Cognitive meritocracy is the main cause of racial income gaps in the United States: an analysis of 5 large datasets

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Abstract

Socially defined racial groups usually differ in average incomes, though the causes of this are contested. We used 5 large datasets with relevant variables to distinguish between cognitive meritocracy, cultural models, and discrimination models (NLSY79, NLSY97, Add Health, GSS, ANES2012; total $n =$). Furthermore, we carried out a meta-analysis of the results as far as was possible. The use of both self- and other-perceived race/ethnicity group allowed one to distinguish between effects related to how others perceive one's race/ethnicity vs. how individuals perceive themselves. Results indicated that other-perceived Black and Hispanic racial statuses were associated with either no differences or slightly *higher* incomes when cognitive ability was controlled for ($\beta =$), whereas self-perceived Black status was negatively related to income ($\beta =$). Other self-perceived racial statuses had no clearly detectable effect. Results were interpreted as being congruent with meritocracy and inconsistent with market-irrelevant discrimination models.

Key words: race, ethnicity, skin tone, income, gap, IQ, intelligence, cognitive ability, g factor, discrimination, United States, NLSY79, NLSY97, Add Health, GSS, ANES

1. Introduction

Racially linked social inequality is nearly ubiquitous and is a much researched topic (Bonilla-Silva, 2009; Herrnstein & Murray, 1994; Lynn, 2008, 2015; Telles, 2014). A particular topic of contention is the relative importance of racial discrimination and human capital causes of racial gaps in educational attainment, income, health etc. A number of scholars have argued that such social gaps primarily, but

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not exclusively, are caused by gaps in cognitive ability (Gottfredson, 2004; Herrnstein & Murray, 1994; Lynn, 2015), while other scholars have argued that market-irrelevant racial discrimination explains the majority of the gaps (M. Hunter, 2007; Kaplan, 2015; Telles, 2014). In this study, the relative validity of these explanations were tested using both the National Longitudinal Study of Youth 1979 and its 1997 near-replication sibling. We used income as the outcome of interest because it is a plausible target of market-irrelevant racial discrimination by means of biased hiring and promotion. We avoided using educational attainment because affirmative action policies distort the gaps (Antman & Duncan, 2015; Detterman, 2000; Herrnstein & Murray, 1994). The use of the term *market-irrelevant* discrimination is done to avoid confusion with rational or statistical discrimination, which is where employers (and others) rely on imperfect, but (well beyond chance levels) accurate stereotypes to inform decision making (Balsa & McGuire, 2001; Jussim, 2012; Southwood, 2014). Thus, if some job relevant characteristic is difficult to observe (e.g. cognitive ability, work ethics) but is known to be related to an easily observable trait (e.g. sex, racial group/ancestry, name, clothing, manner of speech), employers might reasonably use the proxy trait until they can clarify the status of the desired trait (Caplan, 2018). In contrast, irrelevant (‘taste’) discrimination refers to employers preferring members of particular ancestries or racial groups (usually their own) for job-irrelevant reasons.

1.1. Theoretical model and approach

Before going into the data analysis, it is worth clarifying the theoretical causal network employed in this model via path analysis diagrams. Figure 1 shows the primary theoretical causal path model used in this study.

Figure 1: Theoretical causal path model. Arrows are causes, dotted lines are non-causal statistical relations.

In the model, income is explained by 3 factors (aside from randomness, not shown): 1) cognitive ability, 2) other human capital traits including both specific ability, more narrow skills (e.g. programming ability), practical interests, work ethic, and 3) irrelevant discrimination. No specific causes of human capital traits are assumed except that these covary with racial ancestry (dotted line) as measured by modern genomic approaches. Racial ancestry itself is taken to be a statistical cluster in high-dimensional genomic space and roughly corresponds to the traditional racial classifications

(Baker, 1974; Fuerst, 2015; Jensen, 1998; Sarich & Miele, 2004; Wade, 2014). Skin tone and other racial physical traits are linked to racial ancestry and together cause a person's racial appearance. Social actors then use this appearance to discriminate between various causes of action related to income, including hiring and promotion.

The goal of this study was to assess the relative importance of the three specified causes of income, with focus on the first and third. To assess the relative importance of causes, one must have the relevant variables which strongly limited the available datasets to choose from. We relied on a number of large, public datasets for this purpose:

1. National Longitudinal Study of Youth 1979
2. National Longitudinal Study of Youth 1997
3. National Longitudinal Study of Adolescent to Adult Health (Add Health)
4. General Social Survey

The datasets do not all contain all the relevant variables, however, they all contain a minimal set of variables including: 1) income, 2) a measure of racial ancestry such as self-perceived race/ethnicity (SPRE), other perceived race/ethnicity (OPRE) or genomic ancestry, and 3) cognitive ability. Together, these three variables allows one to estimate the relative predictive validity of cognitive ability and racial ancestry in explaining observed income variation. If a dataset more relevant variables, a more detailed model can be fit. Specifically, skin tone allows a direct estimate of the relationship of the most commonly claimed mediator of racial discrimination. The availability of both SPRE and OPRE allows one to distinguish between other-mediated effects and self-identity.

