v8: 13 July 2023

Research Article

Deep Roots of Admixture-Related Cognitive Differences in the USA?

Peer-approved: 20 April 2023

© The Author(s) 2023. This is an Open Access article under the CC BY 4.0 license.

Qeios, Vol. 5 (2023)
ISSN: 2632-3834

John Fuerst[1,2], Meng Hu[1]

1. University of Maryland, College Park, United States; 2. Cleveland State University, United States

Introduction: There are well-known cognitive ability differences between socially-identified racial/ethnic groups in the United States. Ameliorating these differences is considered a top grand challenge for the American social sciences. However, reducing these achievement gaps requires a better understanding of the nature of these group differences and also of the mechanisms by which these differences are intergenerationally transmitted. As a result, it is necessary to understand how cognitive differences relate to admixture among admixed groups. Recent studies show a linear positive relationship between European ancestry and cognitive ability in admixed African-European-Amerindian descent groups.
Objectives: This study attempts to determine if the association between admixture and cognitive ability among African, European, and Amerindian descent groups in the USA holds across a large time period.
Methods: First, we use the large and nationally representative Adolescent Brain Cognitive Development Study (ABCD) sample to examine the associations between cognitive ability, socially identified-race, genetically-predicted color, and genetic ancestry among Puerto Ricans, and non-Hispanic Whites, Blacks, and American Indians in the 21st century. Second, we use the 1850 to 1930 US censuses to see if we can trace ancestry-associated cognitive differences back to the 19th and early 20th century by taking advantage of early census distinctions by blood and also by using age-heaping based numeracy as a proxy for cognitive ability.
Results: In the ABCD sample, we find that European ancestry is positively associated with cognitive ability within race/ethnic groups (rs =.05 to.47; $r_{weighted\text{-}average}$ =.10). In the census data, among African Americans and American Indians but not among Puerto Ricans, we find that greater apparent European admixture is associated with higher numeracy and that this holds when we subset data by age, sex, and literacy-status.
Conclusions: In the 19th and early 20th century, European admixture was associated with numeracy among African Americans and Native Americans. To better understand these associations a systematic review of 20th century admixture studies is called for.

Correspondence: papers@team.qeios.com — Qeios will forward to the authors

1. Introduction

Differences in cognitive test scores exist between socially-identified racial and ethnic groups in the United States (Murray, 2021), with disparities being reported since the early 20th century (Shuey, 1966). The cause of these cognitive achievement gaps is of importance as academic outcomes are strongly tied to socioeconomic outcomes and because cognitive test scores measured during adolescence can explain many disparities in educational attainment, income, and health later in life (Fryer, 2014). Indeed, because of their socioeconomic impact, figuring out the mechanisms by which cognitive skill gaps are perpetuated and reducing the magnitude of these differences was ranked as number 4 in the social science's top 10 list of "grand challenge questions that are both foundational and transformative" (Giles, 2011). Therefore, the topic of racial/ethnic-related achievement gaps remains heavily researched.

Researchers mostly group American individuals according to their own or their parents' identification with one or more of the main federally defined racial/ethnic categories. The National Assessment of Educational Progress (NAEP), which measures students' academic performance, uses eight racial/ethnic categories: American Indian/Alaska Native; Asian; Black or African American; Hispanic; Native Hawaiian or other Pacific Islander; Two or More Races; White. These categories are based on those of the U.S. Office of Management and Budget

(Office of Management and Budget, 1997) which recognizes that U.S. race/ethnicity categories "may be viewed in terms of social and cultural characteristics as well as ancestry."

While race/ethnicity is frequently treated categorically, many 20th-century researchers recognized that members of the same socially- and culturally-delineated racial/ethnic groups could differ substantially in genetic ancestry. The first admixture studies – which used either phenotype, recorded genealogy, or blood groups to index ancestry – were conducted during the 20th century to determine if European admixture was related to better scholastic achievement and cognitive test scores among admixed African (e.g., Bruce, 1940; Ferguson, 1916; Ferguson, 1919; Iles, 1927; Peterson, 1934), Native American (e.g., Garth & Garrett, 1928; Garth, 1933; Hansen, 1937; Hunter & Sommermier, 1922; Paschal & Sullivan, 1925), Puerto Rican (Vincenty, 1930; Green, 1972) and other populations. While most of these admixture studies only report means, approximately twenty percent of them report correlation coefficients (whether Spearman's correlation, Pearson correlation, phi coefficient, or point-biserial correlation) or, alternatively, report raw data which can be used to compute correlations. The studies conducted in the 20th century or based on 20th century samples, reporting correlations or providing raw data, are detailed in Tab 14-15 of the supplementary material. The results of these studies, grouped by Office of Management and Budget race/ethnic group, are summarized in Table 1 below.

Set	*K*	*N*	*Median r*	*r-weighted*
All	35	16087	.16	.14
Black American	17	7572.5	.13	.12
American Indian	9	3685	.19	.27
Latin American or Hispanic	7	1106.5	.09	.18
White America	1	3603	.04	.04
Australian Aborigine	1	120	.18	.18

Table 1. Summary of Admixture Studies, Conducted on 20th Century Populations, which Correlated Indexes of European Ancestry with Intelligence or Academic Achievement Scores.

Notes: r is the N-weighted r of the correlations for studies on 20th century populations which report correlations between indexes of European admixture and either intelligence or academic achievement test scores. When multiple correlations were reported for the same sample (based on different tests), these correlations, and their sample sizes, were averaged within samples first. K = the number of independent samples. See the supplementary file for details.

As seen in Table 1 and in Supplementary Tab 14-15, and as noted by others (Loehlin et al., 1975; Berry, 1969), most studies found only a modest positive correlation between measures of European ancestry and cognitive/achievement test scores (r_{median} =.16). As a result, the correlations between ancestry and test scores were often interpreted as too small to be practically significant. This interpretation, which is fundamentally flawed due to a failure to recognize the impact of range restriction in ancestry on magnitudes of correlations, was found in some older studies (e.g., Herskovits, 1926; Scarr et al., 1977) and also in contemporaneous narrative reviews (e.g., Nisbett, 2009).

The results of many large-scale nationally representative studies have confirmed earlier 20th-century findings. For instance, research has shown that African Americans who have lighter skin tone and/or who have higher self-reported or parent-reported European ancestry have higher general intelligence scores than those who are darker in color and/or who do not have reported European ancestry (Fuerst et al., 2019; Hu et al., 2019; Hu, 2022). Additionally, children with mixed heritage (e.g. a Black and a White parent) generally score in between the scores of children from each parental population, as has been shown based on several large national studies (Gullickson, 2005; Fuerst et al., 2019; Rowe & Rodgers, 2005). More recently, 21st-century admixture regression studies have found a linear relationship between genetic ancestry and cognitive ability within and between self-identified racial and ethnic groups (Fuerst, Hu, & Connor, 2021; Kirkegaard et al., 2019; Lasker et al., 2019; Warne, 2020).

These latter studies also find small-to-modest correlations between ancestry and cognitive ability scores, as expected given the range restriction in ancestry within American race/ethnic groups (e.g., Lasker et al.2019 report an $r_{\text{European\% x } g}$ = 0.086 among monoracial blacks). This range restriction can occur due to endogamous mating after an initial admixture event, in which case the variability in ancestry decreases with each subsequent generation as illustrated in Kirkegaard et al. (2019; Supplementary File 1). However, these studies also demonstrate that small-to-modest correlations are consistent with a large effect (B) of ancestry on standardized cognitive ability scores (see: Lasker et al., 2019). This is because the unstandardized beta (B) expresses the effect on scores in terms of a change from 0% to 100% in genetic ancestry, and is thus not attenuated by range restriction in ancestry. These genetic ancestry studies have been supported by other research that has identified a linear relationship between educational attainment and genetic ancestry in mixed American groups (Kirkegaard et al., 2017). So, contrary to what some have argued (Colman, 2016), a very large body of evidence, based on over 100 years of research, indicates that European admixture within American groups such as Hispanics, Blacks, and Native Americans is associated with academic and cognitive outcomes.

While this link between admixture and outcomes could be accounted for in a couple of different ways, one obvious scientific hypothesis is that of inherited disadvantage (Hu et al., 2019; Shibaev & Fuerst, 2023). According to this hypothesis, there were original cognitive differences between source populations such as Europeans, Africans, and Amerindians; and the original differences are largely being vertically passed on along genealogical lines. Given initial trait differences between parental populations, the inherited disadvantage model predicts a relation between the number of ancestors from different parental populations and trait outcomes in admixed populations. Strictly speaking, this model does not specify whether differences are being transmitted by genetic or environmental mechanisms, but only that the differences are vertically transmitted, from parents to children, across generations.

This model of inherited disadvantage can be contrasted with a horizontal transmission model such as a cultural-group model according to which race-related differences are due to common factors affecting members of the same socially-defined race/ethnic groups, irrespective of ancestry. Examples of factors which have similar effects on members of the same socially-defined race/ethnic group, regardless of ancestry, include cultural norms, dialect, language, involuntary minority status, and socially defined race/ethnicity (SIRE)-based segregation. This list also includes most examples of systematic racism commonly provided, for example, voter suppression of Blacks, political gerrymandering, predatory financial services, mass incarceration, police violence, sending American Indian children to boarding schools, Jim Crow laws, segregated residence, and redlining (e.g., Braveman et al.., 2022; Erikson et al., 2022). To give a specific example, James Flynn, famous for popularizing the Flynn effect, argued that differences between Black and White Americans are due to the purported cognitive depressing effects of black subculture (Flynn, 2019). However, if differences are due to subculture effects common to all Black Americans, then they would not be proportional to genetic ancestry among this group. Thus, the issue of whether academic and cognitive outcomes track admixture within groups is clearly relevant to understanding the origin and the transmission of cognitive differences. Moreover, focusing exclusively on Office of Management and Budget -defined racial/ethnic categories may leave a large portion of academic disadvantage undiagnosed insofar as differences track genetic ancestry within groups.

