



## Estimating the strength of genetic selection against heritable $g$ in a sample of 3520 Americans, sourced from MIDUS II



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### ARTICLE INFO

#### Article history:

Received 15 November 2014

Received in revised form 21 May 2015

Accepted 23 May 2015

Available online xxx

#### Keywords:

Fertility

General intelligence

Jensen effect

USA

### ABSTRACT

The relationship between IQ and completed fertility among a sample of 3520 Americans from MIDUS II (1960's birth cohorts) is examined using a common factor comprised of eight cognitive ability measures, in order to determine the rate of phenotypic IQ loss due to genetic selection. Negative correlations are present in both the male and female subsamples, and are associated with a predicted loss in heritable  $g$  ( $g.h$ ) of  $-.262$  points per decade, increasing to  $-1.072$  points when the additive effect of mutation accumulation is considered. The ability–fertility associations showed Jensen effects at the level of the whole sample ( $.167$ ), and also separately for each sex ( $.185$  and  $.147$  for the females and males respectively). The magnitude of the expected  $g.h$  loss in this cohort due to selection is comparable to that derived from a meta-analysis of disattenuated decadal  $g.h$  declines from eight US studies ( $-.44$  points per decade;  $N = 127,389$ ). There is a Flynn effect in the US amounting to gains of 3.6 points per decade, which are concentrated on more environmentally plastic and specialized sources of ability variance ( $s.e$ ) suggesting co-occurrent socio-ecological specialization with respect to narrower cognitive abilities in the present cohort.

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### 1. Introduction

The *co-occurrence model* (Woodley & Figueredo, 2013) posits that the widely observed secular increases in aggregate phenotypic IQ (the so-called Flynn effect) are concentrated on the environmentally influenced variances associated with specialized mental abilities (*s.e*, Woodley & Figueredo, 2013). Genetic selection effects and other genetic changes (such as accumulating mutations) are by contrast reducing the level of heritable general intelligence ( $g.h$ ). This prediction that different variance components of IQ may be trending on opposing directions is consistent with evidence that despite secular gains on pencil-and-paper IQ tests, there are apparent simultaneous long-term secular losses in population-level cognitive indicators believed to be closely allied to  $g$  such as *creativity* (per capita rates of macro-innovation and genius; Huebner, 2005; Murray, 2003), *working memory* (digit span backwards; Woodley of Menie & Fernandes, 2015), *processing speed* (simple visual reaction time; Woodley, te Nijenhuis, & Murphy, 2014) and *crystallized ability* (vocabulary usage evaluated using the frequencies of high-

difficulty words in lexicographic databases; Woodley of Menie, Fernandes, Figueredo, & Meisenberg, 2015).

The co-occurrence model also predicts that the historically recent environmental enrichments likely responsible for enhancing *s.e* (i.e. industrialization, sanitation, nutrition, medicine, enhanced environmental quality and generalized education) have simultaneously increased the selective pressures against  $g.h$  (Woodley & Figueredo, 2013).

In the US, IQ has been negatively correlated with reproductive success (measured in terms of completed fertility or sibling numbers) since the beginning of the 20th century (Lynn & van Court, 2004; van Court & Bean, 1985). Proxies for IQ, such as socio-economic status and educational attainment, appear to have been negatively correlated with reproductive success in the West since the early 19th century (Skirbekk, 2009).

Several studies have attempted to determine the degree to which negative ability–fertility correlations should reduce IQ within a population over time, using US samples. This expectation is based on the premise that the heritable components of IQ (such as  $g$ ) should decrease owing to selection. One of the earliest studies into this question was conducted by Lentz (1927) who estimated that IQ should be declining at a rate of  $-4$  points per generation, based on the negative correlation between IQ (evaluated using various group tests) and sibling number in a sample of 4330 US citizens.

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Retherford and Sewell (1988) attempted to estimate the generational decline in 'genotypic IQ', i.e. the heritable variance component of full-scale IQ ( $IQ_h$ ; Woodley & Figueredo, 2013), based on the negative fertility–IQ relationship among a sample of 10,317 US citizens evaluated using the AirCorps aviation qualifying examination. Employing a very low estimate of the additive heritability of IQ (.4) they estimated a decline of  $-.32$  points per generation.