A productive scientific research framework should be able to generate testable predictions that succeed in empirical testing. For this purpose, it is helpful to clearly state a number of predictions that follow from specific models. By *meritocracy* we mean the model where human capital traits explain the income gaps between racial groups. Similarly, by *cognitive meritocracy* we mean the same except that it is limited to cognitive ability, not other human capital traits. In contrast, *irrelevant racism* refers to non-human capital causes of racial income gaps. The models in their pure forms generate precise predictions (i.e. 0 validity of the other options), but they can of course be combined.

2. Analyses

All analyses were done in R. A notebook with extensive output and code can be found at http://rpubs.com/EmilOWK/race_income_meritocracy_2018.

2.1. NLSY79

2.1.1. Data and coding

Data were used from the NLSY1979, downloading using the NLS Investigator

(<https://www.nlsinfo.org/investigator/pages/search.jsp>). The NLSY79 is a large ($n \approx 12k$), longitudinal study of US residents began in 1979. It was the dataset used by *The Bell Curve* (Herrnstein & Murray, 1994), though the particular analyses presented here were not carried out in that study (but see their Chapter 14).

For the basic demographics of age and sex, the variables R0000600 and R0214800 were used. All numeric variables were standardized before modeling to provide the output with standardized betas.

A number of variables are available for interviewer-perceived racial group (one for most waves of collection). Unfortunately, nearly all of them concern only three groups, namely, White, Black and Other (e.g. R0172700). However, one collected at time of first screening in 1979 concern the three explicitly defined groups Hispanic, Black, non-Black & non-Hispanic. The latter group can be taken to refer to Whites and a very small number of others such as Asians and American Indians.

In 2002, a set of questions (R709310 etc.) were added asking the subjects “What race or races do you consider yourself to be?” with a list of 6 non-mutually exclusive choices: White, Black, Asian, Pacific Islander, American Indian, Other and Hispanic. The cross-tabulation between the self- and other-perceived racial group is given in Table 1.

Self/other-perceived racial group	<i>White</i>	<i>Black</i>	<i>Hispanic</i>
<i>White</i>	0.85	0.01	0.14
<i>American Indian</i>	0.76	0.07	0.17
<i>Asian</i>	0.65	0.17	0.17
<i>Black</i>	0.00	0.99	0.01
<i>Hispanic</i>	0.01	0.01	0.98
<i>Multi-racial</i>	0.37	0.43	0.21
<i>Other</i>	0.08	0.04	0.87
<i>Pacific Islander</i>	0.40	0.10	0.50

Table 1: Cross-tabulation between self- and other-perceived racial group. Row marginalized.

IQ was scored from the AFQT centiles. These were converted to z-scores using the inverse normal cumulative distribution function.

To measure income, the income variant “total income from wages and salary in past calendar year” was used. This variable was available for the years 1979-1994, 1996, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, and 2014 (25 years in total). All the intercorrelations between the income measures were positive, with a mean of .45 (range .08 to .86). There was extensive missing data. Cases with 17 or few missing datapoints had their remaining datasets imputed using IRMI (deterministic) (Templ, Alfons, Kowarik, & Prantner, 2015). The goal with the imputation was to preserve as many cases for analysis

as possible, and the chosen number preserved 86% of cases. There is necessarily a quality-quantity trade-off here, and due to the pervasive positive correlations, a judgment call relatively in favor of quantity was made.

2.1.2. Results

Theoretical models concerning the relationships between self- and other-perceived race/ethnicity (SPRE and OPRE, respectively), IQ and income give rise to different predictions. On a simple, pure meritocracy model, racial group is simply a correlate of IQ (for whatever reason), and the predictive validity of racial group is expected to go to 0 once IQ is included in the model. Though note that this is only true in so far as the IQ measure perfectly captures the relevant human capital differences between the groups. Due to the existence of measurement error, some residual validity of the racial group measures is expected (Westfall & Yarkoni, 2016). If there are any human capital differences not perfectly captured even by a perfectly reliable measure of the construct underlying IQ scores – general cognitive ability – then one would also expect to see some residual validity for racial group measures.

The irrelevant racial discrimination model predicts that other-perceived racial group should be relevant even when IQ is controlled. Furthermore, the directions should be such that non-White status predicts lower incomes because Whites (and sometimes others) are claimed to favor their own racial group over others, even when relevant human capital traits have been controlled. Finally, the cultural self-identification model holds that individuals of mixed ancestry tend to identify more strongly with the racial group whose values and average social status match most strongly with their own (Saperstein & Penner, 2012). In case of income, one would expect successful mixed race persons to have a tendency to identify as White (or other high performing groups such as Asians) despite equal racial appearance to a less successful mixed race person.

To make the predictions more concrete: 1) a pure cognitive ability meritocracy model predicts near null validity of racial groups after the inclusion of IQ in the model, but some validity before, 2) irrelevant racial discrimination model predicts negative betas for other-perceived racial group before and after the inclusion of IQ in the model, 3) cultural self-identification model predicts negative betas for non-White (and non-Asian) self-perceived racial groups before and after the inclusion of IQ in the model.

The results of the models are shown in Table 2.

