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The gender gap in top jobs – the role of overconfidence

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ABSTRACT
There is a large gender gap in the probability of being in a "top job" in mid-career. Top jobs bring higher earnings, and also have more job security and better career trajectories. Recent literature has raised the possibility that some of this gap may be attributable to women not "leaning in" while men are more overconfident in their abilities. We use longitudinal data from childhood into mid-career and construct a measure of overconfidence using multiple measures of objective cognitive ability and subjective estimated ability. Our measure confirms previous findings that men are more overconfident than women. We then use linear regression and decomposition techniques to account for the gender gap in top jobs including our measure of overconfidence. Our results show that men being more overconfident explains 5-11 percent of the gender gap in top job employment. This indicates that while overconfidence matters for gender inequality in the labor market and has implications for how firms recruit and promote workers, other individual, structural, and societal factors play a larger role.

JEL codes: I24, I26, J24
Keywords: gender gaps, inequality, overconfidence, labor market

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A nemek közötti különbség vezető állásokban: a túlzott önbizalom szerepe

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ÖSSZEFOGLALÓ

Nők számottevően kisebb valószínűséggel dolgoznak vezető állásokban, mint férfiak. A vezető állások magasabb béreket fizetnek, nagyobb munkapiaci biztonságot nyújtanak és jobb karrierlehetőségeket jelentenek, mint egyéb pozíciók. Az irodalom felveti azt a lehetőséget, hogy a nők azért kerülnek kisebb valószínűséggel vezető állásokba, mert kevésbé magabiztosak a képességeikben, miközben a férfiakra inkább jellemző a túlzott önbizalom. Túlzott önbizalmon azt értjük, ha valaki jobbnak ítéli a képességeit, mint amilyenek azok valójában, objektív mércével mérve. Egy kohorsz kutatás longitudinális adatait használjuk, melyek születéstől 42 éves korig követik a kohorsz tagjait. Gyermek- és serdülőkorban mért kognitív készségekkel és teszteredményekkel mérjük a mintában szereplő emberek objektív készségeit, amelyeket összevetünk azzal, hogyan ítélik meg ők maguk a képességeiket. Az eredményeink igazolják, hogy a férfiakra inkább jellemző a túlzott önbizalom. Lineáris regressziós és dekompozíciós módszerekkel vizsgáljuk, hogy a férfiak túlzott önbizalma mennyiben járul hozzá ahhoz, hogy nagyobb valószínűséggel kerülnek vezető állásokba. Azt találjuk, hogy a különbség 5-11 százalékát magyarázza a túlzott önbizalom, a többi más egyéni, társadalmi és munkapiaci forrásokból származik. A túlzott önbizalom tehát valóban hozzájárul a nemek közötti munkaerőpiaci különbségekhez, de a nemi szerepekkel kapcsolatos egyéb egyéni és társadalmi folyamatok nagyobb szerepet játszanak.

JEL: I24, I26, J24

Kulcsszavak: nemek közötti különbségek, egyenlőtlenség, túlzott önbizalom, munkapiac

1. Introduction

Improving gender equality in the labor market remains a challenge in all countries. Currently no country has achieved gender equality according to the UN's Gender Inequality Index (United Nations 2021). There are well established gender gaps in key labor market outcomes including labor supply, wages, and representation in certain occupations, especially in "top jobs". As we will discuss in more detail, "top jobs" refers to high-status occupations that tend to have higher earnings, more job security, and better career trajectories than most other jobs (Goldthorpe and McKnight 2006). For example, women are less likely to make partner at law firms (Azmat, Cuñat, and Henry 2020) and reach corporate leadership positions (Bertrand and Hallock 2001; Bertrand, Goldin, and Katz 2010). The overrepresentation of men in top jobs may be an important driver of the gender pay gap and other gender inequalities in the labor market. It is therefore important to understand why men have a higher probability of being in a top job.

The debate around the gender gap at the top of the career ladder has centered on institutional (e.g. lack of childcare, poor parental leave policies, lack of flexible working arrangements, etc.) vs. individual factors (e.g. gender differences in non-cognitive skills, preferences for certain types of jobs or industries, etc.). The popularity of the book *Lean In* by Sheryl Sandberg has put a focus on the role of women's underconfidence as a barrier to climbing the career ladder. In addition to highlighting institutional barriers holding women back, Sandberg focused on the ways in which women "hold themselves back" (Sandberg 2013). This is related to academic literature, which has found that women are more likely to shy away from competition and underestimate their abilities (Azmat and Petrongolo 2014; Niederle and Vesterlund 2007; Reuben, Sapienza, and Zingales 2015; Sarsons and Xu 2021), but are also less likely to overclaim knowledge (Jerrim, Parker, and Shure 2019) than men. These findings show that not only are women more likely to be underconfident, but men are more likely to be overconfident in their abilities, which may exacerbate gender inequality in who climbs the career ladder.

In this paper we explore how much of the gender gap in top jobs can be explained by overconfidence. Despite the acknowledgement in the psychological literature that "the significance of overconfidence to the conduct of human affairs can hardly be overstated" (Griffin and Tversky 1992: 432) and an "individual's choice, persistence, and performance can be explained by their beliefs about how well they will do on the activity and the extent to which they value the activity" (Eccles et al. 1983: 68), no previous studies on gender gaps in access to top jobs have explored the role of overconfidence.

Psychologists typically differentiate between three types of overconfidence: overplacement of one's skills compared to others, overestimation of own abilities compared to objective measures, and overestimation of the precision of certain beliefs (overprecision) (Moore and Healy 2008). We use the second definition and measure overconfidence by looking at whether one's self-assessed cognitive skills (how well individuals think they do in mathematics and how clever they are) are higher than their performance on a series of tests. Overconfidence is thus different from confidence since overconfidence implies individuals have an inflated sense of self relative to their actual ability. There is much discussion in the literature as to the existence and magnitude of gender differences in overconfidence. While some papers find everyone to be overconfident and no difference between men and women (Bandiera et al. 2022), others emphasize the existence of stronger male overconfidence, especially in domains traditionally regarded as "male" (Bertrand 2011; Sarsons and Xu 2021; Exley and Kessler 2022).

While there is no evidence on the contribution of overconfidence to the gender gap in top jobs, men being more overconfident than women contributes to the gender gap in expected wages.[1] Briel et al. (2021) look at the role of overplacement in the gender gap in future wage expectations of prospective university students in Germany while Reuben, Wiswall, and Zafar (2017) examine this among undergraduate students at New York University. They both find that men are more likely to have upward-biased beliefs about their abilities and overplacement plays a major role in explaining the gender gap in wage expectations. Briel et al. (2021) find that 7.7% of the gender gap in wage expectations is attributable to a higher overconfidence of males, while Reuben, Wiswall, and Zafar (2017) find that 18% of the gap is due to men being more overconfident and competitive.

We investigate the role of overconfidence in the gender gap in top jobs using representative data from a British birth cohort study to follow men and women from childhood into the labor market in mid-career. We define top jobs following the literature as occupations in the top National Statistics Socio-economic classification (NS-SEC) categories. We use linear probability models and decomposition techniques to show that overconfidence is a significant explanatory factor in the gender gap in top jobs, especially for top jobs in Law, Economics, and Management (LEM). It also appears as though some of the overconfidence effect works through

[1] There is also a literature on the role of self-confidence or self-esteem in explaining the gender wage gap (e.g. Fortin (2008) and Manning and Swaffield (2008)), which we do not review here because our outcome is the gender gap in top jobs, not wages, and overconfidence is different from self-confidence or self-esteem since it is about the inability to accurately assess ability.

previous educational channels, highlighting the importance of overconfidence in shaping educational pathways into the labor market.

We make four contributions to the literature. First, we use representative data to quantify the impact of overconfidence on labor market outcomes. This is unlike previous studies looking at the role of overconfidence in expected wages, which have used samples of university students. Second, as opposed to a one-time measure of overconfidence, we exploit objective measures of cognitive abilities measured at ages 5, 10 and 16, and subjective estimation of abilities from ages 5 and 10 to construct a measure of overestimation. Using data from multiple points in time reduces measurement errors and provides a long-run estimate of overconfidence that is robust to potential individual changes (Golsteyn and Schildberg-Hörisch 2017). Thus, our measure of overconfidence is more likely to capture a meaningful latent construct than one-time measures captured in a university course or laboratory setting. It is also captured before labor market entry, eliminating concerns around reverse causality. Third, our outcomes are real labor market outcomes, not expected wages.

Lastly, while a growing literature aims to explain who ends up in top jobs focusing on social mobility (Laurison and Friedman 2016; Macmillan, Tyler, and Vignoles 2015; Sullivan et al. 2018), we are the first to explicitly investigate the gender gap in top jobs. We look at those in full time employment and document that the gender gap in top jobs emerges in the late 20s and grows into mid-career. By age 42, full time employed women are six percentage points (or 25 percent) less likely to be in a top job than men, conditional on family background, early educational attainment, university course, partnership status and children. Interestingly, the conditional gap is large amongst full time employed university graduates as well, at 9.5 percentage points (or 20 percent). We also confirm that men are significantly more overconfident than women. When we decompose the gender gap in top jobs, accounting for education, partnership, children, and a range of other factors, we find that overconfidence accounts for a statistically significant portion (5-11 percent) among those in full time employment. Given that overconfidence is measured in adolescence and that it still explains labor market outcomes at age 42, over 25 years later, we argue that its contribution is meaningful, but of course not the entire picture.

We go one step further and descriptively look at the gender gap in terms of the costs and benefits of working in a top job. Practically, we compare hours worked, hourly earnings, having a cohabiting partner, and having children among women and men working in top jobs vs. regular jobs. We find that while the gender wage gap is not smaller among those in top jobs than in regular jobs, women work on average more hours in top jobs than in regular jobs. Among men, we do not find such difference: full time employed men work about the same weekly hours in both top and regular jobs. Overall, women in top jobs still work somewhat fewer hours than men. Furthermore, we find that full time employed women who work in top jobs are less likely to have children (even conditional on having a cohabiting partner) than women working in regular jobs. Thus, we find a substitution effect for women between working in top jobs vs. having children, and we find no such effect for men.

We conclude that many of the barriers to women ending up in top jobs are not the result of them "holding themselves back", but rather societal or workplace based. This conclusion is further supported by the fact that the gender gap in top jobs becomes small and statistically insignificant once we restrict the sample to those who do not have partners (or children). Overconfidence still predicts the probability of being in a top job for those women without partners or children, but not for the subsamples with partners and children. Thus, once the decision to start a family is made, overconfidence seems to lose its importance.

The rest of this paper is structured as follows. In section 2 we discuss the data used and present key descriptive statistics. In section 3 we present the methods used to conduct our decomposition. Section 4 contains our results. In section 5, we look at the costs and benefits of working in a top job while we conclude in section 6.

2. Data

We use data from the British Cohort Study 1970 (BCS70, CLS n.d.).[2] The BCS70 is a birth cohort study that follows the lives of 17,000 individuals born in the UK in a specific week in 1970. The BCS70 collects rich data on family background, childhood and adolescent cognitive and non-cognitive skills, preferences, and labor market and other life outcomes up until the early 40s.

We restrict the sample to those individuals who participated in the age 5, 10 and 16 waves and have data on at least one objective cognitive measure and at least one measure of subjective estimated ability (number of individuals: 9,664). Out of this sample, 6,544 individuals participated in the age 42 wave that we use to measure top job employment (main sample). We investigate whether sample selection (attrition and non-response) might bias our results in two ways. First, we look at how the individual characteristics of those in the main

[2] We use safeguarded data (accessed through the UK Data Service) from the birth sweep (SN: 2666), the age 5 sweep (SN: 2699), the age 10 sweep (SN: 3732), three data collections of the age 16 sweep (SN: 3535, 6095 and 8288), the age 42 sweep (SN: 7473), and the activity history data file (SN: 6943).

sample (6,544 individuals) relate to the characteristics of those who dropped out or did not report data (16,932-6,544=10,388 individuals). It could hinder the external validity of our results if those in the main sample were a selected subsample of the data. We explore the possibility of sample selection using characteristics that are available for everybody: gender, region of birth, socio-economic background of parents, whether their mother and father had any qualifications, ethnicity, low (<2500 g) birthweight and mother's year of birth. As we find that there are some differences between the two groups (Figure A3 in Appendix A), we apply a balancing technique, entropy balancing (Hainmueller 2011), to construct individual-level weights to equate the first moments of these variables across the two groups. Using these entropy-balanced weights, we weight individuals in the main sample such a way that their individual characteristics have the same distribution as the individual characteristics of those who were excluded from the sample. We show in Figure A3 in Appendix A that using these weights eliminates statistical differences between those in the main sample and those who were excluded. Re-estimating our (unweighted) main results using these entropy balanced weights leads to similar results; thus, we are confident that (observed) sample selection is not driving our results. Obviously, we cannot exclude potential unobserved sources of sample selection.

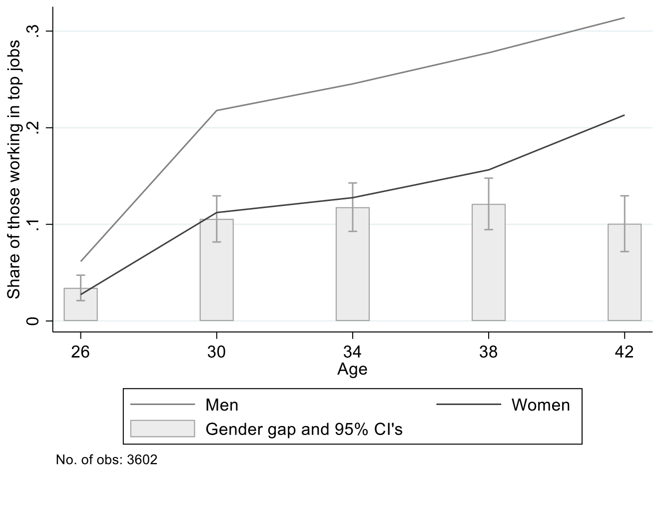
Second, within the sample of those for whom we can construct an overconfidence score (9,664 individuals), we investigate whether overconfidence is statistically related to the probability of participating in the main sample, as well as the probability of participating in various subsamples that we use for analysis (Table A5 in Appendix A). Such a statistical relationship could pose a threat to the internal validity of our results. Reassuringly, we find that overconfidence is not related to the probability of being in the main sample, as well as being employed, being employed full time, having a partner, or having children. Thus, following the convention in the gender wage gap literature (Blau and Kahn 2017), in our main analysis, we look at those in full time employment (number of individuals: 3,602). We appreciate the fact that people make a joint decision about whether they work, whether they work full time, what positions they apply for, and what offers they accept. This paper however follows a simplified approach and investigates the probability of working in a top job after these decisions have been made. To make sure that this sample choice does not affect our conclusions, on top of showing that overconfidence is not statistically related to employment and full-time employment (Table A5 in Appendix A), we replicate our main results on the total sample (number of individuals: 9,664) and on the sample of those employed (full time and part time together; 5,659 individuals) and they point to similar conclusions.

Top jobs and other labor market outcomes

Following Macmillan, Tyler, and Vignoles (2015) and Sullivan et al. (2018), we define top jobs as occupations in the top National Statistics Socio-economic classification (NS-SEC) categories, 1.1 and 1.2. NS-SEC is a classification system that measures class by combining aspects of employment relations and conditions of occupations (Rose and O'Reilly 1998). We use NS-SEC to create our measure of top jobs so that these results may speak to a range of economics and sociological literature that also explores gaps in access to high status labor market outcomes (e.g. Chan and Goldthorpe, 2007). NS-SEC 1.1 consists of large employers and higher managerial and administrative occupations such as chief executives, production managers, and senior police officers. NS-SEC 1.2 consists of higher professional occupations, such as lawyers and doctors. We do not classify NS-SEC 2 graduate occupations such as teachers, librarians, and social workers as top jobs as they are not managerial positions. As a robustness check, we create an alternative measure of top jobs defined by earnings. We look at jobs in the top quintile of the distribution of log hourly wages in our data and define these as top jobs.