Vining (1995) re-examined a sample of 2196 individuals, tested on a large IQ battery as part of the National longitudinal study of labor market experience that had completed fertility, and predicted declines in  $IQ_h$  of  $-.5$  points per generation, assuming a parent–child similarity correlation on IQ of .5. An earlier study by Vining (1982) examined a larger subset of this cohort, and found larger declines, however these were attributed to incomplete fertility.

Loehlin (1997) estimated the  $IQ_h$  loss among a sample of 16,781 Americans at .8 points per generation, utilizing data on educational level and assuming a parent–child similarity of .5.

Lynn (1999) and Lynn and van Court (2004) examined the negative association between IQ and fertility on the WORDSUM test in the General Social Survey. Using a subset ( $N = 1645$ ), Lynn (1999) estimated the generational  $IQ_h$  loss due to selection at .49 points per generation, assuming an  $IQ_h^2$  of .8. Using a larger subset of the GSS ( $N = 5885$ ), Lynn and van Court (2004) estimated the decline at .9 points per generation, assuming an  $h^2$  value of .71.

Meisenberg (2010) and Meisenberg and Kaul (2010) examined the negative ability–fertility relationship in the National Longitudinal Survey of Youth, using the Armed Services Vocational Aptitude Battery. The estimated sample-wide loss due to selection was .8 points per generation, assuming a parent–child similarity of .5.

The most recent estimate of the  $IQ_h$  loss in the US population comes from Reeve, Lyster, and Peach (2013), who estimate losses of .83 points per generation, utilizing a sample of 79,734 individuals evaluated using the Project Talent Ability Battery, and assuming an  $h^2$  value of .5.

A recent psychometric meta-analysis of 10 predicted declines in heritable general intelligence ( $g_h$ ) computed on the basis of the magnitude of the negative ability–fertility correlation in various US and UK samples, and corrected for reliability, validity and heterogeneity, revealed an aggregate decline in  $g_h$  of  $-.39$  points per decade ( $-1.37$  points per generation), assuming a high-end estimated generational length of 3.5 decades (which would tend to underestimate the rate of decline) and a high heritability (.86) of general intelligence (Woodley of Menie, 2015). In order to estimate the US specific decline, the two UK estimates can be excluded, yielding a meta-analytic estimate of the  $g_h$  loss due to selection in the US of  $-.44$  points per decade (95% CI = .418 to .426,  $N = 127,389$ ,  $K = 8$ ).

In the present analysis, another relatively large and population-representative US dataset (Mid-Life in the United States [MIDUS] II) will be examined for evidence of genetic selection effects on the heritable components of intelligence. An attempt will be made to quantify the degree to which  $g_h$  should be declining due to the effects of genetic selection and mutation accumulation. Also the data will be examined for the presence of "Jensen effects" (Rushton, 1998), meaning the correlations of observed effects upon specific tests of various cognitive abilities with their common factor loadings. The latter is a test of the co-occurrence model, as it is predicted that the magnitude of genetic selection should be largest when the common factor loading is highest.

## 2. Methods

MIDUS II (Ryff et al., 2004–2006) constitutes the second wave of data collection involving large-scale longitudinal examination of adult development within the United States. Data collection was completed in 2009 for a full sample of 4963 participants aged between 32 and 84. In MIDUS II, data were collected on several cognitive ability measures as part of the Brief Test of Adult Cognition (BTACT). These include two Recall Tasks (delayed and immediate), Digit Span Backwards, Category

Fluency measures, Number Series, Backwards Counting (a measure of processing speed) and measures of Task Switching Efficiency (in milliseconds). Lachman, Agrigoroaei, Tun, and Weaver (2014) identified a hierarchical structure among these measures, with the two Recall Tasks loading on an Episodic Memory common factor, and the others (Digit Span Backwards, Category Verbal Fluency, Number Series, Backwards Counting and the Mixed Switching Task) forming an Executive Functioning common factor. Both factors correlated with one another at .43, indicating the presence of a higher-order  $g$ -like (Stratum III; Carroll, 1993) common factor among these lower-order factors (Stratum II; Carroll, 1993).

In constructing a phenotypic IQ ( $IQ_p$ ) factor, the seven ability scales employed by Lachman et al. (2014) were utilized (see Lachman et al., 2014 for details concerning these variables). The 12-point Educational Attainment measure was also incorporated into the common factor computed for the present study. Educational attainment serves as a proxy for crystallized ability, as it relates to learned knowledge, and is routinely found to correlate with  $g$  (e.g. Herrnstein & Murray, 1994).