Model 1 – other-perceived race/ethnicity, n = 10,960, adj. r² = .18				
<i>Predictor</i>	<i>Beta</i>	<i>SE</i>	<i>CI lower</i>	<i>CI upper</i>
OPRE: White	0.00			
OPRE: Black	-0.47	0.02	-0.51	-0.43
OPRE: Hispanic	-0.24	0.02	-0.29	-0.20
sex: Female	0.00			

sex: Male	0.65	0.02	0.62	0.69
age	0.20	0.01	0.18	0.22
Model 2 – self-perceived race/ethnicity, n = 7,692, adj. r² = .21				
<i>Predictor</i>	<i>Beta</i>	<i>SE</i>	<i>CI lower</i>	<i>CI upper</i>
SPRE: White	0.00			
SPRE: American Indian	-0.42	0.13	-0.67	-0.16
SPRE: Asian	0.17	0.19	-0.19	0.54
SPRE: Black	-0.55	0.02	-0.60	-0.51
SPRE: Hispanic	-0.37	0.04	-0.45	-0.29
SPRE: Multi-racial	-0.22	0.09	-0.40	-0.05
SPRE: Other	-0.38	0.05	-0.49	-0.28
SPRE: Pacific Islander	0.05	0.28	-0.50	0.60
sex: Female	0.00			
sex: Male	0.67	0.02	0.63	0.71
age	0.19	0.01	0.17	0.21
Model 3 – other-perceived race/ethnicity and cognitive ability, n = 10,430, adj. r² = .34				
<i>Predictor</i>	<i>Beta</i>	<i>SE</i>	<i>CI lower</i>	<i>CI upper</i>
OPRE: White	0.00			
OPRE: Black	-0.03	0.02	-0.07	0.01
OPRE: Hispanic	0.10	0.02	0.06	0.15
IQ	0.45	0.01	0.43	0.47
sex: Female	0.00			
sex: Male	0.66	0.02	0.62	0.69
age	0.13	0.01	0.12	0.15

Model 4 – self- and other-perceived race/ethnicity and cognitive ability, n = 7,372, adj. r² = .36				
<i>Predictor</i>	<i>Beta</i>	<i>SE</i>	<i>CI lower</i>	<i>CI upper</i>
OPRE: White	0.00			
OPRE: Black	0.15	0.08	0.00	0.31
OPRE: Hispanic	0.11	0.03	0.04	0.18
SPRE: White	0.00			
SPRE: American Indian	-0.24	0.12	-0.48	0.00
SPRE: Asian	0.05	0.18	-0.30	0.39
SPRE: Black	-0.24	0.08	-0.40	-0.09
SPRE: Hispanic	-0.07	0.05	-0.17	0.02
SPRE: Multi-racial	-0.17	0.09	-0.34	0.00
SPRE: Other	-0.09	0.06	-0.19	0.02
SPRE: Pacific Islander	0.02	0.25	-0.48	0.52
IQ	0.45	0.01	0.42	0.47
sex: Female	0.00			
sex: Male	0.66	0.02	0.63	0.70
age	0.13	0.01	0.11	0.15

Table 2: Regression model results. Outcome: average z-scored income of 25 years.

Models 1 and 2 are baseline models. They show that in the presence of basic control – age and sex – both self- and other-perceived race/ethnicity (SPRE and OPRE) have predictive validity. Though the validity is not as strong as might be expected, and corresponds to correlations of .20 and .25, respectively.² In comparison, the corresponding values are .33 and .20 for sex and age, respectively (in both models).

In model 3, IQ is included as a predictor along with OPRE. The prediction here based on irrelevant racial discrimination models was that there should remain *negative* betas for the non-White categories.

2 These are based on the ANOVA-versions of the same models. From ANOVA, it is possible to compute eta², which is a variance-like metric for predictor validity. Taking the square root of this produces eta, a correlation-like metric. This procedure is useful when comparing the relative importance of categorical vs. numerical predictors while also taking into account their non-independence.

However, this was not observed; the beta for Black was tiny at -0.03 (compared to -0.47 before) while the beta for Hispanic was positive at 0.10 (vs. -0.24 before), well beyond chance levels ($p = .00001$).

Finally, in model 4, both measures of perceived racial group were included. Like in model 3, the betas for OPRE were inconsistent with the discrimination model's predictions, as both were *positive* not negative. The betas for SPRE varied in direction. Only the beta for Black was clearly beyond chance-levels ($p = .002$), and was negative (-0.24). This is in line with the prediction from the cultural self-identification model.

For both model 3 and 4 the validity of IQ was quite substantial (beta = 0.45, eta = .38 i.e. 14% variance). This increase in effect sizes has also been found in other studies that employed averages of many years of income instead of just a single year (Benjamin et al., 2012; Dalliard, 2016; Hyytinen, Ilmakunnas, Johansson, & Toivanen, 2013). In contrast, the validity of both variants of social race were near-zero with etas of .03 and .04 for OPRE and SPRE, respectively.

2.2. NLSY97

2.2.1. Data and coding

Since the NLSY97 was intended as a near-replication of NLSY79, the dataset contains most of the same measures. However, there are a few differences. First, since the dataset began collection in 1997, the age of the subjects is approximately 20 years younger than those in NLSY79. This has implications for the accuracy of the long-term income estimate. Second, a measure of skin tone was included in the survey which allows for more detailed testing. Third, the NLSY97 is smaller, at $n \approx 9k$ instead of $\sim 12k$. Fourth, NLSY97 has additional measures of cognitive ability: Peabody vocabulary test (3 testings), SAT and ACT.

