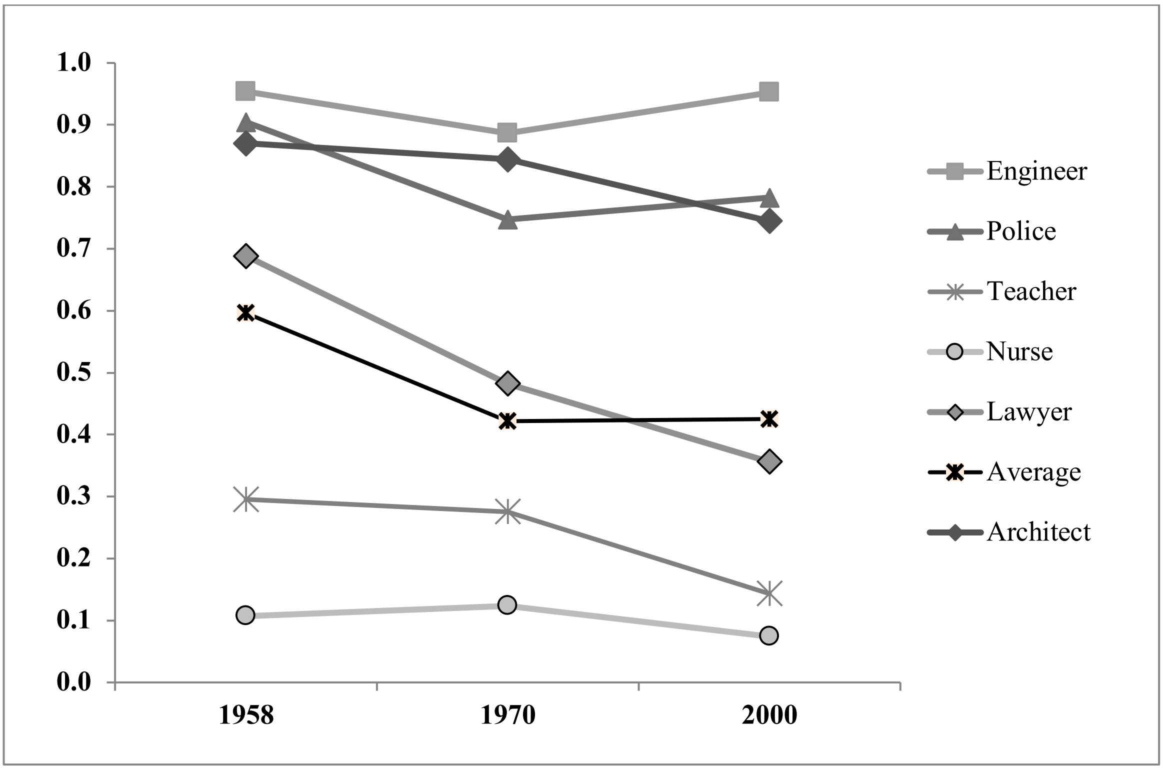
Van Den Berg, Gerard, Maarten Lindeboom, and France Portrait. 2006. "Economic conditions early in life and individual mortality." *The American Economic Review*: 290-302.

Yeung, Jean, John F Sandberg, Pamela E Davis-Kean, and Sandra L Hofferth. 2004. "Children's Time with Fathers in Intact Families." *Journal of Marriage and Family* 63: 136–54.

Zafar, Basit. 2011. "How do college students form expectations?" *Journal of Labor Economics* 29(2): 301-348.

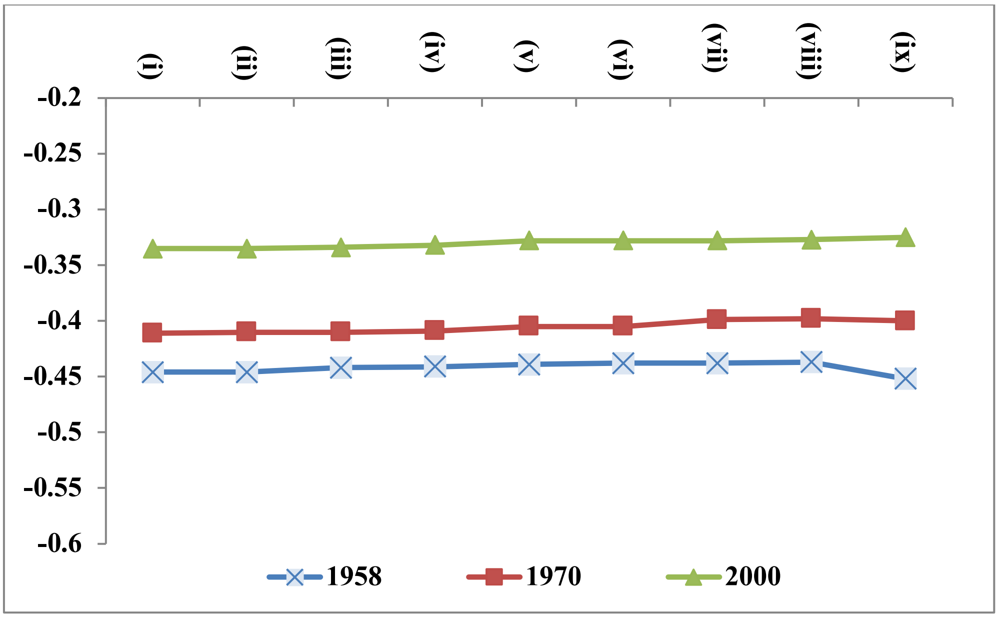
Zafar, Basit. 2013. "College major choice and the gender gap." *Journal of Human Resources* 48(3): 545-595.