The first wave of MIDUS data collection was conducted in 1995–1996 on a sample with a minimum age of 25; the second wave (MIDUS II) was conducted in 2004–2006, indicating that the minimum age of continuing participants was 35. To capture completed fertility, we excluded the subset of that cohort aged  $<41$ , so that the remainder of the MIDUS II sample had achieved anywhere from 99.8%–100% of their completed fertility, based on 2012 estimates of completed fertility by respondent age cohorts reported by the US Census Bureau (Martin, Hamilton, Osterman, Curtin, & Mathews, 2013). MIDUS II contains an indicator that measures total numbers of children (Variable Code = B1PC2). This variable includes adopted and stepchildren in addition to biological ones, and cannot be disaggregated. Given that adoption is relatively rare, it is unlikely to substantially compromise potential negative ability–fertility correlations in this dataset, therefore it is used in the present analysis, albeit with the caveat that any adopted and stepchildren counted will necessarily function to underestimate the magnitude of the expected negative ability–fertility correlation.

### 2.1. Estimating the loss in $g$ due to genetic selection

The eight cognitive ability measures from MIDUS II were aggregated into an  $IQ_p$  common factor using Unit Weighted factor analysis. Unit-weighted common factor scales (Gorsuch, 1983) were estimated as the means of the standardized scores for all non-missing indicators on each factor (Figueredo, McKnight, McKnight, & Sidani, 2000). The common factor loadings on each specific ability are then computed by correlating the standardized ability scores with the Unit Weighted  $IQ_p$  factor.

The factor structure identified by Lachman et al. (2014) was replicated using Unit Weighted analysis to derive the common factor loadings of each ability scale (Stratum I in Carroll, 1993) on the Semantic Memory and Executive Functioning group factors (Stratum II). Educational Attainment was treated as both a Stratum II (Crystallized Ability) and Stratum I indicator. The loadings of the  $IQ_p$  factor on each Stratum II ability were calculated also for use in the analyses.

The ability–fertility correlation constitutes the selection differential that predicts the inherited change in  $IQ_p$  in the following generation. Generation length was estimated at 3.5 decades (Woodley of Menie, 2015). The decline resulting from the negative selection differential was computed case-wise with Equation 1, first developed by Lentz (1927).

$$S = \frac{1}{N} \sum_{i=1}^N (X_i - \bar{X}) \frac{f_i}{f} \quad [1]$$

$X$  and  $f$  are the mean  $IQ_p$  and fertility of the sample,  $X_i$  and  $f_i$  are the  $IQ_p$  and fertility of the individual, and  $N$  is the sample size. To convert

the  $IQ_p$  decline ( $S$ ) into a genotypic IQ ( $IQ_h$ ) decline, the Breeder's equation (equation 2) is employed (Fisher, 1929):

$$R = S * h^2 \quad [2]$$

where  $S$  is the selection differential scaled as a decline in  $IQ_p$  (as computed using Equation 1),  $h^2$  is the additive heritability of  $g$ , and  $R$  is the responsiveness to selection, which equates to the expected generational change in  $IQ_g$  given the aforementioned parameters. In selecting a reference estimate (Schmidt & Hunter, 2015) of the additive heritability of  $g$  in the US, the value of .86 derived from the study of Panizzon, Vuoksimaa, Spoon, et al. (2014) is employed, which was derived using latent variable models that permitted direct estimation of the heritability of  $g$ .

Decline estimates will be computed for both males and females together and separately, and will be corrected for psychometric validity by division by .9 (from Jensen, 1998, p. 383). This correction rescales the  $IQ_h$  declines in terms of  $g.h$  declines. This is theoretically significant, as studies involving the method of correlated vectors have repeatedly demonstrated, consistent with predictions from the co-occurrence model, that the magnitudes of negative ability–fertility relationships are positively associated with the  $g$  saturation of indicators (Peach, Lysterly, & Reeve, 2014; Woodley & Meisenberg, 2013; Woodley of Menie, Fernandes, et al., 2015; Woodley of Menie, et al., 2015). This indicates that the effects of genetic selection are concentrated on the more heritable  $g$  factor, as opposed to the less heritable specialized abilities (Woodley & Figueredo, 2013). Therefore the decline estimate in terms of  $IQ_h$  necessarily underestimates the true decline in  $g$  and must be disattenuated. A final adjustment to these decline estimates will be made on the basis of the decadal loss in  $g$  expected due to mutation accumulation – which is predicted to have additive effects on the loss in  $g$  via selection (Woodley of Menie, 2015). On this basis .84 points per decade will be added to the  $g.h$  losses. This estimate of the impact of mutation accumulation on  $g$  was derived using the results of a high-quality study examining the effects of paternal age (a strong proxy for *de novo* germ-line mutations) on offspring  $g$ , controlling for paternal age and education (Arslan, Penke, Johnson, Iacono, & McGue, 2014).

