Racial income disparities in the United States. Discrimination or human capital?

Simon Wright, Emil O.W. Kirkegaard

Replication code is available at: https://osf.io/2pb3d/

[1] Independent researcher, UK; email: simonwright50392@protonmail.com
[2] Ulster Institute for Social Research, UK; email: emil@emilkirkegaard.dk

Abstract
The persistence of race-based income disparities in the United States, particularly between Black and White populations, has been a significant focus of academic research. This study aims to investigate the extent to which differences in average intelligence test performance can account for these income gaps, rather than labour market discrimination or other factors. Utilising five large, nationally representative US datasets, we employ structural equation modelling to adjust our intelligence measures for random measurement error, addressing underestimation of group differences in average intelligence. Our findings reveal that, with the exception of the NLSY97 dataset, performance on intelligence tests mediates the entire income disparity between Black and White individuals when personal income is considered. However, racial gaps in household income persist, indicating that race may influence spousal income and marital choices. This study highlights the importance of accounting for intelligence differences in understanding race-based income disparities.

Introduction
Despite civil rights legislation prohibiting race based employment legislation since 1964 (Congress, 1964), the United States continues to grapple with persistent and pronounced differences in income across racial groups (Semega et al., 2021). As researchers seek to uncover the factors driving these disparities, two primary hypotheses have emerged: the human capital model, which attributes the gaps to differences in productivity and intelligence, and the discrimination model, which contends that employer bias and discrimination play a significant role in perpetuating these disparities (Gaddis, 2013). Existing literature offers mixed evidence and leaves open questions about the extent to which each of these factors contributes to race-based income disparities (Gaddis, 2013; Kanazawa, 2005; Neal & Johnson, 1996).

This study aims to advance our understanding of these issues by investigating the role of intelligence in explaining income disparities between Black and White populations in the United States. We apply structural equation modelling to 5 large, nationally representative datasets to estimate racial differences in average intelligence and the influence of these differences on both personal and household income. In doing so, we address the underestimation of racial differences in intelligence due to attenuation bias (Kirkegaard, 2022).

By focusing on intelligence as a key variable, this study builds on prior literature that has demonstrated a robust correlation between intelligence and income (Marks, 2022), as well as the causal relationship between intelligence and job performance, educational achievement, and productivity (Jensen, 1998). Furthermore, we argue that by utilising intelligence as our sole proxy for human capital, we are able to address the limitation of previous research that some measures of human capital are plausibly influenced by discrimination themselves (Gaddis, 2013).

In the sections that follow, we first provide a review of the existing literature on the human capital and discrimination models, highlighting the limitations of research supporting each hypothesis. We then detail our data and methodology, emphasising the advantages of our approach in addressing limitations in prior research. Finally, we present our findings, which reveal that, across all but one of our datasets, intelligence mediates the entire income

disparity between Black and White individuals when considering personal income, but not household income. This suggests that while intelligence plays a critical role in understanding race-based income disparities, other factors related to spousal income and marital choices may also contribute to persistent gaps in household income.

In three of our datasets, there are separate measures available for self perceived and other perceived races (SPRE and OPRE respectively). After controls for self perceived race are introduced other perceived race is never a significant predictor of either household or personal income.

Our findings suggest that it is unlikely for the United States labour market to still be characterised by widespread irrational discrimination. Instead, if present day discrimination plays any major role in racial earnings disparities it more likely takes place in childhood, where intelligence gaps emerge.

Literature review

Significant disparities in earned income across racial groups persist within the United States. According to the US Census, in 2019, Asians exhibited the highest median household income of $98,174, followed by non-Hispanic Whites ($76,057), Hispanics ($56,113), and Blacks with the lowest median income of $45,438 (Semega et al., 2021).

Furthermore, considerable gaps in measured intelligence among racial groups in the US have been well documented, although the underlying causes remain a topic of ongoing debate. A meta-analysis conducted in 2001 found a Black-White mean IQ gap of 1.1 standard deviations (Roth et al., 2001), and subsequent research has continued to report Black-White average discrepancies in the general factor of intelligence (g) to be around 1 standard deviation (Frisby & Beaujean, 2015; Fuerst et al., 2021; Hu et al., 2019; Lasker et al., 2019).

A robust correlation between IQ and earned income has been consistently identified in academic literature. A 2007 meta-analysis estimated the strength of this association to be an average correlation of r = 0.21 across multiple studies (Strenze, 2007). More recent research supports these findings (Marks, 2022). The correlation of 0.21 is an underestimate of the association between IQ and permanent (long-term average) income: year to year fluctuations in an individual's earned income increases the variance in income, reducing the estimated correlation. The correlation between IQ and permanent income is estimated to be r = 0.36 in the NLSY79 dataset (Dalliard, 2016), a nationally representative survey utilised in the present study.

There exists compelling evidence to indicate that intelligence is a causally contributing factor to higher income earnings. Jensen (1998) provides an overview of evidence concerning IQ and job performance, revealing that IQ is positively associated with learning speed, the rate at which employees acquire new skills, and supervisor-rated job performance. The general factor of intelligence is also positively associated with maths, reading and writing abilities (Caemmerer et al., 2018; Rohde & Thompson, 2007). These findings strongly imply that

intelligence is likely to be positively associated with productivity, and consequently, higher wages.

Moreover, concerns regarding reverse causation (i.e., occupation increasing intelligence) are mitigated by the fact that intelligence demonstrates a high degree of stability during adulthood. In a sample of Vietnam veterans, the estimated Pearson's correlation between intelligence at approximately ages 20 and 37 is 0.945 (Lasker & Kirkegaard, 2022). Similarly, the Scottish Mental Surveys indicate that the disattenuated correlation between intelligence at age 11 and age 70 is 0.78 (Deary, 2014). Similar results have been found in Luxemburg (Schalke et al., 2013) These robust correlations between intelligence prior to entering the labour market and subsequent measurements offer limited scope for occupation to influence intelligence. Feinkohl et al. (2021) examined this relationship directly, finding no significant association between cognitive ability measured at age 65 or older and occupation, after controlling for early adulthood IQ, sex, and age.

Lastly, several studies have employed within-sibling analysis to ascertain whether the relationship between IQ and income is causal. Since siblings typically share the same common environment during their upbringing, analysing whether IQ differences between siblings are associated with income disparities substantially reduces the likelihood of omitted variable bias. One such study, using Danish register data, determined that the estimated within-sibling effect of a higher IQ is not significantly different from the population effect, after accounting for other factors such as region of birth (Hegelund et al., 2019). A Comparable analysis has been conducted in the United States using the NLSY79 dataset, also used in the present study, albeit with considerably smaller sample size (Murray, 2002).

These findings lead into the human capital hypothesis of income disparities, which states that earning differences between groups can be attributed to differences in average productivity (Gaddis, 2013). This hypothesis holds that employers are accurately assessing the intelligence skill, knowledge and effort of their employees and potential employees, making wage and hiring decisions accordingly. In this model, taste discrimination does not have any impact on earned income.

This hypothesis receives some support from regression analysis. Researchers regress income against race, IQ and other human capital factors. A failure to find a significant impact of race after introducing these control variables is taken to suggest that human capital and not discrimination is responsible for racial income disparities (Kanazawa, 2005). The Black-White IQ gap reaches the approximately 1 SD seen in adulthood by the age of 3 (Malloy, 2013; Rushton & Jensen, 2005) meaning that discrimination *in the labour market* cannot be responsible for this gap. However, the same cannot be said for other measures of human capital such as Occupational prestige and Union membership, which could plausibly be influenced by racial prejudice in hiring (Gaddis, 2013). Therefore, controlling for these variables, as is done in Kanazawa, (2005), closes off potential pathways through which discrimination can influence wages. Herrnstein and Murray (Herrnstein & Murray, 1994, p. 323) avoid this issue by only controlling for IQ, however this analysis used a single year (1989) of a single dataset (NLSY79) and still found a 2% gap Black-White gap in earnings, net of IQ.

The alternative hypothesis to the human capital model is the discrimination model (Gaddis, 2013). This model allows for human capital to play some role in earnings differences between groups, but asserts that there remains a substantial gap, which is explained by employer bias and discrimination.

Some results that employ regression analysis appear to support this hypothesis. To account for human capital, one paper has taken a fixed effects approach to testing for discrimination (Tomaskovic-Devey et al., 2005). The authors believe that by taking fixed effects they are able to remove pre-labour market human capital from the wage equation. They find that racial gaps in income increase as workers age, indicating discrimination. However, such a model fails to account for the possibility of increasing returns to human capital with age. This possibility is intuitively very plausible; workers of differing intelligence may begin at the same entry level employment, but with those of higher intelligence being more likely to attain promotion over time. In fact, the authors find an increasing return to human capital in the form of education, but fail to control for other forms of human capital such as intelligence.

A more direct method to test for discrimination is to send out fake job applications to various businesses, varying nothing except the race of the applicant. Such studies consistently find that White applicants are significantly more likely to receive a callback than Blacks and Latinos (Quillian et al., 2017). However, the literature demonstrates substantial evidence of publication bias in favour of finding such an effect (Zigerell, 2017). Additionally, to interpret such experiments as proof of irrational discrimination is premature. Consider, for instance, two groups: A and B. A has a mean IQ of 100 and B; 85. Both have a standard deviation of 15. Assume there is qualification obtained by everyone with an IQ of at least 110 (figure 1) and that there is no other way for an employee to signal their skill (a qualification that can perfectly measure whether some is above a given IQ is an unrealistically optimistic scenario). An employer should rationally favour applicants from group A over group B. The mean IQ, of those with the qualification, would still be higher for a group A member than a group B member (119.0 vs 116.2 in this instance). Absent a perfect measure of human capital, members of group A will, on average, make more productive employees than members of group B, given the same qualifications (Kirkegaard, 2015). This is a related problem to attenuation bias, addressed in this paper, where imperfect measures of intelligence tend to understate the Black-White intelligence gap (Kirkegaard, 2022).