Figure 1: Share of men in an occupation in the NCDS, BCS and MCS



Notes: For the NCDS (1958) and the BCS (1970), share of men in an occupation is calculated from the occupation cohort member held at age 33 and 34 years old, respectively. For the MCS (2000), the occupation is the occupation cohort members (at age 11) aspired to be when they turn 30 years old.

Figure 2: Coefficients of "female" on "Share of men in the occupation" (Full sample)



Notes: Full sample. i) is the model with only female dummy variable, (ii) is the preceding model with a set of baseline variables, (iii) added cognitive skills, (iv) added motor skills, (v) added non-cognitive skills, (vi) added health conditions, (vii) added parental investments, (viii) added parent's aspirations for the child, and (ix) added external influences.

Table 1: Estimates for Share of Males regressions

	NCDS (1958) 1991			BCS (1970) 2004			MCS (2000) 2012		
	Coefficient	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**
Panel A: Share of men in an occupation									
(i) +Female	-0.446	[0.005]	0.458	-0.411	[0.005]	0.412	-0.335	[0.005]	0.306
(ii) +Baseline	-0.446	[0.005]	0.463	-0.41	[0.005]	0.412	-0.335	[0.005]	0.313
(iii) +Cognitive Skills	-0.442	[0.005]	0.469	-0.41	[0.005]	0.413	-0.334	[0.005]	0.314
(iv) +Motor Skills	-0.441	[0.005]	0.47	-0.409	[0.005]	0.414	-0.332	[0.005]	0.314
(v) + Non Cognitive Skills	-0.439	[0.005]	0.47	-0.405	[0.005]	0.416	-0.328	[0.005]	0.316
(vi) +Health attainment	-0.438	[0.005]	0.47	-0.405	[0.005]	0.418	-0.328	[0.005]	0.316
(vii) + Parent's investments	-0.438	[0.005]	0.47	-0.399	[0.006]	0.42	-0.328	[0.005]	0.318
(viii) + Parent's aspirations	-0.437	[0.006]	0.471	-0.398	[0.006]	0.42	-0.327	[0.005]	0.319
(ix) + External influences	-0.452	[0.006]	0.482	-0.4	[0.006]	0.42	-0.325	[0.005]	0.319
Panel B: Share of men is 80% or higher in an occupation									
(i) +Female	-0.486	[0.008]	0.281	-0.486	[0.008]	0.28	-0.459	[0.008]	0.256
(ii) +Baseline	-0.487	[0.008]	0.301	-0.484	[0.008]	0.291	-0.459	[0.008]	0.26
(iii) +Cognitive Skills	-0.488	[0.008]	0.324	-0.481	[0.008]	0.3	-0.455	[0.008]	0.263
(iv) +Motor Skills	-0.486	[0.008]	0.324	-0.48	[0.008]	0.301	-0.452	[0.008]	0.264
(v) + Non Cognitive Skills	-0.482	[0.009]	0.325	-0.473	[0.008]	0.303	-0.447	[0.008]	0.268
(vi) +Health attainment	-0.481	[0.009]	0.325	-0.473	[0.008]	0.305	-0.448	[0.008]	0.268
(vii) + Parent's investments	-0.48	[0.009]	0.326	-0.462	[0.009]	0.306	-0.447	[0.009]	0.269
(viii) + Parent's aspirations	-0.479	[0.009]	0.328	-0.46	[0.009]	0.308	-0.443	[0.009]	0.272
(ix) + External influences	-0.506	[0.009]	0.342	-0.464	[0.009]	0.31	-0.438	[0.009]	0.275
N of Panels A and B		9722			8973			11200	
Panel C: Probability of Being Dis-Employed									
(i) +Female	0.211	[0.008]	0.082	0.09	[0.005]	0.032	-0.066	[0.008]	0.006
(ii) +Baseline	0.211	[0.008]	0.085	0.09	[0.005]	0.032	-0.066	[0.008]	0.014
(iii) +Cognitive Skills	0.204	[0.008]	0.092	0.09	[0.005]	0.032	-0.066	[0.008]	0.019
(iv) +Motor Skills	0.208	[0.008]	0.091	0.091	[0.005]	0.031	-0.065	[0.008]	0.019
(v) + Non Cognitive Skills	0.211	[0.008]	0.093	0.091	[0.005]	0.031	-0.061	[0.008]	0.019
(vi) +Health attainment	0.212	[0.008]	0.096	0.091	[0.006]	0.032	-0.062	[0.008]	0.019
(vii) + Parent's investments	0.211	[0.008]	0.097	0.092	[0.006]	0.032	-0.063	[0.009]	0.018
(viii) + Parent's aspirations	0.212	[0.008]	0.095	0.092	[0.006]	0.032	-0.062	[0.009]	0.019
(ix) + External influences	0.216	[0.009]	0.097	0.094	[0.006]	0.032	-0.062	[0.009]	0.019
N of Panel C		13610			11695			12271	

Notes: The tables show the estimated coefficient and the standard error associated to the female dummy in each specification. (I) is the regression with only female dummy. (II) is (I) with the family variables. (III) is (II) with childhood cognitive skills. (IV) is (III) with childhood motor skills. (V) is (IV) with childhood non-cognitive skills. (VI) is (V) with childhood physical and psychological health conditions. (VII) is (VI) with parental investment variables. (VIII) is (VII) with variables indicating parental aspirations for children. Finally, (IX) is (VIII) with external influences from school peer and class teacher around age 16.