The earliest analyses of the relationship between admixture and cognitive ability date back to the 1910s and 1920s. However, these admixture results are based on small convenience samples. Since intelligence tests were first developed and employed in the early 20th century, it is not possible to determine if intelligence test scores relate to admixture before this time, let alone in large national samples. However, we can possibly gain some insight by using age heaping as a means of assessing human capital in the pre-mass testing era. Age heaping refers to measuring the tendency for individuals to inaccurately report their age and age heaping has been used in economic research to measure innumeracy (A'Hearn et al., 2009; Blum & Krauss, 2018).

Age-heaping rates, measured in the 19th century, have been found to bear a strong relationship with national achievement scores from the late 20th and 21st centuries (Baten & Juif, 2014; Francis & Kirkegaard, 2022). Moreover, 19th century age-heaping rates have been found to strongly predict provincial-level scholastic test scores, one hundred and fifty years later, in Italy (Kirkegaard & Piffer, 2022).

Additionally, at the family level, the extent of parents' age-heaping was found to predict children's mathematical achievement scores in 20th and 21st-century Sub-Saharan Africa (Baten et al., 2022). Finally, using data from the Spanish Inquisition records, Baten and Nalle (2022) found a positive association between age-heaping and a numerical measure on the individual level. So, there are several convergent lines of evidence indicating that age-heaping measures, to some extent, population-, family-, and even individual-level numeracy. Also, age-heaping has previously been used to compare the numeracy of ethnic groups. For example, Sohn (2014) compared the numeracy of Black and White soldiers during the Civil War, while Pérez-Artés (2021) compared the numeracy of Indians, Black, Mestizos, Mulattos, and Spaniards in 18th-century Mexico. Moreover, Juif and Baten (2013) compared the age-heaping of 15th to 17th century Native Peruvians and Spanish.

The point of this study is to determine if European ancestry is related to cognitive ability in admixed American race/ethnic groups of African-European-Amerindian origin. The first analysis examines the relationship between genetic ancestry, skin color, and general cognitive ability among 10-year-old individuals from different racial and ethnic groups – specifically, Whites, Blacks, American Indians, and Puerto Ricans – by using data from the Adolescent Brain Cognitive Development Study (ABCD). No previous studies that we are aware of use the ABCD sample to examine associations within American Indian and Puerto Rican ethnic/racial groups. The second analysis examines age-heaping based numeracy scores based on the 1850-1930 censuses data, which made distinctions based on ancestral admixture among Black Americans, Native Americans, and Puerto Ricans. No previous studies that we are aware of have computed age-heaping based numeracy for admixed groups based on the USA censuses. Our hypothesis is that, within American race/ethnic groups, admixture, assessed based on phenotype, will predict cognitive ability in the 19th and early 20th century and that admixture, assessed based on DNA, will also predict cognitive ability in the 21st century. More specifically, we predict that European ancestry will be positively associated with higher cognitive ability in admixed African-European-Amerindian descent groups. This would be in line with the inherited disadvantage model, according to which inequalities are primarily being inter-generationally transmitted.

2. Methods

2.1. Analysis of the Adolescent Brain Cognitive Development (ABCD) study

2.1.1. Data

The Adolescent Brain Cognitive Development Study (ABCD) is a recent collaborative longitudinal project involving 21 collection sites across the USA, created to research the psychological and neurobiological bases of human development. At baseline, around 2016, approximately 11,000 9-10-year-old children were sampled, mostly from public and private elementary schools. The sample, when weighted, is nationally representative of 9-10-year-olds.

2.1.2. Variables for ABCD analysis

For the purpose of analysis using the ABCD data, various variables were computed. These are listed below.

2.1.2.1. Ethnic group

In this study, the categorization of individuals into race/ethnicity groups was based on parent-reported data. Four mutually exclusive race/ethnicity groups were created: non-Hispanic White (referred to as White), non-Hispanic Black (referred to as Black), non-Hispanic American Indian (referred to as American Indian), and Hispanic Puerto Rican (referred to as Puerto Rican). The White group was composed of individuals who were identified solely as White without belonging to another race/ethnicity category. The Black group was defined as those individuals who were reported as Black but not Hispanic. The American Indian group included individuals who were reported as American Indian and who were not also identified as Black or Hispanic. This classification approach is broadly in line with how groups are typically classified in the USA.

2.1.2.2. Admixture estimates

The ABCD Research Consortium conducted the imputing and genotyping using Illumina XX. Quality control was conducted using PLINK 1.9; a total of 516,598 variants survived the quality control. The ABCD Research Consortium pre-computed a genetic ancestry variable using a k = 4 solution (European, African, Amerindian, and East Asian). The ABCD researchers used 1000 Genomes populations as the reference samples and fastStructure as the algorithm (Hatton, 2018). We divided the ancestry estimates by the sum of European, African, Amerindian, and East Asian ancestry so that the sum of the four ancestries add up to 1. Based on the European admixture estimate, we additionally computed European ancestry quartiles (75 to 100% European; 50 to < 75% European; 25 to < 50% European; < 25% European). Note, an alternative method would be to use ROC analysis to select ancestry cutoffs. We chose a symmetric quartile distribution instead, in part, to allow for comparison with results reported in the 20th century. However, future research should consider employing ROC analysis to delineate cutoffs.

2.1.2.3. Fitzpatrick Category

The data did not include measures of appearance, so we opted to impute these based on genotypes, using the HIrisPlex-S web application (https://hirisplex.erasmusmc.nl/). The HIrisPlex-S web application was developed for use in forensic investigations by the U.S. Department of Justice. This application has been validated on thousands of people from various parts of the world (Chaitanya et al., 2018; Walsh et al., 2017; Walsh et al., 2014). It uses 41 SNPs that are functionally related to traits associated with skin, hair, and eye color to impute probabilities for these physical characteristics. Of the 41 SNPs, 36 are related to skin color, 22 to hair color, and 6 to eye color. HIrisPlex-S provides probabilities that an individual falls into one of five levels of the Fitzpatrick Scale skin type. These levels include Type I, which represents the palest and freckled skin (scores 0-6); Type II (scores 7-13); Type III-IV combined (scores 14-27); Type V (scores 28-34); and Type VI, which represents deeply pigmented dark brown to darkest brown skin (scores 35-36). To create a single measure of color, we calculated the weighted medium score of each type using the probability of each type as detailed in (Lasker et al., 2019). Based on the Fitzpatrick scores, we also computed three broad color categories (Type I-IV, "palest to moderate brown"; Type V, "dark brown", Type VI, "deeply pigmented dark brown").

2.1.2.4. General cognitive ability

The dataset used in this study, known as ABCD, includes data from 11 cognitive tests primarily obtained from the NIH Toolbox battery. These tests include Picture Vocabulary, Flanker, List Sorting, Card Sorting, Pattern Comparison, Picture Sequence Memory, Oral Reading Recognition, the Matrix test from the WISC-4, Little Man Test, and Rey's Auditory Learning immediate and delayed recall tests. To ensure that age and sex differences did not impact the study's results, the test data were adjusted for these variables. We utilized the IRMI algorithm to impute missing data, as this approach has been validated and produces reproducible results. Only 10.3% of the cells were missing, and 48% of the cases had some missing data. We imputed data for subjects with no more than five missing data points. After the data were imputed, 1.3% of the cells were missing, and 98.2% of the subjects had complete data. Subjects with remaining missing data were not included in the analyses. For our study, we employed exploratory factor analysis (EFA) utilizing the **psych** package (Revelle & Revelle, 2015) to extract the first factor from the 11 neurocognitive tests administered at baseline. The resulting general factor accounted for 35% of the variance in test scores, which is slightly lower than the typically observed percentage of >40%. We attributed this finding to the inclusion of a larger number of working memory tests in our set. In contrast to multigroup confirmatory factor analysis – as used in previous studies (e.g., Fuerst, Hu, & Connor, 2021) – we opted to focus on EFA. The reason for this decision was that we did not want to commit to a specific model regarding the nature of cognitive differences between race/ethnic groups, such as the popularly known Spearman's Hypothesis. Thus, our approach allowed for a more exploratory and flexible analysis, which is particularly relevant when investigating complex constructs such as cognitive ability. However, to address a reviewer's concern we also include *g* scores saved from a multi-group confirmatory factor analysis based on a model in which strict measurement invariance held (both between groups and along European ancestry). The computation of these scores were previously detailed (Fuerst, Hu, & Connor, 2021). Owing to different data preparation, imputation, and quality control methods the number of *g* scores for EFA and MGCFA differ, so we additionally report the sample sizes for the MGCFA scores.

2.1.3. Statistical approach

We computed sample-weighted means and standard deviations for ancestry, skin color, and *g* using the **survey** package. We additionally reported the unweighted sample sizes. When relevant, means and standard deviations were computed for each ethnic group by parent-identified race, Fitzpatrick color category, and European-ancestry quartiles. We additionally report the correlation matrices, by race/ethnic group, for ancestry, skin color, and *g*.

We also ran regression analyses, with skin color, SIRE, and genetic ancestry predicting *g*. In accordance with the recommendation of Heeringa and Berglund (2021), we utilized a linear mixed-effects model instead of ordinary least squares. This entailed breaking down the residual term into linear random effects components linked to the identifiers of the data collection site and same-family identifiers within the sample. This approach enables the possibility of correlations in the error term within data collection sites or families with multiple tested individuals. This model aligns with the one used in the ABCD Data Exploration and Analysis Portal (DEAP), as noted by Heeringa and Berglund (2021). Consequently, using this multilevel model facilitates replication. To execute the mixed-effects regression models, we utilized the lmer command from the **lme4** package (Bates et al., 2009). For these analyses, Fitzpatrick color scores were standardized on the study sample of N = 8344 individuals.