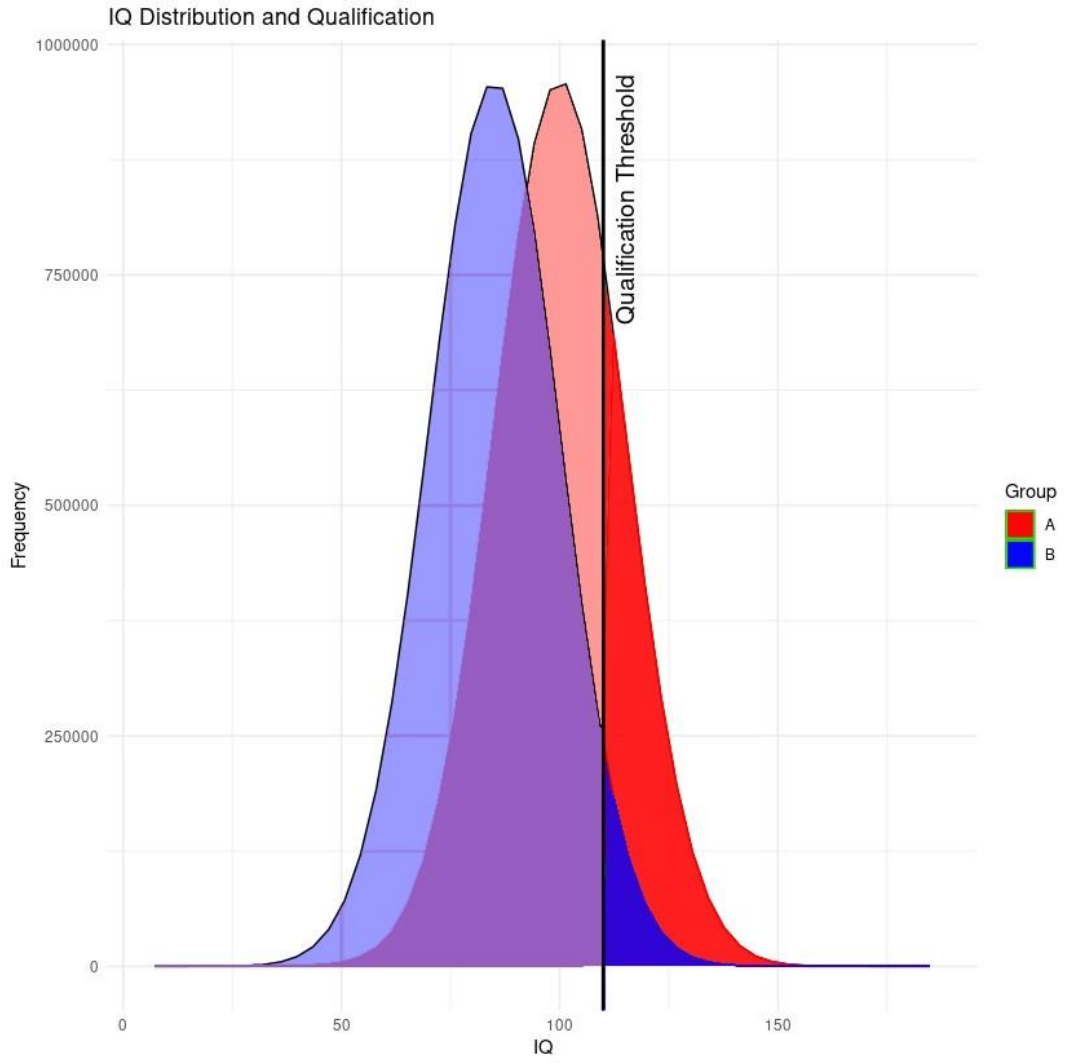

Figure 1 Visualisation of the effect of being able to signal an IQ of at least 110.

Overall therefore the literature does not provide a certain answer as to whether human capital can explain the entire gap in labour market earnings or if discrimination in the labour market also plays a role. Evidence favouring the human capital model introduces controls that could themselves be the result of discrimination. Whilst evidence seemingly pointing towards discrimination has alternative potential explanations.

Data and Methodology

The basic model of our analysis is a structural equation model (SEM) shown in figure 2. Indicator variables are used to estimate the latent factor for intelligence “g”. Races are allowed to differ in their average g. Finally, race and g are allowed to influence earned income. The only control variables are for sex and age. Because previous literature has found the relationship between income and intelligence to be logarithmic (Strenze, 2007), the logarithm of income is used as the outcome measure. We employ the R package **lavaan** to conduct the SEM (Rosseel et al., 2022).

This methodology has two advantages over previous literature. Firstly, because racial differences in measured intelligence do not grow in adulthood (Malloy, 2013; Rushton & Jensen, 2005) they cannot be a result of discrimination *in the labour market*. This mitigates

the concern of introducing bad controls, where measures of human capital are themselves influenced by discrimination (Cinelli et al., 2021). Secondly, by employing structural equation modelling we are able to correct for attenuation bias, resulting from random measurement error in intelligence. Failure to correct for attenuation bias results in an underestimation standardised mean difference in mean intelligence of groups (Kirkegaard, 2022; Kline, 2016, p. 127).

Where possible we measure race by the interviewer's perception (OPRE). This is because labour market discrimination must occur by an employer's belief about an employee's race, which can differ from one's self perception. In some datasets, race is also proxied by skin colour, we code our data so that darker skin tones are always represented by a larger number. In all of our analysis, White is taken as the omitted variable, therefore regression coefficients for Black estimate the income gap between the Black and the non-hispanic White population.

Within three of our datasets (NLSY79, NLSY97, Add Health) enough data was available for a further test. These datasets separately recorded the respondent's self perception of their race (SPRE) and the interviewer's perception of the respondent's race (OPRE). This allows for a much stronger test of discrimination in the labour market: if discrimination drives racial differences in income then others' perception of a person's race should influence their wages independently of their actual race. This model is shown in figure 3 where OPRE and SPRE are allowed to influence income.

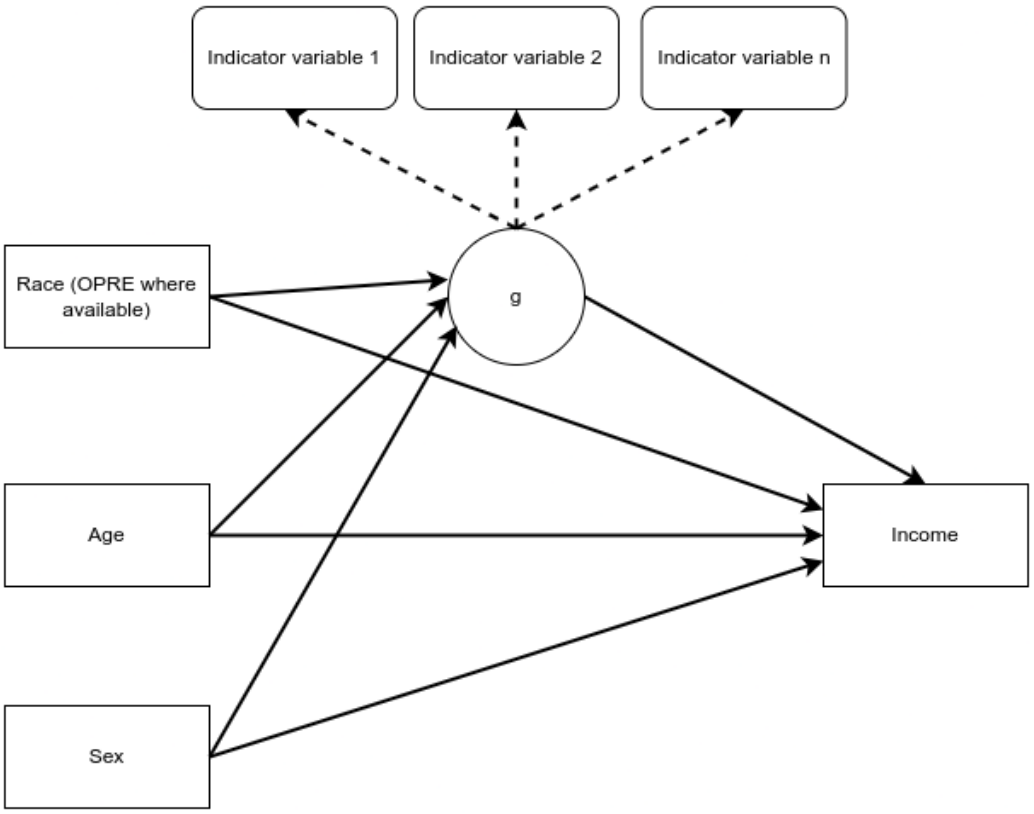

Figure 2 Basic income model.

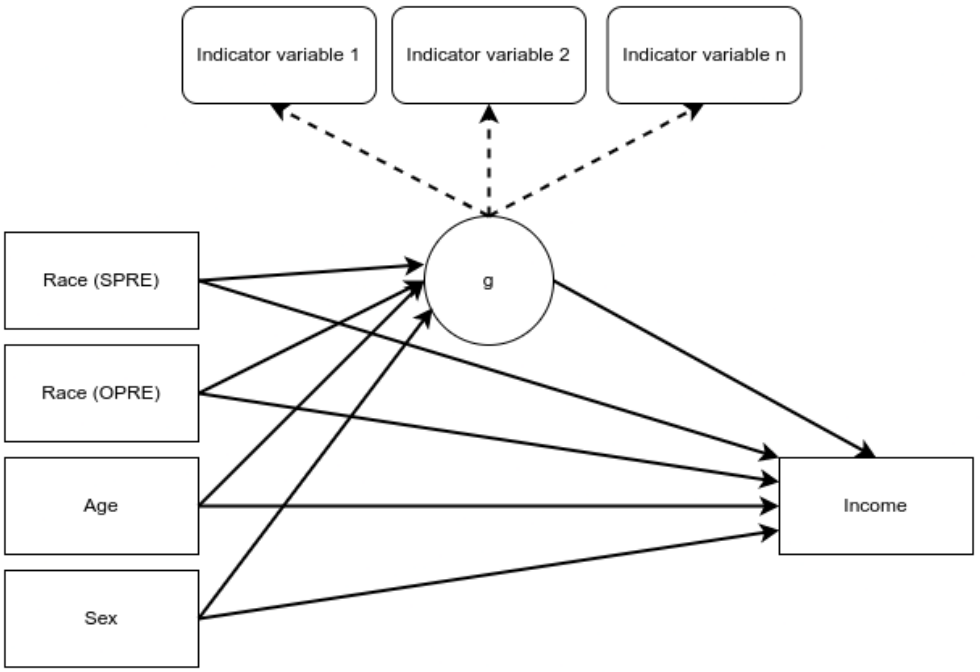

Figure 3 Income model including a control for one's self perception of race.

NLSY79

Variable name(s)	Our coding
R0214700	OPRE (Other perceived race or Ethnicity)
R7093101 to R7093107	SPRE (Self perceived race or Ethnicity)
R0000600	Age (in 1979)
R0214800	Sex
R0217900, R0406010, R0618410, R0898600, R1144500, R1519700, R1890400, R2257500, R2444700, R2870200, R3074000, R3400700, R3656100, R4006600, R4417700, R5080700, R5166000, R6478700, R7006500, R7703700, R8496100, T0987800, T2210000, T3107800, T4112300, T5022600, T5770800, T8218700	Household income
R0155400, R0482600, R0782101, R1024001, R1410701, R1778501, R2141601, R2350301, R2722501, R2971401, R3279401, R3559001, R3897101, R4295101, R4982801, R5626201, R6364601, R6909701, R7607800, R8316300, T0912400, T2076700, T3045300, T3977400, T4915800, T5619500, T8115400	Personal income
R0615000, R0615100, R0615200, R0615300, R0615400, R0615500, R0615600, R0615700, R0615800, R0615900	g indicator variables: Armed Services Vocational Aptitude Battery subtests

Table 1 Variable names in the NLSY79 dataset and our re-coding.

Our first dataset is the NLSY79 (BLS, 2016). This is a large dataset of approximately 12 thousand individuals which began surveying in 1979. The coding for our variables is shown in Table 1. Other perceived race is broken into Black, Hispanic and non-hispanic & none-black, the latter is taken to be roughly equivalent to White, although it will also encompass a very small number of Asians and Native americans. A cross tabulation of SPRE and OPRE is shown in Table 2. The indicator variables for g are taken from the subtests of the Armed Services Vocational Aptitude Battery subtests (ASVAB) (BLS, 2015). Summary statistics are shown in table 3.