Table 2: Estimates for Income, Average Hours, Flexibility and Probability of Being Employed regressions

	NCDS (1958) 1991			BCS (1970) 2004			MCS (2000) 2012		
	Coefficient	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**
Panel A: Log of average gross income									
(i) +Female	-0.238	[0.007]	0.1	-0.145	[0.008]	0.033	-0.314	[0.008]	0.126
(ii) +Baseline	-0.237	[0.007]	0.212	-0.149	[0.008]	0.158	-0.313	[0.008]	0.142
(iii) +Cognitive Skills	-0.23	[0.007]	0.327	-0.158	[0.007]	0.231	-0.311	[0.008]	0.148
(iv) +Motor Skills	-0.234	[0.007]	0.329	-0.163	[0.008]	0.238	-0.31	[0.008]	0.148
(v) + Non Cognitive Skills	-0.238	[0.007]	0.33	-0.167	[0.008]	0.24	-0.309	[0.008]	0.154
(vi) +Health attainment	-0.238	[0.007]	0.331	-0.168	[0.008]	0.241	-0.309	[0.008]	0.154
(vii) + Parent's investments	-0.237	[0.007]	0.332	-0.175	[0.008]	0.244	-0.308	[0.009]	0.154
(viii) + Parent's aspirations	-0.238	[0.007]	0.336	-0.174	[0.008]	0.259	-0.313	[0.009]	0.158
(ix) + External influences	-0.244	[0.008]	0.342	-0.173	[0.008]	0.261	-0.312	[0.009]	0.158
Panel B: Average hours									
(i) +Female	-8.213	[0.116]	0.343	-6.917	[0.123]	0.265	-2.71	[0.088]	0.083
(ii) +Baseline	-8.194	[0.116]	0.348	-6.926	[0.122]	0.277	-2.703	[0.087]	0.111
(iii) +Cognitive Skills	-8.125	[0.125]	0.352	-6.954	[0.123]	0.281	-2.71	[0.089]	0.112
(iv) +Motor Skills	-8.127	[0.126]	0.354	-6.969	[0.124]	0.284	-2.695	[0.090]	0.113
(v) + Non Cognitive Skills	-8.107	[0.128]	0.354	-6.881	[0.125]	0.286	-2.628	[0.092]	0.114
(vi) +Health attainment	-8.101	[0.128]	0.354	-6.898	[0.126]	0.287	-2.631	[0.092]	0.113
(vii) + Parent's investments	-8.082	[0.130]	0.354	-6.823	[0.131]	0.288	-2.633	[0.094]	0.113
(viii) + Parent's aspirations	-8.077	[0.130]	0.355	-6.794	[0.133]	0.289	-2.621	[0.094]	0.115
(ix) + External influences	-8.447	[0.143]	0.363	-6.844	[0.135]	0.289	-2.584	[0.095]	0.116
Panel C: Flexibility of an occupation									
(i) +Female	0.184	[0.005]	0.127	0.164	[0.005]	0.101	0.063	[0.005]	0.014
(ii) +Baseline	0.183	[0.005]	0.129	0.164	[0.005]	0.106	0.063	[0.005]	0.016
(iii) +Cognitive Skills	0.174	[0.005]	0.13	0.165	[0.005]	0.106	0.062	[0.005]	0.016
(iv) +Motor Skills	0.175	[0.005]	0.131	0.165	[0.005]	0.107	0.062	[0.005]	0.016
(v) + Non Cognitive Skills	0.174	[0.005]	0.131	0.164	[0.005]	0.107	0.059	[0.006]	0.017
(vi) +Health attainment	0.174	[0.005]	0.13	0.165	[0.005]	0.107	0.059	[0.006]	0.016
(vii) + Parent's investments	0.175	[0.005]	0.13	0.16	[0.005]	0.108	0.057	[0.006]	0.017
(viii) + Parent's aspirations	0.174	[0.005]	0.131	0.161	[0.006]	0.11	0.059	[0.006]	0.018
(ix) + External influences	0.181	[0.006]	0.132	0.161	[0.006]	0.11	0.058	[0.006]	0.018
Observations		9722			8973			11200	

Notes: See notes to Table 1. For the MCS probability of being employed equals 1 if the child expects to have their own children, and also does expects to have a good job by age 30, and 0 otherwise.