We additionally include partial residual plots, a type of influence plot for predictors as described by Fox & Weisberg (2018). These plots show the influence of European descent on cognitive ability, while holding other factors in the regression model constant. These plots were implemented using the **jtools** package (Long, 2020).

One of the reviewers suggested that there may be serious collinearity, which could potentially bias our regression results, between our ancestry variables and color. However, in admixed populations, genetic crossover and segregation would theoretically attenuate the correlations between race-associated traits and global genetic ancestry, especially for relatively simple traits such as color. The extent of this attenuation is an empirical question. To address this concern, we have included the correlation matrices for ancestry components and color in the supplemental file. As can be seen, African ancestry is the non-European ancestry which has the highest correlation with color. For the White, Black, Indian, and Puerto Rican samples, the sample weighted correlations are, respectively, rs =.16,.52,.56, and.46. These correlations are in line with previously reported results (Fuerst, Hu, & Connor, 2021; Lasker et al., 2019) and indicate that two members of the same race/ethnic group can have the same amount of African ancestry and yet differ substantially in skin color.

2.2. Census-based age-heaping analyses

2.2.1. Data

Age-heaping was computed using USA census records. The census data were drawn from the Integrated Public Use Microdata Series (IPUMS) US population census (Ruggles et al., 2023). The IPUMS USA collects decennial censuses from 1790 to 2010 and American Community Surveys (ACS) from 2000 to the present. Selected years for the present study include 1850, 1860, 1870, 1880, 1990, 1910, 1920, and 1930.

2.2.2. Variables for age-heaping analyses

For the purpose of the analysis using the census data, various variables were computed. These variables, which are detailed in Table 2, are listed below.

doi.org/10.32388/CCN648.8

2.2.2.1. Sex

Interviewers were asked to record the sex of the household inhabitants (Male =1; Female =2).

2.2.2.2. Age

Interviewers were notified about the tendency for individuals to age-heap and were instructed to ascertain exact ages if possible. Based on the age variable, we created an age 23-62 cohort and four ten year interval subcohorts (23-32; 33-42; 43-52; 53-62). Results for the age 23-62 cohort are of primary interest, while those for the four ten year subcohorts were computed to assess if the primary results are due to age structure effects. This is possible since different age cohorts are known to have different age-heaping patterns and since admixture groups could differ in their age structure.

2.2.2.3. Color or Race

Interviewers were asked to record “Color” (1850-1880) or “Color or Race” (1900-1930). We focus on the White, Black, and American Indian groups. In the 1850-1880 and the 1910-1920 census, interviewers were also asked to carefully distinguish between Blacks who were “full-blooded negroes” and Mulattoes who were “Negroes having some proportion of white blood” (1920). Dummy variables for Black, Mulatto, White, and Indian race/color were created. Note, while some may perhaps find the term “Mulatto” offensive, we retain the term since it was the official designation used by census enumerators for the admixed group at the time. We believe changing this term to avoid possible offense obscures important information about the classification and introduces confusion, when careful discussion on the topic is needed.

2.2.2.4. Blood Quantum

In 1900 and 1910, special Indian schedules were included in the census. Interviewers were asked to ascertain, through inquiry with older men of the tribe, if an individual was a full-blooded American Indian. If not, interviewers were instructed to record the fraction of White blood which the American Indian had. Following Thornton and Young-DeMarco (2021), we created four blood quantum categories for American Indians: Full-blooded Indians, greater than 0% White and less than 25%, greater than 25% White and less than 50%, and greater than 50% White. A small number of American Indians were recorded as having 100% White blood (despite being marked as belonging to the Indian, and not White, race). These individuals were included in the greater than 50% White category; their inclusion/exclusion did not have an interpretatively significant effect on the results.

2.2.2.5. Full-blooded and Mixed-blooded Indian

Using the Blood Quantum data in the 1900 and 1910 censuses, we coded American Indians (excluding Whites living on reservations) as Full-blooded (meaning 0% White blood) and Mixed-blooded Indians (meaning greater than 0% White blood). In 1930, interviewers were asked to record if Indians were Full-blooded or Mixed-blooded. Some interviewers reported % of Indian blood. For 1930, we coded American Indians as Full-blooded if they were either reported as having 100% Indian blood or as being Full-blooded and as Mixed-blooded Indians if they were either reported as having less than 100% Indian blood or as being Mixed-blooded.

2.2.2.6. Slavery legal in 1861 and Slavery illegal in 1861

We coded the 50 USA states by whether they corresponded with a slave state/territory in 1861 or a slavery-free state /territory. We then created two dummy variables for residence, Slavery legal in 1861 and Slavery illegal in 1861.

2.2.2.7. USA-born

Interviewers were asked to record the state, territory, or nation of birth of the household members. We created a dummy-coded USA-born variable, coded “1” if the respondent was born in a contemporaneous US state and “0” if otherwise.

2.2.2.8. Literate

Interviewers assessed whether respondents were literate. How this was done was not reported. Respondents were coded as literate if they could both read and write. Literacy was used to control for familiarity with written material which might include records about the participants’ age.

doi.org/10.32388/CCN648.8

Variables	Description	Code
Sex	respondent sex	Sex = 1 (male) Sex = 2 (female)
Age	Respondent age	Age = 023 to 062
White race/color		raced = 100 & 120
Black race/color	"negro or of negro descent" (1900); "all Negroes of full blood" (1920)	raced = 200
Mulatto race/color	"word is here generic, and includes quadroons, octoroons, and all persons having any perceptible trace of African blood" (1880); "includes all Negroes having some proportion of white blood" (1920)	raced = 210
American Indian race/color		raced = 300
Full-blooded (1910-1920)	0% White blood	BLOODW == 0000 & raced = 300
Mixed-blooded (1910-1920)	> 0%White blood	1000 <= BLOODW > 0000 & raced = 300
Full-blooded (1930)	Full-blooded Indian	BLOODI = 1000 & raced = 300
Mixed-blooded (1930)	Mixed-blooded Indian	BLOODI = 9995 & raced = 300
% White Blood	Proportion of White blood in Indians	BLOODW
Slavery legal in 1861	Slavery was legal in the state or territory in 1861 in which individual resides	STATEICP == -c(11; 34; 40-49; 51-54; 56; 61; 65-66)
Slavery illegal in 1861	Slavery was not legal in the state or territory in 1861 in 1861 in which individual resides	STATEICP == 11; 34; 40-49; 51-54; 56; 61; 65-66
Indian Schedule	Special Inquiries Relating to American Indians	SAMP1900 == 4; SAMP1910 == 4
USA born	Person was born in a currently recognized state of the USA	BPL < 100
Literate	The respondent could read and write in any language	LIT = 4

Table 2. Variable Description for the Study Sample

2.2.3. Samples

2.2.3.1. 1850 and 1860 Black and Mulatto Slave samples

The 1850 and 1860 Slave samples are representative 5% samples of slaves enumerated in those years. On separate slave schedules, as part of the 1850 and 1860 census, interviewers reported the age, color, sex, and number of slaves held by a slave-holder. The source of information, specifically whether it was based on interviews with the slaves or with the slave owners, is not noted, so we treat results based on these samples tentatively. For these samples, we computed numeracy for enslaved Mulattos and Blacks by census year and by age cohort. Literacy levels were not reported for slaves, so we could not decompose results by literacy level. In addition to the 1850 and 1860 5% samples, we analyzed data from the 1860 complete sample which is not representative of the slave population but which has a higher count number. This dataset includes all individuals in a random selection of census reels from the Southern States.

2.2.3.2 .1850, 1860, 1870, 1880, 1910, 1920 free White, Mulatto, and Black samples

We computed numeracy for USA-born Whites, free Mulattoes, and free Blacks for the 1850 to 1920 censuses. First, we analyzed data for individuals aged 23-62 using the 10% random sample, and then we analyzed data for individuals aged 33-42 using the 40% random sample. We only computed numeracy for the 23-62 and 33-42 age cohorts since the 33-42 age subsample was large, making it unnecessary to compute numeracy for all age groups. Estimates were decomposed by residence (Slavery legal in 1861 vs. Slavery illegal in 1861) and literacy. Note, in the 1900 census, enumerators were instructed to record whether the person was either white or black, with no mixed race option available. For this reason, we do not calculate results for the 1900 census.

2.2.3.3. 1900 & 1910 Indian schedule samples and the 1930 5% Indian sample

Beginning in 1890, all American Indians, including those on reservations, were enumerated. However, the 1890 data were mostly lost due to a fire, so data on all American Indians is first available in 1900. In the 1900 and 1910 censuses, information on Indians on reservations and in the general population was added to an Indian Schedule (along with information on non-Indians living with Indian families on reservations). Those listed on the Indian Schedule were uniquely asked questions about tribal affiliation and blood quantum. For these analyses, we first computed numeracy for American Indians by census year, blood quantum, and literacy. For comparison, we also computed numeracy for Whites living on reservations with Indian families. Next, we divided the Indian samples by age cohort. Owing to small numbers for older age groups, we computed numeracy only by Full- or Mixed-blooded status when splitting the data by age cohorts.

In 1930, interviewers were asked to report if an American Indian was Full-blooded or Mixed-blooded. While some interviewers reported blood quantum, most simply categorized American Indians as either Full- or Mixed-blooded. As such, we did not compute numeracy by blood quantum for the 1930 census. Instead, we divided the Indian samples by age cohort and we computed numeracy by Full- or Mixed-blooded status and by literacy.

2.2.3.4. 1910 & 1920 12% Puerto Rican sample

The first USA-based census for Puerto Rico was conducted in 1910. We computed numeracy for USA-born Whites residing in Puerto Rico, and Puerto Rican-born individuals identified as White, Mulatto, or Black in the 1910 and 1920 censuses. The USA-born Whites would have been mostly of European ancestry in origin, while Puerto Rican-born individuals would have been of admixed African, European, and Amerindian ancestry.

