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Contemporary phenotypic selection on intelligence is (mostly) directional: An analysis of three, population representative samples

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ABSTRACT

Three large and nationally representative datasets (NCDS, $N = 5225$, NLSY′79, $N = 7598$ and Project Talent, $N = 76{,}150$) are here examined in order to determine if models incorporating negative quadratic effects of IQ on fertility (which would indicate the presence of stabilizing phenotypic selection) improve model fit, relative to ones that only consider linear effects (which indicate directional phenotypic selection). Also considered were possible interactions among these terms and sex and race. For two datasets (NCDS and NLSY′79) the best fitting models did not include quadratic terms, however significant sex*IQ and race*IQ interactions were found respectively. Only in Project Talent did the inclusion of a quadratic effect (along with IQ*sex and IQ^{2}* sex interactions) yield the best-fitting model. In this instance a small magnitude, significant negative quadratic term was found in addition to a larger magnitude linear term. *Post hoc* power analysis revealed that power was lacking in the two smaller samples (NCDS and NLSY′79) to detect the quadratic term, however the best fitting and most parsimonious models selected for these datasets did not include the quadratic term. The quadratic terms were furthermore several times smaller in magnitude than the linear terms in all models incorporating both terms. This indicates that stabilizing phenotypic selection is likely only very weakly present in these datasets. The dominance of linear effects across samples therefore suggests that phenotypic selection on IQ in these datasets is principally directional, although the magnitude of selection is relatively small, with IQ explaining at most 1% of the variance in fertility.

1. Introduction

A common assumption in studies examining the negative association between fertility and IQ in contemporary populations is that the relationship between the two can best be described using a linear term, whereby fertility (the numbers of offspring produced) scales negatively as a function of level of IQ. On this basis it has been argued that IQ, or at least its more heritable variance components, should be declining over time – consistent with the action of *directional phenotypic selection* (i.e. Lynn, 2011; Meisenberg, 2010; Meisenberg & Kaul, 2010; Woodley of Menie, Figueredo, Dunkel, & Madison, 2015; Reeve, Lyerly, & Peach, 2013; Vining, 1982, 1995). The possibility that there may be indications of *non-directional phenotypic selection* in the association between trait-levels and fitness outcomes (i.e. the genetic contribution made by individuals to subsequent generations, as measured by fertility) is seldom considered in studies of human populations however (Stearns, Byars, Govindaraju, & Ewbank, 2010, p.6). To the best of our knowledge, and consistent with this observation, no studies on the relationship between IQ and fertility have explicitly considered the possibility of non-directional selection operating on IQ.

In the case of IQ, there are indications that among those that fall into the *intellectually disabled* (ID) range (i.e. IQ ≤ 70), fertility may in fact scale *positively* with IQ (e.g. Meisenberg, 2010; Meisenberg & Kaul, 2010; Vining, 1995), however among those with higher IQ, the relationship becomes negative. The apparent sharp drop-off in fertility among those whose IQ is lower than the fitness optimum, might specifically be consistent with the operation of *purifying selection* (i.e. selection against deleterious mutations) - an important cause of ID-range IQ being rare *de novo* mutations with deleterious effects on cognitive functioning (Rauch et al., 2012). This suggests that the relationship between

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IQ and fertility may be more complex than is currently assumed in studies examining the linear relationship between the two.

The *Chicago School* approach to categorizing and quantifying different types of phenotypic selection (Kingsolver & Pfennig, 2007; Lande, 1979; Lande & Arnold, 1983; Stearns et al., 2010) recommends the use of linear and quadratic terms to differentiate between directional and non-directional forms of selection. There are two categories of non-directional selection; *stabilizing selection* (where selection promotes the fitness of the mean of the trait-distribution) and *disruptive selection* (where selection acts to promote the fitness of the extremes of the distribution). The former non-directional selection type can be captured via the finding of a *negative* quadratic (inverse U-shaped) effect of trait level on fitness outcomes, whereas the latter can be captured via the finding of a *positive* quadratic (U-shaped) effect. Proponents of this approach sometimes use the term *quadratic selection* to refer collectively to the two forms of non-directional selection (e.g. Kingsolver & Pfennig, 2007).