Following Macmillan, Tyler, and Vignoles (2015), we also look at two subgroups of top jobs: jobs in business, law and economics (LEM), including managers, lawyers, accountants, etc., and jobs in science, technology, engineering and mathematics (STEM). This speaks to a broader literature assessing the under-representation of women in high-earning, high-status leadership positions in the corporate world (Bertrand and Hallock 2001) and a literature on gender gaps in STEM (Speer 2021).

Figure 1: The share of those in top jobs by gender



Source: BCS70 (CLS n.d.), activity history data (SN: 6943). Sample of those in full time employment at age 42. Top jobs refers to NS-SEC 1.1 and NS-SEC 1.2.

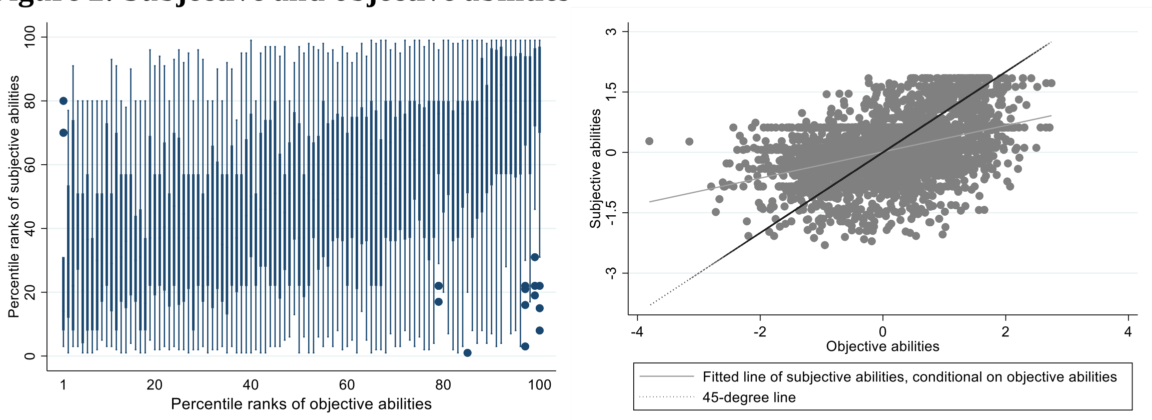
Figure 1 highlights the raw gender gap in who reaches a top job over early and mid-career among those employed full time. Early in career at age 26, there is only a small difference in the proportion of men and women who reach a top job (note the means are low for both groups). By age 30, however, this gap has widened to approximately 10 percentage points and remains stable into mid-career.

Measuring overconfidence

As mentioned above, we construct a measure of overestimation to capture overconfidence by comparing individuals' subjective estimated abilities (what individuals think about how clever they are and how good they are in school) to an objective measure of their cognitive abilities. We measure objective cognitive abilities via tests taken at age 5, 10 and 16 (see the explanation of measures in Table A1 and their descriptive statistics in Table A3). The advantage of using longitudinal data is that we have many measures from several points in time, which we can combine to create a more robust measure of cognitive ability. As in previous studies exploring the importance of cognitive ability, we combine existing survey measures into an index (Bütikofer and Peri 2021; Lindqvist and Vestman 2011). We create a standardized index of the resulting continuous scores of these 18 tests using Confirmatory Factor Analysis (CFA) (Thompson and Daniel 1996). See more details on how we created the index under Table A1 in Appendix A. We also use a binary version of this measure capturing whether one's cognitive ability index is above or below the sample mean. We measure subjective estimated abilities via questions taken at age 10 and 16 (see the full list of measures in Table A2 and their descriptive statistics in Table A3) and create an index of these categorical variables (measured using a Likert scale) using Item Response Theory (IRT) (Edelen and Reeve 2007). Example questions include: *Are you good at mathematics? (Yes/No/I don't know)* and *Please say whether the following applies to you: I am clever. (Applies very much/Applies somewhat/Does not apply).* See more details on how we created the index under Table A2 in Appendix A. Figure A2 in Appendix A shows the distribution of these two component variables by gender.

Figure 2 shows the relationship between these two indices. The left panel shows the relationship between how individuals in our sample perceive their ability compared to their actual ability. In particular, we plot subjective ability percentiles vis-à-vis objective ability percentiles to show the variation of subjective ability among individuals with similar objective abilities. On average, objective and subjective ability are correlated (0.42, Table B12 in Appendix B), but there are people with both higher and lower subjective ability percentiles than their objective ability percentiles across the distribution of objective ability. The right panel of Figure 2 plots the raw measures and again highlights that there are individuals both below and above the 45-degree line

Figure 2: Subjective and objective abilities



Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. N= 3,602

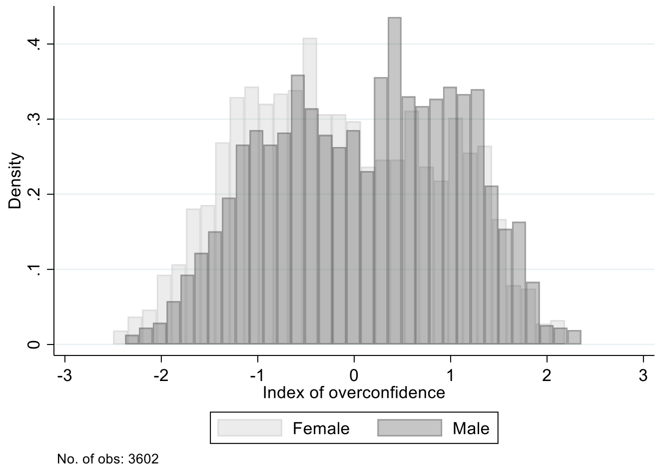
Following Anderson et al. (2012), we construct an index of overconfidence by regressing each cohort member's percentile rank in the distribution of subjective estimated ability on their percentile rank in the distribution of objective cognitive ability and predict the residuals (*overconfidence residual score*). The *overconfidence residual score* captures the variability in self-perceived rank after the variance predicted by actual rank has been removed and is one of the most used methods to capture overconfidence in the psychology literature (Belmi et al. 2019). Graphically, our overconfidence measure is the distance of each individual's subjective ability from the fitted line (of regressing subjective ability on objective ability). Those with a positive overconfidence score are higher on the subjective estimated ability distribution than the percentile predicted by their objective ability (i.e., they are above the fitted line), while negative scores reflect a lower-than-predicted percentile, which can be interpreted as underconfidence.

Note that as residuals have a mean of zero by construction, our overconfidence score is not suitable to test whether people assess their abilities higher on average than their objective abilities are but rather measures how overconfident people are compared to the average level of self-assessment in the sample. As we are interested in the role of overconfidence in the gender gap in top jobs (and the gender gap in overconfidence itself), this measure allows us to interpret regression results in terms of effect sizes and to pin down gender differences, our goal. However, it cannot be used to test how overconfident people are in general.

Figure 3 shows the distribution of the overconfidence score by gender while Table B12 in Appendix B reports its correlation with objective and subjective ability. Like most of the previous literature, we find that men are more likely to be overconfident than women (note that women have more density to the left of zero). Men have a mean overconfidence score of 0.10 and women of -0.15, leading to a gender difference of 0.25 standard deviations (Table 1).

In addition to the continuous overconfidence score, which allows us to look at the linear relationship between the probability of being in a top job and overconfidence, we construct alternative versions to test potential non-linear relationships. This includes a quadratic term, quintiles, a binary variable capturing the top quintile compared to the rest of the distribution, and the bottom and top tercile compared to the middle tercile. The top quintile versus the rest of the distribution allows us to capture those who are highly overconfident as compared to everyone else. The middle tercile captures those who have a realistic estimation of their abilities while the lowest tercile captures underconfidence and the highest tercile overconfidence.

Figure 3: The distribution of the overconfidence score by gender



Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42.

We provide three robustness checks to probe our overconfidence measure in Table B14 in Appendix B. First, for our main measure as introduced above, we construct percentile ranks of subjective and objective abilities to extract the residuals. The BCS70 cohort members do not attend the same schools and do not know each other (it is not a school-based survey design), so these rankings are unknown to them. Still, as ranking directly captures their (unknown) place in the skill distribution, we add a robustness check where we do not use the ranks to construct the overconfidence measure. We simply regress the index of subjective ability on the index of objective ability and extract the residuals. The resulting non-ranked residual score (see its descriptive statistics in Table B13 in Appendix B) is highly correlated with the original rank-based overconfidence residual score (Table B12 in Appendix B).

Second, as shown on the right panel of Figure 2, there are people between the fitted line and the 45-degree line: at low objective ability levels, the overconfidence score will be negative for some people whose subjective ability is above the 45-degree line, and at high objective ability levels, the overconfidence score will be positive for some people whose subjective ability is below the 45-degree line. This phenomenon comes from the nature of our overconfidence measure. To see how our results compare to just simply looking at where people are compared to the 45-degree line, we provide a robustness check where we use the difference score instead of the overconfidence score. The difference score captures the difference between subjective and objective ability percentiles (i.e. +/- distance from the 45-degree line). This measure (see its descriptive statistics in Table B13 in Appendix B) is again strongly correlated with our main overconfidence measure (Table B12 in Appendix B).

Third, those at the very bottom (top) of the objective ability distribution might be less likely to be underconfident (overconfident) by construction, although the literature argues that these *floor* and *ceiling* effects are less of a concern in the residual score context (Belmi et al. 2019). To further probe this potential issue, we provide a robustness check where we exclude individuals in the bottom and top five percentiles of the cognitive ability distribution from the estimation sample. All three robustness checks show similar results as the main approach.

Control variables

We exploit the rich nature of the longitudinal data to control for a range of characteristics. Taking into account prior literature (Dickson and Harmon 2011), we control for background characteristics that have been shown to be related to labor market success. This includes:

- Demographics and parental background
    - Region in the UK when born;
    - Parental SES based on NS-SEC categories when the cohort members were born. This is captured via a binary variable of low vs. high SES. *Low SES*: parental NS-SEC includes “Single parent or not working”, “Other category”, “V unskilled”, “IV partly-skilled”, “III manual”. *High SES*: parental NS-SEC is “III non manual”, “II managerial and technical” or “I professional”.

    - Whether the cohort member’s mother had a qualification when the cohort member was born;
    - Ethnicity (English, Irish, Other European, West Indian, Indian, Pakistani, Bangladeshi, other).
- Educational attainment and outcomes:
    - University graduation by university status and course (nine categories): non-graduate; graduate from a ‘non-elite’ university in the following UK Labour Force Survey (LFS) subject categories: STEM, LEM, Other Social Sciences, Arts, and Humanities (OSSAH), Combined, Other; graduate from an elite (Russell Group) university in the following subject categories: STEM, LEM, OSSAH, Combined, Other. This use of elite vs. non-elite and LFS subject classification draws on Walker and Zhu (2018; 2011).
    - Attended a private secondary school or a grammar school (binary);
    - Math exam grades at age 16 (O-level or CSE examinations, seven categories);
    - Whether completed any A-level examinations (binary).
- Current family situation:
    - Living with a partner at age 42 (binary);
    - Number of children in the household at age 42 (0,1,2+);
- Self-esteem measured at age 16. As self-esteem is only available for about half of the sample, we use mean imputation for the missing values and employ a dummy variable for missing flags.

Analytic sample and descriptive statistics

The aforementioned sample restrictions provide us with an analytic sample of 3,602 individuals. Their descriptive statistics are presented in Table 1 (and in Table A3 by gender and Table A4 by top job vs. regular job status in Appendix A) while the same statistics on the alternative samples are presented in Table B1 and B2 in Appendix B. Table 1 shows that women are less likely to work in a top job at age 42 and this difference holds across STEM and LEM top jobs.

In terms of objective cognitive ability, there are differences between men and women in the 18 measures used to create the standardized score. Women tend to have higher scores on the literacy and several of the spatial reasoning tests while men tend to have higher scores on the numeracy tests. When combined into one index, the difference between men and women is small (-0.03 SD) and not significant. Similarly, men have higher average scores on the numeracy components of the subjective estimated ability index. Here they have more favorable estimations of their ability in math while women view their ability in spelling more favorably (difference is only statistically significant at age 10). Men are also more likely to think that they are clever than women (Table A3). This leads to overall lower subjective estimation of ability in the index score for women as compared to men (difference is -0.18 SD). As previously highlighted in Figure 3, women have lower average overconfidence than men (mean difference is -0.25 SD).

Table 1: Descriptive statistics

	Obs	Mean men	Mean women	Diff. (Women-men)	SE	Two-tailed t-test p-values
Works in a top job	3602	0.24	0.16	-0.08	0.01	0.00
Works in a STEM top job	3602	0.08	0.02	-0.06	0.01	0.00
Works in a LEM top job	3602	0.15	0.12	-0.03	0.01	0.00
Log hourly pay	3441	2.39	2.20	-0.19	0.02	0.00
Weekly hours worked	3602	45.97	40.68	-5.29	0.33	0.00
Objective cognitive ability, STD	3602	0.02	-0.03	-0.05	0.03	0.15
Subjective estimated abilities score, STD	3602	0.07	-0.11	-0.18	0.02	0.00
Overconfidence score, STD	3602	0.10	-0.15	-0.25	0.03	0.00
Overconfidence score, squared	3602	0.96	1.06	0.10	0.04	0.01
Overconfidence score quintiles	3602	3.13	2.80	-0.34	0.05	0.00
Overconfidence score quintiles	3602	0.22	0.17	-0.04	0.01	0.00
Overconfidence score terciles compared to the middle	3602	2.02	1.97	-0.04	0.03	0.10
Has cohabiting partner	3602	0.82	0.72	-0.09	0.01	0.00
No. of children in HH	3602	1.18	1.04	-0.15	0.03	0.00

Notes: Positive difference indicates that women have higher score or probability. Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42.

3. Empirical methods

We are interested in explaining the gender gap in top jobs highlighted in Figure 1. To do this, we use a mix of linear regressions and Kitagawa-Blinder-Oaxaca decompositions (Elder, Goddeeris, and Haider 2010). These methods allow us to measure the gaps in mean outcomes and see how they change when accounting for our variable of interest, overconfidence. Our main specification takes the following form:

$$y_{it} = \propto + \beta_1 gender_i + + \beta_2 Overconfidence_{it} + \beta_3 X_{it} + \varepsilon_{it} \qquad (1)$$

Where y_{it} is our binary outcome variable for being in a top job at age 42;

$gender_i$ is our binary variable for female (0 denotes male, 1 denotes female);

$Overconfidence_{it}$ is either our standardized residual score measure of overestimation or one of the alternative measures previously outlined (i.e., top quintile dummy or tercile categories); and

X_{it} is a vector of individual and family characteristics including region of birth, ethnicity, and parental SES.

We present the regression results using a series of models in each table. In our main specification (as presented by Equation 1), we limit the inclusion of "bad controls" (Angrist and Pischke 2008), and aim at modelling the relationship between overconfidence and the gender gap in top jobs by controlling for variables that are assumed to be independent of overconfidence. In the most basic specification, we include only the female dummy to capture the raw gender gap in the probability of being in a top job at age 42 (Model 1). We then add our measure of overconfidence in Model 2 and we introduce demographic controls and parental SES in Model 3.