As before, we downloaded the variables of interest using the NLSY explorer. As in NLSY79, there were available variables for both self-perceived race/ethnicity (SPRE) and other perceived race/ethnicity (OPRE). We used the variables S122490 and R0538600 to code SPRE into the standard categories as before. For OPRE, we used R2395200 which places persons into 3 groups: White, Black, and Other. Table 3 shows the cross-tabulation between the two racial measures.

Self/other-perceived racial group	<i>White</i>	<i>Black</i>	<i>Other</i>
<i>White</i>	0.99	0.00	0.01
<i>American Indian</i>	0.52	0.00	0.48
<i>Asian</i>	0.15	0.01	0.84
<i>Black</i>	0.01	0.98	0.01
<i>Hispanic</i>	0.64	0.04	0.32
<i>Multi-racial</i>	0.61	0.30	0.09
<i>Other</i>	0.38	0.21	0.41
<i>Pacific Islander</i>	0.29	0.04	0.67

Table 3: NLSY97 - Cross-tabulation between racial measures. Row marginalized.

Skin tone was measured at 3 waves though without overlap on an 0-10 scale (T3173000, T4584700, T6217800). We combined the data from the 3 measures. Because some have raised concerns that the interviewer's own race affects skin tone ratings (Kreisman & Rangel, 2014), we created a version of this variable where we regressed out the interview's race (T2023300, T3614100, T5214000) with OLS. The two variables correlated at .99 with very few outlying values to be seen in a scatterplot.

For cognitive ability, we used all the available variables, which were combined as needed. We combined the 3 testings of PIAT by averaging the z scores (mean $r = .77$) and we combined the SAT verbal and math to a total score (average of Z scores). AFQT centiles were converted to z scores. Finally, we averaged the z scores of AFQT and PIAT to create a best estimate of general cognitive ability (g).

Coding income was done similarly to NLSY79. There were income variables available for 16 years (age 15-31). The correlations with cognitive ability were low ($r < .15$) before age ~25, so we only used the data from age 25-31 for the estimate of long-term income. We tried the same four coding variants of the data and chose the one that maximized the relations with the other variables. As in NLSY79, this was found to be the imputed, non-log version. For imputation, we used the cases with at least 6 datapoints.

2.2.2. Results

Table 4 shows the correlation matrix between major variables. Correlations for sex were calculated as latent correlations (biserial).

	g	AFQT	PIAT	SAT	ACT	Income	Skin tone	Skin tone fixed	Age	Sex
g	1.00	0.96	0.92	0.61	0.66	0.26	-0.37	-0.36	-0.02	-0.03

AFQT	0.96	1.00	0.78	0.60	0.67	0.25	-0.36	-0.36	-0.01	-0.05
PIAT	0.92	0.78	1.00	0.61	0.58	0.23	-0.35	-0.34	0.02	0.08
SAT	0.61	0.60	0.61	1.00	0.55	0.18	-0.26	-0.28	-0.02	0.09
ACT	0.66	0.67	0.58	0.55	1.00	0.13	-0.33	-0.31	0.00	0.05
Income	0.26	0.25	0.23	0.18	0.13	1.00	-0.15	-0.14	0.16	0.24
Skin tone	-0.37	-0.36	-0.35	-0.26	-0.33	-0.15	1.00	0.99	0.02	0.03
Skin tone fixed	-0.36	-0.36	-0.34	-0.28	-0.31	-0.14	0.99	1.00	0.01	0.02
Age	-0.02	-0.01	0.02	-0.02	0.00	0.16	0.02	0.01	1.00	-0.01
Sex	-0.03	-0.05	0.08	0.09	0.05	0.24	0.03	0.02	-0.01	1.00

Table 4: NLSY97 correlation matrix.

Compared to NLSY97, the correlation between cognitive ability and income was weaker. This is not just because fewer years were used to form the average, the correlation is stronger at every age in NLSY79 (figure shown later). Nevertheless, associations to the other variables were in the expected directions and approximate relative magnitude. Correlations were also calculated by the three major SPREs (White, Black, Hispanic) and are shown in the supplementary materials. Of particular interest were the observed correlations between skin tone and IQ which were -.11, -.11, and -.13, respectively for Whites, Blacks and Hispanics. For Blacks and Hispanics, the values are similar to previously reported estimates (Kirkegaard & Fuerst, 2017; Lynn, 2002). The negative correlation for Whites is somewhat puzzling. There was a small outlying group of (self-identified) Whites with relatively dark skin (7-8 on 0-10 scale). However, excluding them had no effect on the correlation (at 2 decimals).

Proceeding to modeling, we fit a total of 9 main models. Models 1-4 were fit to establish baseline validity of the racial predictors as single predictors of income as well as the pure age+sex model. Models 5-7 combined one of the racial measures with cognitive ability. Model 8 was the final full mode. Table 5 shows the model summary statistics, while Table 6 shows the fit from the full model.

Model	SPRE	OPRE	Skin tone	g	Adj. R2	n
1	(age and sex only)				0.065	6340
2	yes				0.097	6339
3		yes			0.081	6107
4			-0.16		0.091	5309
5				0.29	0.139	5420
6	yes			0.26	0.148	5419
7		yes		0.27	0.139	5275
8			-0.07	0.27	0.152	4563
9	yes	yes	-0.06	0.27	0.159	4456

Table 5: NLSY97 model summary statistics. SPRE = self-perceived race/ethnicity, OPRE = other-perceived race/ethnicity. g = cognitive ability.