Virtually no traits are purely under one or the other form of selection. In most cases selection is mixed, however one type of selection will typically predominate. In instances where the dominant selection pressure is directional (i.e. linear term > quadratic term), the optimum trait level will be skewed towards one or the other extremes (depending on the direction of the selection), with a sharp drop-off in fitness when the optimum level is exceeded, whereas in the case of dominant quadratic selection (i.e. quadratic term > linear term), the optimum trait levels will either correspond to the population mean, or to the extremes of the distribution, depending on the direction of the quadratic selection (Kingsolver & Pfennig, 2007). In the case of IQ, it is expected that the linear effect should predominate however there may be a weaker negative quadratic effect of IQ on fertility present in sufficiently population representative datasets, owing to the aforementioned finding of positive associations between IQ and fertility among those with ID range levels of the trait.

To test for the presence of possible stabilizing selection in the IQ-fertility relationship, the degree to which the addition of quadratic effects enhances model fit once the linear component and other covariates have been included, will here be examined utilizing three, large and population representative samples from the US and UK.

2. Methods

2.1. Data

Three large, population representative datasets (National Child Development Study, National Longitudinal Survey of Youth'79 and Project Talent), all of which have a) been utilized in previous studies examining the negative association between fertility and measures of cognitive ability (i.e. Kanazawa, 2014; Meisenberg, 2010; Meisenberg & Kaul, 2010; Peach, Lyerly & Reeve, 2013), and b) contain data on a broad array of cognitive ability measures, spanning a wide range of domains, were selected in order to determine the presence of non-linearity in the IQ-fertility relationship. Two of the three studies selected (NCDS and NLSY'79) employed cohorts that had either completed their fertility (i.e. finished producing offspring), or were very near to having done so. In modern Western countries fertility is typically completed between the ages of 40 and 50 (with the onset of menopause) in women (Monte & Ellis, 2014). In the case of men, while those over the age of 50 are able to conceive, in practice the vast majority (96.5% to 97.5%) of males in Western countries complete their fertility by 45 (Fieder & Huber, 2007; Boschini, Håkanson, Rosén, & Sjögren, 2011). The participants in the third dataset (Project Talent) were not at completed fertility (they were in their late teens to early 30s) however.

What follows is a more detailed description of the three datasets employed in the present study. The particulars of these datasets (i.e. the variable codes, details of variable construction and participant exclusion criteria etc.) are included in the Appendix:

i) *National Child Development Study* (*NCDS*) (UK): A prospective longitudinal study that has tracked an *entire population* (born in Britain during the week of 03–09 March 1958) for more than half a century. The respondents were interviewed in eight sweeps (Sweep 1 = age 7 to Sweep 8 = age 50–51). Various cognitive ability measures were administered to NCDS respondents at ages 7 (Sweep 1), 11 (Sweep 2), and 16 (Sweep 3). At age 7, the respondents took four tests: the Copying Designs Test, the Draw-a-Man Test, the Southgate Group Reading Test and the Problem Arithmetic Test. At age 11, they took a further five tests: the Verbal General Ability Test, the Nonverbal General Ability Test, the Reading Comprehension Test, the Mathematical Test, and the Copying Designs Test. At age 16, they took two additional cognitive tests: the Reading Comprehension Test and Mathematics Comprehension Test. Fertility data were obtained among the subset of individuals aged between 41.5 and 50.5 years (Sweeps 6 to 8; $M = 48.77$, SD = 3.31). For the majority of participants (76.29%), Sweep 8 (age 50.5) fertility values were available. In 23.71% of instances, participants only report fertility in Sweep 6 (age 41.5; 65.7%) or 6 and 7 (age 46.5; 34%), in which case the values from the next most recent Wave were used instead. In total, data were available for 2492 White males and 2733 White females. Non-White minorities are rare in NCDS (2.2% of respondents); these along with those for whom race is not reported were excluded from the analysis. For further information on this dataset see Kanazawa (2014).

ii) *National Longitudinal Survey of Youth 1979 (NLSY'79)* (US): All subjects were aged between 14 and 22 (born between 1957 and 1965) at the inception of the study in 1979. Data on cognitive ability were obtained using the Armed Services Vocational Aptitude Battery, which includes five academic tests (Science, Arithmetic, Word Knowledge, Paragraph Comprehension, Mathematics Knowledge), three vocational tests (Auto & Shop Info, Mechanical Comprehension, Electronics Info), and two speeded tests (Numerical Operations, Coding Speed). Fertility data (number of children) were collected among those aged between 39 and 47 years in 2004 ($M = 42.54$, SD = 2.24). Data were available for 3812 males and 3786 females, and are available for three different racial groups (Blacks $N = 2195$, Hispanics $N = 1216$ and Whites $N = 4187$). For further information on this dataset see Meisenberg (2010) and Meisenberg and Kaul (2010).