Income data for these individuals is taken across 27 waves of data, this allows us to use these individual waves as indicator variables for permanent income. One can view the income an individual receives in a year as being composed of a stable (permanent) component and random year to year fluctuations, for instance from being out of work for some of a year or having a child. Removing these random fluctuations from our income measure should increase the strength of estimated correlations between our dependent variables and income (Osborne, 2002).

OPRE/SPRE	American Indian	Asian	Black	Hispanic	Multi-racial	Other	Pacific Islander	White
White	31	13	9	5	35	22	4	3462
Black	3	4	2113	4	40	13	1	36
Hispanic	8	3	16	439	20	236	5	571

Table 2 Cross tabulation of individuals by self identification and others perception of their race in the NLSY79 dataset.

	mean	sd	median	min	max	skew	kurtosis	se
born in	1961.10	2.31	1961.00	1957.00	1965.00	0.05	-1.14	0.02
ASVAB_3	14.32	5.25	14.00	0.00	25.00	-0.09	-0.63	0.05
ASVAB_4	15.82	7.22	15.00	0.00	30.00	0.34	-0.96	0.07
ASVAB_5	23.55	8.53	25.00	0.00	35.00	-0.54	-0.72	0.08
ASVAB_6	9.94	3.71	11.00	0.00	15.00	-0.60	-0.67	0.03
ASVAB_7	31.73	11.52	32.00	0.00	50.00	-0.31	-0.55	0.11
ASVAB_8	42.19	16.76	44.00	0.00	84.00	-0.27	-0.28	0.15
ASVAB_9	12.61	5.55	12.00	0.00	25.00	0.34	-0.69	0.05
ASVAB_10	12.00	6.17	11.00	0.00	25.00	0.50	-0.79	0.06
ASVAB_11	12.63	5.30	12.00	0.00	25.00	0.33	-0.71	0.05
ASVAB_12	10.18	4.37	10.00	0.00	20.00	0.13	-0.80	0.04
Years since 1979	14.51	8.07	15.00	1.00	28.00	0.00	-1.20	0.01
Household income	42447.74	70733.35	25800.00	0.00	1057448.00	8.00	89.35	151.82
Personal income	20327.07	33101.39	11000.00	0.00	396970.00	5.18	41.19	69.00

Table 3 NLSY79 summary statistics.

NLSY97

Variable name(s)	Our coding
R2395200	OPRE (Other perceived race or Ethnicity)
S1224900 to S1224908, "R0538600"	SPRE (Self perceived race or Ethnicity)
R0536402	Year born
R0536300	Sex
T3173000, T4584700, T6217800	Skin tone
S3812400, S5412800, S7513700, T0014100, T2016200, T3606500, T5206900, T6656700, T8129100, U0008900, U1845500, U3444000	Household income
R0490200, R2341200, R3650200, R5098900, R6827500, S1055800, S3134600, S4799600, S6501000, S8496500, T0889800, T3003000, T4406000, T6055500, T7545600, T8976700, U0956900, U2857200, U4282300	Personal income
(R9705200, R9705300 …, R9707500), R1318200, R3961900	g indicator variables. ASVAB subtests, PIAT

Table 4 Variable names in the NLSY97 dataset and our re-coding.

A more recent near replication of the NLSY79 is NLSY97 (BLS, 2017). This contains a substantially younger cohort than the NLSY79 as well as two IQ tests, the ASVAB as before and the PIAT (BLS, 2014). A cross table of racial identification is provided in table 5. And summary statistics are table 6.

OPRE/SPRE	American Indian	Asian	Black	Hispanic	Multi-racial	Other	Pacific Islander	White
White	16	18	28	1137	474	11	7	3619
Black	0	1	1925	65	230	6	1	9
Other	15	98	18	564	67	12	16	26

Table 5 Cross tabulation of individuals by self identification and others perception of their race in the NLSY97 dataset.

Variable	mean	sd	median	min	max	skew	kurtosis	se
born	1982.01	1.40	1982.00	1980.00	1984.00	0.00	-1.27	0.01
PIAT	-0.03	0.97	-0.23	-2.01	2.90	0.53	-0.29	0.01
Skin Colour	3.23	2.34	2.00	0.00	10.00	1.03	-0.02	0.03
ASVAB_GS_ABILITY	-0.44	0.85	-0.42	-2.70	2.57	0.07	-0.35	0.01
ASVAB_AR_ABILITY	-0.46	0.99	-0.36	-3.21	2.40	-0.37	-0.07	0.01
ASVAB_WK_ABILITY	-0.63	0.94	-0.61	-3.20	2.55	-0.16	-0.22	0.01
ASVAB_PC_ABILITY	-0.35	0.94	-0.29	-2.40	1.82	-0.12	-0.80	0.01
ASVAB_NO_ABILITY	16.17	6.32	16.00	-9.20	43.35	0.01	0.05	0.08
ASVAB_CS_ABILITY	5.95	3.37	5.70	-10.00	19.00	-0.20	0.80	0.04
ASVAB_AI_ABILITY	-1.11	0.59	-1.10	-2.61	1.77	0.41	0.70	0.01
ASVAB_SI_ABILITY	-1.01	0.67	-1.00	-2.90	2.05	0.32	0.19	0.01
ASVAB_MK_ABILITY	-0.17	1.03	-0.12	-2.80	2.68	-0.07	-0.52	0.01
ASVAB_MC_ABILITY	-0.64	0.82	-0.52	-2.80	2.70	-0.21	-0.29	0.01
ASVAB_EI_ABILITY	-0.91	0.85	-0.91	-2.91	2.91	0.34	0.37	0.01
ASVAB_AO_ABILITY	-0.50	0.97	-0.54	-2.40	1.94	0.10	-0.86	0.01
Household Income	65401.84	65877.09	49450.00	0.00	469576.00	2.63	9.81	240.78
Personal Income	24409.75	28953.72	17000.00	0.00	328451.00	3.54	23.61	96.77

Table 6 NLSY97 summary statistics

GSS

Variable name(s)	Meaning
race	SPRE (Self perceived race or ethnicity)
age	age
sex	Sex
ratetone	Skin tone
coninc	Household income
conrinc	Personal income
worda to wordj	g indicator variables. From the wordsum paper

Table 7 Variable names in the GSS dataset and our re-coding.

We further obtained data from the General Social Survey (GSS) (Smith et al., 2019). We used individual performance data. The indicator variables used are the performance on individual questions on the wordsum dataset, given that these performance indicators are binary, **lavaan** estimates these using a DWLS estimator, as opposed to the ML estimator used for continuous indicator variables (Beaujean, 2014; Rosseel et al., 2022). The measure of race in the dataset ("race") roughly corresponds to SPRE; prior to 2002, interviewers were allowed to code race themselves if they were "absolutely sure", but otherwise they were asked (Smith et al., 2019). The GSS does have OPRE and SPRE data available ("racesee" and "raceself" respectively), but only for two years and they show near perfect multicollinearity. Year fixed effects are taken in this dataset. Summary statistics are shown in table 8 and table 9.

	mean	sd	median	min	max	skew	kurtosis	se
Personal Income	31758.06	32317.10	24882.00	350.50	434612.42	4.28	36.33	233.600
year	1996.44	13.30	1996.00	1974.00	2018.00	0.02	-1.16	0.074
age	45.84	17.46	43.00	18.00	89.00	0.43	-0.76	0.098
Household Income	45209.68	36448.65	35471.00	350.50	178712.46	1.41	1.94	214.141
Colour	2.42	1.90	2.00	1.00	10.00	1.71	2.43	0.025
Male	0.44	0.50	0.00	0.00	1.00	0.26	-1.93	0.003
ln(Personal Income)	9.91	1.10	10.12	5.86	12.98	-1.04	1.52	0.008
ln(Household Income)	10.34	0.99	10.48	5.86	12.09	-1.11	2.34	0.006
worda	0.83	0.38	1.00	0.00	1.00	-1.74	1.02	0.002
wordb	0.93	0.25	1.00	0.00	1.00	-3.52	10.37	0.001
wordc	0.26	0.44	0.00	0.00	1.00	1.09	-0.81	0.003
wordd	0.95	0.22	1.00	0.00	1.00	-4.01	14.10	0.001
worde	0.79	0.41	1.00	0.00	1.00	-1.44	0.08	0.002
wordf	0.82	0.38	1.00	0.00	1.00	-1.67	0.78	0.002
wordg	0.36	0.48	0.00	0.00	1.00	0.57	-1.67	0.003
wordh	0.37	0.48	0.00	0.00	1.00	0.53	-1.72	0.003
wordi	0.77	0.42	1.00	0.00	1.00	-1.30	-0.32	0.002
wordj	0.26	0.44	0.00	0.00	1.00	1.12	-0.75	0.003

Table 8 GSS summary statistics.

SPRE	Frequency
Black	4692
Other	1791
White	25497

Table 9 Racial identification frequency in the GSS dataset

Add Health

Datafile	Variable name(s)	Meaning
w1inhome_dvn	H1GI6A to H1GI6E	SPRE
	H1GI9	OPRE
	BIO_SEX	Sex
	H1KQ1A to H1KQ10A	Knowledge quiz
w3pvt_dvn	PVTSTD3L, PVTSTD1	Indicator variables for g
w3inhome_dvn	h3od4a to h3od4d	SPRE
	h3ir4	OPRE
	h2kq1a to h2kq10a	Knowledge quiz
w4inhome_dvn	H4OD1Y and IYEAR4	Age
	H4IR4	OPRE
	H4EC1	Household income
	H4EC2	Personal income
	C4WD90_1 and C4WD60_1	Word recall
	C4NUMSCR	Digit span
21600-0032-Data.dta	H5EC1	Personal income
	H5EC2	Household income
	C5WD90_1 and C5WD60_1	Word recall
	H5MH3A to H5MH9A	Digit span

Table 10 Variable names in the Add Health dataset and our re-coding.

Add health data is part of the NLSY family, although it only comes from five waves (Harris & Udry, 2018, 2015a, 2015b, 2015c, 2015d) and income data is only available in the last two, which were used as indicator variables for permanent income. The Peabody verbal IQ test (taken in waves 1 and 3), a knowledge quiz (waves 1 and 2), and a digit span and word recall test (waves 4 and 5) were taken as indicator variables for g. Where OPRE differs across waves the most common opinion is taken. A cross table of racial identification is shown in table 12 and summary statistics in table 11.

Variable	mean	sd	median	min	max	skew	kurtosis	se
Age	28.9	1.78	28.9	24.4	33.9	-0.00619	-0.892	0.0248
Birth	1980	1.75	1980	1970	1980	0.0318	-0.892	0.0217
Birth in wave 4	1980	1.75	1980	1970	1980	0.00733	-0.938	0.0245
Colour	4.19	1.28	5	1	5	-1.36	0.498	0.0183
DigitSpan in wave 4	4.19	1.54	4	0	7	0.179	-0.736	0.0215
DigitSpan in wave 5	3.55	1.43	3	0	7	0.303	-0.325	0.0574
Hispanic	0.142	0.555	0	0	8	9.7	127	0.00688
Household Income averaged across waves	69700	43100	62500	1750	175000	0.569	-0.424	735
Knowledge1	5.05	1.79	5	0	10	-0.14	-0.138	0.0278
Knowledge2	5.09	1.78	5	0	10	-0.0612	-0.21	0.0296
p1	0	1	-0.0244	-5.98	2.42	-0.556	1.56	0.0146
p3	0	1	0.289	-6.16	1.42	-1.81	7.53	0.0146
Personal Income averaged across waves	45900	37300	38500	1250	600000	3.61	34.2	632
PincomeL in wave 5	10.5	1.16	10.7	7.82	12.2	-0.999	0.349	0.018
Recall in wave 4	6.66	2	7	0	15	0.288	0.545	0.028
Recall in wave 5	6.2	2.1	6	1	15	0.547	0.707	0.0842
Recall Long term in wave 4	5.22	2.07	5	0	15	0.444	1.09	0.029
Recall Long term in wave 5	4.65	2.05	5	0	12	0.471	0.639	0.0823

Table 11 Add Health summary statistics.