In the second step, we extend the model with variables that might have been affected by overconfidence, i.e. could be interpreted as the channels behind the relationship between overconfidence and the gender gap in top jobs. We add pre-university educational attainment, objective cognitive ability, and private school attendance in Model 4, university attainment measures in Model 5, partnership and number of children at age 42 in Model 6 and Model 7. Lastly, we add self-esteem measured at age 16 in Model 8. In all specifications we use robust standard errors.

In addition to the results obtained from linear regressions, we also implement a Kitagawa-Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973) to probe the role of overconfidence in explaining the gender gap in access to top jobs. This decomposition technique allows us to measure how much of the gender gap comes from different distributions of individual characteristics (*endowments*) between the two groups and how much of it remains *unexplained* (follows from men and women showing different returns to these characteristics). We apply common coefficients estimated from a pooled regression (Neumark 1988). This means the estimated coefficient of the unexplained gap is the same as the gender coefficient in our pooled regression models.

4. Results

Main regression results

We begin by decomposing the gender gap in reaching a top job by age 42 using linear regressions and the linear, standardized measure of overconfidence. These results are presented in Table 2. Column (1) shows the raw gender gap in the probability of being in a top job at age 42 (8.1 percentage points or 34 percent). In Column (2), when we introduce the measure of overconfidence, this gap is reduced by 0.8 percentage points or roughly 10 percent. This difference is statistically significant on a 1% level[3]. The coefficient on overconfidence is statistically significant. It is equivalent to a one standard deviation increase on the overconfidence scale leading to a 3.5 percentage points increase in the probability of being in a top job. In Column (3), the gender gap remains stable when demographic variables are added to the model.

Table 2: The gender gap in the probability of working in a top job: continuous overconfidence score

	(1)	(2)	(3)
	Model 1	Model 2	Model 3
Female	-0.081***	-0.073***	-0.072***
	(0.013)	(0.013)	(0.013)
Overconfidence score, STD		0.035***	0.035***
		(0.007)	(0.007)
Constant	0.243***	0.239***	0.141***
	(0.009)	(0.009)	(0.024)
Observations	3,602	3,602	3,602
R-squared	0.009	0.017	0.061
Further control variables			
Region, parental background, ethnicity			yes

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The potential channels of the association between overconfidence and the gender gap in top jobs

In Table 3, we extend the model with further control variables that could already have been affected by overconfidence, i.e., they could be interpreted as potential channels behind the association between overconfidence and the gender gap in top jobs. These channels are broadly

[3] Hausman test estimated using sureg and test in Stata. H0: beta1-beta2=0. Chi2(1) = 16.68, Prob > chi2 = 0.0000.

grouped into school characteristics and achievement, university participation, family formation, and other non-cognitive characteristics. We work our way through these channels until we have included all of them.

We begin with school characteristics and achievement. Model 4 in Table 3 shows that adding pre-university educational attainment (mathematics exam score from age 16 and A-level examinations), objective cognitive ability, and private school attendance slightly increases the gender gap in top jobs (from 0.072 in Model 3 in Table 2 to 0.074) but reduces the coefficient of overconfidence from 0.035 in Model 3 in Table 2 to 0.02 (significant at the 1% significance level). Adding information on university degrees decreases the gender gap to 0.068, and also decreases the coefficient of overconfidence further to 0.013 (significant on 5%). Thus, school achievement and the choice of university subject and institution are important channels behind the relationship between overconfidence and the gender gap in top jobs.

In Column (3) and (4) the gender gap is again slightly reduced through the inclusion of family situation variables at age 42 to around six percentage points, while the coefficient on overconfidence stays similar (0.014, significant on 5%). Lastly, controlling for self-esteem in Column (5) results in similar estimated coefficients for both the female dummy (0.06) and the overconfidence score (0.013).[4] As mentioned before, self-esteem is missing for a substantial share of the sample. Thus, we consider Model 7 as our main *channel model* in the forthcoming analysis. According to the results obtained from this model, a one-standard deviation increase on the overconfidence scale leads to a 1.4 percentage point increase in the probability of being in a top job, even after taking pre-university educational outcomes, university graduation, and family circumstances into account. Taken together, our results show that overconfidence plays a statistically significant role in explaining the gender gap in the probability of being in a top job at age 42.

Table 3: The gender gap in the probability of working in a top job: potential channels

	(1) Model 4	(2) Model 5	(3) Model 6	(4) Model 7	(5) Model 8
Female	-0.074***	-0.068***	-0.063***	-0.061***	-0.060***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Overconfidence score, STD	0.020***	0.013**	0.014**	0.014**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)

[4] Using this last specification to look at how the estimated coefficient on female changes when overconfidence is added to the model would result in again a small but significant change (0.03 percentage point (5%) from 0.063 to 0.060. H0: beta1-beta2=0. Chi2(1) = 3.89, Prob > chi2 = 0.0485.

Constant	0.112***	0.092***	0.054*	0.057**	-0.021
	(0.027)	(0.026)	(0.028)	(0.028)	(0.046)
Observations	3,602	3,602	3,602	3,602	3,602
R-squared	0.123	0.178	0.180	0.181	0.182
Region, parental background, ethnicity	yes	yes	yes	yes	yes
Private school	yes	yes	yes	yes	yes
Pre-uni educational attainment and objective cognitive ability	yes	yes	yes	yes	yes
University degree: elite*subject		yes	yes	yes	yes
Cohabiting partner			yes	yes	yes
No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We support these results with several robustness checks in Appendix B. We use the total sample of 9,664 individuals in Table B3 and the subsample of those employed full or part time in Table B4. In Table B5, we redefine top job employment based on log hourly wages (top 20%) while in Table B6, we use the age 34 wave instead of the age 42 wave.[5] The results using the age 34 data show that overconfidence already matters for getting into a top job at an earlier stage in career. The contribution of overconfidence to the gender gap in top jobs is even slightly higher at age 34 than at age 42. This supports the idea that overconfident individuals may be able to propel themselves up the career ladder and maintain this position into midcareer. The results using the top earners are very similar to those obtained using the occupational measure of top jobs. In Table B11, we apply the entropy balanced weights mentioned in the Data section. Lastly, we employ two alternative measures of overconfidence (non-ranked residual score and difference score) and exclude those at the bottom and top five percentiles of the objective skill distribution in Table B14. All these methods lead to a similar conclusion to our main results.

Potential non-linearities in the association between overconfidence and top jobs

We now turn our attention to possible non-linearities in how overconfidence explains the probability of being in a top job at age 42. We compare results using the standardized, linear overconfidence score with results from using the linear term plus a quadratic term, quintile

[5] We use the age 42 data for our main results due to a larger sample size, the availability of university degree information from this wave, and to assuage concerns about childbirth affecting labor market outcomes at age 34.

dummies, and tercile dummies. The goal here is to capture the effect of having very high overconfidence or very low overconfidence (i.e., being underconfident).

The results in Table 4 compare the results across these specifications. Column (1) replicates Column (4) from Table 3 and serves as a point of comparison for the alternative models. The first takeaway from this table is that the gender gap in the probability of being in a top job at age 42 is stable across all specifications and equal to roughly half of the raw magnitude. The results in Column (2) indicate that there are no convexities in the returns to overconfidence since the coefficient on the quadratic term is not statistically significant. Columns (3)-(5) present the results of using quintile dummies. In Column (3) we include a dummy for each quintile with the lowest quintile serving as the base category. This shows that being in the top quintile, i.e., being the most overconfident, has a positive and statistically significant impact on the probability of being in a top job at age 42. The magnitude of this coefficient is somewhat higher than previous estimates (five percentage points). This is confirmed in Column (4) where we compare just the top quintile to the rest of the distribution and again the coefficient is positive, statistically significant, and has a magnitude of 3.8 percentage points.

In Column (5) we change the base group to the middle quintile, the people who more accurately estimate their ability as compared to the objective measure. We again find that the coefficient of the top quintile is the highest in magnitude, but it is not significant. We probe these non-linearities further in Column (6) by focusing on terciles and comparing the bottom and top tercile to the middle one, i.e., to those who more accurately estimate their abilities. This again reveals that the coefficient on the highest tercile is the largest, but it is not significant. Overall, these results indicate that there is little difference in whether a linear measure or alternative measure of overconfidence is used in how it explains the gender gap in top jobs. Interestingly, however, it appears that being in the top quintile of the overconfidence score is associated the most positively with the probability of working in a top job. We find no evidence that being underconfident is significantly negatively associated with this probability.

Table 4: The gender gap in the probability of working in a top job: non-linear overconfidence measures

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model	(6) Model
	Linear	Quadratic		Quintiles		Terciles
Female	-0.060*** (0.013)	-0.060*** (0.013)	-0.061*** (0.013)	-0.063*** (0.013)	-0.061*** (0.013)	-0.062*** (0.013)
Overconfidence score, STD	0.016** (0.006)	0.016** (0.006)				

Overconfidence score, squared		-0.005				
		(0.006)				
Overconfidence quintiles						
Overconfidence, lowest quintile					-0.018	
					(0.019)	
Overconfidence, lower middle quintile			0.006		-0.012	
			(0.019)		(0.019)	
Overconfidence, middle quintile			0.018			
			(0.019)			
Overconfidence, upper middle quintile			0.021		0.003	
			(0.020)		(0.020)	
Overconfidence, top quintile			0.050**		0.031	
			(0.021)		(0.021)	
Overconfidence top quintile compared to the rest of the distribution						
Overconfidence, top quintile				0.038**		
				(0.017)		
Overconfidence terciles						
Underconfident						-0.002
						(0.015)
Overconfident						0.024
						(0.016)
Constant	0.070**	0.075**	0.051*	0.061**	0.069**	0.061**
	(0.028)	(0.029)	(0.030)	(0.028)	(0.032)	(0.030)
Observations	3,602	3,602	3,602	3,602	3,602	3,602
R-squared	0.181	0.182	0.182	0.181	0.182	0.181

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. These models extend Model 7 in Table 3 with non-linear overconfidence measures. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16, whether having a cohabiting partner, number of children in the household.

The heterogeneity of the association between overconfidence and top jobs

In Table 5, we explore the role of overconfidence in the gender gap in working in a top job over various subsamples. Until now, the coefficient on the overconfidence term was estimated in a pooled sample of men and women. While its inclusion reduced the raw gender gap by approximately 10 percent, this does not tell us about how overconfidence predicts individuals' probability of being in a top job differentially by gender. Thus, we start by estimating the same model (Model 7 in Table 3) we had before, separately for men and women (Column (1) and (2) in Table 5). Interestingly, the association between overconfidence and the probability of working in a top job is almost identical for men (0.017) and women (0.018), both significant at the 10% significance level.

Then, we turn to looking at whether the role of overconfidence in the gender gap is heterogenous by partnership, children, and university graduation. As these factors are key determinants of being in a top job (Folke and Rickne 2020; Duta, Wielgoszewska, and Iannelli 2021), we want to probe their interaction with overconfidence. In Column (3) and (4), we split the sample by partnership status. Interestingly, the gender gap in top jobs decreases to close to zero among those who do not have a partner. In this same group, the association between overconfidence and top job employment goes up to 2.6 percentage points (significant at the 5% level). Among those who live with a partner (Column (4) in Table 5), the gender gap increases to 7.1 percentage points (significant at the 1% level), while overconfidence loses its significance.

We see a similar picture if we repeat this exercise by having children. The gender gap in top jobs is small (3.6 percentage points) and insignificant among those who do not have children in the home, while the association between overconfidence and top jobs is relatively high (0.03) and significant. Among those who have children, the gender gap is again large, over seven percentage points, and the association between overconfidence and top jobs is small and insignificant. Thus, it seems that although overconfidence matters on average in terms of top job employment, the at-home responsibilities of women related to partnership and children are more important barriers in terms of labor market success. These results are similar in the total sample (Table B7 in Appendix B) and in the sample of those employed (Table B8 in Appendix B) as well.

Lastly, in Columns (7) and (8) of Table 5 we look at heterogeneity by university graduation. Note that the probability of being a graduate is statistically related to overconfidence (Table A5 in Appendix A): more overconfident people are more likely to be a graduate in the first place. Thus, our graduate subsample is selected in this respect which may hinder the external validity of these results. Interestingly, the gender gap in top jobs is considerably larger among (full time employed) university graduates, at 9.5 percentage points (or 20%), compared to non-graduates (4.7 percentage points or 37%). Similarly, overconfidence matters more for university graduates (3.2 percentage points per one standard deviation) while for non-graduates, the association between overconfidence and top job employment is insignificant and close to zero. These results suggest that overconfidence might matter in addition to other resources of human capital, like university graduation; thus, overconfidence is not a substitute for human capital, but rather a complementary resource for labor market success. This conclusion is also supported by Table A6 in the Appendix that shows similar heterogeneity by parental SES and objective cognitive skills: overconfidence matters only for those with high parental SES and high cognitive skills.

Table 5: Heterogeneity of the relationship between overconfidence and the probability of being in a top job by gender, partnership, children, and university graduation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men	Women	No	Has	No	Has	Non-	Graduates

			partner	partner	children	children	graduates	
Female			-0.014	-0.069***	-0.036	-0.070***	-0.047***	-0.095***
			(0.026)	(0.015)	(0.022)	(0.016)	(0.013)	(0.029)
Overconfidence	0.017*	0.018*	0.027**	0.012	0.031***	0.009	0.008	0.032**
score, STD	(0.009)	(0.010)	(0.012)	(0.008)	(0.010)	(0.008)	(0.007)	(0.014)
Constant	0.062*	0.038	0.042	0.122***	0.046	0.089**	0.073**	0.075
	(0.036)	(0.045)	(0.045)	(0.035)	(0.044)	(0.041)	(0.029)	(0.083)
Observations	2,176	1,426	792	2,810	1,200	2,402	2,443	1,159
R-squared	0.201	0.161	0.233	0.181	0.220	0.184	0.060	0.159

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables (if applicable): region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16, whether having a cohabiting partner, number of children in the household.

The decomposition of the gender gap

We use a Kitagawa-Oaxaca-Blinder decomposition to decompose the gender gap in access to top jobs (Elder, Goddeeris, and Haider 2010) to endowment effects coming for men and women having different individual characteristics (endowments) and showing different returns to these characteristics. As previously discussed, the value added of this method is to identify the relative contribution of each endowment to the gender gap, as well as to identify which characteristics might bring higher or lower returns to women than men.

Table 6 suggests that men being more overconfident than women explains five percent of the gender gap (0.004/0.081), while it accounts for 20 percent (0.004/0.021) of the explained or endowment gap (Columns (1) and (2) of Table 6). Interestingly, the magnitude of this coefficient (0.004) is twice as large as the contribution of the objective cognitive ability score (0.002); thus, conditional on family background, pre-university test scores, university course, elite university status and current family circumstances (partnership and children), overconfidence is somewhat more important for top job employment than objective cognitive skills. Of the included variables, the contribution of university subject, and specifically having studied a STEM subject, is the largest (0.016) and accounts for 20 percent (0.016/0.081) of the gender gap and 76 percent (0.016/0.021) of the endowment gap.