2.2.4. Analyses

2.2.4.1. Calculation of numeracy

We limited ourselves to individuals aged 23 to 62 since these are the most stable age groups for computing age-heaping using the Whipple Index (Szołtysek et al., 2018). Age heaping was computed for both males and females separately. We focus on the results for males because during this time period, the head of the household was more often male and because the census questions were directed to the household head. Results for females are provided in the supplemental file.

The Whipple index, which is applied to test for age-heaping, is calculated as the sum of the number of persons who report ages ending in 5 or 0, divided by the sum of the total number of persons and then multiplied by 5. The formula is:

$$WI = 5 * \frac{P25 + P30 + \ P35 + \cdots P60}{P23 + P24 + P25 + \cdots P62} * 100 \qquad (1)$$

where *Px* is the population of age *x* in completed years.

The Whipple index can be transformed into an index, called ABCC, which is an estimation of the proportion of the population that can accurately report ages, without rounding. The formula is:

$$ABCC \ = \left(1 \ - \ \frac{WI \ - 100}{400}\right) * 100, \qquad (2)$$

where W is the Whipple index. The ABCC value represents the share of the population who know their correct age. The ABCC index can be transformed into a standard-deviation-unit metric using an inverse cumulative transformation, which Reardon and Ho (2015) denote as dtpac. The formula is:

$$dtpac = \Phi - 1(ABCCa/100) - \Phi - 1(ABCCb/100) \qquad ($$

where $ABCC_a$ and $ABCC_b$ are the ABCC variables for population a and b, respectively. On the assumption of normality and equal variances, dtpac is equivalent to Cohen's *d* (Reardon and Ho, 2015).

2.2.4.2. Analyses

Sampling weight (variable PERWT) was applied as recommended by the IPUMS because the person-level analysis is conducted on "flat" samples in which each observation, whether a household or individual, represents a fixed number of persons in the general US population. The analyses were performed in R, using the

doi.org/10.32388/CCN648.8

following packages: ipumsr, dplyr, simPop, psych. We used the whipple() function of the simPop package.

While the hypothesis is that admixture will be related to cognitive ability both in the 19^{th} / early 20^{th} century and also in the early 21^{st} century, we do not attempt to compare magnitudes of effects across centuries because the two cognitive measures (age-heaping based numeracy and *g*, respectively) are psychometrically very different. As such, we focus on a qualitative evaluation.

3. Results

3.1. 21^{st}-century results based on the ABCD sample

Table 3 presents the means and standard deviations for genetic ancestry, Fitzpatrick scale color, and *g* for Whites, Blacks, American Indians, and Puerto Ricans. Whites with more European ancestry have lighter skin color and higher *g* scores. Similarly, among Blacks, those with lighter skin tones (Type I–IV) have higher *g* scores compared to those with darker skin tones (Type V and VI). Moreover, Blacks who were identified as both Black and White by their parents have higher *g* scores than those who were not identified as such. Additionally, Blacks with higher percentages of European ancestry score higher on cognitive tests compared to those with lower percentages. Regarding American Indians, those who were identified as White by their parents have higher *g* scores than those who were not identified as such. Furthermore, American Indians with higher percentages of European ancestry have higher cognitive test scores compared to those with lower percentages. Concerning Puerto Ricans, those classified as White have more European ancestry, lighter skin tones, and higher *g* scores compared to those classified as White and Black or Black. Puerto Ricans with higher percentages of European ancestry have higher cognitive test scores than those with lower percentages. However, surprisingly, Puerto Ricans with lighter skin tones (Type I–IV) nonetheless score worse on cognitive tests than those with darker skin tones (Type V and VI).

doi.org/10.32388/CCN648.8

	N	%European		%Amerindian		%African		%East Asian		Fitzpatrick Score		EFA *g*		*N*	MGCFA *g*	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*			
White	5803	0.98	0.05	0.00	0.03	0.01	0.03	0.01	0.02	18.22	4.96	0.23	0.90	5905	0.20	0.89
Ancestry group																
75 to 100% European	5751	0.98	0.03	0.00	0.01	0.01	0.02	0.01	0.01	18.14	4.85	0.23	0.89	5853	0.21	0.89
50 to < 75% European	52	0.61	0.16	0.17	0.22	0.12	0.17	0.10	0.15	25.53	8.51	−0.21	0.94	52	−0.10	1.01
Black	2142	0.24	0.16	0.00	0.02	0.72	0.16	0.03	0.04	33.31	4.38	−0.79	0.99	2129	−0.68	1.08
Identified race																
White-Black	411	0.57	0.12	0.01	0.03	0.40	0.12	0.02	0.05	27.87	6.70	−0.33	0.99	396	−0.23	1.08
Black	1731	0.19	0.10	0.00	0.02	0.77	0.10	0.03	0.04	34.10	3.25	−0.86	0.97	1733	−0.74	1.07
Fitzpatrick Category																
Type I–IV color	295	0.46	0.22	0.00	0.02	0.50	0.21	0.03	0.05	21.62	3.56	−0.59	1.15	286	−0.48	1.19
Type V color	676	0.27	0.16	0.01	0.03	0.69	0.16	0.03	0.04	33.42	1.69	−0.72	1.00	669	−0.63	1.11
Type VI color	1171	0.18	0.10	0.00	0.02	0.78	0.10	0.03	0.03	35.37	0.13	−0.87	0.94	1174	−0.74	1.04
Ancestry group																
75 to 100% European	54	0.80	0.04	0.00	0.01	0.18	0.04	0.01	0.01	22.43	7.39	−0.27	0.93	55	−0.13	0.91
50 to < 75% European	332	0.59	0.05	0.00	0.02	0.39	0.05	0.02	0.02	28.12	6.30	−0.31	0.98	331	−0.20	1.07
25 to < 50% European	334	0.33	0.07	0.01	0.03	0.63	0.09	0.03	0.04	33.08	4.07	−0.73	0.94	321	−0.61	0.99
< 25% European	1422	0.16	0.05	0.00	0.02	0.80	0.06	0.04	0.04	34.35	2.91	−0.89	0.98	1422	−0.77	1.08
American Indian	189	0.80	0.26	0.09	0.15	0.08	0.20	0.03	0.08	22.23	7.20	−0.25	1.05	176	−0.16	1.13
Identified race																
White-Indian	152	0.91	0.13	0.05	0.08	0.02	0.03	0.03	0.09	20.09	5.68	−0.04	0.92	141	0.09	0.95
Indian	37	0.71	0.31	0.13	0.19	0.13	0.26	0.03	0.07	24.06	7.93	−0.44	1.14	35	−0.36	1.23
Ancestry group																
75 to 100% European	152	0.95	0.07	0.03	0.06	0.01	0.02	0.01	0.02	18.83	4.76	0.00	0.86	150	0.13	0.92
50 to < 75% European	23	0.64	0.00	0.19	0.00	0.06	0.01	0.11	0.01	27.45	5.48	−0.32	1.00	16	−0.55	1.05
< 50% European	14	0.29	0.13	0.25	0.27	0.39	0.36	0.07	0.11	32.36	4.28	−1.31	1.25	10	−1.15	1.45
Puerto Rican	210	0.67	0.20	0.08	0.07	0.24	0.20	0.02	0.03	27.68	6.64	−0.45	0.95	210	−0.38	1.08
Identified race																
White	125	0.79	0.11	0.08	0.07	0.12	0.07	0.01	0.02	25.12	6.47	−0.33	0.97	124	−0.26	1.10
White-Black	13	0.59	0.11	0.04	0.02	0.35	0.12	0.02	0.03	31.39	4.32	−0.46	0.82	13	−0.32	0.89
Black	39	0.37	0.11	0.05	0.07	0.55	0.15	0.03	0.05	31.99	5.20	−0.64	0.92	40	−0.52	1.10

doi.org/10.32388/CCN648.8

	N	%European		%Amerindian		%African		%East Asian		Fitzpatrick Score		EFA *g*		*N*	MGCFA *g*	
		M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*			
Fitzpatrick Category																
Type I–IV color	94	0.77	0.16	0.07	0.06	0.15	0.14	0.01	0.01	20.73	3.41	-0.55	0.97	94	-0.40	1.06
Type V color	91	0.64	0.17	0.09	0.08	0.25	0.18	0.02	0.02	32.20	1.94	-0.36	1.00	90	-0.41	1.16
Type VI color	25	0.41	0.17	0.06	0.07	0.49	0.23	0.04	0.07	35.29	0.15	-0.43	0.67	26	-0.24	0.87
Ancestry group																
75 to 100% European	91	0.86	0.06	0.04	0.03	0.09	0.04	0.01	0.01	23.93	6.31	-0.24	0.95	89	-0.17	1.03
50 to < 75% European	80	0.64	0.07	0.12	0.07	0.23	0.10	0.02	0.03	28.92	5.74	-0.47	0.91	81	-0.41	1.10
< 50% European	39	0.35	0.09	0.06	0.09	0.56	0.15	0.03	0.05	32.59	4.58	-0.84	0.93	40	-0.73	1.06

Table 3. Genetic Ancestry, Color, and *g* for Whites, Blacks, American Indians, and Puerto Ricans by Identified Race, Color Category, and Ancestry Quartile

Table 4 shows the weighted correlation matrices for each of the four race/ethnic groups. The magnitudes of the correlations depend on the variance in genetic ancestry proportions within groups. Since the variability of genetic ancestry is often low, the correlations are correspondingly often low. Moreover, since variance in ancestry differs substantially across groups (as seen in Table 3), the correlation coefficients are not directly comparable across groups.