OPRE/SPRE	Asian	Black	Native	Other	White
Asian	210	4	4	20	26
Black	1	1521	2	34	77
Other	1	1	2	90	7
Native	0	2	49	18	17
White	4	6	24	200	4176

Table 12 Cross tabulation of individuals by self identification and others perception of their race in the Add Health dataset.

ANES

Variable names	**Meaning**
iwrobspre_skintone	Skin Colour
wordsum_setb, wordsum_setd, wordsum_sete, wordsum_setf, wordsum_setg, wordsum_seth, wordsum_setj, wordsum_setk, wordsum_setl, wordsum_seto	Indicator variables for g
dem_raceeth_x	SPRE
incgroup_prepost_x	Household income
dem_age_r_x	Age

Table 13 Variable names in the ANES dataset and our re-coding.

The ANES (American National Election Studies) dataset (ANES, 2014) only contains household income as an income measure, which threatens to be more influenced by non-labour market factors such as marriage decisions. It also contains no measure of OPRE. Summary statistics are available in table 14 and table 15.

	mean	sd	median	min	max	skew	kurtosis	se
Colour	3.47	2.30	3.00	1.00	10.00	0.85	-0.25	0.05
Sex	0.48	0.50	0.00	0.00	1.00	0.08	-1.99	0.01
Household Income	58415.62	53785.92	42500.00	2500.00	250000.00	1.51	2.31	711.48
Age	49.44	16.82	51.00	17.00	90.00	-0.03	-0.87	0.22
ln(Household Income)	10.43	1.23	10.66	7.82	12.43	-0.82	-0.05	0.02
wordb	0.89	0.31	1.00	0.00	1.00	-2.50	4.27	0.00
wordd	0.92	0.27	1.00	0.00	1.00	-3.19	8.19	0.00
worde	0.82	0.39	1.00	0.00	1.00	-1.64	0.69	0.01
wordf	0.91	0.29	1.00	0.00	1.00	-2.76	5.64	0.00
wordg	0.44	0.50	0.00	0.00	1.00	0.26	-1.93	0.01
wordh	0.40	0.49	0.00	0.00	1.00	0.40	-1.84	0.01
wordj	0.43	0.49	0.00	0.00	1.00	0.30	-1.91	0.01
wordk	0.69	0.46	1.00	0.00	1.00	-0.80	-1.36	0.01
wordl	0.67	0.47	1.00	0.00	1.00	-0.71	-1.49	0.01
wordo	0.62	0.48	1.00	0.00	1.00	-0.51	-1.74	0.01

Table 14 NLSY79 summary statistics.

SPRE	Freq
Asian	92
Black	1021
Hispanic	1009
Native	34
Other	220
White	3509

Table 15 Racial identification frequency

Results

Complete models for g-loadings and coefficients with g as the dependent variable are available in Appendix A and intelligence gaps are summarised in table 16, showing the Cohen's d in g between whites and other groups. The results support previous literature in finding a Black-White Cohen's d of approximately 1 (Roth et al., 2001). There is however, a large range of estimates for the White-Hispanic gap, with the largest coming from NLSY79 and the smallest, the Add Health dataset.

	Mean	Median	Min	Max
Black	-1.05	-1.01	-1.30	-0.88
Hispanic	-0.62	-0.66	-0.98	-0.21
Native american	-0.89	-0.89	-0.89	-0.89
Asian	-0.41	-0.41	-0.41	-0.41

Table 16 Cohen's d for the racial intelligence gaps between whites and others.

NLSY79

Independent Variable	Personal income 1	Personal Income 2	Household Income 1	Household Income 2
born	0.0969*** (0.011)	0.0421** (0.013)	0.0304** (0.0111)	0.0279* (0.0131)
g	0.364*** (0.012)	0.407*** (0.014)	0.562*** (0.013)	0.57*** (0.02)
OPRE_Black	0.0618* (0.0285)	0.196 (0.105)	-0.129*** (0.029)	0.00487 (0.10566)
OPRE_Hispanic	0.166*** (0.031)	0.14** (0.05)	0.157*** (0.032)	0.0933* (0.0463)
sex_Male	0.479*** (0.021)	0.493*** (0.026)	-0.172*** (0.022)	-0.153*** (0.026)
SPRE_Asian		-0.0562 (0.2335)		0.189 (0.233)
SPRE_Black		-0.175 (0.105)		-0.248* (0.106)
SPRE_Hispanic		0.0159 (0.0641)		-0.00895 (0.0647)
SPRE_Multi		-0.184 (0.118)		-0.134 (0.119)
SPRE_Native		-0.575*** (0.161)		-0.637*** (0.163)
SPRE_Other		-0.087 (0.073)		0.0362 (0.0734)
SPRE_Pacific		0.177 (0.343)		0.47 (0.35)
Observations	12686	7718	12686	7718

Table 17 The impact of race on personal and household income in the NLSY79 dataset.. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas (path coefficients). Year fixed effects. HAC standard errors.

The results pertaining to the association between race and g on income in the NLSY79 dataset are presented in table 17. Examining the outcome measure of personal income, our findings reveal no statistically negative significant impact of being perceived as Black. There is a small and statistically weak positive association between being perceived as black and income, prior to controlling for race. Although it should be noted that given the number of statistical tests in this paper some false positives at this level of significance are to be expected. Interestingly, Hispanics demonstrate a marginal income advantage over their non-Hispanic White counterparts. Nonetheless, when considering household income as the outcome measure, a negative association is observed for individuals perceived as Black, prior to controlling for self-perceived race. After self perceived race is controlled for, no significant associations remain.

NLSY97

Independent variable	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
born	-0.121*** (0.015)	-0.115*** (0.015)	-0.0819*** (0.0163)	-0.0878*** (0.0161)	0.068*** (0.014)	0.0707*** (0.0141)	0.0804*** (0.0153)	0.0801*** (0.0151)
Colour			-0.0243 (0.0238)	-0.0665*** (0.0163)			-0.051* (0.023)	-0.185*** (0.016)
g	0.392*** (0.016)	0.386*** (0.016)	0.411*** (0.018)	0.414*** (0.018)	0.427*** (0.016)	0.418*** (0.016)	0.436*** (0.017)	0.456*** (0.017)
OPRE_Black	-0.182*** (0.035)	0.0201 (0.08)			-0.535*** (0.034)	-0.458*** (0.078)		
OPRE_Other	0.166*** (0.047)	0.0799 (0.0549)			0.0525 (0.0462)	0.031 (0.054)		
sex_Male	0.394*** (0.027)	0.392*** (0.027)	0.392*** (0.03)	0.399*** (0.029)	-0.181*** (0.026)	-0.182*** (0.026)	-0.128*** (0.029)	-0.108*** (0.028)
SPRE_Asian		0.148 (0.123)	0.254* (0.125)			-0.136 (0.122)	-0.129 (0.125)	
SPRE_Black		-0.193* (0.085)	-0.0834 (0.0594)			-0.0603 (0.0825)	-0.401*** (0.058)	
SPRE_Hispanic		0.156*** (0.041)	0.231*** (0.042)			0.0952* (0.0405)	0.131** (0.041)	
SPRE_Multi		0.0866 (0.0601)	0.0468 (0.0645)			-0.0238 (0.0603)	-0.161* (0.064)	
SPRE_Native		-0.263 (0.215)	-0.246 (0.243)			0.0365 (0.2125)	-0.113 (0.243)	
SPRE_Other		0.329 (0.235)	0.453 (0.249)			-0.388 (0.231)	-0.305 (0.241)	
SPRE_Pacific		0.234 (0.247)	0.372 (0.262)			0.272 (0.24)	0.41 (0.26)	
Observations	8365	8363	6721	6723	8365	8363	6721	6723

Table 18 The impact of race on personal and household income in the NLSY97 dataset. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas. Year fixed effects. HAC standard errors.

Table 18 presents the findings from the NLSY97 dataset. In contrast to the NLSY79 outcomes, a negative coefficient is observed for being perceived as Black in relation to personal income, prior to controlling for self-perception of race. Furthermore, darker skin tones exhibit negative association with income, net of g, although this effect is very small. These effects disappear when controlling for self perceived race. The household income results closely resemble those of the NLSY79; a negative correlation exists between being perceived as Black and income, which dissipates after adjusting for self-perception. Consistent with the NLSY79 findings, a modest positive association is identified between being Hispanic and both measures of income.

GSS

	Personal income 1	Personal Income 2	Personal income 3	Household Income 1	Household Income 2	Household Income 3
Age	0.192*** (0.01)	0.172*** (0.027)	0.169*** (0.028)	-0.041*** (0.007)	-0.0409* (0.0189)	-0.0532** (0.0201)
Colour		0.00735 (0.03307)	0.021 (0.029)		-0.00171 (0.02574)	-0.0318 (0.0234)
g	0.227*** (0.013)	0.287*** (0.037)	0.292*** (0.038)	0.333*** (0.011)	0.411*** (0.03)	0.43*** (0.03)
Male	0.546*** (0.017)	0.369*** (0.04)	0.365*** (0.04)	0.236*** (0.014)	0.18*** (0.03)	0.187*** (0.034)
SPRE_Black	0.0313 (0.0284)	-0.000278 (0.081003)		-0.212*** (0.023)	-0.178** (0.064)	
SPRE_Other	0.0702 (0.036)	0.0768 (0.0773)		-0.00318 (0.03124)	0.104 (0.068)	
Observations	14114	2819	2819	20855	4304	4304

Table 19 The impact of race on personal and household income in the GSS dataset. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas (path coefficients). Year fixed effects.

Table 19 displays the results from the GSS dataset, which is similar to those of the NLSY79. In terms of personal income, no significant associations are identified with respect to race or skin tone. However, being perceived as Black is negatively correlated with household income.