iii) *Project Talent* (US): Cognitive ability data were collected between 1960 and 1963 from among a large sample of students enrolled in high-school aged between 8 and 21 years (born between 1939 and 1952), utilizing the Project Talent Ability Battery, which evaluates fluid intelligence (Abstract Reasoning, Arithmetic Reasoning, Mechanical Reasoning, Reading Comprehension, 2D Rotation, 3D Rotation, and Table Reading) and crystallized intelligence (Vocabulary, Biological Sciences Knowledge, Social Sciences Knowledge, and Literature Knowledge). Fertility data were collected among those aged from 19 to 32 ($M = 26.87$, SD = 1.24) in an 11 year follow-up study conducted between the years 1971 and 1974. Data are available for 36,001 males and 40,149 females, and are available for three different racial groups (Asians $N = 420$, Blacks $N = 1976$ and Whites $N = 73,754$). For further information on this dataset see Peach et al. (2013) and Reeve et al. (2013).

2.2. Covariates and model selection

We computed an IQ score via extraction of the principal axis factor from the set of tests within each sample. As count data were used for the dependent variable (numbers of children), zero inflated negative binomial regression (NLSY'79 and Project Talent) and zero inflated

Poisson regression (NCDS) analyses were performed using Proc Genmod in SAS 9.3. Poisson regressions were used in place of negative binomial regression in instances were convergence was an issue, as recommended by Silvestrini et al. (2011). A zero order Poisson model was selected in this instance as the NCDS data contained indications of overdispersion (variance > mean).

To estimate possible quadratic effects of IQ upon fertility, each IQ-score was first standardized (thus mean-centered), with the quadratic term being computed from the standardized first order term, consistent with the recommendations of Cohen, Cohen, West, and Aiken (2003). Centering helps enhance the meaning of the first order regression coefficients when multiplicative terms are entered into a regression model and also helps to reduce non-essential multi-collinearity.

A potentially important confound stems from the fact that the Project Talent and NLSY′79 cohorts were not of uniform age evaluation, this might be problematic as average numbers of children increase as both men and women approach completed fertility. While the NCDS participants were all born in the same year (1958), fertility data were obtained from the participants at three different ages 41.5 (Wave 6), 46.5 (Wave 7) and 50.5 (Wave 8), thus age may still be a factor in predicting fertility. The effects of age can be controlled by entering it into each model as an independent predictor of fertility.

Given that there exist both sex and race differences in the apparent strength of the association between IQ and fertility (e.g. Meisenberg, 2010; Meisenberg & Kaul, 2010; Vining, 1982, 1995), more complex models (involving sex and race differences in fertility, IQ^2, and interactions of sex and race with IQ and IQ^2) were constructed in order to determine whether they better explained the variance in fertility than when it is simply predicted with IQ and age. Several models, each with increasing complexity were tested. First we added sex and race and their interaction with IQ. The subsequent and more complex models also included IQ^2 and its interactions with sex and race. Finally, the most complex models combined all terms included in all previous models. Model fit to the data was assessed with the Akaike (1973) Information Criterion (AIC) and was compared against alternatives with Akaike weights (i.e. the relative likelihood of a model, on a scale of 0 to 1, compared to the alternative models tested; Wagenmakers & Farrell, 2004). The results are presented in Table 1. In each sample, the model with the highest Akaike weight was retained as the better fitting model for the data, except in instances where there was no significant difference in fit between two values, in which case the more parsimonious model was selected.

3. Results

3.1. Main analyses

Tables 2, 3 and 4 present the selected models showing the results of the regression analyses for each sample (NCDS, NLSY′79 and Project Talent respectively).

Table 1
Comparison of fit among models including different possible predictors and combinations of predictors of fertility for each of the datasets.