Table 6: The Kitagawa-Blinder-Oaxaca decomposition of the gender gap in top jobs

	Sample of those employed full time	Sample of graduates employed full time
Share of men in top jobs	0.243***	0.465***
	(0.009)	(0.019)
Share of women in top jobs	0.162***	0.298***
	(0.010)	(0.021)
Gender gap in top jobs	0.081***	0.167***

	(0.013)	(0.028)
Explained	0.021***	0.072***
	(0.007)	(0.016)
Unexplained	0.060***	0.095***
	(0.013)	(0.029)
	Explained by endowments	Explained by endowments
Overconfidence score, STD	0.004**	0.010**
	(0.002)	(0.005)
Objective cognitive ability, STD	0.002	0.004
	(0.002)	(0.003)
Family background	0.000	0.001
	(0.002)	(0.006)
Pre-university educational attainment	0.000	0.007
	(0.002)	(0.006)
Graduation and university subject		
STEM	0.016***	0.051***
	(0.003)	(0.012)
LEM	-0.002	-0.000
	(0.002)	(0.006)
OSSAH	-0.002	-0.002
	(0.002)	(0.008)
Other	-0.005***	-0.010**
	(0.002)	(0.005)
Having a co-habiting partner	0.004***	0.008*
	(0.002)	(0.004)
Having one child	0.001	0.003
	(0.001)	(0.003)
Having at least two children	0.001	-0.001
	(0.002)	(0.004)
Constant	0.025	0.106
	(0.057)	(0.160)
Observations	3,602	1,159

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. The model estimated here is the same as Model 7 in Table 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

When we turn our attention to the graduate subsample, overconfidence becomes slightly more important: men being more overconfident than women contributes six percent (0.010/0.161) to the gender gap and 14 percent (0.010/0.072) to the endowment gap. The results are otherwise broadly similar to the earlier results, with studying STEM being the most important factor in terms of both endowments and differential returns. Taken together, these results highlight the statistically significant contribution of overconfidence to the gender gap in the probability of being in a top job. Relative to university subject, specifically studying a STEM degree, its contribution is small. As previously discussed, it could be the case that overconfidence already shaped these decisions, i.e., whether to study STEM, so the fact that it still captures some of the endowment gap at age 42 is noteworthy.

The previous results highlight the importance of studying a STEM subject at university in explaining the gender gap in having a top job at age 42. Because of this and in line with Macmillan, Tyler, and Vignoles (2015), we disaggregate the top job category into two separate categories: top jobs in STEM and top jobs in LEM. The focus on Law, Economics, and Management (LEM) allows us to examine whether overconfidence plays a role in explaining the gender gap in jobs that may rely less on technical experience or be more susceptible to overconfident behavior.

Table 7: The Kitagawa-Blinder-Oaxaca decomposition of the gender gap in STEM and LEM top jobs: the role of overconfidence (sample of full time employed)

	STEM top jobs	LEM top jobs
Share of men in top jobs	0.080***	0.155***
	(0.006)	(0.008)
Share of women in top jobs	0.022***	0.121***
	(0.004)	(0.009)
Gender gap in top jobs	0.058***	0.034***
	(0.007)	(0.012)
Explained	0.018***	0.009*
	(0.004)	(0.005)
Unexplained	0.040***	0.026**
	(0.007)	(0.011)
	Explained by endowments	Explained by endowments
Overconfidence score, STD	0.001	0.004***
	(0.001)	(0.002)
Objective cognitive ability, STD	0.001	0.002
	(0.000)	(0.001)
Family background	0.001	-0.001
	(0.001)	(0.002)
Pre-university educational	0.001	-0.000
attainment	(0.001)	(0.002)
Graduation and university subject		
STEM	0.013***	0.002
	(0.003)	(0.002)
LEM	0.000	-0.002
	(0.000)	(0.002)
OSSAH	0.002**	-0.000
	(0.001)	(0.002)
Other	-0.001	-0.003**
	(0.001)	(0.001)
Having a co-habiting partner	-0.000	0.004***
	(0.001)	(0.001)
Having one child	0.000	0.001
	(0.001)	(0.001)
Having at least two children	-0.000	0.002
	(0.001)	(0.002)
Constant	0.051*	-0.032
	(0.027)	(0.050)
Observations	3,602	3,602

Source: BCS70 (CLS n.d.). Sample includes those individuals in full time employment. The model estimated here is the same as Model 7 in Table 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7 presents the separate decomposition results for the gender gap in STEM and LEM top jobs estimated on the sample of those who are full time employed. Unsurprisingly, the gender gap in STEM jobs is somewhat larger (0.058) than in LEM jobs (0.034). What emerges in terms of overconfidence, however, is interesting. Overconfidence no longer explains the endowment gap for STEM top jobs (its coefficient is small and no longer statistically significant), but it still matters for the LEM top jobs. Men being more overconfident than women explains 12 percent (0.004/0.034) of the gender gap, and 44 percent (0.004/0.009) of the endowment gap in LEM top jobs. This provides some indication that there are differences in the types of top jobs by sector and that overconfidence may be more important for reaching a top job in LEM.

5. Gender gap in the costs and benefits of working in a top job

As a final step in this paper, we probe some of the costs and benefits associated with working in a top job and examine how these differ by gender. If men and women in top jobs face different costs and benefits than men and women who are employed in regular jobs, this may explain some of the gender gap we observe in the probability of being in a top job at age 42.

Table 8: The gender gap in the costs and benefits of working in a top job (sample of those full time employed)

	(1)	(2)	(3)	(4)
	Outcome variables			
	Log hourly wage	Weekly hours worked	Having a cohabiting partner	Having children
Female	-0.149***	-5.763***	-0.066***	0.023
	(0.020)	(0.386)	(0.016)	(0.017)
Works in a top job	0.232***	-0.398	0.038**	0.031
	(0.033)	(0.541)	(0.016)	(0.021)
Female*top job interaction	0.029	3.077***	0.029	-0.101**
	(0.057)	(0.779)	(0.033)	(0.039)
Has cohabiting partner	0.039	0.799*		0.461***
	(0.024)	(0.448)		(0.018)
No. of children in HH: 1	0.012	-0.321	0.287***	
	(0.030)	(0.467)	(0.020)	
No. of children in HH: at least 2	0.079***	0.506	0.381***	
	(0.023)	(0.433)	(0.016)	
Constant	2.093***	44.161***	0.535***	0.280***
	(0.039)	(0.966)	(0.033)	(0.036)
Observations	3,441	3,602	3,602	3,602
R-squared	0.199	0.089	0.201	0.181

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, private/grammar secondary school at age 16.

Table 8 presents the results from a series of linear regressions that compares log hourly pay, weekly hours worked, the probability of living with a partner and having children among men and women who work in top vs regular jobs. We capture the gender difference in the costs and benefits of working in top jobs with an interaction term of top jobs and gender.

The results for log hourly pay highlight that working in a top job brings 23 log points higher hourly earnings (equivalent to 26 percent), while women face a gender pay gap of 15 log points (14 percent). The interaction term is small in magnitude and is not statistically significant; thus, the gender pay gap is not lower in top jobs than in regular jobs. In terms of hours worked, women work on average 5.7 hours less per week than men. This measure of weekly hours worked includes all hours, including contracted hours as well as paid and unpaid overtime. Interestingly, working in a top job is not associated with working higher hours on average. However, the interaction term is positive and significant, indicating that women work three hours more per week in top jobs than men in top jobs. Thus, while the gender pay gap is the same in top and regular jobs, women work relatively more in top jobs than in regular jobs. This may be a potential driver of why women are less likely to work in top jobs at age 42.

Lastly, we look at how the probability of having a partner and children are related to working in a top job. While these are not direct costs or benefits of working in a top job, it is interesting to see how top jobs are related to having a family. On average, women are less likely to have a cohabiting partner than men, while there is no gender difference in the probability of having children. Those in top jobs are more likely to have partners, as well as children, although this latter coefficient is not significant. The interaction term is insignificant when looking at partners, but it is large and significantly negative in predicting having children. Women in top jobs are 10 percentage points less likely to have children than men. This result, along with our earlier results, which showed no significant gender gap in top jobs among those having no partner or children (Table 5), suggest that for women, there is a substitution effect between working in top jobs and having a family. We find no evidence for a substitution effect for men.

6. Discussion

There is a large gender gap in the probability of being in a top job in mid-career. This gap emerges in late 20s and remains relatively stable throughout mid-career. This is problematic since top jobs are jobs with high earnings, high job security, and strong career prospects and trajectories. While previous literature, especially psychology and popular literature, has highlighted the importance of overconfidence in explaining gender inequality in the labor market, no previous work had explored the role of overconfidence in explaining the gender gap in who climbs the career ladder to a top job.

We set out to fill this gap in the literature using longitudinal data from the UK, which follows individuals from birth into mid-career. We construct a measure of overconfidence that affirms previous literature: men are more overconfident than women. Our measure of overconfidence is an improvement on previous measures used in the gender inequality literature. We use multiple measures of objective cognitive ability from a range of tests conducted at ages 5, 10, and 16, as well as multiple subjective estimated measures of ability from ages 10 and 16 to capture overestimation. By combining these, we construct an overconfidence measure that covers broad types of cognitive and self-assessment measures as well as multiple ages in one's life. Our measure is also captured before labor market entry, which should also assuage concerns about reverse causality. This gives us a more robust measure than the ones constructed using one-time measures of objective and subjective ability, often gathered in a laboratory or university classroom setting at the same time as the outcome measures.

We also use this measure of overconfidence to explain a gender gap in a real labor market outcome. When we use our measure of overconfidence to explain the gender gap in top jobs, we find that men being more overconfident than women explains 5-11 percent of the gender gap in top jobs, depending on the methods we use and subsamples we explore. This contribution is statistically significant. It indicates that overconfidence matters for gender inequality in the labor market. Those who are more overconfident, i.e., men, have a higher probability of being in a top job in mid-career even when we account for a range of previous educational and other labor market decisions.

Our work has some limitations. We construct our measure of overconfidence using secondary data, which were not originally captured to construct a measure of overconfidence. While we closely follow the psychological literature in how we define overconfidence, as the self-assessment questions in the survey are related to the individual's own ability, without a direct comparison to others, what we measure is closer to overestimation than to overplacement (comparing oneself to an explicit peer group or cohort). However, everyone lives in a social environment, and they might implicitly judge themselves compared to others, norms, or expectations, even if they are not asked to compare themselves explicitly to other people. It is possible that an individual answering these questions is implicitly comparing his/herself to a reference group (e.g. a class), which we cannot observe.

It may also be that our measure captures other facets of personality, i.e. self-esteem, laziness, or other traits. For example, overconfidence could be related to traits that would induce people to put less effort into their jobs. While we show that our measure continues to explain the same proportion of the gender gap in top jobs even when we control for self-esteem, we do not have measures available to test every possible trait. We believe, however, that such unobserved "negative" traits would decrease the contribution of overconfidence to the gender gap in top jobs. They would bias our estimated coefficients on overconfidence downwards, so in the worst-case scenario, our estimates are overly conservative.

The magnitude of our findings, between 5-11 percent of the gender gap in the probability in being in a top job, is somewhat smaller than previous estimates using expected wages, but still meaningful. In the gender wage gap papers which explored overconfidence using expected wages amongst university students, overconfidence accounted for between 8-18% of the expected gender wage gap (Briel et al. 2020; Reuben, Wiswall, and Zafar 2017). The fact that overconfidence accounts for a larger portion of this gap as compared to ours is logical since it is based purely on expectations, not on actual labor market outcomes. Our measure is captured in adolescence and still explains a gender gap in actual labor market outcomes at age 42. This highlights its importance.

Previous literature using non-cognitive skills to explain the gender wage gap (again, not our outcome) found results of a similar magnitude for a range of traits including self-confidence, self-esteem, and locus of control (Blau and Kahn 2017). These factors were found to explain between 4-14 percent of the gender wage gap using survey data (Cattan 2013; Fortin 2008; Nyhus and Pons 2012). Even though we examine a different outcome and use overconfidence, our results seem in line with previous work on non-cognitive traits.

Interestingly, overconfidence is not significantly related to the probability of working in a top job when we restrict the sample to only those with a partner or with children. This indicates that other factors, including children, partnership, and university subject studied (especially STEM), matter more for explaining the gender gap in top jobs, which has already been shown in the literature for wages (Blau and Kahn 2017). Of course, overconfidence may drive these decisions as well, and the fact that including educational outcomes in the models reduces the magnitude of the overconfidence coefficient highlights this.

Our findings have important policy implications. Our results show that overconfidence contributes to the gender gap in who ends up in a top job. This may be because men are more likely to assess themselves favorably at work and therefore apply for promotion at an earlier stage. Gender differences in self-assessment and promotion may be an important channel through which overconfidence manifests (Exley and Kessler 2022). Employers should consider these inaccurate self-assessments when promoting employees in order to improve gender equity in the workplace.

Taken together, the results in this paper show that overconfidence is a statistically significant explanatory factor in the gender gap in the probability of being in a top job in mid-career. Overconfidence matters, but our results do not support the story that women are "holding themselves" back in the labor market because they are underconfident. Instead, other individual and societal factors create barriers that prevent women from entering top jobs while overconfidence helps to propel some individuals forward. Improving gender equality in access to top jobs will require more than confidence building interventions.

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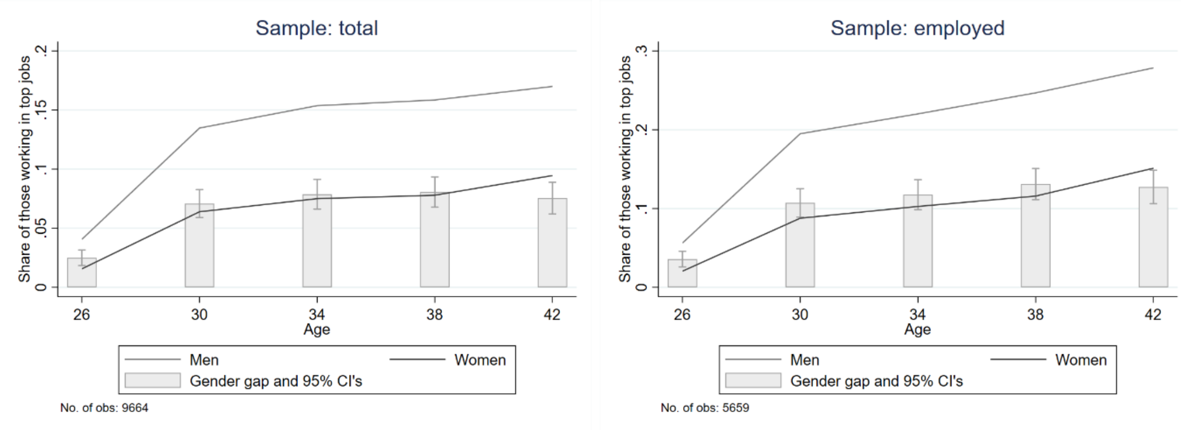
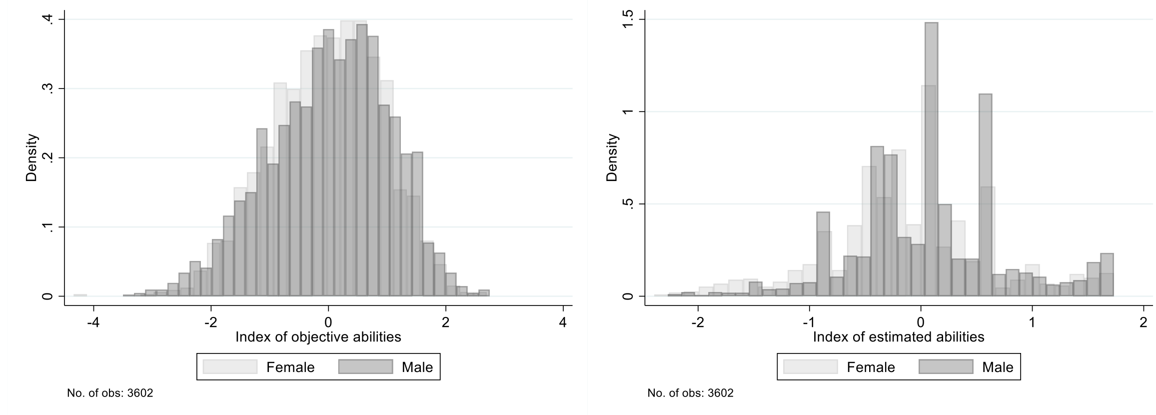
Appendix A

Figure A1: The share of those in top jobs by gender (alternative samples)