Predictor	Beta	se	p
OPRE=Black	0.13	0.10	0.18
OPRE=Other	0.13	0.06	0.03
SPRE=American Indian	-0.44	0.21	0.04
SPRE=Asian	0.68	0.13	0.00
SPRE=Black	-0.13	0.10	0.18
SPRE=Hispanic	-0.02	0.04	0.59
SPRE=Multi-racial	-0.12	0.07	0.11
SPRE=Other	0.49	0.28	0.08
SPRE=Pacific Islander	0.28	0.26	0.28
Skin tone	-0.06	0.02	0.01
g	0.27	0.02	0.00

Table 6: NLSY97 full model (8).

There are a number of findings of interest. First, the three racial variables were roughly equivalent in

that they added incremental validity beyond age and sex, SPRE being the most predictive and OPRE the least. Second, SPRE and skin tone both added a small amount of validity (~1% variance) beyond cognitive ability (models 6+8), while OPRE did not (model 7). Third, the validity of skin tone was reduced by about 50% when cognitive ability was added (model 4 vs. 8). Fourth, in the full model, OPRE Black and Other had positive betas (both .13), the latter somewhat beyond chance levels ($p = .03$). For SPRE, Asian had a strong beta of .68 while American Indian had a strong negative of -.44. Neither Black nor Hispanic had any detectable validity. Both skin tone and cognitive ability kept their betas at about the same levels.

A non-zero beta for skin tone while cognitive ability is controlled indicates that one of the two alternative causal paths from Figure 1 are operating. However, how important is the effect size in comparison to cognitive ability? Here one cannot rely on the standardized betas because the independent validity of a predictor depends on its variation and relation to co-variables. Instead we utilized the ANOVA (SS type 3; (Dan Navarro, 2015)) approach which allows calculation of η^2 , a variance-like metric. To do this, it was necessary to use a linear age term due to software limitations.³ Table 7 shows the η s (sqrt of η^2) for each predictor, which are a correlation-like metric.

Predictor	Eta
OPRE	0.03
SPRE	0.09
Skin tone	0.04
g	0.24
Sex	0.20
Age	0.07
Sex:age	0.06

Table 7: NLSY97 full model (8) η s.

The irrelevant discrimination model predicts that skin tone and OPRE should have validity, while cognitive meritocracy predicts that g should have validity. In fact we see that cognitive ability (g) has the largest validity followed by SPRE, while both OPRE and skin tone have near-zero validity.

2.3. Add Health

The Add Health dataset is also part of the NLSY family, though it differs in some ways (Harris, Halpern, Habershtick, & Smolen, 2013). First, it has only 4 waves of data collection. These were which collected in: 1) 1994-1995, 2) 1996, 3) 2001-2002, and 4) 2007-2008. Second, large parts of the sample are 'protected' from public use. This understandably includes the genomic data, but even most of the

³ The **lsr** package (Daniel Navarro, 2015) does not seem to support cubline splines in its calculation of η^2 .

non-genomic sample is restricted. The current study could only rely upon the public release subsample which has a markedly smaller sample size of 6.5k out of ~20k in wave 1 and ~15k in later waves. The very strict rules regarding release of the genomic data (including a 1000 USD application fee) is unfortunate because this likely severely limits the use of the dataset for many scientific questions, including those related to the present study. Third, it contains a variety of measures of self-reported maltreatment, including those perceived to be racially motivated, which were recently investigated in a related study (Boutwell et al., 2017).

2.3.1. Data and coding

Some questions were asked repeatedly, e.g. age/date of birth, while others were only asked once. Because some data are missing in each wave, one can to some degree rely on data from the other waves to avoid losing cases.

For sex, we used the variable in wave 1 (*BIO_SEX*). There were no outright missing data for this wave, though one participant out of 6,504 refused. This person was recoded to missing data. Temporal stability of sex/gender self-identity was extremely strong. Only 3 persons of 5,114 changed their status between wave 1 and wave 4, i.e. a timespan of approximately 13 years.

For age, we used the wave 1 data (year and month of birth; *H1GI1Y*, *H1GI1M*). 3 persons had missing data which were imputed with wave 4 data (*H4OD1Y*, *H4OD1M*) resulting in 0 missing cases. To calculate age, we used the individual interview date from wave 4. When this was missing, we imputed the modal date (2008-03-08). Mean age at interview was 29, with a standard deviation of 1.8.

For self-perceived race/ethnicity (SPRE), data were available for wave 1 and 3. The main difference is that wave 1 had an Other option, which was absent in wave 3. The difference here is that this means that respondents in wave 1 can explicitly indicate they consider themselves to belong to a non-mentioned group, while for wave 3 one would have to infer this from their denial of every offered option. As before, we coded the data in line with the standard practice of giving precedence to Hispanic status and coding multiple affirmations as *multi-racial*. Table 8 shows the cross-tabulation of the two resulting SPRE variables.