Add Health

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
Age	0.0569* (0.0254)	0.0561* (0.0252)	0.0341 (0.0265)	0.0366 (0.0267)	0.091*** (0.025)	0.089*** (0.025)	0.071** (0.027)	0.0743** (0.0269)
Colour			0.0622 (0.0568)	0.0561 (0.0421)			-0.0266 (0.0561)	-0.166*** (0.041)
g	0.551*** (0.054)	0.54*** (0.05)	0.52*** (0.06)	0.531*** (0.056)	0.587*** (0.057)	0.566*** (0.055)	0.544*** (0.057)	0.552*** (0.058)
Hispanic	0.031 (0.03)	0.00296 (0.0305)			0.0728* (0.0315)	0.0473 (0.0323)		
OPRE_Asian	0.504*** (0.139)	-0.0284 (0.258)			0.472*** (0.137)	-0.0476 (0.255)		
OPRE_Black	0.146 (0.086)	0.201 (0.192)			-0.394*** (0.082)	-0.0229 (0.182)		
OPRE_Native	-0.228 (0.249)	-0.509 (0.289)			-0.00294 (0.24836)	0.00614 (0.28308)		
SEX_Male	0.735*** (0.063)	0.724*** (0.062)	0.691*** (0.063)	0.701*** (0.064)	0.199*** (0.051)	0.189*** (0.05)	0.186*** (0.055)	0.202*** (0.055)
SPRE_Asian		0.662* (0.294)				0.67* (0.29)		
SPRE_Black		-0.0671 (0.1993)	-0.0434 (0.1204)			-0.405* (0.189)	-0.423*** (0.12)	
SPRE_Native		0.43 (0.29)				-0.0679 (0.2892)		
SPRE_Other		0.316* (0.128)	0.292* (0.13)			0.274* (0.127)	0.4** (0.1)	
Observations	5113	5108	4201	4203	5113	5108	4201	4203

Table 20 The impact of race on personal and household income in the Add Health dataset. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas (path coefficients).

The results from Add Health are similar to the results of previous surveys (Table 20). Being perceived as Black does not negatively impact personal income, but does affect household income before controlling for self perception. There is also evidence that Asians may have a higher household income than whites, after controlling for g. Skin colour is never negatively associated with personal income.

ANES

	Household Income 1	Household Income 2	Household Income 3
Age	-0.008 (0.013)	0.000129 (0.021169)	0.00643 (0.02089)
Colour		-0.118** (0.037)	-0.0989*** (0.0235)
g	0.325*** (0.016)	0.28*** (0.03)	0.285*** (0.026)
Male	0.13*** (0.03)	0.14** (0.04)	0.132** (0.044)
SPRE_Black	-0.158*** (0.036)	0.045 (0.094)	
SPRE_Hispanic	-0.16*** (0.04)	-0.0768 (0.0673)	
SPRE_Other	-0.0458 (0.0589)	0.106 (0.098)	
Observations	5558	1797	1803

Table 21 The impact of race on household income in the ANES dataset. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas (path coefficients).

Lastly, the ANES dataset corroborates our findings that being perceived as Black is negatively correlated with household income (Table 21). However, diverging from results obtained from the other datasets, being Hispanic also exhibits a negative association with household income. Skin colour presents a negative relationship with income, both before and after controlling for self-perceived race.

Skin colour and income

	NLSY97		**GSS**		**Add Health**	
	No Control for g	Control for g	No Control for g	Control for g	No Control for g	Control for g
Colour	-0.235*** (0.014)	-0.0665*** (0.0163)	-0.086*** (0.02)	0.021 (0.029)	-0.174*** (0.025)	-0.0561 (0.0421)
born	-0.209* (0.015)	-0.0878*** (0.0161)			-0.003 (0.024)	
Age			0.254 (0.021)	0.169*** (0.028)		0.0366 (0.0267)
sex_Male	0.41* (0.028)	0.399*** (0.029)	0.346*** (0.04)	0.365*** (0.04)	0.612*** (0.053)	0.701*** (0.064)
g		0.414*** (0.018)		0.292*** (0.038)		0.531*** (0.056)

Table 22 the estimated impact of skin colour on personal income, after and before controlling for g. *p<0.05; ** p <0.01; *** p <0.001 Standardised betas (path coefficients).

One common belief related to the discrimination hypothesis is the colourism hypothesis (Hunter, 2007; Tulshyan, 2023). The essence of the colourism hypothesis posits that employment-related decisions reflect taste discrimination, in which employers exhibit bias against individuals with darker skin complexions.

Table delineates the estimated influence of darker skin tone on personal income, in datasets where measurements of skin tone and personal income are present. Results are shown both with and without controlling for intelligence.

The results show largely a consistent pattern across the datasets. Without accounting for g, there exist robust negative associations between darker skin tones and income. Nevertheless, controlling for g eliminates these effects.

However, one deviation from this pattern arises within the NLSY97 dataset. In this case, despite a 70% reduction in the estimated impact of darker skin tones post the g adjustment, there remains a minor but statistically significant effect of darker skin tones on personal income. These results therefore mirror the anomalous result of the NLSY97 when measuring the effect of OPRE on income.

Meta analysis

We further conduct a meta analysis of our two primary measures: The impact of being Black, absent any controls for self perception on personal income (Figure 4) and the impact of others perception of whether an individual is black, after self perception is controlled for (Figure 5). This latter meta analysis is of particular importance as very few individuals in each study have others' perception of their race differing from their own, and a meta analysis allows us to pool all such cases from the data. Across all our datasets where this test was available there are 122 individuals where SPRE is Black but OPRE is white and 43 where the opposites are true. These analyses were conducted using the **Meta** and **Metafor** packages in R (Schwarzer, 2023; Viechtbauer, 2023).

The results confirm the findings of our individual datasets. Under a fixed effects model, without SPRE controls, the estimated effect is exactly 0. Using a random effects model estimates almost identical results. Introducing controls for self perception of race also fails to produce an effect statistically significantly different from zero.

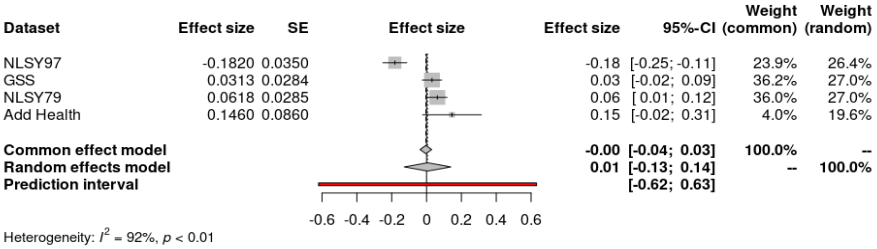

Figure 4 Impact of being perceived as black on personal income, no controls for SPRE.

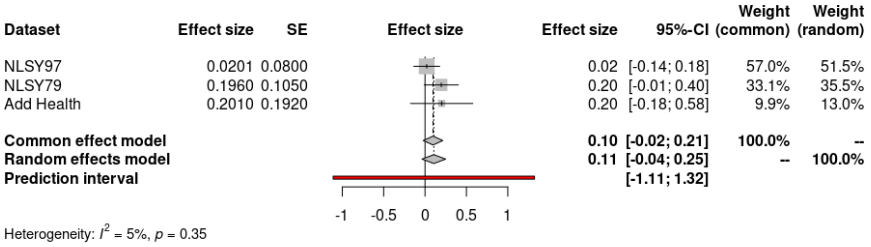

Figure 5 Impact of being black on personal income, with controls for SPRE

Discussion

The findings of this study provide robust support for the human capital hypothesis, positing that disparities in cognitive ability may entirely account for the Black-White earnings gap in the United States labour market. We employed structural equation modelling in our analysis,

controlling exclusively for sex, age and measured intelligence, thereby addressing concerns related to introducing measures of human capital that could be influenced by discrimination (Gaddis, 2013).

Across all datasets, except for NLSY97, our results did not reveal a significant negative impact of being Black on personal income, net of g. The meta-analysis strengthens this conclusion, as the random effects model demonstrates a mean impact of zero for being Black on personal income. All of our datasets support the finding of a positive association between intelligence and income.

In all datasets, we observed a negative association between being perceived as Black and household income. This finding implies that racial differences in household dynamics, unexplained by cognitive ability of one member of the household, may exist. Such disparities could encompass decisions on whom to marry and the number of working household members.

Our research also attempts to disentangle the relative importance of self-perception and others' perception of one's race. As employers base employment decisions on their perception of an individual's race, individuals who identify with one race but are perceived as another offer a critical test of discrimination. We found no evidence in any of our models suggesting that others' perceptions of an individual's race influenced income once self-perceived race was controlled for.

Overall, these 5 datasets present strong evidence supporting the human capital hypothesis, indicating that differences in cognitive ability primarily account for the Black-White earnings gap in the United States labour market.

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Appendix A
NLSY79

Indicator Variable	Personal Income 1	Personal Income 2	Household Income 1	Household income 2
ASVAB_10	0.653*** (0.007)	0.646*** (0.008)	0.655*** (0.007)	0.649*** (0.008)
ASVAB_11	0.647*** (0.007)	0.626*** (0.008)	0.651*** (0.007)	0.629*** (0.008)
ASVAB_12	0.681*** (0.006)	0.648*** (0.008)	0.694*** (0.006)	0.66*** (0.01)
ASVAB_3	0.756*** (0.006)	0.737*** (0.008)	0.755*** (0.006)	0.737*** (0.008)
ASVAB_4	0.697*** (0.006)	0.682*** (0.008)	0.689*** (0.006)	0.675*** (0.008)
ASVAB_5	0.753*** (0.006)	0.738*** (0.008)	0.74*** (0.01)	0.726*** (0.008)
ASVAB_6	0.682*** (0.007)	0.678*** (0.008)	0.71*** (0.01)	0.704*** (0.009)
ASVAB_7	0.567*** (0.007)	0.564*** (0.009)	0.555*** (0.007)	0.554*** (0.009)
ASVAB_8	0.519*** (0.007)	0.509*** (0.009)	0.518*** (0.007)	0.508*** (0.009)
ASVAB_9	0.585*** (0.007)	0.561*** (0.008)	0.605*** (0.007)	0.58*** (0.01)

Table 23 g-loadings of indicator variables for the NLSY79 dataset.

Indicator Variable	Personal Income 1	Personal Income 2	Household Income 1	Household income 2
born	-0.234*** (0.01)	-0.172*** (0.013)	-0.234*** (0.01)	-0.175*** (0.012)
OPRE_Black	-1.3*** (0)	-0.846*** (0.102)	-1.28*** (0.02)	-0.812*** (0.101)
OPRE_Hispanic	-0.984*** (0.028)	-0.862*** (0.044)	-0.996*** (0.028)	-0.874*** (0.044)
sex_Male	0.227*** (0.02)	0.265*** (0.025)	0.253*** (0.02)	0.292*** (0.025)
SPRE_Asian		0.0934 (0.2237)		0.0895 (0.2224)
SPRE_Black		-0.64*** (0.1)		-0.666*** (0.102)
SPRE_Hispanic		-0.484*** (0.063)		-0.482*** (0.062)
SPRE_Multi		0.118 (0.115)		0.101 (0.115)
SPRE_Native		-0.434** (0.158)		-0.481** (0.157)
SPRE_Other		-0.443*** (0.071)		-0.431*** (0.071)
SPRE_Pacific		0.267 (0.332)		0.265 (0.33)

Table 24 Regression coefficients for the NLSY79, where g is the dependent variable. Clustered standard errors.