Models	NCDS	NLSY′ 79	Project talent
IQ, age	<0.001	0.000	<0.001
IQ, age, sex, IQ*sex	**0.581**	0.000	<0.001
IQ, age, sex, IQ*sex, IQ^2, IQ^2*sex	0.419[a]	0.000	>**0.999**
IQ, age, race, IQ*race		**0.483**	<0.001
IQ, age, race, IQ*race, IQ^2, IQ^2*race		0.486[a]	<0.001
IQ, age, sex, race, IQ*sex, IQ*race, IQ^2, IQ^2*sex, IQ^2*race		0.031	<0.001

Note: The Akaike weight for the model that was retained for each sample is bolded.
[a] The difference between the two models (computed based on their respective log likelihoods) is not statistically significant; thus the model with fewer assumptions (i.e. the more parsimonious model) was selected.

Table 2
Model parameters for the zero inflated Poisson regression analysis of NCDS ($N = 5225$).

Predictor	*b* (*s.e.*)	NDF, DDF
IQ	0.004[a] (0.016)	1,5219
Female (Sex)	0.052* (0.021)	1,5219
IQ*Female	−0.073* (0.021)	1,5219
Age	0.003 (0.003)	1,5219

* $p < 0.05$.
[a] Effect estimated for men as the comparison group. Relative effects for women are displayed in the IQ*Female interaction term.

Table 3
Model parameters for the zero inflated Negative Binomial Regression analysis of NLSY′79 ($N = 7598$).

Predictor	*b* (*s.e.*)	NDF, DDF
IQ	−0.029[a,*] (0.014)	1,7590
Black (Race)	0.067* (0.025)	1,7590
Hispanic (Race)	0.137* (0.027)	1,7590
IQ*Black	−0.072* (0.025)	1,7590
IQ*Hispanic	−0.147* (0.026)	1,7590
Age	0.011* (0.004)	1,7590

* $p < 0.05$.
[a] Effect estimated for Whites as the comparison group. Relative effects for Blacks and Hispanics are displayed in the interaction terms.

Table 4
Model parameters for the Zero Inflated Negative Binomial Regression analysis of Project Talent ($N = 76{,}150$).

Predictor	*b* (*s.e.*)	NDF, DDF
IQ	−0.165[a,*] (0.005)	1,76142
IQ^2	−0.034* (0.004)	1,76142
Female (Sex)	0.202* (0.008)	1,76142
IQ*Female	0.022* (0.007)	1,76142
IQ^2*Female	0.004 (0.005)	1,76142
Age	0.063* (0.003)	1,76142

* $p < 0.05$.
[a] Effect estimated for men as the comparison group. Relative effects for women are displayed in the IQ*Female interaction term.

3.2. Post hoc power analyses

Post hoc power analyses were conducted using G*Power v.3.1 (Faul, Erdfelder, Lang, & Buchner, 2007) in order to determine the degree to which analyses involving the two smaller samples (NCDS and NLSY′ 79) had the power to detect quadratic terms, once the other predictors are considered. In the case of NCDS, the regression model that included the following covariates: IQ, age, sex, IQ*sex, IQ^2, IQ^2*sex, yielded an IQ^2 β[1] of −0.018, which given a sample size of 5225, yielded a power estimate (1-β error probability) of 0.240 to detect a significant quadratic effect. In order to detect a significant quadratic effect with a power estimate of >0.80 (considered high power), the sample size would have needed to have been ≥26,200. In the case of NLSY′79, the regression model that included the following covariates: IQ, age, race, IQ*race, IQ^2, IQ^2*race, yielded an IQ^2 β of −0.007, which given a sample size of 7598, yielded a (very low) power of 0.095 to detect a significant effect. In order to detect a significant effect with a power estimate of >0.80, a sample size of ≥157,000 would be needed.

3.3. Visualizing the IQ-fertility relationship

As was mentioned in the introduction, previous studies (e.g. Meisenberg, 2010) have considered the IQ-fertility relationship across a large range of IQ values. In some studies attempts have even been

[1] These coefficients were computed from *b* values derived from the regression models using the formula $\beta = b(SD_x/SD_y)$.