	White	American Indian	Asian	Black	Hispanic	Multi-racial	Other
White	1896	0	0	1	7	34	1
American Indian	12	18	0	3	2	6	0
Asian	4	1	97	1	2	4	0
Black	1	2	2	749	6	23	0
Hispanic	50	2	7	44	303	7	0
Multi-racial	142	3	15	72	10	61	1
Other	26	0	4	3	4	0	1

Table 8: Cross-tabulation of self-perceived race/ethnicity in Add Health sample, wave 1 and 3. Wave 1 in rows.

There were notable overlap between them, and many discrepancies, meaning that people tend to somewhat change their self-identity over ~7 years, as least with regards to this way of asking (which also differed slightly across years). The concordance rate was 86% and this did not change at 2 decimal mark if one removes the *Other* categories. We used the data from wave 3 and filled in missing values from wave 1.

Likewise, for other-perceived race/ethnicity (OPRE), data were available for multiple waves: 1, 3 and 4. Also likewise, wave 1 had the more detailed response options. However, the other-perceived questions asked the reviewer to put the subject into one best fitting category. In wave 1, there were 5 categories: White, Black, American Indian/Native American, Asian/Pacific Islander, and Other; while in waves 3/4 the Other category was left out. However, the wave 4 dataset had only 28 missing cases, so simply using it would be mostly unproblematic with regards to sample loss and was done. Stability across the identically framed wave 3 and 4 ratings was very high at .97 (~6 years), showing that OPRE is a highly reliable variable. It was not possible to calculate stability with wave 1 because the response variables were different. However, inspection shows that the most notable pattern is that people perceived as Other when given the option get mostly moved to White when Other is not available. Table 9 shows the cross-tabulation between wave 1 and 4.

	White	Black or African American	American Indian or Alaska Native	Asian or Pacific Islander
White	3419	16	7	11
Black or African American	28	1196	1	0
American Indian or Native American	20	3	27	2
Asian or Pacific Islander	21	1	2	132
Other	182	20	4	11

Table 9: Cross-tabulation between other-perceived race/ethnicity in wave 1 (rows) and 3.

Skin tone was only rated (by interviewer using a color guide; *H3IR17*) in wave 3 which was used for this study.

For income, the Add Health is problematic. Only one wave of data collection is after the age of 25 (i.e. post-education), and thus useful as an outcome variable while avoiding under-education confounding with income (brighter students stay in school longer). This leaves us with only a single year of data for the outcome, which is not as satisfactory as the other datasets. There were two relevant variables, one with personal income (*H4EC2*: “In {2006/2007/2008}, how much income did you receive from personal earnings before taxes, that is, wages or salaries, including tips, bonuses, and overtime pay, and income from self-employment?”) and one with household (*H4EC1*: “What was the total household income before taxes and deductions in {2006/2007/2008}”). The choice is between increased reliability by relying on possible spousal/co-dweller income, which can be assumed to be correlated with the recipient’s own long-term income, but increased based from co-dwelling confounding (i.e. it is not random who lives with other people). Furthermore, household income was binned, which introduces artificial imprecision into the data, thus reducing relationships to other variables. The household data were converted to the mean of the reported range (e.g. 50k to 75k → 62.5k), and using just the lower bound for the end ranges. The raw income variables correlated .39 ($n = 4625$), but self-reported income allowed for very large values (fairly extreme outliers) while household income was binned. As before, we investigated a variety of ways to code personal income: 1) raw, 2) $\log_{10}(\text{raw} + 1)$, and 3) $\log_{10}(\text{raw} + 1)$ with winsoring for extreme low values (below 2.5). Using the same procedure as previously, we tried a variety of combinations but found that combining personal income (coding #3) and household income produced the largest criterion relationships, i.e. relations with age, sex and IQ. Becomes sometimes personal income was available when household was missing and reversely, this combined coding also enabled us to include about ~120/~220 more cases than personal/household income alone, respectively. This was thus chosen as our main coding.

2.3.2. Results

The modeling approach followed the same approach as for NLSY97, the main difference being the robustness checks carried out. Table 10 shows the model summary statistics.

Model	SPRE	OPRE	Skin tone	g	Adj. R2	n
1	(age and sex only)				0.023	4981
2	yes	no	no	no	0.054	4730
3	no	yes	no	no	0.050	4976
4	no	no	-0.14	no	0.046	4107
5	no	no	no	0.23	0.083	3941
6	yes	no	no	0.22	0.098	3941
7	no	yes	no	0.22	0.093	3937
8	no	no	-0.07	0.21	0.087	3936
9	yes	yes	-0.08	0.22	0.099	3932

Table 10: Add Health models summary.

The results in general mirrored those from before in that IQ has essentially constant validity no matter which other predictors are included. Skin tone has notably lower validity once IQ is controlled. The full model (i.e. model 9) is shown in Table 11.