	White						Black					
	[1]	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**
[1] *g*	1.00	.05	-.05	-.04	.02	-.01	1.00	.18	-.01	-.20	.06	-.09
[2] NIH European ancestry	.05	1.00	-.70	-.64	-.54	-.24	.18	1.00	-.01	-.96	-.17	-.53
[3] NIH Amerindian ancestry	-.05	-.70	1.00	.12	.03	.17	-.01	-.01	1.00	-.13	-.03	.00
[4] NIH African ancestry	-.04	-.64	.12	1.00	.13	.16	-.20	-.96	-.13	1.00	-.07	.52
[6] NIH East Asian ancestry	.02	-.54	.03	.13	1.00	.12	.06	-.17	-.03	-.07	1.00	.06
[7] Fitzpatrick Score	-.01	-.24	.17	.16	.12	1.00	-.09	-.53	.00	.52	.06	1.00
	American Indian						Puerto Rican					
	[1]	[2]	[3]	[4]	[5]	[6]	[1]	[2]	[3]	[4]	[5]	[6]
[1] *g*	1.00	.47	-.18	-.45	-.04	-.41	1.00	.21	-.13	-.17	.02	.07
[2] NIH European ancestry	.47	1.00	-.54	-.73	-.40	-.79	.21	1.00	-.10	-.93	-.31	-.54
[3] NIH Amerindian ancestry	-.18	-.54	1.00	-.09	.07	.44	-.13	-.10	1.00	-.24	-.09	.12
[4] NIH African ancestry	-.45	-.73	-.09	1.00	.06	.56	-.17	-.93	-.24	1.00	.19	.46
[6] NIH East Asian ancestry	-.04	-.40	.07	.06	1.00	.32	.02	-.31	-.09	.19	1.00	.24
[7] Fitzpatrick Score	-.41	-.79	.44	.56	.32	1.00	.07	-.54	.12	.46	.24	1.00

Table 4. Correlation Matrices for *g*, Genetic Ancestry, and Fitzpatrick Scale Color by Race/ethnicity

Table 5 shows the mixed-effects regression results for the models, which include ancestry, SIRE, and Fitzpatrick scale color as predictors of *g*. Note, visual inspection of the Q-Q plots of the residuals, provided in the supplementary material, indicates approximately normal distributions. Among Whites (Model 1), both African and Amerindian ancestry are predictors of lower *g* scores. Among Blacks (Model 2), African ancestry is associated with lower *g* scores. In this group, White SIRE, but not color, is also statistically significantly related to *g*. Among American Indians (Model 3), African ancestry is associated with lower *g* scores. Among Puerto Ricans (Model 4), both African and Amerindian ancestry are negatively associated with *g* scores, while the reverse holds for color. Across all groups, we see that African ancestry tends to be negatively related to lower *g* scores, whereas this is not the case with color when also taking into account ancestry.

	SIRE: White: g ~ ancestries + color			SIRE: Black: g ~ ancestries + color			SIRE: American Indian: g ~ ancestries + color			SIRE: Puerto Rican: g ~ ancestries + color		
Predictors	*B*	*S.E.*	*P*	*B*	*S.E.*	*p*	*B*	*S.E.*	*p*	*B*	*S.E.*	*p*
(Intercept)	0.33	0.04	**<0.001**	−0.07	0.17	0.69	0.01	0.21	0.98	0.08	0.25	0.76
Amerindian ancestry	-1.69	0.41	**<0.001**	-1.75	0.96	0.07	-1.02	0.72	0.16	-2.85	0.98	**0.00**
African ancestry	-1.20	0.53	**0.02**	−0.95	0.21	**<0.001**	-2.18	0.66	**0.00**	-1.73	0.50	**0.00**
East Asian ancestry	0.42	0.54	0.44	0.87	0.45	0.05	−0.20	0.69	0.77	0.33	1.84	0.86
Fitzpatrick Score	0.00	0.02	0.98	0.03	0.04	0.42	−0.01	0.11	0.96	0.23	0.09	**0.02**
White SIRE				0.23	0.09	**0.02**	0.13	0.19	0.51	0.06	0.19	0.75
Random Effects												
σ^2	0.43			0.49			0.79			0.4		
τ_{00}	0.31 $_{\text{site\_id\_l:rel\_family\_id}}$			0.42 $_{\text{site\_id\_l:rel\_family\_id}}$			0.08 $_{\text{site\_id\_l:rel\_family\_id}}$			0.40 $_{\text{site\_id\_l:rel\_family\_id}}$		
	0.02 $_{\text{site\_id\_l}}$			0.05 $_{\text{site\_id\_l}}$			0.00 $_{\text{site\_id\_l}}$			0.00 $_{\text{site\_id\_l}}$		
ICC	0.43			0.49								
N	22 $_{\text{site\_id\_l}}$			22 $_{\text{site\_id\_l}}$			20 $_{\text{site\_id\_l}}$			21 $_{\text{site\_id\_l}}$		
	4756 $_{\text{rel\_family\_id}}$			1820 $_{\text{rel\_family\_id}}$			166 $_{\text{rel\_family\_id}}$			192 $_{\text{rel\_family\_id}}$		
Obs.	5803			2142			189			210		
Marginal R^2	0.005			0.06			0.116			0.206		

Table 5. Mixed-effect Regression Results for Models Predicting *g* from Genetic Ancestry, SIRE, and Fitzpatrick Scale Color

Notes: Beta coefficients (B) and p-values (p) from the mixed-effects models, with recruitment site and family common factors treated as random effects are shown. The marginal R^2s of the mixed-effects model are shown at the bottom. ICC = Intraclass Correlation Coefficient. Model 1 does not include SIRE, since only individuals with White SIRE were included in the White group.

Figure 1 additionally shows the partial residual plots and the univariate regression line associated with European ancestry for each of the admixture regression samples. These plots show the effect of European ancestry on cognitive ability, holding everything else in the regression models from Table 5 equal.

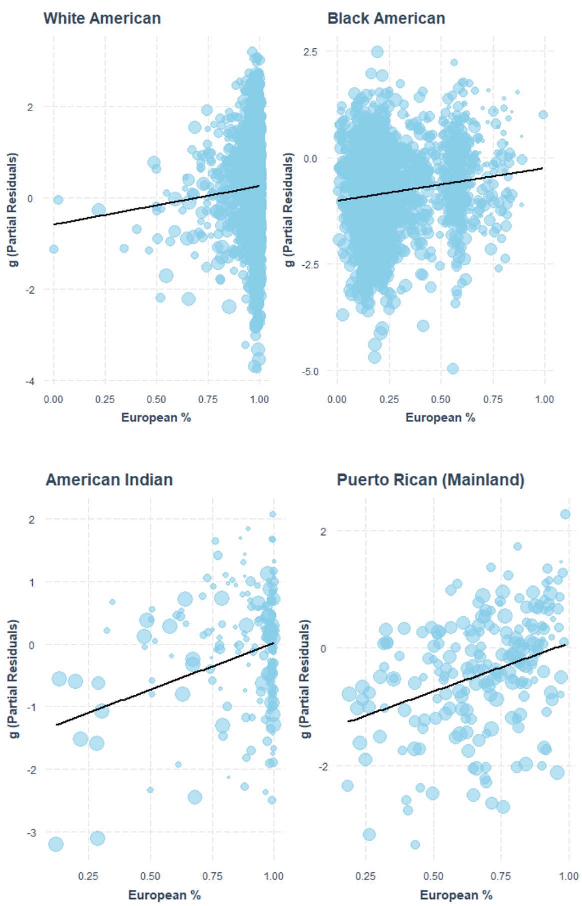

Figure 1. Partial Residual Plots for European Ancestry in the Admixture Regressions for the White, Black, American Indian, and Puerto Rican Samples

3.2. 19th and early 20th-century census-based results

3.2.1. Results for White and African Americans

Table 6 reports the results for African American slaves in 1850 and 1860. The results for the 1860 complete samples are similar to those of the 1860 representative 5% samples, so we concern ourselves with the representative 5% samples. In the 1850-1860 slave samples, the Black-Mulatto gap, expressed in terms of Cohen's *d*, is small and ranges between -0.08 and 0.32, with no clear pattern by age. Across all ages, the gap is approximately d = 0.18. For comparison, the average difference between free Blacks and free Mulattos during the same years and also in slave states is d = 0.28. So, the age-heaping gap among slaves is about 64% the size of that among free individuals. If the Black-Mulatto gap in 1860 was truly smaller than that among free individuals, one might expect the Black-Mulatto gap to decrease in 1870, seven years after the emancipation proclamation freed large numbers of slaves in the South. However, instead, the Black-Mulatto gap stays the same in slave states at d = 0.30. So, it is likely that numeracy differences in the slave samples are underestimated, probably due to the slaves not being interviewed in every case.

doi.org/10.32388/CCN648.8

		Mulatto		Black		M/B *d*
		N	ABCC	*N*	ABCC	
1850	All	1515	63.33	23613	56.27	0.18
1850	23-32	806	74.41	10699	68.90	0.16
1850	33-42	402	57.46	6516	52.71	0.12
1850	43-52	217	44.38	4196	42.10	0.06
1850	53-62	90	36.12	2202	32.47	0.10
1860	All	2835	64.50	30829	57.72	0.18
1860	23-32	1423	73.26	13862	69.75	0.10
1860	33-42	819	63.92	8619	53.54	0.27
1860	43-52	406	42.23	5447	45.18	-0.07
1860	53-62	187	48.81	2901	36.27	0.32
1860 Complete	All	7660	61.10	89702	54.51	0.17
1860 Complete	23-32	4085	72.71	40914	67.50	0.15
1860 Complete	33-42	2038	53.42	25194	49.97	0.09
1860 Complete	43-52	1059	41.08	15656	38.80	0.06
1860 Complete	53-62	478	38.96	7938	32.91	0.16

Table 6. Results for 1850 and 1860 Slave Samples

Note: A positive M/B d-value indicates that Mulattoes have higher numeracy than Blacks.