Table 3: Estimates for People, Brains, Brawn and competitiveness regressions

	NCDS (1958) 1991			BCS (1970) 2004			MCS (2000) 2012		
	Coefficient	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**
Panel A: People									
(i) +Female	0.421	[0.019]	0.05	0.439	[0.019]	0.057	0.272	[0.019]	0.02
(ii) +Baseline	0.42	[0.019]	0.054	0.439	[0.019]	0.06	0.271	[0.019]	0.026
(iii) +Cognitive Skills	0.418	[0.020]	0.056	0.442	[0.019]	0.062	0.277	[0.019]	0.035
(iv) +Motor Skills	0.416	[0.020]	0.057	0.442	[0.019]	0.063	0.275	[0.019]	0.035
(v) + Non Cognitive Skills	0.415	[0.020]	0.057	0.452	[0.020]	0.064	0.277	[0.020]	0.038
(vi) +Health attainment	0.413	[0.020]	0.056	0.452	[0.020]	0.065	0.276	[0.020]	0.038
(vii) + Parent's investments	0.41	[0.021]	0.058	0.461	[0.021]	0.065	0.277	[0.020]	0.04
(viii) + Parent's aspirations	0.411	[0.021]	0.059	0.462	[0.021]	0.065	0.274	[0.020]	0.04
(ix) + External influences	0.424	[0.023]	0.061	0.464	[0.021]	0.065	0.28	[0.020]	0.04
Panel B:Brains									
(i) +Female	-0.091	[0.019]	0.002	0.06	[0.021]	0.001	0.532	[0.020]	0.066
(ii) +Baseline	-0.089	[0.018]	0.091	0.05	[0.020]	0.097	0.532	[0.020]	0.072
(iii) +Cognitive Skills	-0.058	[0.019]	0.189	0.032	[0.020]	0.147	0.532	[0.020]	0.079
(iv) +Motor Skills	-0.066	[0.019]	0.19	0.024	[0.020]	0.15	0.528	[0.021]	0.079
(v) + Non Cognitive Skills	-0.079	[0.019]	0.192	0.012	[0.020]	0.151	0.522	[0.021]	0.081
(vi) +Health attainment	-0.08	[0.019]	0.192	0.008	[0.021]	0.152	0.525	[0.021]	0.081
(vii) + Parent's investments	-0.08	[0.019]	0.193	-0.006	[0.022]	0.153	0.53	[0.021]	0.081
(viii) + Parent's aspirations	-0.083	[0.019]	0.198	-0.005	[0.022]	0.163	0.516	[0.021]	0.09
(ix) + External influences	-0.056	[0.021]	0.204	-0.001	[0.022]	0.165	0.509	[0.022]	0.09
Panel C: Brawn									
(i) +Female	-0.81	[0.020]	0.149	-0.823	[0.019]	0.167	-0.523	[0.015]	0.104
(ii) +Baseline	-0.812	[0.019]	0.194	-0.816	[0.019]	0.209	-0.523	[0.015]	0.126
(iii) +Cognitive Skills	-0.79	[0.020]	0.258	-0.803	[0.019]	0.238	-0.518	[0.016]	0.138
(iv) +Motor Skills	-0.783	[0.020]	0.259	-0.797	[0.019]	0.24	-0.515	[0.016]	0.139
(v) + Non Cognitive Skills	-0.767	[0.020]	0.26	-0.774	[0.019]	0.244	-0.502	[0.016]	0.143
(vi) +Health attainment	-0.769	[0.020]	0.261	-0.772	[0.019]	0.245	-0.503	[0.016]	0.143
(vii) + Parent's investments	-0.761	[0.020]	0.265	-0.742	[0.020]	0.247	-0.502	[0.016]	0.143
(viii) + Parent's aspirations	-0.755	[0.020]	0.267	-0.739	[0.020]	0.251	-0.491	[0.016]	0.151
(ix) + External influences	-0.791	[0.022]	0.277	-0.748	[0.020]	0.254	-0.48	[0.016]	0.153
Panel D:Competitiveness									
(i) +Female	-0.407	[0.020]	0.041	-0.383	[0.022]	0.033	-0.841	[0.028]	0.084
(ii) +Baseline	-0.406	[0.020]	0.051	-0.386	[0.022]	0.057	-0.842	[0.028]	0.094
(iii) +Cognitive Skills	-0.4	[0.021]	0.058	-0.393	[0.022]	0.063	-0.844	[0.028]	0.094
(iv) +Motor Skills	-0.405	[0.021]	0.058	-0.402	[0.022]	0.066	-0.84	[0.028]	0.095

(v) + Non Cognitive Skills	-0.407	[0.022]	0.06	-0.396	[0.022]	0.066	-0.83	[0.029]	0.099
(vi) +Health attainment	-0.406	[0.022]	0.06	-0.4	[0.023]	0.066	-0.835	[0.029]	0.099
(vii) + Parent's investments	-0.408	[0.022]	0.059	-0.397	[0.024]	0.065	-0.843	[0.029]	0.101
(viii) + Parent's aspirations	-0.41	[0.022]	0.059	-0.392	[0.024]	0.067	-0.836	[0.029]	0.102
(ix) + External influences	-0.388	[0.024]	0.06	-0.395	[0.024]	0.067	-0.84	[0.030]	0.102
Observations		9722			8973			11200	

Notes: See notes to Table 1.

Table 4 Estimates for Share of Males and probability of dis-employment regressions for children with the highest cognitive ability