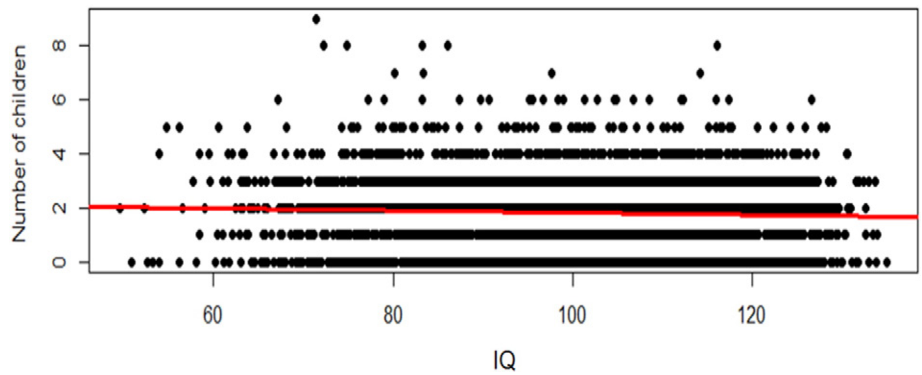

Fig. 1. Scatter plot of numbers of children by IQ level (mean = 100) (Full Sample, NCDS dataset, $N = 5225$). The linear regression line is shown in red (Spearman's *Rho* = −0.042, $p < 0.05$).

made to visualize the relationships using bar charts in which IQ is binned based on deciles and the fertility of each IQ decile is represented via the height of each bin. A higher resolution method for visualizing the IQ-fertility relationship involves generating scatter plots of the numbers of children on the y-axis against the IQ of the participants on the x-axis (Figs. 1, 2, and 3). These plots potentially allow for the density of fertility as a function of participant IQ-level to be visualized. The IQ-scores from each of the three datasets were standardized such that the mean score on IQ was 100 and the standard deviation was 15 in all cases. Fertility declines at the extremes of the distribution in all three datasets, which would be consistent with previous observations that those with very low levels of IQ, especially values lower than 70, exhibit lower than average fertility. The positive (leftward) skew in fertility as a function of level of IQ is especially visually prominent in the NLSY′79 dataset, consistent with the finding that directional selection is the dominant mode of phenotypic selection in these data. The gradient of directional selection in these graphs is illustrated via the inclusion of a linear regression line through the scatter and the computation of Spearman's *Rho* correlations for each sample.

4. Discussion

The pattern of magnitudes among the Spearman's *Rho* correlations computed for the combined samples in Fig.s 1, 2 and 3 are consistent with the expectation that the strength of the negative IQ-fertility relationship declines as fertility reaches completion, with the biggest value of *Rho* being found among the youngest cohort (Project Talent), and the smallest being found among the oldest (NCDS). This trend is driven by the tendency for higher-IQ individuals to postpone fertility untill later in life, which leads to them registering as childless when younger cohorts are examined (Vining, 1995).

In the regression analyses, the level of IQ had no effect on fertility among men in the NCDS dataset, whereas a negative effect was observed among females. Moreover, females had significantly more children on average than males. In the NLSY′79 dataset, among the White reference sample IQ had a negative effect on fertility. The best-fitting model did not include IQ^2, sex differences or interactions with sex; however, the negative effect of IQ on fertility was strongest among Hispanics, intermediate among Blacks, and weakest among Whites. Hispanics also had on average the largest numbers of children, Blacks were intermediate, and Whites had the fewest. Finally, in the Project Talent dataset, among the male reference population, IQ was associated with a negative effect on fertility. This was significantly but slightly weaker (as indicated by the positive term), among females, and the best fitting model did not include race differences or interactions. As with NCDS, females had significantly more children than males, however the effect was stronger than in NCDS, which is consistent with the latter population being at completed fertility. This may furthermore help to account for the observation that the sign of the IQ*Female interaction was negative in the case of NCDS vs. positive in the case of Project Talent, as higher-IQ males take longer to complete their fertility and may ultimately produce proportionately more children than females of equivalent IQ, by virtue of being more willing to engage in hypogamous mating (Johnson, McGue & Iacono, 2012), which would have the effect of attenuating the apparent magnitude of the correlation between IQ and fertility at completion in this sex.