Next, Table 7 presents the results for the 1850-1920 free samples. We see that the White-Mulatto differences tend to be larger than the Mulatto-Black differences for all years and for all regions. This is not surprising, since we would expect the difference in European ancestry, and thus ancestry-associated traits, to be less between Blacks and Mulattos than between Whites and Mulattos for the simple reason that, owing to anti-miscegenation laws, Blacks and Mulattos would have more frequently mated together and thus have been more similar in ancestry. For literates and illiterates aged 23-62, the across-year average of the White-Mulatto gap is d = 0.65 while the corresponding Mulatto-Black gap is d = 0.27. When we restrict the sample to literates only, the White-Mulatto gap is d = 0.57 while the Mulatto-Black gap is d = 0.26. Among 32-to- 43-year-olds, the gaps are about the same as for all age cohorts, so the results are not due to age-structure confounding. Regions in which slavery was legal in 1861 generally display larger numeracy gaps but only between Whites and Mulattos. This pattern holds true regardless of census year and whether the samples include illiterates. With respect to the difference over time between Whites and Mulattos/Blacks, the ABCC index increases rapidly after 1880 and by 1910 and 1920 a very large portion of Mulattos and Black individuals accurately report their age. However, this does not necessarily mean that Blacks and Mulattos reduced the true numeracy gaps with Whites because a ceiling effect may mask the true numeracy score of Whites, who had an ABCC of 98 by 1920.

				White		Mulatto		Black			
Sample	**Age**	**Year**	**Region**	***N***	**ABCC**	***N***	**ABCC**	***N***	**ABCC**	**W/M *d***	**M/B *d***
Literate & illiterate	23-62	1850	All	315872	90.87	2347	75.84	5649	66.69	0.63	0.27
Literate & illiterate	23-62	1850	Slavery legal in 1861	105734	88.54	1338	69.97	2575	60.24	0.68	0.26
Literate & illiterate	23-62	1850	Slavery illegal (1861)	214398	91.94	1009	83.62	3074	72.10	0.42	0.39
Literate & illiterate	23-62	1860	All	411271	90.96	3019	75.60	6295	67.30	0.64	0.25
Literate & illiterate	23-62	1860	Slavery legal in 1861	134059	89.38	1561	69.67	2704	58.57	0.73	0.30
Literate & illiterate	23-62	1860	Slavery illegal (1861)	277212	91.72	1458	81.96	3591	73.87	0.47	0.27
Literate & illiterate	23-62	1870	All	487996	92.07	9837	76.54	75423	64.61	0.69	0.35
Literate & illiterate	23-62	1870	Slavery legal in 1861	151247	89.89	8154	74.26	69473	63.71	0.62	0.30
Literate & illiterate	23-62	1870	Slavery illegal (1861)	336749	93.05	1683	87.32	5950	75.13	0.34	0.46
Literate & illiterate	23-62	1880	All	678234	94.33	15946	79.75	98466	70.77	0.75	0.29
Literate & illiterate	23-62	1880	Slavery legal in 1861	218287	92.66	13089	78.71	89266	69.91	0.65	0.27
Literate & illiterate	23-62	1880	Slavery illegal (1861)	459947	95.13	2857	84.33	9200	79.09	0.65	0.20
Literate & illiterate	23-62	1910	All	1481176	97.32	39606	91.14	167590	86.36	0.58	0.25
Literate & illiterate	23-62	1910	Slavery legal in 1861	487509	96.95	32079	90.71	146038	85.62	0.55	0.26
Literate & illiterate	23-62	1910	Slavery illegal (1861)	993667	97.50	7527	92.82	21552	91.36	0.50	0.10
Literate & illiterate	23-62	1920	All	1794866	98.00	30702	93.15	203389	89.62	0.57	0.23
Literate & illiterate	23-62	1920	Slavery legal in 1861	578670	97.88	24279	92.52	166403	88.68	0.59	0.23
Literate & illiterate	23-62	1920	Slavery illegal (1861)	1216196	98.05	6423	95.43	36986	93.86	0.38	0.14
Literate & illiterate	33-42	1850	All	356833	89.78	2837	69.13	6601	61.81	0.77	0.20
Literate & illiterate	33-42	1850	Slavery legal in 1861	119879	88.24	1602	64.45	2844	55.60	0.82	0.23
Literate & illiterate	33-42	1850	Slavery illegal (1861)	241607	90.49	1235	75.20	3757	66.51	0.63	0.25
Literate & illiterate	33-42	1860	All	461924	89.56	3719	73.78	7382	64.23	0.62	0.27
Literate & illiterate	33-42	1860	Slavery legal in 1861	148337	88.10	1908	67.28	3222	56.45	0.73	0.29
Literate & illiterate	33-42	1860	Slavery illegal (1861)	313587	90.25	1811	80.62	4160	70.25	0.43	0.33
Literate & illiterate	33-42	1870	All	536097	90.75	10917	70.44	82302	58.05	0.79	0.33
Literate & illiterate	33-42	1870	Slavery legal in 1861	164522	88.36	9106	67.92	75492	57.04	0.73	0.29
Literate & illiterate	33-42	1870	Slavery illegal (1861)	371575	91.81	1811	81.82	6810	69.24	0.48	0.41
Literate & illiterate	33-42	1880	All	717246	92.50	17725	75.35	101619	64.05	0.75	0.33
Literate & illiterate	33-42	1880	Slavery legal in 1861	230004	91.12	14169	74.22	90463	62.91	0.70	0.32
Literate & illiterate	33-42	1880	Slavery illegal (1861)	487242	93.15	3556	79.25	11156	73.32	0.67	0.19
Literate & illiterate	33-42	1910	All	1721856	96.52	45949	90.44	194660	84.87	0.51	0.28
Literate & illiterate	33-42	1910	Slavery legal in 1861	562866	96.19	36334	89.76	165680	84.00	0.51	0.27
Literate & illiterate	33-42	1910	Slavery illegal (1861)	1158990	96.68	9615	93.00	28980	89.84	0.36	0.20
Literate & illiterate	33-42	1920	All	2059336	97.69	36800	92.55	242317	88.12	0.55	0.26
Literate & illiterate	33-42	1920	Slavery legal in 1861	679754	97.75	28333	92.30	192331	87.05	0.58	0.30
Literate & illiterate	33-42	1920	Slavery illegal (1861)	1379582	97.66	8467	93.33	49986	92.21	0.49	0.08

doi.org/10.32388/CCN648.8

				White		Mulatto		Black			
Sample	**Age**	**Year**	**Region**	***N***	**ABCC**	***N***	**ABCC**	***N***	**ABCC**	**W/M *d***	**M/B *d***
Literate	23-62	1850	All	293117	91.33	1477	77.78	3262	70.55	0.60	0.22
Literate	23-62	1850	Slavery legal in 1861	90498	89.50	737	70.39	1183	63.61	0.72	0.19
Literate	23-62	1850	Slavery illegal (1861)	206879	92.04	740	85.14	2079	74.49	0.37	0.38
Literate	23-62	1860	All	386311	91.28	2037	76.83	3953	69.92	0.63	0.21
Literate	23-62	1860	Slavery legal in 1861	117130	90.10	943	70.52	1357	59.78	0.75	0.29
Literate	23-62	1860	Slavery illegal (1861)	269181	91.80	1094	82.27	2596	75.21	0.47	0.24
Literate	23-62	1870	All	440261	92.56	3286	83.23	13266	68.99	0.48	0.47
Literate	23-62	1870	Slavery legal in 1861	121252	90.79	2060	79.73	10024	65.87	0.50	0.42
Literate	23-62	1870	Slavery illegal (1861)	319009	93.24	1226	88.59	3242	78.66	0.29	0.41
Literate	23-62	1880	All	627243	94.69	6721	83.53	26862	76.13	0.64	0.26
Literate	23-62	1880	Slavery legal in 1861	184762	93.30	4644	82.28	21118	74.62	0.57	0.26
Literate	23-62	1880	Slavery illegal (1861)	442481	95.27	2077	86.43	5744	81.65	0.57	0.20
Literate	23-62	1910	All	1427593	97.42	30752	92.59	110036	89.20	0.50	0.21
Literate	23-62	1910	Slavery legal in 1861	448692	97.20	23717	92.25	90775	88.64	0.49	0.21
Literate	23-62	1910	Slavery illegal (1861)	978901	97.52	7035	93.51	19261	91.80	0.45	0.12
Literate	23-62	1920	All	1751029	98.05	25256	94.11	149738	91.48	0.50	0.19
Literate	23-62	1920	Slavery legal in 1861	545099	98.02	19104	93.49	115131	90.70	0.54	0.19
Literate	23-62	1920	Slavery illegal (1861)	1205930	98.06	6152	96.03	34607	94.04	0.31	0.20
Literate	33-42	1850	All	331816	90.12	1843	71.28	3829	64.28	0.73	0.20
Literate	33-42	1850	Slavery legal in 1861	103571	88.96	954	65.38	1271	55.47	0.83	0.26
Literate	33-42	1850	Slavery illegal (1861)	232898	90.58	889	77.83	2558	68.66	0.55	0.28
Literate	33-42	1860	All	434598	89.86	2550	74.90	4672	67.21	0.60	0.23
Literate	33-42	1860	Slavery legal in 1861	129967	88.65	1194	66.37	1642	58.08	0.79	0.22
Literate	33-42	1860	Slavery illegal (1861)	304631	90.38	1356	82.41	3030	72.15	0.37	0.34
Literate	33-42	1870	All	485804	91.28	3625	78.90	14376	62.71	0.56	0.48
Literate	33-42	1870	Slavery legal in 1861	133623	89.45	2342	75.04	10793	59.12	0.57	0.45
Literate	33-42	1870	Slavery illegal (1861)	352181	91.97	1283	85.93	3583	73.51	0.33	0.45
Literate	33-42	1880	All	666691	92.83	7469	79.76	27535	68.66	0.63	0.35
Literate	33-42	1880	Slavery legal in 1861	196878	91.72	4924	78.77	20694	66.37	0.59	0.38
Literate	33-42	1880	Slavery illegal (1861)	469813	93.29	2545	81.13	6841	75.59	0.62	0.19
Literate	33-42	1910	All	1666839	96.61	37396	91.62	136797	87.28	0.45	0.24
Literate	33-42	1910	Slavery legal in 1861	523388	96.39	28252	91.10	110278	86.58	0.45	0.24
Literate	33-42	1910	Slavery illegal (1861)	1143451	96.71	9144	93.17	26519	90.19	0.35	0.20
Literate	33-42	1920	All	2010834	97.73	31124	93.26	185327	89.70	0.50	0.23
Literate	33-42	1920	Slavery legal in 1861	641757	97.85	22921	93.18	138066	88.78	0.53	0.27
Literate	33-42	1920	Slavery illegal (1861)	1369077	97.67	8203	93.39	47261	92.37	0.48	0.07

Table 7. Results for 1850 to 1920 Free Samples

Note: Positive W/M and M/B d-values indicate that Whites and Mulattoes have higher numeracy than, respectively, Mulattoes and Blacks.