Indicator Variable	Personal Income 1	Personal Income 2	Household Income 1	Household income 2
Log(Income)_1979	0.296*** (0.012)	0.261*** (0.012)	0.226*** (0.009)	0.248*** (0.01)
Log(Income)_1980	0.387*** (0.009)	0.334*** (0.01)	0.243*** (0.009)	0.255*** (0.011)
Log(Income)_1981	0.425*** (0.009)	0.363*** (0.01)	0.277*** (0.009)	0.26*** (0.01)
Log(Income)_1982	0.445*** (0.008)	0.387*** (0.01)	0.284*** (0.009)	0.268*** (0.011)
Log(Income)_1983	0.492*** (0.008)	0.432*** (0.009)	0.32*** (0.01)	0.314*** (0.011)
Log(Income)_1984	0.529*** (0.009)	0.48*** (0.01)	0.342*** (0.009)	0.323*** (0.011)
Log(Income)_1985	0.564*** (0.009)	0.517*** (0.01)	0.335*** (0.009)	0.311*** (0.011)
Log(Income)_1986	0.606*** (0.009)	0.562*** (0.01)	0.398*** (0.009)	0.35*** (0.01)
Log(Income)_1987	0.616*** (0.009)	0.569*** (0.009)	0.491*** (0.009)	0.455*** (0.011)
Log(Income)_1988	0.639*** (0.009)	0.598*** (0.009)	0.496*** (0.009)	0.467*** (0.011)
Log(Income)_1989	0.66*** (0.01)	0.628*** (0.009)	0.527*** (0.009)	0.487*** (0.01)
Log(Income)_1990	0.676*** (0.009)	0.641*** (0.009)	0.53*** (0.01)	0.491*** (0.01)
Log(Income)_1991	0.687*** (0.009)	0.65*** (0.01)	0.581*** (0.009)	0.552*** (0.01)
Log(Income)_1992	0.686*** (0.009)	0.647*** (0.009)	0.585*** (0.009)	0.544*** (0.01)
Log(Income)_1993	0.674*** (0.009)	0.636*** (0.009)	0.586*** (0.01)	0.544*** (0.01)
Log(Income)_1994	0.647*** (0.009)	0.621*** (0.009)	0.621*** (0.01)	0.592*** (0.01)
Log(Income)_1996	0.594*** (0.01)	0.562*** (0.01)	0.572*** (0.01)	0.546*** (0.01)
Log(Income)_1998	0.571*** (0.01)	0.542*** (0.01)	0.568*** (0.01)	0.53*** (0.01)
Log(Income)_2000	0.545*** (0.01)	0.522*** (0.01)	0.59*** (0.01)	0.557*** (0.01)
Log(Income)_2002	0.532*** (0.01)	0.511*** (0.01)	0.556*** (0.01)	0.527*** (0.01)
Log(Income)_2004	0.506*** (0.01)	0.486*** (0.01)	0.595*** (0.01)	0.56*** (0.01)
Log(Income)_2006	0.497*** (0.01)	0.476*** (0.01)	0.54*** (0.01)	0.516*** (0.009)
Log(Income)_2008	0.476*** (0.01)	0.457*** (0.01)	0.557*** (0.01)	0.527*** (0.01)
Log(Income)_2010	0.488*** (0.01)	0.47*** (0.01)	0.525*** (0.01)	0.499*** (0.01)
Log(Income)_2012	0.459*** (0.01)	0.442*** (0.01)	0.531*** (0.01)	0.509*** (0.01)
Log(Income)_2014	0.461*** (0.01)	0.442*** (0.01)	0.472*** (0.011)	0.451*** (0.01)
Log(Income)_2016	0.422*** (0.011)	0.407*** (0.011)	0.482*** (0.011)	0.459*** (0.011)
Log(Income)_2018	0.0969*** (0.011)	0.0421** (0.013)	0.505*** (0.011)	0.501*** (0.012)

Table 25 factor loadings for permanent income.

	Personal income 1	Personal Income 2	Household Income 1	Household Income 2
chisq	26840.846	20910.892	19489.973	14709.988
CFI	0.907	0.905	0.909	0.907
RMSFE	0.076	0.066	0.055	0.05

Table 26 Fit measures for the NLSY79 dataset.

Note: For the model to reach acceptable levels of fit, we utilized the modindices function in Lavaan (Rosseel et al., 2022). In line with the principles delineated in (Collier, 2020, p. 69), the following indicator variables were permitted to covary: "PincomeL_1983 ~~ PincomeL_1984", "ASVAB_7 ~~ ASVAB_8", "PincomeL_2016 ~~ PincomeL_2018", "PincomeL_1982 ~~ PincomeL_1983", "ASVAB_4 ~~ ASVAB_10", "PincomeL_2014 ~~ PincomeL_2016", "PincomeL_1984 ~~ PincomeL_1985", "PincomeL_1985 ~~ PincomeL_1986", "PincomeL_1981 ~~ PincomeL_1982", "PincomeL_2012 ~~ PincomeL_2014", "PincomeL_2008 ~~ PincomeL_2010", "ASVAB_5 ~~ ASVAB_6", "PincomeL_2006 ~~ PincomeL_2008", "ASVAB_9 ~~ ASVAB_11", "ASVAB_9 ~~ ASVAB_12", "PincomeL_1987 ~~ PincomeL_1988", "PincomeL_2004 ~~ PincomeL_2006", "PincomeL_1989 ~~ PincomeL_1990", "PincomeL_2002 ~~ PincomeL_2004", "PincomeL_1988 ~~ PincomeL_1989", "PincomeL_1986 ~~ PincomeL_1987", "PincomeL_1993 ~~ PincomeL_1994", "PincomeL_1992 ~~ PincomeL_1993", "PincomeL_2000 ~~ PincomeL_2002", "PincomeL_2006 ~~ PincomeL_2010", "PincomeL_1991 ~~ PincomeL_1992", "PincomeL_1990 ~~ PincomeL_1991", "PincomeL_2004 ~~ PincomeL_2008", "ASVAB_5 ~~ ASVAB_11", "PincomeL_2010 ~~ PincomeL_2012", "PincomeL_2014 ~~ PincomeL_2018", "ASVAB_11 ~~ ASVAB_12", "PincomeL_1983 ~~ PincomeL_1985", "PincomeL_1981 ~~ PincomeL_1983", "PincomeL_1984 ~~ PincomeL_1986", "PincomeL_1982 ~~ PincomeL_1984", "PincomeL_1996 ~~ PincomeL_1998", "PincomeL_2012 ~~ PincomeL_2016", "PincomeL_2010 ~~ PincomeL_2014", "PincomeL_1998 ~~ PincomeL_2000", "PincomeL_1979 ~~ PincomeL_1981", "PincomeL_1985 ~~ PincomeL_1987", "PincomeL_1989 ~~ PincomeL_1991", "PincomeL_2008 ~~ PincomeL_2012", "PincomeL_1988 ~~ PincomeL_1990", "PincomeL_1986 ~~ PincomeL_1988", "PincomeL_2004 ~~ PincomeL_2010", "PincomeL_2000 ~~ PincomeL_2004", "PincomeL_1994 ~~ PincomeL_1996", "PincomeL_1992 ~~ PincomeL_1994".

NLSY97

rhs	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
ASVAB_AI_ ABILITY	0.505*** (0.01)	0.485*** (0.01)	0.494*** (0.011)	0.518*** (0.011)	0.51*** (0.01)	0.49*** (0.01)	0.498*** (0.011)	0.522*** (0.011)
ASVAB_AO _ABILITY	0.636*** (0.009)	0.607*** (0.009)	0.615*** (0.01)	0.651*** (0.011)	0.635*** (0.009)	0.607*** (0.009)	0.613*** (0.01)	0.647*** (0.011)
ASVAB_AR _ABILITY	0.744*** (0.009)	0.712*** (0.008)	0.72*** (0.01)	0.761*** (0.01)	0.758*** (0.009)	0.726*** (0.008)	0.733*** (0.009)	0.773*** (0.01)
ASVAB_CS _ABILITY	0.493*** (0.01)	0.471*** (0.01)	0.465*** (0.011)	0.492*** (0.011)	0.511*** (0.01)	0.489*** (0.01)	0.481*** (0.011)	0.508*** (0.011)
ASVAB_EI_ ABILITY	0.697*** (0.009)	0.668*** (0.009)	0.675*** (0.01)	0.711*** (0.01)	0.7*** (0)	0.671*** (0.009)	0.678*** (0.01)	0.713*** (0.01)
ASVAB_GS _ABILITY	0.768*** (0.009)	0.736*** (0.008)	0.746*** (0.009)	0.786*** (0.01)	0.759*** (0.009)	0.729*** (0.008)	0.738*** (0.009)	0.776*** (0.01)
ASVAB_MC _ABILITY	0.697*** (0.009)	0.667*** (0.009)	0.674*** (0.01)	0.71*** (0.01)	0.717*** (0.009)	0.687*** (0.009)	0.693*** (0.01)	0.729*** (0.01)
ASVAB_MK _ABILITY	0.738*** (0.009)	0.706*** (0.008)	0.702*** (0.009)	0.742*** (0.01)	0.743*** (0.009)	0.711*** (0.008)	0.707*** (0.009)	0.746*** (0.01)
ASVAB_NO _ABILITY	0.539*** (0.01)	0.516*** (0.01)	0.507*** (0.011)	0.536*** (0.011)	0.539*** (0.01)	0.516*** (0.01)	0.506*** (0.01)	0.534*** (0.011)
ASVAB_PC _ABILITY	0.751*** (0.009)	0.717*** (0.008)	0.713*** (0.009)	0.754*** (0.01)	0.76*** (0.01)	0.727*** (0.008)	0.721*** (0.009)	0.761*** (0.01)
ASVAB_SI_ ABILITY	0.56*** (0.01)	0.538*** (0.009)	0.552*** (0.01)	0.579*** (0.011)	0.542*** (0.01)	0.521*** (0.009)	0.537*** (0.01)	0.562*** (0.011)
ASVAB_WK _ABILITY	0.759*** (0.009)	0.726*** (0.008)	0.732*** (0.009)	0.772*** (0.01)	0.757*** (0.009)	0.725*** (0.008)	0.729*** (0.009)	0.767*** (0.01)
PIAT	0.623*** (0.011)	0.597*** (0.01)	0.602*** (0.012)	0.635*** (0.012)	0.653*** (0.011)	0.626*** (0.01)	0.629*** (0.011)	0.663*** (0.012)

Table 27 g-loadings of indicator variables for the NLSY97 dataset. Clustered standard errors.

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
born	-0.343*** (0.013)	-0.36*** (0.01)	-0.35*** (0.01)	-0.335*** (0.014)	-0.327*** (0.013)	-0.342*** (0.013)	-0.336*** (0.014)	-0.322*** (0.014)
Colour			-0.231*** (0.022)	-0.454*** (0.014)			-0.231*** (0.022)	-0.454*** (0.014)
OPRE_Black	-1.04*** (0.03)	-0.715*** (0.069)			-1.04*** (0.03)	-0.716*** (0.068)		
OPRE_Other	-0.619*** (0.043)	-0.241*** (0.051)			-0.59*** (0.04)	-0.218*** (0.05)		
sex_Male	0.038 (0.024)	0.0371 (0.0246)	0.0813** (0.0275)	0.109*** (0.027)	0.0267 (0.0243)	0.0244 (0.0244)	0.0711** (0.0273)	0.1*** (0)
SPRE_Asian		0.205 (0.112)	0.176 (0.118)			0.213 (0.112)	0.199 (0.118)	
SPRE_Black		-0.603*** (0.074)	-0.852*** (0.055)			-0.593*** (0.073)	-0.848*** (0.054)	
SPRE_Hispanic		-0.861*** (0.037)	-0.865*** (0.039)			-0.849*** (0.037)	-0.846*** (0.038)	
SPRE_Multi		-0.295*** (0.049)	-0.44*** (0.06)			-0.294*** (0.049)	-0.449*** (0.061)	
SPRE_Native		-0.312 (0.189)	-0.39 (0.22)			-0.298 (0.189)	-0.37 (0.22)	
SPRE_Other		-0.136 (0.211)	-0.127 (0.235)			-0.114 (0.21)	-0.0978 (0.2333)	
SPRE_Pacific		-0.425 (0.231)	-0.613* (0.247)			-0.425 (0.229)	-0.62* (0.25)	

Table 28 Regression coefficients for the NLSY97, where g is the dependent variable. Clustered standard errors, year fixed effects.