	NCDS (1958) 1991			BCS (1970) 2004			MCS (2000) 2012		
	Coefficient	S.E.	Adjusted R2	Coefficient	S.E.	Adjusted R2	Coefficient	S.E.	Adjusted R2
Panel A: Share of men in an occupation									
(i) +Female	-0.318	[0.009]	0.297	-0.317	[0.009]	0.3	-0.27	[0.008]	0.225
(ii) +Baseline	-0.318	[0.009]	0.297	-0.317	[0.009]	0.299	-0.271	[0.009]	0.228
(iii) +Cognitive Skills	-0.304	[0.010]	0.301	-0.315	[0.009]	0.3	-0.271	[0.009]	0.229
(iv) +Motor Skills	-0.305	[0.010]	0.302	-0.315	[0.009]	0.301	-0.27	[0.009]	0.228
(v) + Non Cognitive Skills	-0.302	[0.010]	0.302	-0.311	[0.009]	0.304	-0.265	[0.009]	0.229
(vi) +Health attainment	-0.3	[0.010]	0.302	-0.311	[0.009]	0.306	-0.265	[0.009]	0.229
(vii) + Parent's investments	-0.297	[0.010]	0.302	-0.307	[0.010]	0.305	-0.262	[0.009]	0.228
(viii) + Parent's aspirations	-0.297	[0.010]	0.306	-0.306	[0.010]	0.305	-0.26	[0.009]	0.232
(ix) + External influences	-0.327	[0.013]	0.316	-0.307	[0.010]	0.306	-0.258	[0.009]	0.234
Panel B: Share of men is 80% or higher in an occupation									
(i) +Female	-0.279	[0.013]	0.124	-0.359	[0.014]	0.181	-0.380	[0.014]	0.184
(ii) +Baseline	-0.277	[0.013]	0.134	-0.356	[0.014]	0.191	-0.381	[0.014]	0.188
(iii) +Cognitive Skills	-0.265	[0.015]	0.148	-0.357	[0.014]	0.199	-0.377	[0.014]	0.191
(iv) +Motor Skills	-0.265	[0.015]	0.147	-0.357	[0.014]	0.198	-0.376	[0.014]	0.191
(v) + Non Cognitive Skills	-0.262	[0.015]	0.147	-0.349	[0.015]	0.2	-0.374	[0.015]	0.192
(vi) +Health attainment	-0.26	[0.015]	0.146	-0.348	[0.015]	0.2	-0.374	[0.015]	0.191
(vii) + Parent's investments	-0.256	[0.015]	0.146	-0.338	[0.016]	0.202	-0.369	[0.015]	0.191
(viii) + Parent's aspirations	-0.256	[0.015]	0.152	-0.336	[0.016]	0.207	-0.366	[0.015]	0.195
(ix) + External influences	-0.281	[0.019]	0.167	-0.337	[0.016]	0.209	-0.361	[0.015]	0.199
N of Panels A and B:		2952			3030			3877	
Panel C: Probability of Being Dis-Employed									
(i) +Female	0.209	[0.012]	0.098	0.098	[0.009]	0.037	-0.075	[0.015]	0.007
(ii) +Baseline	0.208	[0.013]	0.096	0.098	[0.009]	0.04	-0.074	[0.015]	0.014
(iii) +Cognitive Skills	0.199	[0.014]	0.095	0.099	[0.009]	0.039	-0.081	[0.015]	0.018
(iv) +Motor Skills	0.2	[0.014]	0.094	0.099	[0.009]	0.038	-0.081	[0.015]	0.019
(v) + Non Cognitive Skills	0.203	[0.014]	0.096	0.099	[0.010]	0.037	-0.076	[0.015]	0.018
(vi) +Health attainment	0.204	[0.014]	0.096	0.099	[0.010]	0.035	-0.078	[0.015]	0.019
(vii) + Parent's investments	0.201	[0.014]	0.096	0.102	[0.010]	0.037	-0.075	[0.016]	0.021
(viii) + Parent's aspirations	0.202	[0.014]	0.094	0.101	[0.010]	0.037	-0.074	[0.016]	0.021
(ix) + External influences	0.216	[0.017]	0.094	0.104	[0.011]	0.032	-0.072	[0.016]	0.022
N of Panel C		N = 4008		N = 3,847				N= 3877	

Notes: See notes to Table 1 and also Appendix A for full details of how the children with highest cognitive ability are determined.

Table 5 Estimates for log of average income, average hours and flexibility regressions for children with the highest cognitive ability