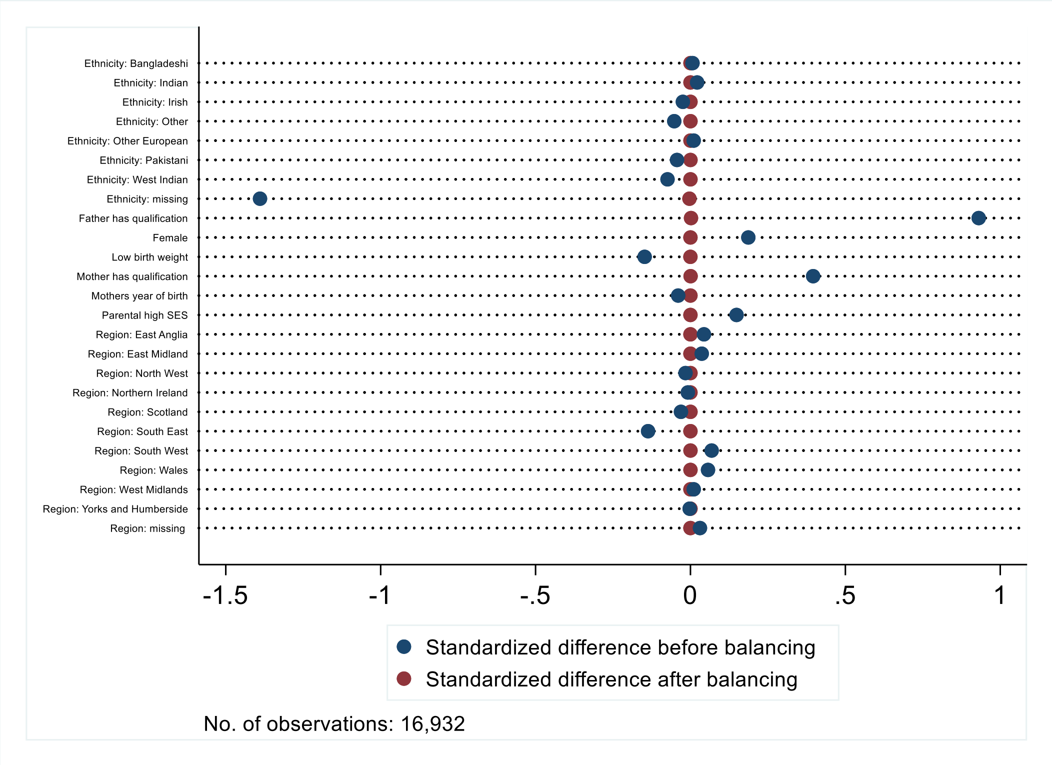
Source: BCS70 (CLS n.d.).

Figure A2: The distribution of objective and subjective abilities by gender



Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42.

Figure A3: The balance of the BCS70 sample: those in the main estimation sample vs. those who dropped out (standardized differences between the two groups before and after entropy balancing)



Source: BCS70 (CLS n.d.). Baseline categories of categorical variables are not plotted (Ethnicity: English; Region: North). Entropy balancing is a reweighting procedure to achieve covariate balance with binary treatments based on the moments of the covariates (Hainmueller 2011).

Table A1: Measures on cognitive abilities in BCS70, age 5, 10 and 16

Age 5	
English Picture Vocabulary Test	56 sets of four different pictures with a particular word associated with each set of four pictures, increasing in difficulty. The child was asked to indicate the one picture that corresponded to the given word until the child made five mistakes in a run of eight consecutive items. The first two words were drum and time, the last two are reel and coast.
Copying Designs Test	The child was given a booklet, and asked to copy 8 drawings, one at a time twice on two consecutive pages of booklet.
Human Figure Drawing	The child was asked to 'make a picture of a man or a lady'. (Terms such as 'daddy', 'mummy', 'boy', 'girl', etc., could be used if the child responded better to those). They were asked to make the best picture they could and to draw a whole person, not just a face or head. When the child had finished, if anything was not clear, the child was asked what the various parts of the drawings were and these were labelled.
Complete a Profile Test	The child was asked to complete an outline picture of a human face in profile by filling in features (eyes, ears, nostrils, mouth, hair etc.).
Schonell Reading Test	Children's reading age (of children between age 5 and 14+ years). Reading age is calculated from the number of words read correctly and compared to the child's chronological age. Before the test was administered, the child's mother was asked if she thought the child had begun to read at all. If the mother said the child could read some words or some sentences the child was given a card with 50 words on it, which were read from left to right. When a child struggled with a word, they were asked to sound it out. If the child still couldn't say what the word was, they were asked to try the next one. The test was stopped when the child made five consecutive mistakes.
Age 10	
Edinburgh Reading Test	A test of word recognition, which examined vocabulary, syntax, sequencing, comprehension and retention. Items were carefully selected to cover a wide age range of ability from seven to thirteen years in a form suitable to straddle the ten-year cohort. Particular attention was paid to the lower limit to allow a score to be allocated for very poor readers.
Friendly Maths Test	Mathematical competence, ranging from early awareness of number operations to expected mathematics ability at 13 years old, including arithmetic, number skills, fractions, measures, algebra, geometry and statistics.
Spelling Dictation Task	A paragraph was dictated to the child including both real and made up words. A sentence could be repeated once and an imaginary word in the middle of the passage could be repeated twice.
British Ability Scales (BAS) Word Definitions	For each item on the scale, a word was orally presented to the child who was asked what the word meant. Items were scored as correct or incorrect according to whether or not the child expressed key concepts of the word's meaning. The assessment was stopped after four successive incorrect or partially incorrect words.
BAS Word Similarities	The test consisted of 21 items made up of 3 words e.g. orange, banana, strawberry. The teacher read the three words and asked the child to name another word consistent with the group i.e. another type of fruit. The child then had to say what the words had in common i.e. they are all fruits. When the child was unable to name a group example and name on four successive attempts the test was stopped.
BAS Recall of Digits	For each item the teacher read out digits and asked the child to repeat them. The exercise increased in difficulty from remembering and repeating two digits to three digits and then up to eight digits. If the child asked for a repeat of the numbers, this was scored as incorrect. The test was stopped after four consecutive incorrect responses.
BAS Matrices	Each matrix was a square consisting of four or nine cells, with a blank cell in the lower right corner of each matrix. The teacher asked the child to complete each item by drawing the appropriate shape in the empty square. There were seven example items, three at the start of the exercise, then four examples when the level of difficulty increased. The task was stopped when four successive items were drawn incorrectly or when it was apparent that the level of difficulty was too great.

Pictorial Language Comprehension Test	The test consisted of 100 sets of four different pictures with a particular word associated with each set of four pictures, increasing in difficulty. The child was asked to indicate the one picture that corresponded to the given word. For the vocabulary Items only, the test continued until the child had five successive failures.
Age 16	
Applied Psychology Unit (APU) Arithmetic Test	Measures general arithmetic attainment (and not aptitude). Designed to test arithmetic concepts through calculation. Covers evaluation of arithmetic expressions, knowledge of proportion, percentage, estimation of area and simple probability. It tests the ability to reproduce and therefore the aptitude to learning arithmetic processes.
APU Vocabulary	75 words in the test. Each word was followed by a multiple-choice list of 5 words from which the respondent picked the one with the same meaning as the first word. The test got progressively harder.
BAS Matrices	Same procedure as at age 10.
Edinburgh Reading Test	Measures reading skills, and includes five sub-scales examining vocabulary, syntax, sequencing, comprehension and retention.
Spelling Test	Spelling was assessed by two tests (A and B). 100 words for each test - some spelt correctly and some incorrectly, CM identifies whether correct or incorrect. The words get harder as the test progresses. Order of test rotated by odd and even days.

Source: Moulton et al. (2020). We construct a summary index from these 18 measures the following way. First, we standardize all these continuous measures to mean 0 and SD 1. Then, we use Confirmatory Factor Analysis (CFA) to estimate the underlying objective cognitive skills variable via Full Information Maximum Likelihood (*Structural Equation Modeling Reference Manual*, 2017). Thus, if at least one of these measures is available for a person, we will estimate the index for them. We standardize the estimated index Table A3 in Appendix A shows the descriptive statistics of the measures by gender and Table 1 in Section 2 shows the estimated index of objective cognitive skills.

Table A2: Measures on subjective estimated abilities in BCS70, age 10 and 16

Age 10	
Good at math	Question: Are you good at mathematics? Yes/No/I don't know.
Good at spelling	Question: Are you good at spelling? Yes/No/I don't know.
Age 16	
Good at math	Question: Are you good at mathematics? *Yes/No/I don't know*
Good at spelling	Question: Are you good at spelling? *Yes/No/I don't know*
Clever	Please say whether the following applies to you. *Applies very much/Applies somewhat/Does not apply* I am clever.
Good at exams	Please say whether the following applies to you. *Applies very much/Applies somewhat/Does not apply* I am good at exams.
Not good at school (inverted)	Please say whether the following applies to you. *Applies very much/Applies somewhat/Does not apply* I am not very good at school.

Source: Public BCS70 TBA. We construct a summary index from these seven categorical (ordinal) measures using Item Response Theory (IRT). We fit graded response models to these measures, and we allow them to vary in their difficulty and discrimination. Again, we exploit all information: if at least one of these measures is available for a person, we will estimate the latent index for them. Table A3 in Appendix A shows the descriptive statistics of the measures by gender and Table 1 shows the estimated index of subjective cognitive skills.

Table A3: Additional descriptive statistics

	Obs	Mean men	Mean women	Diff. (Women-men)	SE of Diff.	Two-tailed t-test p-values
Ethnicity						
English, etc	3602	0.94	0.93	-0.01	0.01	0.33
Irish	3602	0.00	0.00	0.00	0.00	0.77
Other European	3602	0.00	0.00	0.00	0.00	0.14
West Indian	3602	0.00	0.01	0.00	0.00	0.19
Indian	3602	0.01	0.02	0.01	0.00	0.03
Pakistani	3602	0.00	0.00	0.00	0.00	0.90
Bangladeshi	3602	0.00	0.00	0.00	0.00	0.32
Other	3602	0.00	0.00	0.00	0.00	0.16
Region						
North	3602	0.08	0.08	0.01	0.01	0.56
Yorks and Humberside	3602	0.09	0.10	0.01	0.01	0.34
East Midlands	3602	0.06	0.06	-0.01	0.01	0.43
East Anglia	3602	0.04	0.03	-0.01	0.01	0.10
South East	3602	0.26	0.23	-0.03	0.01	0.02
South West	3602	0.06	0.06	0.00	0.01	0.98
West Midlands	3602	0.11	0.11	0.00	0.01	0.89
North West	3602	0.13	0.14	0.01	0.01	0.39
Wales	3602	0.06	0.06	0.00	0.01	0.82
Scotland	3602	0.09	0.11	0.02	0.01	0.02
Northern Ireland	3602	0.00	0.00	0.00	0.00	0.39
Region is missing	3602	0.02	0.03	0.00	0.01	0.94
Mother has a qualification	3602	0.55	0.56	0.00	0.02	0.83
High SES parents	3602	0.37	0.35	-0.02	0.02	0.14
Mother's year of birth	3596	1943.9	1944.3	0.35	0.18	0.05
Cognitive skills at age 5						
Schonell reading score, age 5	3171	1.52	1.89	0.37	0.16	0.02
Standardised Copy Designs	3249	0.17	0.09	-0.08	0.03	0.03
Profile Test Score	3151	7.11	6.93	-0.18	0.14	0.21
Standardised Human Fig Drawing	3227	-0.01	0.19	0.20	0.03	0.00
Standardised EPVT	3083	0.33	0.05	-0.29	0.04	0.00
Cognitive skills at age 10						

Standardised Edinburgh Reading Test score, age 10	2829	0.20	0.26	0.06	0.03	0.09
Friendly Maths Test score, age 10	3192	47.87	46.03	-1.84	0.41	0.00
Spelling Dictation Task, age 10	3283	35.33	37.93	2.60	0.35	0.00
BAS Word Definitions, age 10	3166	11.79	10.32	-1.47	0.18	0.00
BAS Word Similarities, age 10	3152	12.82	12.35	-0.48	0.09	0.00
BAS Recall of Digits, age 10	3161	23.69	23.79	0.09	0.15	0.53
BAS Matrices, age 10	3157	16.42	16.77	0.35	0.19	0.06
Pictorial Language Comprehension Test, age 10	3345	64.31	62.36	-1.95	0.36	0.00
Cognitive skills at age 16						
Arithmetic scores, age 16	1266	38.73	38.82	0.09	0.63	0.89
BAS Matrices, age 16	1110	8.96	9.18	0.22	0.09	0.02
Edinburgh Reading Test score, age 16	1083	56.29	57.29	1.00	0.73	0.17
Spelling, age 16	2027	161.79	167.90	6.12	1.10	0.00
Standardised Vocabulary Test score, age 16	1832	0.09	0.17	0.09	0.04	0.04
Academic self-concept						
Good at math, age 10	3320	2.31	2.14	-0.17	0.03	0.00
Good at math, age 16	1966	2.34	1.99	-0.35	0.04	0.00
Good at spelling, age 10	3297	2.20	2.25	0.04	0.03	0.15
Good at spelling, age 16	1983	2.30	2.27	-0.03	0.04	0.45
Clever	2006	2.23	2.06	-0.17	0.02	0.00
Good at exams	2004	2.04	1.94	-0.10	0.03	0.00
Good at school	1976	2.57	2.56	-0.02	0.03	0.51
University and subject						
No degree	3602	0.73	0.69	-0.03	0.02	0.02
STEM	3602	0.10	0.05	-0.05	0.01	0.00
LEM	3602	0.05	0.05	0.01	0.01	0.39
OSSAH	3602	0.03	0.08	0.06	0.01	0.00
Other	3602	0.01	0.01	0.01	0.00	0.02
Combined	3602	0.01	0.03	0.01	0.00	0.01
Elite STEM	3602	0.05	0.03	-0.02	0.01	0.02
Elite LEM	3602	0.01	0.01	0.00	0.00	0.65
Elite OSSAH	3602	0.02	0.03	0.01	0.01	0.03
Elite other	3602	0.00	0.00	0.00	0.00	0.68
Elite combined	3602	0.01	0.01	0.00	0.00	0.31
Secondary school type						

Public school	3602	0.90	0.92	0.01	0.01	0.15
Private or grammar school	3602	0.09	0.08	-0.01	0.01	0.19
School type is missing	3602	0.00	0.00	0.00	0.00	0.37
Math exam and grade at age 16						
No math O/CSE	3602	0.14	0.15	0.01	0.01	0.35
Grade A/1	3602	0.14	0.10	-0.03	0.01	0.00
Grade B/2	3602	0.15	0.14	-0.01	0.01	0.46
Grade C/3	3602	0.15	0.20	0.05	0.01	0.00
Grade D/4	3602	0.07	0.09	0.02	0.01	0.02
Grade E/5	3602	0.03	0.05	0.02	0.01	0.01
Failed	3602	0.00	0.00	0.00	0.00	0.52
No info	3602	0.32	0.26	-0.06	0.02	0.00
A-levels	3602	0.19	0.23	0.04	0.01	0.00
Self-esteem	3602	15.22	15.05	-0.17	0.08	0.04
Missing flag of self-esteem	3602	0.55	0.44	-0.10	0.02	0.00

Notes: A positive difference denotes women have a higher score or probability. Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42.