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
Log(Income)_1997	0.2*** (0)	0.199*** (0.018)	0.2*** (0)	0.201*** (0.02)				
Log(Income)_1998	0.238*** (0.017)	0.238*** (0.017)	0.226*** (0.019)	0.228*** (0.019)				
Log(Income)_1999	0.28*** (0.02)	0.28*** (0.02)	0.262*** (0.019)	0.264*** (0.019)				
Log(Income)_2000	0.291*** (0.017)	0.29*** (0.02)	0.276*** (0.018)	0.278*** (0.018)				
Log(Income)_2001	0.327*** (0.016)	0.326*** (0.016)	0.326*** (0.017)	0.328*** (0.017)				
Log(Income)_2002	0.365*** (0.016)	0.364*** (0.016)	0.367*** (0.017)	0.368*** (0.017)				
Log(Income)_2003	0.367*** (0.016)	0.366*** (0.016)	0.364*** (0.017)	0.365*** (0.017)				
Log(Income)_2004	0.425*** (0.016)	0.424*** (0.016)	0.413*** (0.017)	0.414*** (0.017)	0.369*** (0.013)	0.369*** (0.013)	0.337*** (0.013)	0.338*** (0.014)
Log(Income)_2005	0.482*** (0.016)	0.481*** (0.016)	0.481*** (0.016)	0.483*** (0.016)	0.357*** (0.012)	0.357*** (0.012)	0.335*** (0.013)	0.336*** (0.013)
Log(Income)_2006	0.543*** (0.016)	0.542*** (0.015)	0.538*** (0.017)	0.541*** (0.017)	0.407*** (0.012)	0.406*** (0.012)	0.379*** (0.013)	0.382*** (0.013)
Log(Income)_2007	0.566*** (0.015)	0.565*** (0.015)	0.562*** (0.015)	0.566*** (0.015)	0.459*** (0.013)	0.458*** (0.013)	0.425*** (0.013)	0.428*** (0.013)
Log(Income)_2008	0.642*** (0.015)	0.641*** (0.015)	0.64*** (0.02)	0.644*** (0.015)	0.527*** (0.012)	0.527*** (0.012)	0.479*** (0.012)	0.482*** (0.012)
Log(Income)_2009	0.686*** (0.015)	0.683*** (0.015)	0.68*** (0.01)	0.685*** (0.015)	0.562*** (0.011)	0.562*** (0.011)	0.519*** (0.011)	0.522*** (0.011)
Log(Income)_2010	0.682*** (0.015)	0.68*** (0.02)	0.687*** (0.016)	0.691*** (0.016)	0.544*** (0.011)	0.543*** (0.011)	0.491*** (0.011)	0.495*** (0.011)
Log(Income)_2011	0.686*** (0.015)	0.686*** (0.015)	0.691*** (0.016)	0.694*** (0.016)	0.581*** (0.011)	0.581*** (0.011)	0.519*** (0.011)	0.524*** (0.011)
Log(Income)_2013	0.624*** (0.015)	0.623*** (0.015)	0.642*** (0.016)	0.645*** (0.016)	0.598*** (0.011)	0.597*** (0.011)	0.563*** (0.012)	0.569*** (0.012)
Log(Income)_2015	0.603*** (0.016)	0.602*** (0.016)	0.586*** (0.016)	0.589*** (0.016)	0.586*** (0.011)	0.586*** (0.011)	0.574*** (0.012)	0.58*** (0.01)
Log(Income)_2017	0.536*** (0.015)	0.536*** (0.015)	0.543*** (0.016)	0.546*** (0.016)	0.552*** (0.012)	0.551*** (0.012)	0.543*** (0.012)	0.549*** (0.012)
Log(Income)_2019	0.515*** (0.014)	0.514*** (0.014)	0.517*** (0.016)	0.519*** (0.016)	0.528*** (0.013)	0.527*** (0.013)	0.53*** (0.01)	0.536*** (0.014)

Table 29 factor loadings for permanent income.

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
chisq	10744.144	11330.908	9632.297	8864.39	9588.029	10127.138	8423.319	7720.68
CFI	0.903	0.9	0.9	0.905	0.905	0.902	0.902	0.907
RMSFE	0.075	0.064	0.068	0.08	0.049	0.041	0.042	0.049

Table 30 Fit measures for the NLSY97 dataset.

Note: To achieve satisfactory levels of model fit, we employed the modindices function in Lavaan (Rosseel et al., 2022). The following indicator variables were allowed to covary, in accordance with the principles outlined in (Collier, 2020, p. 69): "ASVAB_NO_ABILITY ~~ ASVAB_MK_ABILITY", "ASVAB_AI_ABILITY ~~ ASVAB_SI_ABILITY", "ASVAB_NO_ABILITY ~~ ASVAB_CS_ABILITY", "ASVAB_GS_ABILITY ~~ ASVAB_WK_ABILITY", "ASVAB_SI_ABILITY ~~ ASVAB_EI_ABILITY", "ASVAB_AR_ABILITY ~~ ASVAB_MK_ABILITY", "ASVAB_SI_ABILITY ~~ ASVAB_MK_ABILITY", "ASVAB_SI_ABILITY ~~ ASVAB_MC_ABILITY", "ASVAB_AI_ABILITY ~~ ASVAB_EI_ABILITY", "ASVAB_NO_ABILITY ~~ ASVAB_SI_ABILITY", "PincomeL_2002 ~~ PincomeL_2003", "PincomeL_2001 ~~ PincomeL_2002", "ASVAB_CS_ABILITY ~~ ASVAB_MK_ABILITY", "PincomeL_2000 ~~ PincomeL_2001", "PincomeL_1998 ~~ PincomeL_1999", "ASVAB_PC_ABILITY ~~ ASVAB_SI_ABILITY", "PincomeL_1999 ~~ PincomeL_2000", "PincomeL_2003 ~~ PincomeL_2004", "ASVAB_AI_ABILITY ~~ ASVAB_MK_ABILITY", "ASVAB_AR_ABILITY ~~ PIAT", "ASVAB_NO_ABILITY ~~ ASVAB_MC_ABILITY", "ASVAB_CS_ABILITY ~~ ASVAB_SI_ABILITY", "ASVAB_MK_ABILITY ~~ ASVAB_EI_ABILITY", "ASVAB_GS_ABILITY ~~ ASVAB_NO_ABILITY", "PincomeL_2015 ~~ PincomeL_2017", "ASVAB_MC_ABILITY ~~ ASVAB_AO_ABILITY", "ASVAB_WK_ABILITY ~~ ASVAB_AO_ABILITY", "ASVAB_AI_ABILITY ~~ ASVAB_MC_ABILITY", "ASVAB_AR_ABILITY ~~ ASVAB_NO_ABILITY", "PincomeL_2005 ~~ PincomeL_2006", "PincomeL_2000 ~~ PincomeL_2002", "PincomeL_2004 ~~ PincomeL_2005", "ASVAB_MC_ABILITY ~~ ASVAB_EI_ABILITY", "PincomeL_2001 ~~ PincomeL_2003", "ASVAB_WK_ABILITY ~~ ASVAB_PC_ABILITY", "ASVAB_GS_ABILITY ~~ ASVAB_AO_ABILITY", "ASVAB_CS_ABILITY ~~ ASVAB_AO_ABILITY", "ASVAB_MK_ABILITY ~~ PIAT", "PincomeL_2006 ~~ PincomeL_2007", "PincomeL_2002 ~~ PincomeL_2004", "PincomeL_1998 ~~ PincomeL_2000", "PincomeL_2017 ~~ PincomeL_2019", "PincomeL_2010 ~~ PincomeL_2011", "PincomeL_2008 ~~ PincomeL_2009", "PincomeL_1999 ~~ PincomeL_2001","ASVAB_NO_ABILITY ~~ PIAT", "PincomeL_2005 ~~ PincomeL_2007","PincomeL_2015 ~~ PincomeL_2019", "ASVAB_PC_ABILITY ~~ ASVAB_CS_ABILITY","PincomeL_2013 ~~ PincomeL_2015".

GSS

Indicator Variable	Personal income 1	Personal Income 2	Personal income 3	Household Income 1	Household Income 2	Household Income 3
worda	0.398*** (0.02)	0.408*** (0.048)	0.345*** (0.042)	0.402*** (0.014)	0.433*** (0.034)	0.395*** (0.031)
wordb	0.722*** (0.041)	0.822*** (0.098)	0.733*** (0.089)	0.74*** (0.03)	0.783*** (0.059)	0.704*** (0.052)
wordc	0.593*** (0.036)	0.331*** (0.063)	0.342*** (0.059)	0.471*** (0.021)	0.344*** (0.045)	0.351*** (0.041)
wordd	0.524*** (0.032)	0.63*** (0.08)	0.53*** (0.08)	0.66*** (0.02)	0.642*** (0.052)	0.584*** (0.047)
worde	0.52*** (0.03)	0.701*** (0.082)	0.48*** (0.07)	0.599*** (0.02)	0.689*** (0.052)	0.529*** (0.042)
wordf	0.733*** (0.032)	0.573*** (0.061)	0.654*** (0.068)	0.751*** (0.021)	0.606*** (0.041)	0.656*** (0.042)
wordg	0.695*** (0.039)	0.605*** (0.079)	0.623*** (0.08)	0.579*** (0.022)	0.523*** (0.049)	0.548*** (0.048)
wordh	0.591*** (0.03)	0.402*** (0.055)	0.463*** (0.059)	0.516*** (0.017)	0.451*** (0.04)	0.492*** (0.04)
wordi	0.28*** (0.03)	0.211*** (0.055)	0.231*** (0.05)	0.358*** (0.019)	0.295*** (0.038)	0.284*** (0.034)
wordj	0.377*** (0.03)	0.298*** (0.056)	0.4*** (0.1)	0.443*** (0.02)	0.316*** (0.04)	0.369*** (0.038)