## 2.2. Test for Jensen effects

The method of correlated vectors (MCV) was employed to determine whether the magnitude of the negative ability–fertility correlation of each ability is positively correlated with the common factor loading on the indicators comprising the battery. Thus an attempt was made to determine the presence of Jensen effects in the sample. MCV was implemented by the use of the Continuous Parameter Estimation Method (CPEM; Gorsuch, 2005) to calculate the cross-products of the standardized vectors being correlated at both the individual and group levels between the  $IQ_p$  loadings for each ability indicator and the ability–fertility correlations. The application of CPEM to the implementation of MCV uses the raw data to estimate aggregate statistics that are weighted based on sample size, as would be obtained by the logic of meta-analytic data synthesis. Thus, the weighted average of the cross-products becomes the sample-weighted vector correlation, the significance of which can be determined based on the aggregate sample size, rather than the number of subtests. These parameters were computed using the Stratum III ( $IQ_p$ ) loadings on each Stratum II group factor (Education/'crystallized ability', Executive Functioning and Episodic Memory). CPEM also permitted the comparison of parameters across subsamples (female and male) by analysis of variance to determine whether the estimates were significantly different or not from each other by sex.

## 3. Results

Table 1 presents the Unit-Weighted factor loadings, along with the ability–fertility correlations by subtest for the male and female cohorts separately. Vector correlations, are presented for each sex, as is conventional in this area of research (e.g. Woodley & Meisenberg, 2013). Analysis of variance on the CPEs, however, indicated that the Jensen effects did not differ significantly by sex ( $F_{1,3518} = .46, p = .4969$ ).

Table 2 presents the Unit-Weighted factor loadings, along with the ability–fertility correlations by subtest for the combined cohort. Vector correlations were also computed for the combined cohort.

Table 3 presents the estimated generational and decadal losses in  $S$  ( $IQ_p$ ),  $R$  ( $IQ_h$ )  $g.h$  and  $g.h$  adjusted for mutation accumulation (based on Woodley of Menie, 2015, i.e. .84 points per decade) for the combined sample.

## 4. Discussion

The present study replicates many aspects of other studies. The ability–fertility associations are all negative in sign, and there exist Jensen effects, indicating that the effects of selection strengthen as the common factor loading increases. The vector correlations are also weaker in these samples than in those based on the use of other large, population representative samples of the US, such as in the case of Woodley and Meisenberg (2013), where vector correlations (estimated at the subtest level) ranged in magnitude from .5 to .8, and in Peach et al. (2014), where the magnitudes ranged from .8 to .9. It is important to note that there are sources of error in MCV that can be corrected meta-analytically, such as sampling error, range restriction in the standard deviations of the common factor loadings, and vector reliabilities and validities (e.g. te Nijenhuis & van der Flier, 2013), which when corrected, will increase the magnitude of the present findings. These corrections will be applied to the present results and the results of other studies as part of a psychometric meta-analysis of the results of using MCV on the ability–fertility association, currently in preparation. It is important to note that previous studies employed IQ batteries that were highly nomologically variegated by contrast to the present one. Examples of this are the 11 subtests the ASVAB employed in Woodley and Meisenberg (2013), and the 11 subtests the PTAB employed in Peach et al. (2014), both of which cover several very broad psychometric domains as opposed to the three covered in the present analysis. This difference may be a source of attenuation in the present results.

The overall decadal decline in the  $g.h$  variance component due to selection is approximately similar to the meta-analytic mean value estimated in the introduction across eight US studies (–.44 points per decade). The discrepancy might reflect the fact that the ability–fertility correlations in the present analyses were not corrected for reliability, which will attenuate the decline estimates. Also, recall that the ability–fertility correlations based on MIDUS II data are probably underdetermined because of the presence of adopted and stepchildren among the respondent's offspring.