	Coefficient	S.E.	Adjusted R2	Coefficient	S.E.	Adjusted R2	Coefficient	S.E.	Adjusted R2
Panel A: Log of average gross income									
(i) +Female	-0.207	[0.013]	0.074	-0.165	[0.014]	0.042	-0.238	[0.013]	0.093
(ii) +Baseline	-0.213	[0.013]	0.125	-0.163	[0.014]	0.138	-0.239	[0.013]	0.105
(iii) +Cognitive Skills	-0.203	[0.014]	0.171	-0.155	[0.014]	0.184	-0.236	[0.013]	0.109
(iv) +Motor Skills	-0.207	[0.014]	0.172	-0.16	[0.014]	0.189	-0.237	[0.013]	0.109
(v) + Non Cognitive Skills	-0.212	[0.014]	0.172	-0.169	[0.014]	0.193	-0.235	[0.013]	0.116
(vi) +Health attainment	-0.211	[0.014]	0.173	-0.17	[0.014]	0.195	-0.236	[0.013]	0.116
(vii) + Parent’s investments	-0.214	[0.015]	0.176	-0.178	[0.014]	0.198	-0.233	[0.014]	0.116
(viii) + Parent’s aspirations	-0.214	[0.015]	0.179	-0.179	[0.014]	0.22	-0.236	[0.014]	0.121
(ix) + External influences	-0.229	[0.018]	0.183	-0.179	[0.015]	0.22	-0.235	[0.014]	0.122
Panel B: Average hours									
(i) +Female	-5.202	[0.198]	0.194	-4.987	[0.190]	0.182	-1.665	[0.147]	0.035
(ii) +Baseline	-5.233	[0.198]	0.204	-4.973	[0.191]	0.197	-1.701	[0.146]	0.058
(iii) +Cognitive Skills	-4.983	[0.220]	0.213	-4.872	[0.192]	0.201	-1.732	[0.151]	0.057
(iv) +Motor Skills	-5.017	[0.219]	0.212	-4.912	[0.195]	0.206	-1.72	[0.152]	0.057
(v) + Non Cognitive Skills	-4.973	[0.221]	0.212	-4.878	[0.197]	0.207	-1.66	[0.156]	0.057
(vi) +Health attainment	-4.917	[0.221]	0.215	-4.874	[0.198]	0.206	-1.651	[0.157]	0.056
(vii) + Parent’s investments	-4.877	[0.224]	0.215	-4.84	[0.207]	0.206	-1.605	[0.161]	0.055
(viii) + Parent’s aspirations	-4.875	[0.223]	0.214	-4.816	[0.208]	0.206	-1.575	[0.160]	0.062
(ix) + External influences	-5.349	[0.271]	0.218	-4.873	[0.216]	0.208	-1.545	[0.162]	0.062
Panel C: Flexibility of an occupation									
(i) +Female	0.17	[0.009]	0.099	0.145	[0.009]	0.079	0.055	[0.009]	0.01
(ii) +Baseline	0.169	[0.009]	0.1	0.141	[0.009]	0.089	0.055	[0.009]	0.009
(iii) +Cognitive Skills	0.151	[0.010]	0.108	0.139	[0.009]	0.089	0.054	[0.009]	0.008
(iv) +Motor Skills	0.154	[0.010]	0.107	0.139	[0.009]	0.089	0.053	[0.009]	0.008
(v) + Non Cognitive Skills	0.153	[0.011]	0.107	0.136	[0.009]	0.09	0.051	[0.010]	0.008
(vi) +Health attainment	0.151	[0.011]	0.107	0.137	[0.009]	0.089	0.051	[0.010]	0.009
(vii) + Parent’s investments	0.151	[0.011]	0.105	0.138	[0.010]	0.086	0.05	[0.010]	0.011
(viii) + Parent’s aspirations	0.151	[0.011]	0.107	0.139	[0.010]	0.09	0.051	[0.010]	0.013
(ix) + External influences	0.176	[0.013]	0.11	0.142	[0.010]	0.09	0.051	[0.010]	0.011
N		2952			3030			3877	

Notes: See notes to Table 1 and also Appendix A for full details of how the children with highest cognitive ability are determined.

Table 6 Estimates for People, Brains, Brawn and competitiveness regressions for children with the highest cognitive ability

	NCDS (1958) 1991			BCS (1970) 2004			MCS (2000) 2012		
	Coefficient	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**
Panel A: People									
(i) +Female	0.28	[0.034]	0.022	0.383	[0.033]	0.042	0.309	[0.034]	0.022
(ii) +Baseline	0.277	[0.034]	0.028	0.376	[0.033]	0.044	0.308	[0.034]	0.028
(iii) +Cognitive Skills	0.272	[0.037]	0.032	0.376	[0.034]	0.047	0.315	[0.035]	0.043
(iv) +Motor Skills	0.259	[0.037]	0.03	0.373	[0.034]	0.048	0.308	[0.035]	0.044
(v) + Non Cognitive Skills	0.257	[0.038]	0.031	0.375	[0.034]	0.05	0.302	[0.036]	0.045
(vi) +Health attainment	0.268	[0.038]	0.034	0.376	[0.035]	0.054	0.297	[0.036]	0.044
(vii) + Parent's investments	0.264	[0.039]	0.037	0.381	[0.036]	0.052	0.296	[0.037]	0.047
(viii) + Parent's aspirations	0.264	[0.039]	0.045	0.38	[0.036]	0.053	0.29	[0.037]	0.048
(ix) + External influences	0.259	[0.046]	0.054	0.385	[0.037]	0.054	0.298	[0.037]	0.048
Panel B: Brains									
(i) +Female	-0.32	[0.035]	0.027	-0.163	[0.037]	0.006	0.335	[0.036]	0.024
(ii) +Baseline	-0.33	[0.035]	0.057	-0.154	[0.036]	0.078	0.33	[0.036]	0.027
(iii) +Cognitive Skills	-0.283	[0.038]	0.095	-0.13	[0.036]	0.108	0.336	[0.037]	0.034
(iv) +Motor Skills	-0.286	[0.038]	0.098	-0.139	[0.036]	0.11	0.335	[0.037]	0.034
(v) + Non Cognitive Skills	-0.291	[0.038]	0.098	-0.154	[0.037]	0.11	0.325	[0.038]	0.035
(vi) +Health attainment	-0.295	[0.039]	0.095	-0.16	[0.037]	0.111	0.325	[0.038]	0.037
(vii) + Parent's investments	-0.293	[0.039]	0.095	-0.175	[0.039]	0.114	0.323	[0.039]	0.037
(viii) + Parent's aspirations	-0.29	[0.039]	0.101	-0.179	[0.039]	0.131	0.311	[0.039]	0.047
(ix) + External influences	-0.295	[0.048]	0.104	-0.181	[0.040]	0.129	0.303	[0.039]	0.049
Panel C: Brawn									
(i) +Female	-0.488	[0.033]	0.067	-0.526	[0.032]	0.084	-0.343	[0.028]	0.043
(ii) +Baseline	-0.481	[0.033]	0.08	-0.525	[0.032]	0.108	-0.347	[0.028]	0.056
(iii) +Cognitive Skills	-0.459	[0.036]	0.101	-0.529	[0.032]	0.123	-0.346	[0.028]	0.063
(iv) +Motor Skills	-0.464	[0.037]	0.101	-0.531	[0.032]	0.122	-0.346	[0.028]	0.064
(v) + Non Cognitive Skills	-0.449	[0.037]	0.103	-0.504	[0.032]	0.128	-0.343	[0.029]	0.066
(vi) +Health attainment	-0.44	[0.037]	0.102	-0.498	[0.033]	0.13	-0.347	[0.029]	0.066
(vii) + Parent's investments	-0.417	[0.038]	0.108	-0.473	[0.034]	0.13	-0.347	[0.029]	0.066
(viii) + Parent's aspirations	-0.418	[0.038]	0.111	-0.468	[0.035]	0.139	-0.338	[0.029]	0.076
(ix) + External influences	-0.477	[0.046]	0.118	-0.476	[0.036]	0.143	-0.326	[0.029]	0.081
Panel D: Competitiveness									
(i) +Female	-0.508	[0.038]	0.056	-0.427	[0.039]	0.037	-0.702	[0.046]	0.062
(ii) +Baseline	-0.521	[0.038]	0.061	-0.431	[0.039]	0.057	-0.7	[0.046]	0.07
(iii) +Cognitive Skills	-0.472	[0.042]	0.065	-0.419	[0.040]	0.059	-0.71	[0.047]	0.072
(iv) +Motor Skills	-0.473	[0.042]	0.064	-0.432	[0.040]	0.063	-0.712	[0.047]	0.072