Predictor	Beta	SE	p
sex=Female	0.25	2.72	0.93
SPRE=American Indian	-0.26	0.23	0.26
SPRE=Asian	0.55	0.17	0.00
SPRE=Black	-0.13	0.12	0.30
SPRE=Hispanic	0.16	0.06	0.01
SPRE=Multi-racial	-0.10	0.09	0.25
SPRE=Other	-0.11	0.38	0.77
OPRE=Black or African American	0.15	0.12	0.21
OPRE=American Indian or Native American	0.13	0.19	0.48
OPRE=Asian or Pacific Islander	0.09	0.16	0.56
OPRE=Other	-0.04	0.09	0.67
skin tone	-0.08	0.03	0.01
IQ	0.22	0.02	0.00

*Table 11: Add Health full model (age and age*sex omitted).*

The specific results again mirror the previous ones with the exception that most of the betas have $p > \alpha$. This is in part because we used the combined income measure, which reduces the influence of sex, and because the sample size was smaller and the income measure probably less reliable, making smaller patterns harder to detect. Still, the effect of IQ was robust. We furthermore carried out three extra robustness model variations. First, we tried the two component income variables, but this made little difference to the results, except making them generally weaker (because of decreased reliability of the outcome). Second, we used wave 1 SPRE instead of wave 3. This also made little difference. Third, we tried coding skin tone as an ordinal instead of a numeric, but this also had little effect. Table shows the relative importance of the variables from the full model (linear effect of age, as before).

Predictor	Eta
Sex	0.15
Age	0.03
Sex * age	0.01
SPRE	0.07
OPRE	0.02
skin tone	0.04
IQ	0.21

Table 12: Add Health: Relative predictor importance in ANOVA version of full model (linear effect of age only).

Thus, we find the same pattern as before. SPRE is more important than OPRE, and skin tone has barely any importance despite the negative beta in the model and the low p value (.0134 in full model). IQ dwarfs the other predictors except for sex.

2.4. ANES

ANES (American National Election Studies) presents another opportunity for studying cognitive meritocracy. Unfortunately, there is only data for a single year that has skin tone (2012), and even this dataset lacks a measure of other-perceived race/ethnicity. Furthermore, the IQ measure in this dataset is the wordsum, which consists only of 10 items and which shows substantial ceiling effects which reduces the variance ('restriction of range'), and thus the predictive validity (J. E. Hunter & Schmidt, 2004). Finally, the data were gathered using two different sampling methods, namely face to face interviews (n =) and an online sample (n =).

2.4.1. Data and coding

Sex was coded using self-report which resulted in no missing data. Age was coded using self-report and only had a few missing datapoints. The mean age was 49 with a standard deviation of 17. Self-perceived race/ethnicity was coded using the pre-made summary variable which placed the subjects into the following 6 categories: White, Black, Hispanic, Other, Asian, and Native American. This resulted in only 0.49% of cases with missing data. Skin tone was measured by interviewer judgment on a 1-10 scale using a guide.⁴ This resulted in a large amount of missing data because skin tone was only rated in the face to face interviews, not in the online sample. Income was self-reported and limited to intervals in the public dataset. The intervals were recorded to their midranges so that OLS could be

4 The guide can be seen at http://www.electionstudies.org/studypages/anes_timeseries_2012/anes_timeseries_2012_SkinColorScale.htm. (Archived: <http://archive.is/2uzqU>.)

used. IQ was taken as the sum of correct answers on the Wordsum test.

2.4.2. Results

The data were modeled as before with the limitation that we didn't have any measure of OPRE. Table 13 shows summary statistics for the models fitted.

Model	SPRE	Skin tone	IQ	Adj. R2	n
1	(age and sex only)			0.040	5663
2	yes	no	no	0.090	5650
3	no	-0.20	no	0.097	1839
4	no	no	0.32	0.139	5663
5	yes	-0.09	0.21	0.162	1833

Table 13: ANES2012: model summary statistics.

The general pattern follows that seen before, i.e. IQ is the best independent predictor measured in increase in model validity from baseline (i.e. 0.040 to 0.139 vs. 0.040 to 0.090/0.097). The addition of IQ to the model decreased the beta of skin tone by about 50%. Here it should be noted that IQ also decreased its beta in the presence of skin tone by about 33%. This however is due to a large change in the sample due to missing data for skin tone. If one restricts model 4 to cases with data available for skin tone ($n = 1839$), the beta for IQ is .25, similar for the full model (i.e. .21). Table 14 shows the results for the full model.

Predictor	Beta	SE	p
sex=Female	-0.55	0.33	0.10
SPRE=Asian	0.52	0.17	0.00
SPRE=Black	-0.17	0.08	0.03
SPRE=Hispanic	-0.23	0.06	0.00
SPRE=Native American	-0.43	0.28	0.13
SPRE=Other	-0.12	0.09	0.18
skin_tone	-0.09	0.03	0.00
IQ	0.21	0.02	0.00

Table 14: ANES2012: full model results. Nonlinear age terms and their interactions with sex left out.

As before, we calculated relative predictor importance by converting the full model to the ANOVA variant and reducing the age term to a linear one. Table 15 shows the etas from this fitting.

Predictor	Eta
Sex	0.08
Age	0.01
SPRE	0.13
Skin tone	0.04
IQ	0.23
Sex:age	0.01

Table 15: ANES2012: relative predictor importance in full model.

IQ again trumps every other variable, though SPRE has nontrivial validity as well. Skin tone again has limited validity.

2.5. GSS

The GSS (General Social Survey) is a very long-running survey going back to 1972 with an update approximately every 2 years (last updated 2016). The dataset has certain core questions that change little if any between the years and a large number of questions that were only given some years. Each yearly wave of the survey has 1500-4500 subjects.