When adjusted upwards for mutation accumulation, the predicted  $g.h$  decline is –1.072 points per decade for the combined sample. This falls within the range of  $g$  decline values estimated on the basis of the slowing of simple reaction time (–.57 to –1.21 points per decade; Woodley, te Nijenhuis & Murphy, 2013, 2014).

In a meta-analysis of 329 US studies comprising 140,062 individuals, and spanning the years 1909 to 2006, Pietschnig and Voracek (2015) have found a secular increase in Fullscale IQ ( $IQ_p$ ) of 3.6 points per decade. Meta-analyses of the results of studies employing the method of correlated vectors on the relationship between the Flynn effect and subtest  $g$  loadings have found that the effect is most pronounced on specialized abilities consistent with predictions from the co-occurrence model. That is; it is associated with an anti-Jensen effect (te Nijenhuis & van der Flier, 2013; Woodley et al., 2014). Given the small, but

**Table 1**  
Unit-weighted factor loadings of *IQ<sub>p</sub>* for each sex, along with the ability–fertility correlations and sex-specific vector correlations.

	Indicators	Stratum II loadings	Stratum I loadings	Ability–fertility correlations
Females	Educational Level ( <i>N</i> = 1871)		.749*	–.1675*
	Immediate Word List Recall ( <i>N</i> = 1871)	.943*	.732*	–.0676*
	Delayed Word List Recall ( <i>N</i> = 1814)	.943*	.700*	–.0571*
	Episodic Memory ( <i>N</i> = 1871)		.761*	–.0684*
	Digit Span Backwards ( <i>N</i> = 1871)	.560*	.449*	–.0629*
	Category Fluency ( <i>N</i> = 1871)	.676*	.553*	–.1080*
	Number Series ( <i>N</i> = 1863)	.709*	.596*	–.0709*
	Backward Counting ( <i>N</i> = 1870)	.751*	.549*	–.1286*
	Switching Mixed Task (reversed; <i>N</i> = 1869)	.671*	.430*	–.0944*
	Executive Functioning ( <i>N</i> = 1871)		.763*	–.1400*
	<i>IQ<sub>p</sub></i> ( <i>N</i> = 1871)			–.1633*
	CPEM vector correlation <sup>a</sup>		<b>.185*</b>	
	Males	Educational Level ( <i>N</i> = 1649)		.772*
Immediate Word List Recall ( <i>N</i> = 1649)		.939*	.710*	–.0735*
Delayed Word List Recall ( <i>N</i> = 1594)		.936*	.666*	–.0852*
Episodic Memory ( <i>N</i> = 1649)			.735*	–.0867*
Digit Span Backwards ( <i>N</i> = 1648)		.645*	.507*	–.0116
Category Fluency ( <i>N</i> = 1649)		.668*	.542*	–.0673*
Number Series ( <i>N</i> = 1646)		.740*	.610*	–.0252
Backward Counting ( <i>N</i> = 1646)		.797*	.583*	–.0998*
Switching Mixed Task (reversed; <i>N</i> = 1648)		.625*	.420*	–.0652*
Executive Functioning ( <i>N</i> = 1649)			.769*	–.0781*
<i>IQ<sub>p</sub></i> ( <i>N</i> = 1649)				–.0858*
CPEM vector correlation <sup>a</sup>			<b>.147*</b>	

\* *p* < .05.

<sup>a</sup> Coefficients in bold are the weighted average of continuous parameter estimates for correlated vectors, as per the CPEM approach to MCV; signs reversed so that the magnitude of the negative correlation scales positively with the Jensen effects.

statistically significant Jensen effects on ability–fertility associations detected in the present study, coupled with the consistently larger effects detected on other US population–representative samples for which completed fertility and ability could be correlated (Peach et al., 2014; Woodley & Meisenberg, 2013; Woodley of Menie, Fernandes, et al., 2015; Woodley of Menie, et al., 2015), this suggests that genetic selection in the US is somewhat more concentrated at the level of highly heritable *g* within the present and other US population–representative samples (such as those comprising Project Talent, the GSS and the NLSY). Therefore, while environmental improvements might be working to raise the performance of US cohorts on *s.e.*, selection and also mutation accumulation are simultaneously lowering *g.h.*

This is an important observation, as even though *g* might have been declining in this cohort due to genetic changes, the 1960’s birth cohort from which the MIDUS II samples were drawn, was nonetheless becoming simultaneously more socio-ecologically specialized with respect to investments into the development of narrower cognitive abilities, giving rise to the Flynn effect, coupled with a more differentiated ability profile over time (Juan-Espinosa, Cuevas, Escorial, & García, 2006; Kane, 2000; Kane & Oakland, 2000).