(v) + Non Cognitive Skills	-0.47	[0.043]	0.067	-0.437	[0.041]	0.063	-0.687	[0.048]	0.074
(vi) +Health attainment	-0.47	[0.043]	0.069	-0.438	[0.041]	0.064	-0.693	[0.048]	0.075
(vii) + Parent's investments	-0.486	[0.044]	0.068	-0.437	[0.043]	0.062	-0.687	[0.049]	0.077
(viii) + Parent's aspirations	-0.487	[0.044]	0.067	-0.437	[0.043]	0.061	-0.678	[0.049]	0.079
(ix) + External influences	-0.458	[0.053]	0.071	-0.454	[0.045]	0.062	-0.679	[0.049]	0.08
N		2952			3030			3877	

Notes: See notes to Table 1 and also Appendix A for full details of how the children with highest cognitive ability are determined.

Table 7 Lasso Regression Results

	Share of Males	Share of Males +80%	Probability of Being Dis-employed	Log Weekly Income	Hours	Flexibility	People	Brains	Brawn	Competitiveness
				NCDS (1958) All Children						
Female	-0.448	-0.485	0.207	-0.235	-8.346	0.179	0.408	-0.060	-0.797	-0.394
R squared	0.485	0.339	0.100	0.341	0.369	0.135	0.069	0.201	0.279	0.067
N	9722	9722	13610	9722	9722	9722	9722	9722	9722	9722
				BCS (1970) All Children						
Female	-0.303	-0.329	0.077	-0.167	-6.761	0.158	0.425	0.000	-0.740	-0.371
R squared	0.313	0.215	0.037	0.264	0.292	0.114	0.065	0.170	0.258	0.071
N	8973	8973	11695	8973	8973	8973	8973	8973	8973	8973
				MCS (2000) All Children						
Female	-0.325	-0.442	-0.048	-0.307	-2.527	0.055	0.259	0.484	-0.481	-0.808
R squared	0.321	0.276	0.020	0.160	0.116	0.020	0.044	0.090	0.154	0.104
N	11200	11200	11200	11200	11200	11200	11200	11200	11200	11200
				NCDS (1958) Children in Top 25% Cognitive Distribution						
Female	-0.317	-0.248	0.193	-0.218	-5.034	0.148	0.200	-0.223	-0.445	-0.405
R squared	0.330	0.170	0.104	0.204	0.223	0.104	0.070	0.113	0.131	0.065
N	2952	2952	4008	2952	2952	2952	2952	2952	2952	2952
				BCS (1970) Children in Top 25% Cognitive Distribution						
Female	-0.300	-0.331	0.083	-0.157	-4.721	0.131	0.339	-0.116	-0.455	-0.386
R squared	0.307	0.218	0.041	0.231	0.206	0.100	0.059	0.138	0.156	0.071
N	3030	3030	3,847	3030	3030	3030	3030	3030	3030	3030
				MCS (2000) Children in Top 25% Cognitive Distribution						
Female	-0.256	-0.355	-0.055	-0.227	-1.431	0.029	0.273	0.281	-0.297	-0.627
R squared	0.240	0.198	0.031	0.130	0.069	0.008	0.063	0.061	0.086	0.086
N	3877	3877	3877	3877	3877	3877	3877	3877	3877	3877