A weak but statistically significant negative quadratic effect of IQ on fertility was also found in Project Talent, indicating that those with intermediate levels of IQ tended to have slightly more children than

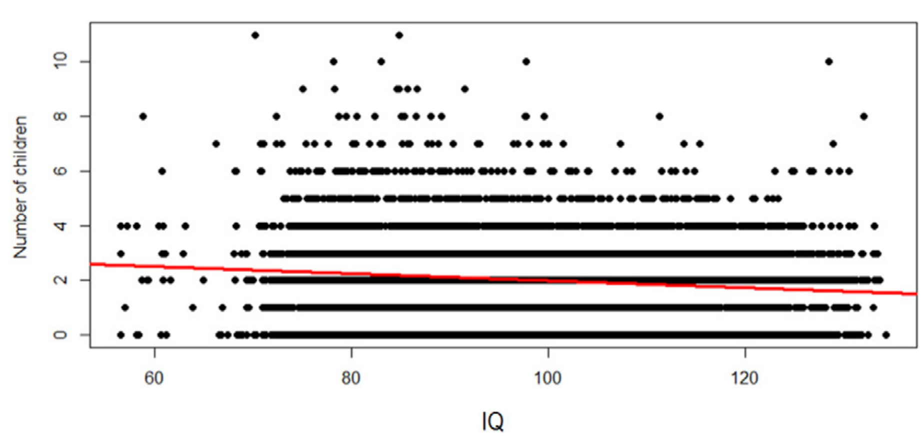

Fig. 2. Scatter plot of numbers of children by IQ level (mean = 100) (Full Sample, NLSY'79 dataset, $N = 7598$). The linear regression line is shown in red (Spearman's *Rho* = −0.115, $p < 0.05$).

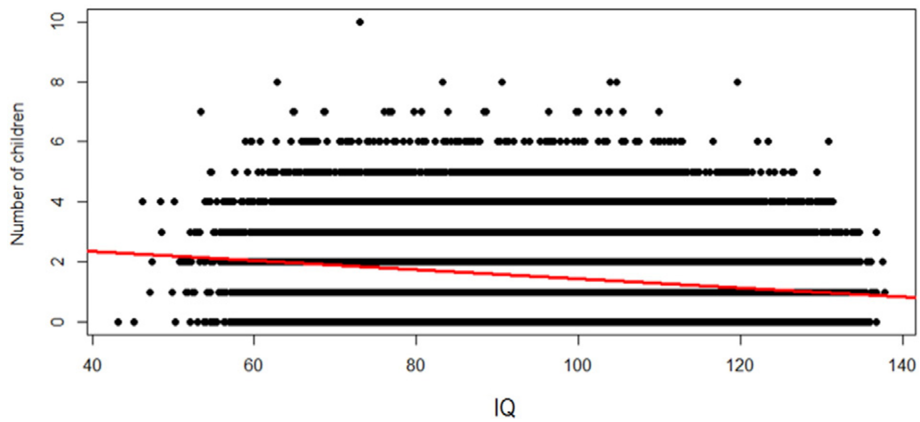

Fig. 3. Scatter plot of numbers of children by IQ level (mean = 100) (Full Sample, Project Talent dataset, $N = 76{,}150$). The linear regression line is shown in red (Spearman's $Rho = -0.192$, $p < 0.05$).

others all else being equal, this term was not observed to interact significantly with sex however.

It is important to note that whilst present in samples for which the analyses had the requisite power (i.e. Project Talent), consistent with the expectation that there should be *some* stabilizing selection operating on IQ, the extremely small magnitude of the negative quadratic term nevertheless implies that any gradient of stabilizing selection operating on IQ is very weak. Consistent with this, IQ explained 15.77 times more variance in fertility than IQ^2. *Post hoc* power analyses revealed that given the very small effect size of the quadratic term in the NLSY'79 and NCDS samples, only samples of 26,200 and 157,000 individuals respectively would have confidently yielded a significant quadratic term. It is important to note furthermore that the NCDS and NLSY′ 79 models incorporating quadratic effects of IQ on fertility and their higher-order interaction with sex, while exhibiting equal goodness-of-fit to models that excluded the terms, were nonetheless less parsimonious, thus were *prima facie* excluded from consideration.

The results of the regressions suggest that linear effects of IQ on fertility (indicating directional selection) are predominant in these samples. This should not be taken to mean however, that the linear effect of IQ has a large impact on fertility: in fact, even though it was consistently identified across samples, its magnitude was weak, explaining at most 1% of the variance in fertility.

Age also appears to have an independent and significant, but small magnitude positive effect on fertility in NLSY′79 and Project Talent. This is consistent with the observation that age and fertility should be positively associated up to the point at which fertility is complete, fertility being much closer to completion in NLSY′79, hence the smaller magnitude effect.