3.2.2. Results for American Indians

Results for American Indians are shown in Table 8 and Table 9. As can be seen in Table 8, among American Indians there is a linear positive relationship between the percentage of White blood and numeracy scores. Additionally, we see that non-Indian Whites living on reservations with Indian families are more numerate than the American Indian average. Unlike as with the free samples of Whites, Mulattos, and Blacks, discussed previously, the gaps are substantially reduced among the literate. However, the positive association between reported White blood and numeracy is nonetheless present in the literate groups.

doi.org/10.32388/CCN648.8

			American Indians								Whites	
				% White Blood								
Sample			*0%*		*>0% to 25%*		*>25% to 50%*		*>50%*			
	Age	**Year**	***N***	**ABCC**	***N***	**ABCC**	***N***	**ABCC**	***N***	**ABCC**	***N***	**ABCC**
Literate & illiterate	23-62	1900	6136	77.39	520	90.87	961	95.34	379	102.57		
Literate & illiterate	23-62	1910	6228	80.48	466	94.69	1112	96.22	1163	98.13	446	98.93
Literate	23-62	1900	1364	89.35	335	94.78	604	96.85	325	102.69		
Literate	23-62	1910	2335	90.26	299	96.99	788	97.87	1046	99.31	417	99.22

Table 8. Results for American Indian Samples across all Age Cohorts

Table 9 shows the results for Mixed and Full-blooded American Indians by age group. As seen, there is substantial variability across ages. This could be due to the modest sample sizes in conjunction with ceiling effects for some of the groups. Nonetheless, the Mixed/ Full-blooded gaps are large in 1900 and 1910, with an average d = 0.97 in the samples with illiterates included and an average d = 0.82 in the samples with literates only. In contrast, the gaps in 1930 are much smaller, at d = 0.30 in the sample with illiterates included and d = 0.24 in the sample with literates only. Generally, those American Indians identified as Mixed-blooded are more numerate than those identified as Full-blooded.

doi.org/10.32388/CCN648.8

			Mixed-blooded		Full-Blooded		M/ F *d*
			N	ABCC	*N*	ABCC	
Literate & illiterate	All	1900	1860	95.56	6136	77.39	0.95
Literate & illiterate	23-32	1900	805	95.96	2096	84.51	0.73
Literate & illiterate	33-42	1900	494	98.18	1713	75.53	1.40
Literate & illiterate	43-52	1900	378	94.58	1454	72.64	1.00
Literate & illiterate	53-62	1900	183	88.80	873	71.88	0.64
Literate	All	1900	1264	97.80	1364	89.35	0.77
Literate	23-32	1900	645	95.93	752	92.92	0.27
Literate	33-42	1900	316	102.85	340	84.56	NA
Literate	43-52	1900	214	100.47	195	83.33	NA
Literate	53-62	1900	89	87.08	77	90.91	-0.21
Literate & illiterate	All	1910	2741	96.77	6228	80.48	0.99
Literate & illiterate	23-32	1910	1146	96.31	2010	87.50	0.64
Literate & illiterate	33-42	1910	787	98.32	1820	80.98	1.25
Literate & illiterate	43-52	1910	477	97.75	1310	74.62	1.34
Literate & illiterate	53-62	1910	331	93.28	1088	73.76	0.86
Literate	All	1910	2133	98.45	2335	90.26	0.86
Literate	23-32	1910	992	96.90	1094	92.44	0.43
Literate	33-42	1910	639	100.16	726	92.63	NA
Literate	43-52	1910	306	99.26	338	82.47	1.50
Literate	53-62	1910	196	99.49	177	81.92	1.66
Literate & illiterate	All	1930	1144	96.14	1625	92.94	0.30
Literate & illiterate	23-32	1930	427	97.92	583	94.53	0.44
Literate & illiterate	33-42	1930	335	91.12	451	93.98	-0.20
Literate & illiterate	43-52	1930	215	96.59	329	86.84	0.71
Literate & illiterate	53-62	1930	167	101.06	262	95.27	NA
Literate	All	1930	1021	96.69	1004	94.47	0.24
Literate	23-32	1930	393	98.43	406	96.36	0.36
Literate	33-42	1930	303	92.06	314	92.75	-0.05
Literate	43-52	1930	187	98.36	182	91.89	0.74
Literate	53-62	1930	138	99.60	102	96.79	0.80

Table 9. Results for American Indian Samples Decomposed by Age Cohort

doi.org/10.32388/CCN648.8

Note: A positive M/F d-value indicates that Mixed-blooded Indians have higher numeracy than Full-blooded Indians.

3.2.3. Results for Puerto Ricans

Finally, Table 10 shows the results for the Puerto Rican samples. As seen, the Puerto Rican numeracy is very low. For comparison, the ABCC of Puerto Ricans is approximately 77 in 1920 as compared to an ABCC of about 90 for mainland Blacks in the same year. Mainland-born Whites, who would be mostly European in ancestry, residing in Puerto Rico have a much higher ABCC-based numeracy than Puerto Ricans. Among Puerto Ricans, Blacks have the highest numeracy, followed by Whites, followed by Mulattos. So, in clear contrast with the other findings, among Puerto Ricans, European phenotype is not associated with numeracy. This holds true for both the samples with illiterates, and also the literate-only samples.

			USA White		PR White		PR Mulatto		PR Black		PR W/M *d*	PR M/B *d*
			N	ABCC	*N*	ABCC	*N*	ABCC	*N*	ABCC		
Literate & illiterate	23-62	1910	119	98.05	17062	71.25	7063	69.01	1183	72.90	0.06	-0.11
Literate	23-62	1910	119	98.05	5460	84.84	1631	83.21	320	83.48	0.07	-0.01
Literate & illiterate	33-42	1910	45	100.90	5124	66.82	2059	64.47	333	69.77	0.06	-0.15
Literate	33-42	1910	45	100.90	1675	81.63	520	76.14	106	87.57	0.19	-0.44
Literate & illiterate	23-62	1920	74	97.63	22347	76.51	6056	76.23	1332	77.50	0.01	-0.04
Literate	23-62	1920	74	97.63	8740	86.45	1921	86.07	457	87.64	0.02	-0.07
Literate & illiterate	33-42	1920	21	98.68	6775	75.53	1814	75.94	405	79.62	-0.01	-0.12
Literate	33-42	1920	21	98.68	2508	86.24	545	84.52	156	87.07	0.08	-0.11

Table 10. Results for Puerto Rican Samples

Note: Positive PR W/M and PR M/B d-values indicate that PR Whites and PR Mulattoes have higher numeracy than, respectively, PR Mulattoes and PR Blacks.

3.2.4. Summary of ABCC results

Figure 2 visually summarizes the ABCC results for the ten race/ethnic groups from section 3.2.1 to 3.2.3. It should be noted that at higher thresholds, smaller raw score differences imply larger standardized differences. For example, a seven point ABCC difference between the 99th and the 92nd percentile is approximately equivalent, in standardized terms, to a 25 point ABCC difference between the 90.04th and the 65th percentile (both being equivalent to *d* =.92).

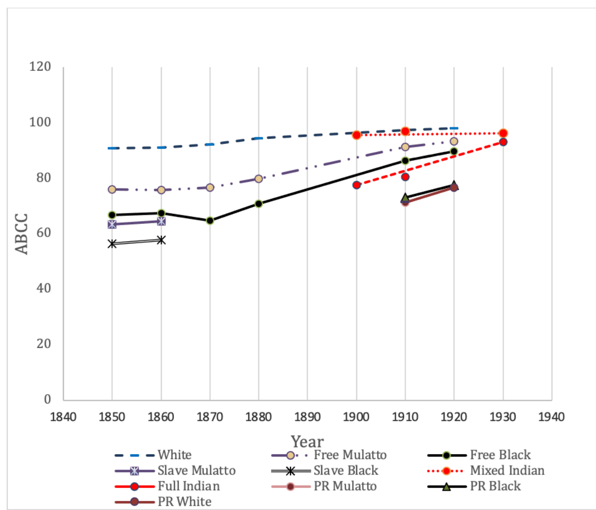

Figure 2. ABCC Values by Racial/ethnic Group from 1850 to 1930

4. Discussion

A large amount of research indicates that ancestry covaries with cognitive outcomes in the Americas. In this article, we compared 21st-century cognitive differences in the USA to 19th-and early 20th-century differences. In particular, we examined the relation between cognitive ability and ancestry among socially-identified White, Black, American Indian, and Puerto Rican groups. We hypothesized that indices of European, in contrast to African and Amerindian, admixture would be positively related to cognitive ability, as measured by age-heaping, in

doi.org/10.32388/CCN648.8

the 19^{th} to early 20^{th} century as in the 21^{st} century. With the exception of early 20^{th}-century Puerto Ricans, the findings are in line with our expectations: more ancestrally African or Amerindian groups had lower mean cognitive scores.