Ability specialization is important, as specialized cognitive abilities have been shown to predict performance variance in academic contexts (i.e. GPA), even when residualized for *g* variance (Coyle & Pillow, 2008). Conversely, functional impairments among specific mental abilities, resulting from various environmental insults, generate real cognitive deficiencies that are independent of *g* (Flynn, te Nijenhuis, & Metzen, 2014). Increasing patterns of cognitive specialization may also account for real world indicators of rising mental ability, such as teacher ratings of pupils indicating increasing practical ‘intelligence’, and increasing precociousness in games of strategy and memory, like Chess, Bridge and Go (Howard, 1999, 2001). More significantly still, by the logic of Ricardo’s Law of Comparative Advantage, this would have translated into wealth growth as competition would have been reduced and aggregate efficiency would have increased (Cabeza de Baca & Figueredo, 2014; Woodley, 2012). What we are therefore observing is selection for higher degrees of *cognitive differentiation effort*, that is the disaggregation of the positive manifold of *g* among those with slow life histories or high *K* in the US population (Woodley, Figueredo, Brown, & Ross, 2013). Enhanced cognitive differentiation effort is consistent with the presence of the related *strategic differentiation effect*

**Table 2**  
Unit-weighted factor loadings of *IQ<sub>p</sub>* presented for the combined sample, along with the ability–fertility correlations.

	Component	Stratum II loadings	Stratum III loadings	Ability–fertility correlation
Combined sexes	Education Level ( <i>N</i> = 3520)		.753*	–.1469*
	Immediate Word List Recall ( <i>N</i> = 3520)	.944*	.706*	–.0646*
	Delayed Word List Recall ( <i>N</i> = 3408)	.942*	.671*	–.0629*
	Episodic Memory ( <i>N</i> = 3520)		.732*	–.0695*
	Digit Span Backwards ( <i>N</i> = 3519)	.592*	.476*	–.0392*
	Category Fluency ( <i>N</i> = 3520)	.673*	.546*	–.0900*
	Number Series ( <i>N</i> = 3509)	.727*	.597*	–.0520*
	Backward Counting ( <i>N</i> = 3516)	.776*	.556*	–.1160*
	Switching Mixed Task ( <i>N</i> = 3517)	.649*	.416*	–.0838*
	Executive Functioning ( <i>N</i> = 3520)		.758*	–.1128*
	<i>IQ<sub>p</sub></i> ( <i>N</i> = 3520)			–.1476*
	CPEM vector correlation <sup>a</sup>		<b>.167*</b>	

\* *p* < .05.

<sup>a</sup> Coefficients in bold are the weighted average of continuous parameter estimates for correlated vectors, as per the CPEM approach to MCV; signs reversed so that the magnitude of the negative correlation scales positively with the Jensen effects.

**Table 3**

Mean selection differentials ( $S$ ) on  $IQ_p$  for the combined sample along with the expected response to selection ( $R$ ) on  $IQ_h$ . Also presented are the decadal declines in heritable general intelligence ( $g_h$ ) corrected for validity and then adjusted for the additive impact of mutation accumulation.

	Combined 2004–2006
$N$ (sample size)	3520
$S$ (selection coefficient) on $IQ_p$	–.851
$R$ (selection coefficient) on $IQ_h$	–.732
Selection on $g_h$	–.813
Generation length in decades	3.5
$S$ ( $IQ_p$ )/decade	–.243
$R$ ( $IQ_h$ )/decade	–.209
$g_h$ /decade	–.232
$g_h$ /decade (mutation-load adjusted)	–1.072

(i.e. the disaggregation of life history into its components at high levels of *Super K* – the common factor variance among life history indicators). This has also been observed in MIDUS-derived samples (Figueredo, Woodley, Brown, & Ross, 2013; Woodley of Menie et al., 2015).

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