Table A4: Descriptive statistics on those working in top jobs vs. regular jobs

	Obs	Mean of those in regular jobs	Mean of those in top jobs	Diff. (top job-regular)	SE of Diff.	Two-tailed t-test p-values
Female	3602	0.42	0.30	-0.12	0.02	0.00
Log hourly pay	3441	2.22	2.65	0.43	0.03	0.00
Weekly hours worked	3602	43.44	45.53	2.10	0.39	0.00
Objective cognitive ability, STD	3602	0.07	0.67	0.60	0.03	0.00
Academic self-concept score	3602	0.00	0.37	0.36	0.03	0.00
Overconfidence score, STD	3602	-0.01	0.22	0.23	0.04	0.00
Overconfidence score, squared	3602	1.02	0.98	-0.05	0.04	0.24
Overconfidence score quintiles	3602	2.98	3.37	0.39	0.06	0.00
Overconfidence score quintiles	3602	0.19	0.29	0.09	0.02	0.00
Overconfidence score tertials compared to the middle	3602	2.00	2.10	0.10	0.04	0.01
Has cohabiting partner, age 42	3602	0.76	0.85	0.09	0.02	0.00
No. of children in HH, age 42	3602	1.10	1.22	0.12	0.04	0.00
Ethnicity						

English, etc	3602	0.93	0.94	0.01	0.01	0.30
Irish	3602	0.00	0.00	0.00	0.00	0.36
Other European	3602	0.00	0.00	0.00	0.00	0.20
West Indian	3602	0.01	0.00	0.00	0.00	0.02
Indian	3602	0.01	0.02	0.01	0.01	0.07
Pakistani	3602	0.00	0.00	0.00	0.00	0.48
Bangladeshi	3602	0.00	0.00	0.00	0.00	0.32
Other	3602	0.00	0.00	0.00	0.00	0.16
Region						
North	3602	0.08	0.07	-0.01	0.01	0.21
Yorks and Humberside	3602	0.09	0.09	0.00	0.01	0.86
East Midlands	3602	0.06	0.08	0.02	0.01	0.04
East Anglia	3602	0.04	0.02	-0.02	0.01	0.00
South East	3602	0.24	0.29	0.06	0.02	0.00
South West	3602	0.07	0.06	-0.01	0.01	0.50
West Midlands	3602	0.11	0.11	0.00	0.01	0.86
North West	3602	0.13	0.11	-0.03	0.01	0.05
Wales	3602	0.06	0.05	-0.01	0.01	0.16
Scotland	3602	0.10	0.09	-0.01	0.01	0.41
Northern Ireland	3602	0.00	0.00	0.00	0.00	0.95
Region is missing	3602	0.02	0.03	0.01	0.01	0.46
Mother has a qualification	3602	0.55	0.73	0.18	0.02	0.00
High SES parents	3602	0.32	0.51	0.18	0.02	0.00
Mother's year of birth	3596	1944.20	1943.44	-0.76	0.21	0.00
Cognitive skills at age 5						
Schonell reading score, age 5	3171	1.48	2.37	0.89	0.21	0.00
Standardised Copy Designs	3249	0.07	0.40	0.33	0.04	0.00
Profile Test Score	3151	6.98	7.24	0.25	0.17	0.14
Standardised Human Fig Drawing	3227	0.05	0.15	0.10	0.04	0.02
Standardised EPVT	3083	0.14	0.51	0.36	0.04	0.00
Cognitive skills at age 10						
Standardised Edinburgh Reading Test score, age 10	2829	0.12	0.61	0.49	0.04	0.00
Friendly Maths Test score, age 10	3192	45.62	52.95	7.33	0.44	0.00
Spelling Dictation Task, age 10	3283	35.50	39.50	4.01	0.37	0.00

BAS Word Definitions, age 10	3166	10.67	13.25	2.58	0.22	0.00
BAS Word Similarities, age 10	3152	12.41	13.50	1.10	0.10	0.00
BAS Recall of Digits, age 10	3161	23.45	24.77	1.32	0.18	0.00
BAS Matrices, age 10	3157	16.12	18.19	2.07	0.21	0.00
Pictorial Language Comprehension Test, age 10	3345	62.43	67.75	5.32	0.42	0.00
Cognitive skills at age 16						
Arithmetic scores, age 16	1266	37.33	43.68	6.35	0.71	0.00
BAS Matrices, age 16	1110	8.95	9.36	0.40	0.10	0.00
Edinburgh Reading Test score, age 16	1083	55.12	62.06	6.94	0.68	0.00
Spelling, age 16	2027	162.86	170.39	7.52	1.17	0.00
Standardised Vocabulary Test score, age 16	1832	0.02	0.47	0.45	0.05	0.00
Academic self-concept						
Good at math, age 10	3320	2.20	2.40	0.20	0.03	0.00
Good at math, age 16	1966	2.10	2.46	0.36	0.05	0.00
Good at spelling, age 10	3297	2.21	2.27	0.07	0.04	0.07
Good at spelling, age 10	1983	2.27	2.36	0.09	0.05	0.04
Clever	2006	2.09	2.37	0.28	0.03	0.00
Good at exams	2004	1.93	2.24	0.31	0.03	0.00
Good at school	1976	2.51	2.75	0.24	0.03	0.00
University and subject						
No degree	3602	0.79	0.43	-0.36	0.02	0.00
STEM	3602	0.06	0.17	0.11	0.01	0.00
LEM	3602	0.03	0.10	0.07	0.01	0.00
OSSAH	3602	0.05	0.05	0.00	0.01	0.89
Other	3602	0.01	0.01	0.01	0.00	0.11
Combined	3602	0.02	0.03	0.02	0.01	0.02
Elite STEM	3602	0.02	0.12	0.10	0.01	0.00
Elite LEM	3602	0.00	0.03	0.03	0.01	0.00
Elite OSSAH	3602	0.02	0.03	0.01	0.01	0.13
Elite other	3602	0.00	0.00	0.00	0.00	0.12
Elite combined	3602	0.01	0.02	0.01	0.01	0.02
Secondary school type						
Public school	3602	0.93	0.84	-0.09	0.01	0.00
Private or grammar school	3602	0.07	0.16	0.09	0.01	0.00

School type is missing	3602	0.00	0.00	0.00	0.00	0.80
Math exam and grade at age 16						
No math O/CSE	3602	0.16	0.07	-0.09	0.01	0.00
Grade A/1	3602	0.09	0.23	0.14	0.02	0.00
Grade B/2	3602	0.14	0.20	0.07	0.02	0.00
Grade C/3	3602	0.17	0.17	0.00	0.02	0.96
Grade D/4	3602	0.08	0.06	-0.02	0.01	0.03
Grade E/5	3602	0.04	0.03	-0.02	0.01	0.01
Failed	3602	0.00	0.00	0.00	0.00	0.00
No info	3602	0.31	0.24	-0.07	0.02	0.00
A-levels	3602	0.16	0.40	0.24	0.02	0.00
Self-esteem	3602	15.04	15.60	0.56	0.10	0.00
Missing flag of self-esteem	3602	0.52	0.47	-0.04	0.02	0.03

Notes: A positive difference denotes that the characteristic is higher for those working in top jobs. Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42.

Table A5: Overconfidence as a potential selection mechanism

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Participation in the age-42 wave	Employed	Employed full time	Graduate	Graduate if employed full time	Has partner	Has partner if employed full time	Has children	Has children if employed full time
Sample	Sample of those who have age 5, 10 and 16 data	Total sample of those who have age 42 data	Employed	Total sample of those who have age 42 data	Full-time employed	Total sample of those who have age 42 data	Full-time employed	Total sample of those who have age 42 data	Full-time employed
Unconditional models									
Female	-0.095***	-0.101***	-0.288***	0.015	0.057***	-0.016	-0.092***	0.225***	-0.149***
	(0.010)	(0.008)	(0.012)	(0.011)	(0.016)	(0.011)	(0.015)	(0.021)	(0.030)
Overconfidence score, STD	-0.000	0.004	0.009	0.066***	0.063***	0.006	0.003	-0.018	-0.023
	(0.007)	(0.005)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)	(0.017)	(0.020)
Female*overconfidence score	0.006	-0.000	0.001	-0.014	-0.014	-0.005	-0.006	0.016	0.028
	(0.009)	(0.008)	(0.012)	(0.011)	(0.016)	(0.011)	(0.015)	(0.021)	(0.030)
Constant	0.371***	0.922***	0.783***	0.266***	0.296***	0.774***	0.816***	1.136***	1.185***

	(0.007)	(0.005)	(0.008)	(0.008)	(0.010)	(0.008)	(0.008)	(0.016)	(0.019)
Observations	9,664	6,523	5,659	6,544	3,602	6,544	3,602	6,544	3,602
R-squared	0.011	0.023	0.091	0.017	0.017	0.001	0.012	0.018	0.007
Conditional models									
Female	0.054***	-0.101***	-0.291***	0.005	0.040***	-0.013	-0.086***	0.234***	-0.135***
	(0.008)	(0.008)	(0.012)	(0.009)	(0.014)	(0.011)	(0.015)	(0.022)	(0.030)
Overconfidence score, STD	-0.001	0.001	0.005	0.028***	0.022**	0.003	0.000	-0.022	-0.029
	(0.006)	(0.005)	(0.008)	(0.007)	(0.009)	(0.008)	(0.009)	(0.017)	(0.020)
Female*overconfidence score	0.002	-0.001	-0.000	-0.012	-0.004	-0.006	-0.006	0.017	0.035
	(0.008)	(0.008)	(0.012)	(0.009)	(0.013)	(0.010)	(0.015)	(0.021)	(0.030)
Objective cognitive ability, STD	0.025***	0.039***	0.028***	0.090***	0.097***	0.039***	0.042***	0.022	0.036*
	(0.005)	(0.006)	(0.008)	(0.006)	(0.009)	(0.007)	(0.009)	(0.014)	(0.020)
Region at birth = 2, Yorks and Humberside	0.010	0.024	-0.031	-0.015	0.002	0.012	-0.001	-0.004	-0.043
	(0.021)	(0.021)	(0.030)	(0.023)	(0.032)	(0.027)	(0.036)	(0.053)	(0.072)
Region at birth = 3, East Midlands	0.024	-0.007	-0.098***	-0.038	0.004	0.011	-0.004	0.026	-0.056
	(0.022)	(0.023)	(0.032)	(0.024)	(0.035)	(0.029)	(0.039)	(0.057)	(0.081)
Region at birth = 4, East Anglia	0.018	-0.005	-0.128***	-0.044	-0.018	0.099***	0.074*	0.215***	0.155
	(0.026)	(0.027)	(0.039)	(0.028)	(0.043)	(0.031)	(0.043)	(0.066)	(0.098)
Region at birth = 5, South East	0.019	-0.007	-0.081***	-0.044**	-0.041	0.018	0.020	0.086*	0.092
	(0.017)	(0.018)	(0.025)	(0.020)	(0.028)	(0.023)	(0.030)	(0.044)	(0.061)
Region at birth = 6, South West	0.046**	0.003	-0.107***	-0.055**	-0.041	0.027	0.048	0.099*	0.074
	(0.022)	(0.022)	(0.032)	(0.023)	(0.035)	(0.028)	(0.038)	(0.055)	(0.080)
Region at birth = 7, West Midlands	0.020	0.005	-0.031	-0.023	-0.021	0.034	0.063*	0.103**	0.177***
	(0.020)	(0.020)	(0.029)	(0.022)	(0.031)	(0.026)	(0.033)	(0.051)	(0.069)
Region at birth = 8, North West	-0.003	-0.003	-0.026	-0.015	-0.016	0.028	0.033	0.038	0.059
	(0.019)	(0.020)	(0.027)	(0.021)	(0.030)	(0.025)	(0.033)	(0.049)	(0.067)
Region at birth = 9, Wales	0.052**	-0.013	-0.065*	0.019	0.033	0.014	0.028	0.095*	0.149*
	(0.021)	(0.024)	(0.033)	(0.025)	(0.037)	(0.029)	(0.039)	(0.057)	(0.080)
Region at birth = 10, Scotland	0.024	0.020	0.000	0.083***	0.102***	0.048*	0.072**	0.081	0.122*
	(0.020)	(0.021)	(0.030)	(0.024)	(0.034)	(0.027)	(0.034)	(0.052)	(0.071)
Region at birth = 11, Northern Ireland	0.020	0.000	0.169	0.170	0.110	0.254***	0.264***	-0.201	-0.003
	(0.106)	(0.120)	(0.194)	(0.131)	(0.160)	(0.027)	(0.037)	(0.353)	(0.390)

Region at birth = 99, Region is missing	0.019	0.009	-0.072	-0.040	-0.055	-0.036	-0.011	0.072	0.199*
	(0.029)	(0.030)	(0.045)	(0.033)	(0.048)	(0.041)	(0.052)	(0.077)	(0.105)
High SES parents	0.009	-0.002	-0.043***	0.043***	0.045***	-0.002	-0.016	0.004	-0.020
	(0.009)	(0.009)	(0.014)	(0.011)	(0.016)	(0.012)	(0.016)	(0.024)	(0.034)
Mother has a qualification	0.004	0.023**	0.010	0.041***	0.033**	-0.000	0.002	0.013	0.006
	(0.009)	(0.009)	(0.014)	(0.010)	(0.015)	(0.012)	(0.015)	(0.023)	(0.033)
ETHNIC GROUP STUDY CHILD 1 = 2, Irish	-0.059	-0.057	0.020	0.054	0.164	-0.175	-0.210	-0.344	-0.320
	(0.064)	(0.092)	(0.114)	(0.073)	(0.130)	(0.113)	(0.165)	(0.213)	(0.299)
ETHNIC GROUP STUDY CHILD 1 = 3, Other European	0.096**	0.077	-0.156	0.001	-0.056	-0.021	-0.121	0.197	0.151
	(0.044)	(0.049)	(0.104)	(0.069)	(0.080)	(0.085)	(0.138)	(0.156)	(0.294)
ETHNIC GROUP STUDY CHILD 1 = 4, West Indian	-0.094*	-0.009	-0.036	0.093	0.105	-0.348***	-0.282**	-0.254*	-0.156
	(0.053)	(0.064)	(0.091)	(0.058)	(0.083)	(0.080)	(0.117)	(0.138)	(0.219)
ETHNIC GROUP STUDY CHILD 1 = 5, Indian	-0.005	0.022	0.090	0.131***	0.071	0.007	-0.018	0.007	-0.012
	(0.041)	(0.045)	(0.063)	(0.050)	(0.061)	(0.054)	(0.071)	(0.111)	(0.146)
ETHNIC GROUP STUDY CHILD 1 = 6, Pakistani	-0.150*	0.040	-0.147	0.152*	0.147	0.093	0.115	0.469***	0.537**
	(0.081)	(0.075)	(0.133)	(0.089)	(0.145)	(0.093)	(0.108)	(0.178)	(0.220)
ETHNIC GROUP STUDY CHILD 1 = 7, Bangladeshi	0.182***	-0.464*	0.450***	0.404	0.239***	-0.073	-0.780***	0.001	-1.052***
	(0.032)	(0.250)	(0.028)	(0.255)	(0.032)	(0.313)	(0.031)	(0.579)	(0.068)
ETHNIC GROUP STUDY CHILD 1 = 8, Other	-0.113	-0.070	-0.136	0.156	0.139	0.029	0.212***	-0.590*	-0.559
	(0.113)	(0.179)	(0.178)	(0.227)	(0.194)	(0.175)	(0.032)	(0.323)	(0.389)
ETHNIC GROUP STUDY CHILD 1 = 99, Ethnicity is missing	-0.059***	0.017	-0.058**	0.007	0.038	-0.018	-0.021	0.043	0.093
	(0.019)	(0.020)	(0.029)	(0.022)	(0.033)	(0.026)	(0.035)	(0.050)	(0.071)
private_grammar = 1, Private or grammar school	0.029*	-0.040***	-0.044*	0.098***	0.093***	0.032*	0.030	0.084**	0.126**
	(0.015)	(0.015)	(0.023)	(0.020)	(0.027)	(0.018)	(0.023)	(0.040)	(0.055)
private_grammar = 99, School type is missing	-0.732***	0.000	0.070	-0.016	-0.015	0.021	0.103	-0.314	0.130
	(0.007)	(0.097)	(0.134)	(0.034)	(0.054)	(0.104)	(0.113)	(0.228)	(0.283)