2.5.1. Data and coding

We searched through the GSS handbook to locate relevant variables needed to test the causal model in Figure 1. We found 2 measures of discrimination, 1 measure of OPRE, 2 measures of SPRE, 2 measures of skin tone, 1 measure of IQ as well as the base minimum variables of age, sex, and income. Unfortunately, the variables did not overlap well, meaning that full models could generally not be fit or could only be fit with strongly reduced sample size, which may introduce selection effects depending on the reason why the data are missing. Figure 2 shows a timeline of the data availability by variable.

Figure 2: GSS: Data availability by year.

Age and sex were given in readily usable format, so no recoded was needed.

For SPRE, two variables were available. First, one based on the question “What race do you consider yourself?” with a 3-way breakdown (White, Black, Other). Second, later this was replaced by a multi-answer item based on the question “What is your race? Indicate one or more races that you consider yourself to be”, where participants could choose between 16 options, including some like “Other Asian (specify)”. We scored the items the same way as those in the previous datasets, namely by giving preference to Hispanic status, coding 1 race as that, and everybody else as multiracial. A few Pacific Islander groups were lumped to prevent tiny classes. The smallest resulting class had 28 members (Vietnamese).

For OPRE, only a single item was available, which asked the interviewer to categorize the person into 22 broad categories. However, most of these had almost no participants, so we lumped the smaller groups into a single Other group yielding a total of 5 groups: White, Black, Hispanic, Asian, Other, all of which had at least 36 persons.

For skin tone, two measures were available which were both interviewer rated. First, one based on the instruction “Respondent’s skin color is” using a 1-5 scale from very light brown to very dark brown. The item was only used for Blacks participants and was only given in 2 years, so the sample size is quite limited. Second, one with the instruction “Please record the color from the color card that most

closely corresponds to the respondent's facial coloring", based on an 1-10 rating scheme from lightest to darkest. The item was used for all individuals.

For discrimination, there were two measures. First, based on the question "Over the past five years, have you been discriminated against with regard to work, for instance when applying for a job, or when being considered for a pay increase or promotion?". The options were binary, except that the participant could also say that they didn't work at all. We recoded this option to missing data. Second, based on the question "Do you feel in any way discriminated against on your job because of your race or ethnic origin?". Only yes/no were acceptable answers.

For IQ, we used the 10 item Wordsum test also used in the ANES sample (Section 2.4). A sumscore was already available, which was then standardized across all years.⁵

Finally, for income, both personal and family income were available. Following the practice from ANES, we tried both variables as well as their combination. For personal income, we also used the $\log_{10}(x+1)$ version to avoid influential outliers. The values were given in constant dollars (i.e. inflation adjusted) based the year 1986. The combined variable (based on z-scores, ignoring missing data) was chosen based on its relations to sex, age and IQ, and because it resulted in a somewhat larger sample size.

2.5.2. Results

Due to the substantial variation in the variables available by year, we had to fit a large number of models with informative combinations of variables. Presenting all model fits or even just their summaries would take too much space, so we chose the arguably three most informative to present. These were chosen based on a combination of included predictors and the sample size, since the latter has a strong effect on the precision of the estimates presented. The remainder of the models can be found in the supplementary materials. The first model fit of choice is shown in Table 16.

5 One could argue that it should be standardized within year to avoid the Flynn effect. Unfortunately, doing so would assume the sample distribution with regards to important covariates such as race are constant. We examined this and found it to be unjustified. In particular, 2 years had a large oversampling of Blacks (1982 and 1987) and there was a steady increase of the non-White groups over time (about 0% Other in 1972 to 10% to in 2016).

Predictor	Beta	SE	p	omega
Intercept	-1.0019	0.2855	0.0005	
sex=Female	-0.2593	0.3869	0.5027	0.104
age				0.244
age * sex			0.825	0.000
skin_tone2	-0.1075	0.0155	<0.0001	
IQ	0.2572	0.0165	<0.0001	

Table 16: GSS: Model 7b. $n = 3988$, $r^2_{adj.} = .146$. “Skin_tone2” refers to the second GSS variable for skin tone. Age terms and their interactions with sex left out.

This is a simple model that simply checks the predictive validity of IQ and skin tone when both are in a regression together. It can be seen that both have beyond chance level validity. Using the ANOVA approach to gauge their relative importance, we find

2.6. Meta-analysis of main modeling results

Relative predictor importance

2.7. IQ and skin tone

3. Discussion and conclusion

What explains racial group-related income inequality in the United States? In this study, the issue was examined by including both other-perceived and self-perceived race/ethnicity. This approach theoretically allows one to distinguish between market-irrelevant racial discrimination models and cultural self-identification models.

The study has a few important limitations. First, other-perceived race was only partially satisfactory and did not include as many options as the self-perceived measure. This may have biased results in unknown ways. Second, the dataset does not have a measure of genomic ancestry which can be used to more precisely test the relative importance of genomic vs. perceived racial ancestry (Kirkegaard,

Meisenberg, & Fuerst, In preparation). Third, the measures of perceived race were not taken at the same time, which may have caused some distortion.

Supplementary material and acknowledgments

Supplementary materials including code, high quality figures and data can be found at <https://osf.io/6rkst/> and http://rpubs.com/EmilOWK/NLSY79_race_income.

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