In summation, these findings indicate that a gradient of stabilizing selection on IQ, whilst present, is weak, with the negative quadratic term capturing it being of very small magnitude in the one model where its inclusion boosted (rather than reduced) model fit, these findings indicate that IQ is primarily under directional selection in modern Western populations.

Finally, it is important to note that it has likely not always been the case that directional selection favours lower IQ, as prior to 1800 potential proxies for IQ such as wealth and occupational status were positively predictive of reproductive success in Western populations, suggesting that historically, in the period leading up to the Industrial Revolution, directional selection may actually have favoured higher IQ (as suggested by the presence of positive correlations between cognitive ability proxies such as occupational and social status and fertility in Western populations living prior to the 19th century; Skirbekk, 2008). Furthermore, no inferences can be drawn about the future of this relationship in these populations from the present findings. There are certain indications that the strength of selection operating on IQ and its proxies may have weakened in some Western populations (such as the UK throughout the first half of the 20th century; Lynn, 2011), but not in others (such as the US where the selection strength appears to be stable over decades; Conley et al., 2016; Lynn & van Court, 2004, or in Sweden, where the selection pressure operating on IQ shifted in direction from positive to negative in the space of just a couple of decades; Madison, Woodley of Menie & Sänger, 2016). In any case, the picture with respect to the future of these trends is unclear.

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Appendix. Codes and descriptions for variables used in the analyses.

NCDS	
Variable codes	Description
Cognitive ability measures	
N457	Copying designs test (Sweep 1)
N1840	Draw a Man Test (Sweep 1)
N92	Southgate group reading test (Sweep 1)
N90	Problem arithmetic test (Sweep 1)
N914	Verbal general ability test (Sweep 2)
N917	Nonverbal general ability test (Sweep 2)
N923	Reading comprehension test (Sweep 2)
N926	Mathematical test (Sweep 2)
N929	Copying designs test (Sweep 2)
N2928	Reading comprehension test (Sweep 3)
N2930	Mathematics comprehension test (Sweep 3)
Sociodemographics	
N1612	Sample race/ethnicity
N622	Sample sex
Custom variable 1	Number of biological children (Sweep 6)
Custom variable 2	Number of biological children (Sweep 7)
Custom variable 3	Number of biological children (Sweep 8)
Custom variable 4	Sweep 6, 7 and 8 participant ages
Project talent	
Fluid intelligence	
R290	Abstract reasoning
R311	Arithmetic reasoning,
R270	Mechanical reasoning
R250	Reading comprehension
R281	2D rotation
R282	3D rotation

(continued on next page)

(*continued*)

Variable codes	Description
F420	Table reading
Crystallized intelligence	
R102	Vocabulary
R108	Biological sciences knowledge
R105	Social sciences knowledge
R103	Literature knowledge
Sociodemographics	
Race	Sample race
Sex	Sample sex
P331	Number of biological children
Age-SR	Age
NLSY'79	
Academic tests	
R06150	Science
R06151	Arithmetic
R06152	Word knowledge
R06153	Paragraph comprehension
R06157	Mathematics knowledge
Vocational tests	
R06156	Auto and shop information
R06158	Mechanical comprehension
R06159	Electronics information
Speed tests	
R06154	Numerical operations
R06155	Coding speed
Sociodemographics	
R00096	Sample race (S01Q30A)
R02148	Sample sex
T22177	Number of biological children ever born (2008)
R02165	Age

Note: For Project Talent and NLSY'79, participants were selected if they had complete data on *g*, sex, race and fertility. For NCDS, participants were selected if they were White and had complete data on IQ, sex, and fertility. In NCDS Sweep 6 fertility is derived from the total numbers of children reported by respondents at Sweep 5, which was computed by going through and summing the entire list of biological children that the respondents have ever had up to that point. Adding to this the numbers of additional children reported by the participants at Sweeps 7 and 8, yielded Sweep 7 and 8 fertility respectively. In NLSY'79, the category of Hispanic was created by merging the Chicano, Cuban, Mexican, Mexican American, Puerto Rican, Other Hispanic and Other Spanish categories. The category of White was created by merging the American, English, French, German, Greek, Irish, Italian, Polish, Portuguese, Russian, Scottish and Welsh categories.

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