math_O_CSE = 1, Grade A/1	0.009	0.038**	0.021	0.146***	0.160***	0.060***	0.049*	0.105**	0.079
	(0.017)	(0.018)	(0.026)	(0.022)	(0.030)	(0.022)	(0.029)	(0.047)	(0.065)
math_O_CSE = 2, Grade B/2	-0.014	0.046***	0.015	0.100***	0.109***	0.032	0.015	0.042	0.082
	(0.016)	(0.016)	(0.024)	(0.019)	(0.026)	(0.021)	(0.028)	(0.042)	(0.059)
math_O_CSE = 3, Grade C/3	0.014	0.055***	0.027	0.062***	0.087***	0.041**	0.020	0.018	0.058
	(0.015)	(0.016)	(0.023)	(0.017)	(0.024)	(0.020)	(0.027)	(0.039)	(0.056)
math_O_CSE = 4, Grade D/4	0.016	0.043**	-0.040	0.003	0.020	0.036	0.028	0.015	0.013
	(0.017)	(0.019)	(0.027)	(0.017)	(0.026)	(0.023)	(0.032)	(0.044)	(0.067)
math_O_CSE = 5, Grade E/5	-0.034	0.012	0.036	-0.013	-0.005	0.034	-0.000	-0.031	-0.073
	(0.023)	(0.025)	(0.034)	(0.022)	(0.034)	(0.030)	(0.042)	(0.057)	(0.082)
math_O_CSE = 6, Failed	-0.005	0.020	0.289***	-0.037	-0.075	-0.099	-0.031	-0.144	-0.092
	(0.085)	(0.101)	(0.090)	(0.092)	(0.114)	(0.134)	(0.154)	(0.240)	(0.298)
math_O_CSE = 99, No info	-0.045***	0.011	-0.015	0.009	0.028	0.037**	0.053**	0.035	0.074
	(0.012)	(0.014)	(0.020)	(0.012)	(0.018)	(0.017)	(0.023)	(0.033)	(0.048)
A_level = 1	0.043***	-0.006	0.018	0.370***	0.367***	0.012	-0.008	-0.068**	-0.079*
	(0.011)	(0.011)	(0.017)	(0.017)	(0.022)	(0.015)	(0.019)	(0.032)	(0.043)
Constant	0.731***	0.883***	0.846***	0.115***	0.109***	0.711***	0.752***	1.026***	1.048***
	(0.019)	(0.020)	(0.027)	(0.020)	(0.028)	(0.026)	(0.033)	(0.050)	(0.067)
Observations	9,664	6,523	5,659	6,544	3,602	6,544	3,602	6,544	3,602
R-squared	0.321	0.046	0.108	0.334	0.307	0.023	0.033	0.027	0.022

Source: public BSC70 TBA. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, pre-university educational attainment, private/grammar secondary school at age 16.

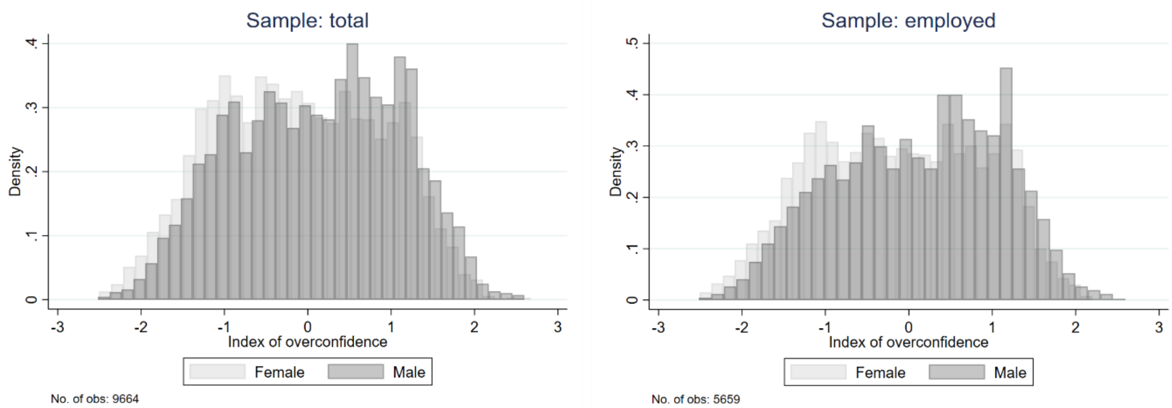
Table A6: Heterogeneity in the probability of being in top job by parental SES and objective cognitive skills

VARIABLES	(1) Low cognitive skills	(2) High cognitive skills	(3) Low parental SES	(4) High parental SES
Female	-0.056***	-0.063***	-0.036**	-0.111***
	(0.015)	(0.021)	(0.015)	(0.024)
Overconfidence score, STD	0.007	0.025**	0.011	0.026**
	(0.008)	(0.010)	(0.007)	(0.012)
Constant	0.046	0.074	0.074**	0.086
	(0.035)	(0.052)	(0.031)	(0.065)
Observations	1,711	1,891	2,299	1,303
R-squared	0.119	0.162	0.150	0.217

Source: public BSC70 TBA. Sample of those in full-time employment at age 42. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16, whether having a cohabiting partner, No. of children in the household.

Appendix B: Robustness checks

Figure B1: The distribution of the overconfidence score by gender for different samples



Source: BCS70 (CLS n.d.).

Table B1: Descriptive statistics: total sample

	Obs	Mean men	Mean women	Diff. (Women-men)	Two-tailed t-test p-values
Works in a top job, age 42	6544	0.20	0.09	-0.11	0.00
STEM top job	9664	0.04	0.01	-0.03	0.00
LEM top job	9664	0.08	0.05	-0.03	0.00
Log hourly pay	4552	2.38	2.14	-0.24	0.00
Weekly hours worked	6544	41.75	26.34	-15.42	0.00
Objective cognitive ability, STD	9664	0.01	-0.01	-0.02	0.41
Academic self-concept score	9664	0.08	-0.08	-0.16	0.00

Overconfidence score, STD	9664	0.11	-0.11	-0.22	0.00
Overconfidence score, squared	9664	0.99	1.01	0.02	0.42
Overconfidence score quintiles	9664	3.15	2.85	-0.30	0.00
Overconfidence score quintiles	9664	0.23	0.17	-0.05	0.00
Overconfidence score tertiles compared to the middle	9664	2.04	1.96	-0.08	0.00
Has cohabiting partner, age 42	6544	0.78	0.76	-0.02	0.10
No. of children in HH, age 42	6544	1.13	1.36	0.23	0.00
Ethnicity					
English, etc	9664	0.91	0.92	0.00	0.41
Irish	9664	0.00	0.00	0.00	0.64
Other European	9664	0.00	0.00	0.00	0.65
West Indian	9664	0.01	0.01	0.00	0.77
Indian	9664	0.01	0.01	0.00	0.35
Pakistani	9664	0.00	0.00	0.00	0.70
Bangladeshi	9664	0.00	0.00	0.00	0.08
Other	9664	0.00	0.00	0.00	0.55
Region					
North	9664	0.08	0.07	-0.01	0.20
Yorks and Humberside	9664	0.08	0.09	0.01	0.16
East Midlands	9664	0.06	0.06	0.00	0.87
East Anglia	9664	0.04	0.04	0.00	0.50
South East	9664	0.25	0.26	0.00	0.63
South West	9664	0.06	0.07	0.01	0.01
West Midlands	9664	0.11	0.10	-0.01	0.17
North West	9664	0.13	0.13	0.00	0.83
Wales	9664	0.06	0.06	-0.01	0.29
Scotland	9664	0.10	0.10	0.00	0.78
Northern Ireland	9664	0.00	0.00	0.00	0.75
Region is missing	9664	0.03	0.02	0.00	0.45
Mother has a qualification	9664	0.51	0.50	-0.01	0.41
High SES parents	9664	0.34	0.33	0.00	0.84
Mother's year of birth	9649	1944.13	1944.16	0.03	0.77
Cognitive skills at age 5					
Schonell reading score, age 5	8329	1.31	1.79	0.48	0.00
Standardised Copy Designs	8548	0.06	0.05	-0.01	0.60
Profile Test Score	8219	7.05	6.89	-0.16	0.07
Standardised Human Fig Drawing	8455	-0.09	0.16	0.25	0.00
Standardised EPVT	8039	0.19	-0.05	-0.24	0.00
Cognitive skills at age 10					
Standardised Edinburgh Reading Test score, age 10	7459	0.02	0.13	0.12	0.00
Friendly Maths Test score, age 10	8607	45.64	44.17	-1.48	0.00
Spelling Dictation Task, age 10	8834	34.32	36.82	2.50	0.00
BAS Word Definitions, age 10	8547	11.00	9.85	-1.14	0.00
BAS Word Similarities, age 10	8504	12.46	12.03	-0.42	0.00
BAS Recall of Digits, age 10	8532	23.44	23.58	0.14	0.14
BAS Matrices, age 10	8524	15.49	15.98	0.49	0.00
Pictorial Language Comprehension Test, age 10	9015	62.60	61.04	-1.56	0.00
Cognitive skills at age 16					
Arithmetic scores, age 16	3276	37.22	36.71	-0.51	0.22
BAS Matrices, age 16	2854	8.82	8.97	0.15	0.01
Edinburgh Reading Test score, age 16	2768	54.05	55.28	1.23	0.01

Spelling, age 16	5057	159.21	167.00	7.78	0.00
Standardised Vocabulary Test score, age 16	4507	-0.01	0.03	0.04	0.20
Academic self-concept					
Good at math, age 10	8938	2.26	2.09	-0.17	0.00
Good at math, age 16	4898	2.27	1.94	-0.33	0.00
Good at spelling, age 10	8881	2.17	2.25	0.08	0.00
Good at spelling, age 10	4932	2.29	2.29	0.00	0.97
Clever	4993	2.20	2.02	-0.18	0.00
Good at exams	4986	2.00	1.89	-0.11	0.00
Good at school	4919	2.52	2.53	0.01	0.69
University and subject					
No degree	6544	0.76	0.76	0.00	0.94
STEM	6544	0.08	0.04	-0.04	0.00
LEM	6544	0.04	0.04	0.00	0.57
OSSAH	6544	0.02	0.07	0.05	0.00
Other	6544	0.01	0.01	0.00	0.45
Combined	6544	0.01	0.02	0.01	0.01
Elite STEM	6544	0.04	0.02	-0.02	0.00
Elite LEM	6544	0.01	0.01	0.00	0.32
Elite OSSAH	6544	0.02	0.02	0.01	0.11
Elite other	6544	0.00	0.00	0.00	0.86
Elite combined	6544	0.01	0.01	0.00	0.47
Secondary school type					
Public school	9664	0.77	0.82	0.05	0.00
Private or grammar school	9664	0.07	0.07	0.00	0.68
School type is missing	9664	0.15	0.11	-0.05	0.00
Math exam and grade at age 16					
No math O/CSE	9664	0.15	0.17	0.02	0.04
Grade A/1	9664	0.10	0.08	-0.02	0.00
Grade B/2	9664	0.12	0.12	0.00	0.95
Grade C/3	9664	0.13	0.16	0.03	0.00
Grade D/4	9664	0.06	0.10	0.04	0.00
Grade E/5	9664	0.03	0.05	0.02	0.00
Failed	9664	0.00	0.00	0.00	0.68
No info	9664	0.39	0.31	-0.09	0.00
A-levels	9664	0.15	0.19	0.04	0.00
Self-esteem	9664	15.13	15.03	-0.10	0.05
Missing flag of self-esteem	9664	0.59	0.48	-0.11	0.01

Source: BCS70 (CLS n.d.).

Table B2: Descriptive statistics: employed

	Obs	Mean men	Mean women	Diff. (Women-men)	Two-tailed t-test p-values
Works in a top job, age 42	5659	0.22	0.12	-0.10	0.00
STEM top job	5659	0.07	0.02	-0.05	0.00
LEM top job	5659	0.14	0.08	-0.06	0.00
Log hourly pay	4552	2.38	2.14	-0.24	0.00
Weekly hours worked	5659	45.43	32.19	-13.23	0.00
Objective cognitive ability, STD	5659	0.18	0.13	-0.05	0.04
Academic self-concept score	5659	0.13	-0.05	-0.17	0.00
Overconfidence score, STD	5659	0.12	-0.11	-0.23	0.00
Overconfidence score, squared	5659	0.99	1.04	0.05	0.07

Overconfidence score quintiles	5659	3.17	2.85	-0.31	0.00
Overconfidence score quintiles	5659	0.23	0.18	-0.05	0.00
Overconfidence score tertiles compared to the middle	5659	2.04	1.98	-0.06	0.00
Has cohabiting partner, age 42	5659	0.80	0.77	-0.04	0.00
No. of children in HH, age 42	5659	1.17	1.33	0.16	0.00
Ethnicity					
English, etc	5659	0.93	0.92	-0.01	0.31
Irish	5659	0.00	0.00	0.00	0.48
Other European	5659	0.00	0.01	0.00	0.19
West Indian	5659	0.01	0.01	0.00	0.55
Indian	5659	0.01	0.01	0.00	0.19
Pakistani	5659	0.00	0.00	0.00	0.17
Bangladeshi	5659	0.00	0.00	0.00	0.32
Other	5659	0.00	0.00	0.00	0.97
Region					
North	5659	0.07	0.07	0.00	0.60
Yorks and Humberside	5659	0.09	0.09	0.01	0.37
East Midlands	5659	0.07	0.07	0.00	0.95
East Anglia	5659	0.04	0.03	-0.01	0.20
South East	5659	0.27	0.25	-0.01	0.22
South West	5659	0.07	0.08	0.01	0.15
West Midlands	5659	0.11	0.10	-0.01	0.11
North West	5659	0.12	0.13	0.01	0.37
Wales	5659	0.06	0.06	0.00	0.68
Scotland	5659	0.09	0.10	0.01	0.18
Northern Ireland	5659	0.00	0.00	0.00	0.96
Region is missing	5659	0.03	0.02	0.00	0.63
Mother has a qualification	5659	0.55	0.55	0.00	0.86
High SES parents	5659	0.38	0.36	-0.01	0.32
Mother's year of birth	5653	1943.95	1944.09	0.14	0.33
Cognitive skills at age 5					
Schonell reading score, age 5	4968	1.44	1.88	0.44	0.00
Standardised Copy Designs	5084	0.17	0.12	-0.04	0.11
Profile Test Score	4915	7.15	6.94	-0.21	0.06
Standardised Human Fig Drawing	5048	-0.02	0.21	0.22	0.00
Standardised EPVT	4800	0.31	0.02	-0.29	0.00
Cognitive skills at age 10					
Standardised Edinburgh Reading Test score, age 10	4414	0.17	0.24	0.07	0.02
Friendly Maths Test score, age 10	5009	47.53	45.64	-1.89	0.00
Spelling Dictation Task, age 10	5159	35.11	37.49	2.37	0.00
BAS Word Definitions, age 10	4974	11.65	10.33	-1.32	0.00
BAS Word Similarities, age 10	4952	12.77	12.26	-0.51	0.00
BAS Recall of Digits, age 10	4964	23.66	23.86	0.20	0.10
BAS Matrices, age 10	4963	16.28	16.65	0.37	0.01
Pictorial Language Comprehension Test, age 10	5250	63.90	62.35	-1.56	0.00
Cognitive skills at age 16					
Arithmetic scores, age 16	2018	38.61	38.11	-0.50	0.33
BAS Matrices, age 16	1756	8.96	9.13	0.16	0.03
Edinburgh Reading Test score, age 16	1703	55.67	56.72	1.05	0.08
Spelling, age 16	3228	161.09	168.05	6.97	0.00
Standardised Vocabulary Test score, age 16	2908	0.06	0.11	0.04	0.21
Academic self-concept					