Table 8 Estimates for other adult outcome regressions

	NCDS (1958)			BCS (1970)		
	Coefficient	**S.E.**	**Adjusted R2**	**Coefficient**	**S.E.**	**Adjusted R2**
Panel A: Log of net earnings	Age 33, N=7653			Age 34, N = 7758		
(i) +Female	-0.894	[0.017]	0.255	-0.600	[0.021]	0.097
(ix) + all childhood variables	-0.904	[0.020]	0.332	-0.645	[0.022]	0.179
Panel B: General health status	Age 33, N=9606			Age 34, N = 8965		
(i) +Female	-0.050	[0.020]	0.001	-0.036	[0.020]	0.000
(ix) + all childhood variables	-0.081	[0.025]	0.056	-0.085	[0.022]	0.022
Panel C: Malaise score (positive)	Age 33, N = 9667			Age 34, N = 8973		
(i) +Female	-0.345	[0.020]	0.030	-0.315	[0.023]	0.021
(ix) + all childhood variables	-0.363	[0.025]	0.078	-0.330	[0.026]	0.027
Panel D: Attitudes towards gender roles	Age 33, N = 9249			Age 26, N = 6169		
(i) +Female	0.553	[0.020]	0.077	0.623	[0.024]	0.100
(ix) + all childhood variables	0.565	[0.024]	0.116	0.598	[0.027]	0.106
Panel E: Attitude towards racial issues	Age 33, N = 9246			Age 30, N = 8442		
(i) +Female	0.172	[0.021]	0.007	0.255	[0.021]	0.016
(ix) + External influences	0.195	[0.025]	0.074	0.186	[0.023]	0.07
Panel F: Smoking behaviour (whether or not smoke)	Age 33, N = 9647			Age 34, N = 8641		
(i) +Female	-0.008	[0.009]	0	-0.061	[0.010]	0.005
(ix) + External influences	0.009	[0.011]	0.105	-0.025	[0.010]	0.061
Panel G: Attended university	Age 33, N = 9719			Age 34, N = 5834		
(i) +Female	-0.035	[0.008]	0.002	0	[0.011]	0
(ix) + External influences	-0.024	[0.007]	0.315	-0.020	[0.010]	0.285
Panel H: Cognitive Ability in Adulthood	Age 50, N = 7167			Age 34, N = 7386		
(i) +Female	0.259	[0.023]	0.017	-0.180	[0.022]	0.009
(ix) + External influences	0.232	[0.027]	0.150	-0.303	[0.019]	0.372

Notes: (I) is the regression with a female dummy only. (IX) includes the fullest set of controls. (See notes for Table 1.) *Log of net earnings* is taken from net family annual income for NCDS and reported as equivalised household income for BCS. *General health status* is the self-rated health rating for both NCDS (4 levels) and BCS (5 levels). We use the standardised value (mean = 0 and sd. =1). *Malaise score (positive)* is derived from the self-rated Malaise score (9 items). The raw score is reversed and standardised (mean = 0 and sd. =1). *Attitudes towards gender roles* is calculated from the opinion on the questions "there should be more women bosses in important jobs in business & industry", "men and women should have the chance to do the same kind of work" (6 levels), and calculate for the average score. *Attitude towards racial issues* is derived from the response to the questions "mixed race marriage is OK", "wouldn't mind if family of diff race moved next door", "would mind kids going to school with diff races" (reversed), "wouldn't mind working with people from other races" and "not want another race person as my boss" (reversed) (6 levels: totally disagree to totally agree) and calculate for the average score. *Smoking behaviour* is an indicator variable equals to 1 if the cohort member smoked at all at present and zero otherwise. *Attended university* is an indicator variable with value 1 if cohort member at least attended university and zero otherwise. Lastly, *Cognitive Ability in Adulthood* of the BCS is taken from 2 inventories: numeracy score (total score of 23), and literacy score (total score of 37). The composite score is the standardised score of the mean of standardised numeracy and literacy scores. *Cognitive Ability in Adulthood* of the NCDS is taken from 4 inventories: Word list recall, Animal naming, Letter cancellation, and Delayed word list recall (see Brown and Dodgeon 2010 for details). The composite score is the standardised value of the mean of standardised score of each item.

Table 9 Summary statistics for occupational choices across three UK birth cohorts

	NCDS (1958)		BCS(1970)		MCS(2000)		Change (2000 - 1958)
	Average	SD	Average	SD	Average	SD	
Panel A: Female							
Share of men in an occupation	0.31	(0.24)	0.34	(0.25)	0.40	(0.25)	0.09
Log of average gross income	2.05	(0.36)	2.18	(0.41)	2.45	(0.4)	0.40
People	0.09	(1.02)	0.18	(0.97)	0.85	(0.95)	0.76
Brains	-0.17	(0.82)	0.14	(0.89)	0.23	(0.9)	0.40
Brawn	-0.3	(0.85)	-0.43	(0.72)	0.06	(0.64)	0.36
Job competitiveness	-0.25	(1.01)	-0.13	(1.13)	0.59	(1.33)	0.84
Flexibility of an occupation	-0.02	(0.19)	-0.04	(0.21)	-0.19	(0.25)	-0.17
Average hours	37.73	(6.73)	38.96	(6.68)	43.57	(4.97)	5.84
Panel B: Male							
Share of men in an occupation	0.76	(0.24)	0.75	(0.24)	0.74	(0.25)	-0.02
Log of average gross income	2.29	(0.35)	2.32	(0.38)	2.76	(0.42)	0.47
People	-0.34	(0.8)	-0.25	(0.82)	0.58	(0.97)	0.92
Brains	-0.07	(1.05)	0.08	(1.13)	-0.30	(1.1)	-0.23
Brawn	0.51	(1.07)	0.39	(1.07)	0.59	(0.89)	0.08
Job competitiveness	0.17	(0.95)	0.25	(0.95)	1.43	(1.45)	1.26
Flexibility of an occupation	-0.21	(0.29)	-0.21	(0.27)	-0.25	(0.28)	-0.04
Average hours	45.98	(4.35)	45.88	(4.72)	46.28	(3.89)	0.30