Table 31

worda	t1	-0.98*** (0.04)	-0.849*** (0.068)	-0.897*** (0.061)	-1.01*** (0.03)	-0.92*** (0.05)	-0.918*** (0.049)
wordb	t1	-1.76*** (0.05)	-1.49*** (0.08)	-1.4*** (0.1)	-1.64*** (0.04)	-1.44*** (0.07)	-1.31*** (0.06)
wordc	t1	0.842*** (0.037)	0.888*** (0.066)	0.956*** (0.06)	0.819*** (0.026)	0.88*** (0.05)	0.946*** (0.049)
wordd	t1	-2.27*** (0.07)	-2.2*** (0.1)	-2.06*** (0.12)	-2.13*** (0.04)	-2.04*** (0.09)	-1.92*** (0.09)
worde	t1	-1.2*** (0)	-1.07*** (0.07)	-1.11*** (0.06)	-1.07*** (0.03)	-0.951*** (0.054)	-0.955*** (0.049)
wordf	t1	-1.17*** (0.04)	-0.993*** (0.066)	-0.789*** (0.059)	-1.1*** (0)	-0.953*** (0.052)	-0.775*** (0.047)
wordg	t1	0.318*** (0.035)	0.494*** (0.063)	0.576*** (0.057)	0.313*** (0.025)	0.463*** (0.05)	0.542*** (0.046)
wordh	t1	0.176*** (0.034)	0.202*** (0.061)	0.285*** (0.055)	0.18*** (0.02)	0.22*** (0.05)	0.321*** (0.044)

wordi	t1	-0.947*** (0.037)	-0.823*** (0.064)	-0.763*** (0.059)	-0.853*** (0.026)	-0.747*** (0.051)	-0.677*** (0.046)
wordj	t1	0.36*** (0.03)	0.489*** (0.062)	0.573*** (0.057)	0.427*** (0.024)	0.497*** (0.05)	0.582*** (0.045)

Table 32

Independent variable	**Personal income 1**	**Personal Income 2**	**Personal income 3**	**Household Income 1**	**Household Income 2**	**Household Income 3**
age	0.282*** (0.018)	0.273*** (0.04)	0.29*** (0.04)	0.133*** (0.01)	0.191*** (0.024)	0.224*** (0.025)
Colour		-0.26*** (0.05)	-0.366*** (0.042)		-0.231*** (0.035)	-0.363*** (0.029)
Male	-0.189*** (0.023)	-0.0814 (0.0533)	-0.0657 (0.0541)	-0.137*** (0.019)	-0.132** (0.044)	-0.125** (0.044)
SPRE_Black	-0.884*** (0.044)	-0.195 (0.1)		-0.949*** (0.033)	-0.322*** (0.084)	
SPRE_Other	-0.715*** (0.053)	-0.692*** (0.108)		-0.838*** (0.044)	-0.734*** (0.085)	

Table 33 Regression coefficients for the GSS, where g is the dependent variable. Year fixed effects.

	Personal income 1	**Personal Income 2**	**Personal income 3**	**Household Income 1**	**Household Income 2**	**Household Income 3**
chisq	2189.804	376.272	287.271	3173.829	547.657	450.046
CFI	0.919	0.908	0.933	0.929	0.924	0.94
RMSFE	0.023	0.037	0.039	0.025	0.038	0.041

Table 34 Fit measures for the GSS dataset.

Note: for model fit to reach acceptable levels, we filled the modindices function in Lavaan (Rosseel et al., 2022). The following indicator variables were allowed to covary: “wordb ~~ wordd", "wordg ~~ wordh", "wordg ~~ wordj", "wordh ~~ wordj", "wordd ~~ worde", "wordd ~~ wordj", "wordc ~~ wordj", "wordc ~~ wordh", "wordb ~~ worde", "wordc ~~ wordg", "wordb ~~ wordh","wordd ~~ wordi","wordb ~~ wordj","wordf ~~ wordg","worde ~~ wordg","worda ~~ wordb","wordf ~~ wordj","wordg ~~ wordi","worde ~~ wordh","wordb ~~ wordf","wordb ~~ wordi","worda ~~ wordg", "wordi ~~ wordj", "worda ~~ wordi", "wordf ~~ wordh", "worda ~~ wordc", "wordb ~~ wordc", "worda ~~ wordj", "worde ~~ wordf", "wordh ~~ wordi", "wordc ~~ wordf","worde ~~ wordj","wordc ~~ worde","wordd ~~ wordg", "wordb ~~ wordg", "wordd ~~ wordf", "wordf ~~ wordi", "wordc ~~ wordi", "worda ~~ wordh", "worde ~~ wordi", "worda ~~ wordd", "worda ~~ worde", "wordc ~~ wordd”.

Add Health

Indicator Variable	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
DigitSpan4	0.339*** (0.028)	0.336*** (0.027)	0.339*** (0.03)	0.34*** (0.03)	0.339*** (0.027)	0.336*** (0.027)	0.335*** (0.03)	0.333*** (0.03)
DigitSpan5	0.463*** (0.04)	0.446*** (0.039)	0.431*** (0.043)	0.442*** (0.043)	0.464*** (0.04)	0.448*** (0.039)	0.431*** (0.043)	0.442*** (0.043)
Knowledge1	0.0873*** (0.0195)	0.0859*** (0.019)	0.092*** (0.02)	0.0946*** (0.0208)	0.0905*** (0.0194)	0.0887*** (0.0189)	0.093*** (0.02)	0.0956*** (0.0208)
Knowledge2	0.0626** (0.0201)	0.0645*** (0.0196)	0.0717*** (0.0205)	0.0736*** (0.0208)	0.0703*** (0.02)	0.0712*** (0.0195)	0.0749*** (0.0204)	0.077*** (0.021)
p1	0.632*** (0.035)	0.647*** (0.036)	0.644*** (0.04)	0.629*** (0.039)	0.623*** (0.035)	0.637*** (0.036)	0.637*** (0.04)	0.621*** (0.039)
p3	0.611*** (0.035)	0.621*** (0.035)	0.632*** (0.039)	0.628*** (0.038)	0.613*** (0.034)	0.622*** (0.035)	0.633*** (0.039)	0.629*** (0.038)
Recall4	0.403*** (0.031)	0.397*** (0.03)	0.391*** (0.033)	0.391*** (0.033)	0.408*** (0.03)	0.402*** (0.03)	0.399*** (0.033)	0.399*** (0.033)
Recall5	0.406*** (0.044)	0.39*** (0.04)	0.351*** (0.046)	0.36*** (0.05)	0.414*** (0.044)	0.398*** (0.043)	0.358*** (0.047)	0.368*** (0.047)
RecallLong4	0.447*** (0.033)	0.441*** (0.033)	0.422*** (0.035)	0.419*** (0.035)	0.446*** (0.032)	0.44*** (0.03)	0.436*** (0.035)	0.434*** (0.035)
RecallLong5	0.447*** (0.045)	0.423*** (0.045)	0.408*** (0.049)	0.419*** (0.05)	0.45*** (0.05)	0.427*** (0.045)	0.415*** (0.05)	0.426*** (0.05)

Table 35 g-loadings of indicator variables for the Add Health dataset.

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
Age	-0.0833*** (0.0188)	-0.0772*** (0.0185)	-0.0732*** (0.0194)	-0.0762*** (0.0197)	-0.0829*** (0.0189)	-0.0772*** (0.0186)	-0.0728*** (0.0193)	-0.0755*** (0.0197)
Colour			0.366*** (0.041)	0.476*** (0.032)			0.364*** (0.041)	0.475*** (0.032)
Hispanic.x	-0.211*** (0.023)	-0.171*** (0.024)			-0.212*** (0.023)	-0.172*** (0.024)		
OPRE_Asian	-0.408*** (0.099)	0.141 (0.191)			-0.406*** (0.1)	0.141 (0.192)		
OPRE_Black	-0.991*** (0.064)	-0.352** (0.135)			-0.996*** (0.064)	-0.353** (0.136)		
OPRE_Native	-0.887*** (0.177)	-0.269 (0.199)			-0.874*** (0.178)	-0.252 (0.2)		
SEX_Male	-0.116** (0.042)	-0.0997* (0.0408)	-0.0174 (0.0423)	-0.015 (0.043)	-0.123** (0.042)	-0.107** (0.041)	-0.0297 (0.0421)	-0.0283 (0.0429)

SPRE_Asian		-0.654** (0.214)				-0.651** (0.215)		
SPRE_Black		-0.704*** (0.141)	-0.289*** (0.084)			-0.711*** (0.141)	-0.291*** (0.084)	
SPRE_Native		-0.987*** (0.204)				-0.995*** (0.205)		
SPRE_Other		-0.572*** (0.094)	-0.558*** (0.093)			-0.574*** (0.094)	-0.551*** (0.093)	

Table 36 Regression coefficients for the Add Health dataset, where g is the dependent variable.

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
Log(Household income) Wave 4					0.52*** (0.03)	0.53*** (0.03)	0.503*** (0.028)	0.505*** (0.028)
Log(Household income) Wave 5					0.435*** (0.023)	0.43*** (0.02)	0.45*** (0.02)	0.454*** (0.025)
Log(Personal income) Wave 4	0.388*** (0.021)	0.387*** (0.021)	0.384*** (0.021)	0.383*** (0.022)				
Log(Personal income) Wave 5	0.558*** (0.031)	0.558*** (0.031)	0.575*** (0.033)	0.571*** (0.033)				

Table 37 factor loadings for permanent income

	Personal income 1	Personal Income 2	Personal income 3	Personal Income 4	Household Income 1	Household Income 2	Household Income 3	Household Income 4
chisq	565.064	622.793	485.216	448.126	596.003	661.858	490.525	453.415
CFI	0.947	0.946	0.95	0.952	0.945	0.943	0.95	0.952
RMSFE	0.045	0.04	0.048	0.052	0.044	0.039	0.046	0.05

Table 38 Fit measures for the Add Health dataset.

ANES

Indicator Variable	Household Income 1	Household Income 2	Household Income 3
wordb	0.637*** (0.019)	0.54*** (0.04)	0.533*** (0.033)
wordd	0.693*** (0.018)	0.64*** (0.03)	0.634*** (0.03)
worde	0.667*** (0.015)	0.642*** (0.027)	0.598*** (0.027)
wordf	0.75*** (0.02)	0.672*** (0.028)	0.677*** (0.027)
wordg	0.49*** (0.02)	0.315*** (0.037)	0.337*** (0.035)
wordh	0.611*** (0.016)	0.49*** (0.04)	0.505*** (0.034)
wordj	0.655*** (0.015)	0.572*** (0.035)	0.588*** (0.033)
wordk	0.674*** (0.014)	0.672*** (0.028)	0.683*** (0.027)
wordl	0.651*** (0.015)	0.573*** (0.03)	0.582*** (0.028)
wordo	0.633*** (0.015)	0.515*** (0.03)	0.534*** (0.029)

Table 39 g-loadings of indicator variables for the ANES dataset.

Independent Variable	Household Income 1	Household Income 2	Household Income 3
Age	0.185*** (0.016)	0.0893** (0.0288)	0.116*** (0.028)
Colour		-0.137** (0.047)	-0.356*** (0.028)
Sex	0.067* (0.033)	0.00209 (0.05959)	0.0577 (0.0586)
SPRE_Black	-1.03*** (0.04)	-0.671*** (0.12)	
SPRE_Hispanic	-0.664*** (0.043)	-0.448*** (0.084)	
SPRE_Other	-0.321*** (0.08)	-0.162 (0.135)	

Table 40 Regression coefficients for the ANES, where g is the dependent variable.

	Household Income 1	**Household Income 2**	**Household Income 3**
chisq	978.639	366.617	341.837
CFI	0.945	0.926	0.928
RMSFE	0.049	0.043	0.054

Table 41 Fit measures for the ANES dataset.

Note: for model fit to reach acceptable levels, we filled the modindices function in Lavaan (Rosseel et al., 2022). The following indicator variables were allowed to covary: “wordb ~~ wordd","worde ~~ wordg","wordd ~~ wordo","wordb ~~ wordl","wordb ~~ worde”.