Good at math, age 10	5207	2.30	2.12	-0.18	0.00
Good at math, age 16	3133	2.33	1.98	-0.36	0.00
Good at spelling, age 10	5172	2.19	2.23	0.04	0.08
Good at spelling, age 10	3154	2.29	2.27	-0.02	0.48
Clever	3185	2.22	2.05	-0.17	0.00
Good at exams	3184	2.04	1.93	-0.11	0.00
Good at school	3142	2.57	2.55	-0.02	0.47
University and subject					
No degree	5659	0.75	0.74	-0.01	0.51
STEM	5659	0.09	0.04	-0.05	0.00
LEM	5659	0.04	0.04	0.00	0.82
OSSAH	5659	0.03	0.08	0.05	0.00
Other	5659	0.01	0.01	0.00	0.30
Combined	5659	0.01	0.02	0.01	0.01
Elite STEM	5659	0.04	0.03	-0.01	0.00
Elite LEM	5659	0.01	0.01	0.00	0.41
Elite OSSAH	5659	0.02	0.02	0.01	0.10
Elite other	5659	0.00	0.00	0.00	0.74
Elite combined	5659	0.01	0.01	0.00	0.29
Secondary school type					
Public school	5659	0.90	0.91	0.01	0.07
Private or grammar school	5659	0.10	0.09	-0.01	0.11
School type is missing	5659	0.00	0.00	0.00	0.12
Math exam and grade at age 16					
No math O/CSE	5659	0.14	0.16	0.02	0.05
Grade A/1	5659	0.13	0.10	-0.03	0.00
Grade B/2	5659	0.15	0.14	-0.01	0.41
Grade C/3	5659	0.15	0.18	0.03	0.00
Grade D/4	5659	0.07	0.11	0.03	0.00
Grade E/5	5659	0.03	0.05	0.02	0.00
Failed	5659	0.00	0.00	0.00	0.81
No info	5659	0.34	0.27	-0.07	0.00
A-levels	5659	0.19	0.22	0.03	0.00
Self-esteem	5659	15.20	15.09	-0.12	0.06
Missing flag of self-esteem	5659	0.55	0.45	-0.11	0.01

Source: BCS70 (CLS n.d.).

Table B3: The gender gap in the probability of working in a top job: continuous overconfidence score (total sample)

	(1) Model 1	(2) Model 3	(3) Model 5	(4) Model 7	(5) Model 8
Female	-0.105***	-0.095***	-0.088***	-0.087***	-0.086***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)
Overconfidence score,		0.027***	0.011***	0.011***	0.011***
STD		(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.200***	0.149***	0.100***	0.075***	0.041
	(0.007)	(0.016)	(0.018)	(0.019)	(0.029)
Observations	6,544	6,544	6,544	6,544	6,544
R-squared	0.022	0.101	0.175	0.177	0.177
Region, parental background, ethnicity		yes	yes	yes	yes
University degree: elite*subject, pre-university educational attainment, objective cognitive ability private/grammar secondary school at age 16			yes	yes	Yes
Cohabiting partner, No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B4: The gender gap in the probability of working in a top job: continuous overconfidence score (sample of those employed)

	(1) Model 1	(2) Model 3	(5) Model 5	(6) Model 7	(7) Model 8
Female	-0.102***	-0.094***	-0.084***	-0.082***	-0.081***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Overconfidence score,		0.033***	0.012***	0.012***	0.012***
STD		(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.218***	0.214***	0.103***	0.080***	0.038
	(0.008)	(0.008)	(0.020)	(0.022)	(0.034)
Observations	5,659	5,659	5,659	5,659	5,659
R-squared	0.019	0.027	0.182	0.183	0.184
Region, parental background, ethnicity		yes	yes	yes	yes
University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16			yes	yes	yes
Cohabiting partner, No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B5: The gender gap in the probability of working in a top job: top job defined as top quintile of log hourly pay (sample of those employed full time)

	(1) Model 1	(4) Model 3	(5) Model 5	(6) Model 7	(7) Model 8
Female	-0.122***	-0.108***	-0.103***	-0.095***	-0.095***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)
Overconfidence score, STD		0.031***	0.011*	0.011*	0.010
		(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.249***	0.126***	0.050**	-0.007	-0.117***
	(0.010)	(0.022)	(0.024)	(0.026)	(0.044)
Observations	3,441	3,441	3,441	3,441	3,441
R-squared	0.022	0.116	0.189	0.197	0.198
Region, parental background, ethnicity		yes	yes	yes	yes
University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16			yes	yes	yes
Cohabiting partner, No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B6: The gender gap in the probability of working in a top job at age 34 (sample of those employed full time at age 34)

	(1) Model 1	(4) Model 3	(5) Model 5	(6) Model 7	(7) Model 8
Female	-0.072***	-0.076***	-0.080***	-0.081***	-0.081***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Overconfidence score, STD		0.045***	0.029***	0.030***	0.030***
		(0.006)	(0.007)	(0.007)	(0.007)
Constant	0.243***	0.123***	0.073***	0.075**	0.098**
	(0.009)	(0.022)	(0.027)	(0.030)	(0.050)
Observations	3,876	3,876	3,252	3,252	3,252
R-squared	0.007	0.144	0.217	0.218	0.218
Region, parental background, ethnicity		yes	yes	yes	yes
University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16			yes	yes	yes
Cohabiting partner, No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B7: Heterogeneity of the relationship between overconfidence and the probability of being in a top job by gender, partnership, children, and university graduation (total sample)

	(1) Men	(2) Women	(3) No partner	(4) Has partner	(5) No children	(6) Has children	(7) Non-graduates	(8) Graduates
Female			-0.016	-0.103***	-0.036**	-0.108***	-0.065***	-0.150***
			(0.017)	(0.010)	(0.016)	(0.010)	(0.008)	(0.022)
Overconfidence	0.011	0.012**	0.020***	0.008	0.020***	0.008*	0.006*	0.022**
score, STD	(0.007)	(0.005)	(0.007)	(0.005)	(0.008)	(0.005)	(0.004)	(0.011)
Constant	0.030	0.055**	0.047*	0.125***	0.052	0.104***	0.070***	0.111*
	(0.028)	(0.024)	(0.027)	(0.024)	(0.032)	(0.024)	(0.018)	(0.063)
Observations	3,019	3,525	1,533	5,011	1,776	4,768	4,748	1,796
R-squared	0.201	0.135	0.184	0.183	0.186	0.188	0.054	0.154

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16, whether having a cohabiting partner, No. of children in the household.

Table B8: Heterogeneity of the relationship between overconfidence and the probability of being in a top job by gender, partnership, children, and university graduation (sample of those employed)

	(1) Men	(2) Women	(3) No partner	(4) Has partner	(5) No children	(6) Has children	(7) Non-graduates	(8) Graduates
Female			-0.016	-0.094***	-0.038**	-0.098***	-0.064***	-0.133***
			(0.021)	(0.011)	(0.019)	(0.011)	(0.009)	(0.024)
Overconfidence	0.011	0.014**	0.026***	0.008	0.023***	0.009	0.007	0.024**
score, STD	(0.007)	(0.006)	(0.009)	(0.005)	(0.009)	(0.005)	(0.004)	(0.012)
Constant	0.047	0.056*	0.060*	0.120***	0.057	0.098***	0.080***	0.108
	(0.032)	(0.029)	(0.036)	(0.026)	(0.038)	(0.028)	(0.021)	(0.067)
Observations	2,775	2,884	1,224	4,435	1,533	4,126	4,014	1,645
R-squared	0.204	0.150	0.199	0.189	0.195	0.193	0.052	0.161

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16, whether having a cohabiting partner, No. of children in the household.

Table B9: The Kitagawa-Blinder-Oaxaca decomposition of the gender gap in top jobs (alternative samples)

	Total sample	Sample of those employed
Share of men in top jobs	0.200***	0.218***
	(0.007)	(0.008)
Share of women in top jobs	0.095***	0.116***
	(0.005)	(0.006)
Gender gap in top jobs	0.105***	0.102***
	(0.009)	(0.010)
Explained by endowments	0.018***	0.020***
	(0.004)	(0.005)
Unexplained	0.087***	0.082***
	(0.008)	(0.009)
Endowments		
Overconfidence score, STD	0.003***	0.003***
	(0.001)	(0.001)
Objective cognitive ability, STD	0.002**	0.002**
	(0.001)	(0.001)
Family background	-0.000	-0.000
	(0.001)	(0.001)
Pre-university educational attainment	-0.000	-0.000
	(0.001)	(0.001)
Graduation and university subject STEM	0.015***	0.016***
	(0.002)	(0.003)
LEM	0.002	0.001
	(0.002)	(0.002)
OSSAH	-0.002	-0.002
	(0.001)	(0.001)
Other	-0.001*	-0.002**
	(0.001)	(0.001)
Having a co-habiting partner	0.001	0.001**
	(0.000)	(0.001)
Having one child	0.000	0.000
	(0.001)	(0.001)
Having at least two children	0.000	0.000
	(0.001)	(0.001)
Constant	-0.025	-0.009
	(0.037)	(0.043)
Observations	6,544	5,659

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B10: The gender gap in the costs and benefits of working in a top job (alternative samples)

	(1)	(2)	(3)	(4)	(5)	(6)
	Total sample			Sample of those employed		
	Outcome variables					
	Having a cohabiting partner	Having children	Log hourly wage	Weekly hours worked	Having a cohabiting partner	Having children
Female	-0.061***	0.169***	-0.189***	-0.930***	-0.068***	0.141***
	(0.010)	(0.011)	(0.017)	(0.027)	(0.011)	(0.012)
Works in a top job	0.048***	0.060***	0.236***	0.025	0.035**	0.047**
	(0.014)	(0.019)	(0.033)	(0.038)	(0.015)	(0.019)
Female*top job interaction	0.016	-0.166***	0.043	0.410***	0.021	-0.138***
	(0.026)	(0.031)	(0.050)	(0.060)	(0.026)	(0.031)
Has cohabiting partner		0.405***	0.071***	0.115***		0.408***
		(0.013)	(0.019)	(0.032)		(0.015)
No. of children in HH: 1	0.293***		0.002	-0.204***	0.268***	
	(0.016)		(0.026)	(0.035)	(0.017)	
No. of children in HH: at least 2	0.403***		0.046**	-0.265***	0.385***	
	(0.013)		(0.021)	(0.031)	(0.014)	
Constant	0.477***	0.327***	2.070***	0.498***	0.531***	0.333***
	(0.025)	(0.026)	(0.034)	(0.066)	(0.027)	(0.028)
Observations	6,544	6,544	4,552	5,659	5,659	5,659
R-squared	0.183	0.185	0.213	0.243	0.176	0.167

Source: BCS70 (CLS n.d.). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Further control variables: region at birth, parental background, ethnicity, University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16.

Table B11: The gender gap in the probability of working in a top job: continuous overconfidence score (sample of those employed full-time, weighted using entropy-balanced weights)

	(1) Model 1	(3) Model 3	(5) Model 5	(6) Model 7	(7) Model 8
Female	-0.087***	-0.078***	-0.073***	-0.067***	-0.066***
	(0.022)	(0.021)	(0.019)	(0.019)	(0.020)
Overconfidence score, STD		0.034***	0.021*	0.022**	0.021**
		(0.012)	(0.011)	(0.011)	(0.011)
Constant	0.216***	0.202***	0.099***	0.078*	0.014
	(0.017)	(0.017)	(0.037)	(0.040)	(0.070)
Observations	3,596	3,596	3,596	3,596	3,596
R-squared	0.011	0.077	0.194	0.196	0.197
Region, parental background, ethnicity		yes	yes	yes	yes
University degree: elite*subject, pre-university educational attainment, objective cognitive ability, private/grammar secondary school at age 16			yes	yes	yes
Cohabiting partner, No. of children in the household				yes	yes
Self-esteem					yes

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Weighted using entropy balanced weights to handle attrition between the initial sample of BCS70 and the main estimation sample. 6 observations were dropped while estimating the entropy weights.

Table B12: Correlations between overconfidence measures and ability

		(1)	(2)	(3)	(4)	(5)
(1)	Overconfidence score	1				
(2)	Objective ability	0.02	1			
(3)	Subjective ability	0.86*	0.42*	1		
(4)	Non-ranked residual score	0.94*	0.063*	0.93*	1	
(5)	Difference score	0.85*	-0.51*	0.51*	0.77*	1

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. No. of observations: 3,602. * indicates the significance of the correlation coefficient on 5% level. Overconfidence score: residuals extracted after regression percentile ranks of subjective ability on the percentile ranks of objective ability. Non-ranked residual score: residuals extracted after regression the index of subjective ability on the index of objective ability, i.e., without ranking individuals. Difference score: percentile rank in subjective ability minus percentile rank in objective ability.

Table B13: Descriptive statistics of the alternative overconfidence measures: non-ranked residual and difference scores

	Obs	Mean men	Mean women	Diff. (Women-men)	Two-tailed t-test p-values
Non-ranked residual score, std	3602	0.13	-0.11	-0.24	0.00
Difference score, std	3602	0.06	-0.10	-0.16	0.00

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. No. of observations: 3,602. Non-ranked residual score: residuals extracted after regression the index of subjective ability on the index of objective ability, i.e., without ranking individuals. Difference score: percentile rank in subjective ability minus percentile rank in objective ability.

Table B14: Robustness checks using different ways to measure overconfidence

	Model 1	Model 2	Model 3	Model 7
A. Models using the non-ranked residual score				
Female	-0.081***	-0.070***	-0.067***	-0.060***
	(0.013)	(0.013)	(0.013)	(0.013)
Non-ranked residual score		0.045***	0.038***	0.018***
		(0.007)	(0.006)	(0.006)
Constant	0.243***	0.237***	0.152***	0.058**
	(0.009)	(0.009)	(0.024)	(0.028)
Observations	3,602	3,602	3,602	3,602
R-squared	0.009	0.022	0.109	0.182
B. Models using the difference score				
Female	-0.081***	-0.086***	-0.069***	-0.061***
	(0.013)	(0.013)	(0.013)	(0.013)
Difference score		-0.028***	0.037***	0.015**
		(0.006)	(0.007)	(0.007)
Constant	0.243***	0.245***	0.150***	0.056**
	(0.009)	(0.009)	(0.024)	(0.028)
Observations	3,602	3,602	3,602	3,602
R-squared	0.009	0.014	0.106	0.181
C. Models dropping individuals in the top and bottom five percentiles of cognitive ability				
Female	-0.078***	-0.071***	-0.066***	-0.060***
	(0.014)	(0.014)	(0.014)	(0.013)
Overconfidence score		0.032***	0.031***	0.013*
		(0.007)	(0.007)	(0.007)
Constant	0.239***	0.235***	0.141***	0.044
	(0.010)	(0.010)	(0.024)	(0.029)
Observations	3,241	3,241	3,241	3,241
R-squared	0.009	0.015	0.086	0.162

Source: BCS70 (CLS n.d.). Sample of those in full-time employment at age 42. Overconfidence score: residuals extracted after regression percentile ranks of subjective ability on the percentile ranks of objective ability. Non-ranked residual score: residuals extracted after regression the index of subjective ability on the index of objective ability, i.e., without ranking individuals. Difference score: percentile rank in subjective ability minus percentile rank in objective ability.