Among 21^{st}-century Black Americans, African genetic ancestry, relative to European, was negatively related to *g*. Regarding 19^{th}- and early 20^{th}-century African Americans, those classified as Mulatto had higher numeracy than those classified as Black. This was true for both slaves and freemen in 1850 and 1860 and for freemen thereafter. While the Mulatto-Black differences in age-heaping were lower in the 1850 and 1860 slave samples than in the free samples (d = 0.18 vs. d = 0.28 for the same years), this finding seems to be an artifact of the enumeration method. As noted prior, we cannot place high confidence in the results based on the slave samples because we do not know which slaves were interviewed or how age data was obtained. The White-Mulatto and the Mulatto-Black differences were similar in magnitude in the combined literate & illiterate samples and the literate-only samples. Overall, these numeracy results for African Americans are consistent with the 21^{st}-century results.

Among 21^{st}-century American Indians, African ancestry, relative to European, was negatively related to *g*. While Amerindian ancestry was also negatively associated with *g*, this effect was not statistically significant due to the small sample size. Regarding early 20^{th}-century American Indians, we found that those with more European admixture tended to have higher numeracy than those with less. Differences between Mixed-Blooded and Full-Blooded Indians were large for both the literate & illiterate samples in 1900 and 1910, though differences were much smaller by 1930. By 1930 the ABCC values were in the mid-90s for both groups, suggesting a possible ceiling effect, which would attenuate group differences. The finding of a linear relationship between age-heaping and admixture among American Indians is in accordance with the results of Thornton and Young-DeMarco (2021), who found that American Indians had higher literacy levels in proportion to White ancestry in a model controlling for birth cohort, region, and cultural-integration.

Among 21^{st}-century Mainland Puerto Ricans, both African and Amerindian ancestries, relative to European, were also negatively related to *g*. However, despite the positive correlation between non-European ancestry and darker color, darker color was not negatively associated with *g*. Interestingly, skin color was also found to be positively associated with *g,* when controlling for European genetic ancestry, in a sample of mostly Puerto Rican Hispanic adolescents residing in Philadelphia; in this sample, European genetic ancestry was also positively associated with *g* (Fuerst, Kirkegaard, & Piffer, 2021). Regarding early 20^{th}-century Puerto Ricans on the island of Puerto Rico, we did not find any association between racial phenotype and numeracy. These results from 1910 and 1920 are inconsistent with the two studies from the 20^{th} century, specifically, Vincenty (1930) and Green (1972), which report that inhabitants of Puerto Rico rated as appearing more African have lower cognitive ability scores than those appearing more European.

The lack of differences based on our analysis of census data could perhaps be due to census classifications being based more on skin color than on ancestry and due to color being positively associated with cognitive ability as a result of assortative mating. Loveman (2007), for example, reports that Puerto Rican enumerators did not follow the Census Bureau's official instructions and, instead, brought their own assumptions regarding the meaning of race into classificatory decisions. If the classifications were based more on skin color than on lineage, these census-based results for Puerto Ricans may be consistent with the early 21^{st}-century results, which show, at least in this sample, that color-associated HIrisPlex-S genes are positively related to general intelligence among Puerto Ricans.

Alternatively, it could be that age-heaping based numeracy, being a population-level measure, does not track individual differences in numeracy well and so that when groups are admixed for many generations, as in much of Latin America, it fails to index subtle ancestry associated differences. Finally, it could be that genetic ancestry is not associated with cognitive ability in Puerto Rico and that differences are not being vertically transmitted on the island. This latter alternative hypothesis seems to be less likely given the results for Mainland Puerto Ricans and since educational attainment has been found to positively correlate with European vs. African genetic ancestry in Puerto Rico (Kirkegaard et al., 2017); nonetheless, this possibility should be investigated in future studies.

Socially-identified race/ethnic groups, whether based on appearance or parent/self-report, need not track genetic ancestry well. This is especially the case after many generations of admixture, as in the case of Puerto Ricans. This is because the correlations between genetic ancestry, self-identified race, and ancestry-associated phenotype, such as color, can become attenuated after a number of generations of admixture. Due to this, modern methods using admixture regression can be used to statistically separate effects related to genetic ancestry from ones related to skin color and/or self-identified group as is done in the present study or in one other recent study (Fuerst, Hu, & Connor, 2021).

Understanding the nature of self-reported race/ethnic-related disparities in cognitive ability, and how these differences are transmitted across generations, is necessary to reduce both the differences and their social impacts. Race/ethnicity is multifaceted and involves appearance, cultural background, self-identity, and geographic ancestry (Roth, 2016). In some cases, government-defined race/ethnic categories, in the USA, describe groups with similar cultural characteristics (e.g., Hispanic: "Spanish culture or origin, regardless of race"), or with similar genetics (e.g., Black: "origins in any of the black racial groups of Africa"), but in other cases there seems to be little genetic or cultural basis for the groupings (e.g., Asian: "A person having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent"). Therefore, evaluating the independent contribution of factors related to genetic ancestry, common culture, and other dimensions related to socially defined race/ethnicity and/or color can help in identifying the source of group differences (Fuerst, Hu, & Connor, 2021). This issue is obviously also relevant to concerns about social inequality, as focusing exclusively on socially identified race/ethnicity, ignores possible race-related inequalities within socially defined groups.

The most obvious explanation for a substantial association between genetic ancestry and cognitive ability within groups – especially when conspicuous phenotypes, and possible discriminatory factors related to them, are controlled for – is inherited disadvantage. This model, as with the similar racial-cognitive ability-socioeconomic (R-CA-S) hypothesis detailed by Fuerst & Kirkegaard (2016) and by Hu et al. (2019), does not specify a reason for the source population differences or a mechanism of inheritance (e.g., family environment or genes). For example, owing to trait-biased migration or to cultural norms related to exogamy, one source population could be a genetically selective sample. And, as a result of this selectivity, there could be phenotypic differences between source (sub) populations and these would transmit across generations when within group heritabilities were nontrivial. Generally, the reasons for the original differences and the mechanisms by which differences are transmitted is a topic for future research.

As noted, the inherited disadvantage model does not specify mechanisms for vertical transmission – this could occur through cultural or genetic pathways. An alternative explanation for the association between ancestry and cognitive ability is phenotypic based discrimination or so-called "colorism". Two designs have been proposed to disentangle intergenerational effects from discriminatory ones: sibling and admixture regressions studies. Shibaev & Fuerst (2023) reviewed published sibling studies and report that while light or more European looking full-siblings tended to have slightly better academic-related outcomes then their darker siblings, the vast majority of the association between appearance and academic outcomes is due to family factors. The authors further ran an admixture-regression analyses and found that European appearance had no effect independent of genetic ancestry on cognitive ability, thus replicating previous results (e.g., Lasker et al., 2019). In the present analyses, genetically-predicted darker skin color was only associated with *g*, independent of ancestry, among Puerto Ricans; moreover, this association was positive not negative and so inconsistent with the predictions of a colorism model. Overall, studies which attempt to disentangle intergenerational and discriminatory models have provided little support for the latter in contrast to the former.

Future studies on ethnic/racial cognitive differences need to consider genetic ancestry, since cognitive ability differences seem to be strongly related to genetic ancestry independent of socially-defined race/ethnicity and color (Fuerst, Hu, & Connor, 2021; Kirkegaard et al., 2019; Lasker et al., 2019; Warne, 2020). To ameliorate ancestry-associated differences and the social consequences of these it will be necessary to better understand the reason for the association between genetic ancestry and *g*. Despite recognizing the importance of general cognitive ability, societal factors such as the declining availability of public housing, which disproportionately affects minorities, can also account for the persistence of race and ethnic differences in economic outcomes to some extent (Goetz, 2011). That genetic ancestry largely statistically explains group differences in cognitive ability does not imply that it must also mostly explain differences in social outcomes, such as income and educational attainment. Whether this is the case is something that could also be explored using the admixture regression design.

Author contributions

J.F. conceived of the idea. Analyses used the ABCD sample were conducted by J.F. under the supervision of B. J. Pesta while at Cleveland State University (2020-2021). Analyses using census data were conducted by M.H. and J.F. Both authors – J. F and M.H – edited and revised the manuscript. Both authors discussed the results and contributed to the final manuscript.

Acknowledgments

Data used in the preparation of this article were obtained from the Adolescent Brain Cognitive Development (ABCD) Study (https://abcdstudy.org), held in the NIMH Data Archive (NDA). This is a multisite, longitudinal study designed to recruit more than 10,000 children aged 9-10 and follow them over 10 years into early adulthood. The ABCD Study® is supported by the National Institutes of Health and additional federal partners under award numbers U01DA041048, U01DA050989, U01DA051016, U01DA041022, U01DA051018, U01DA051037, U01DA050987,

U01DA041174, U01DA041106, U01DA041117, U01DA041028, U01DA041134, U01DA050988, U01DA051039, U01DA041156, U01DA041025, U01DA041120, U01DA051038, U01DA041148, U01DA041093, U01DA041089, U24DA041123, U24DA041147. A full list of supporters is available at https://abcdstudy.org/federal-partners.html. A listing of participating sites and a complete listing of the study investigators can be found at https://abcdstudy.org/consortium_members/. ABCD consortium investigators designed and implemented the study and/or provided data, but did not necessarily participate in the analysis or writing of this report. This manuscript reflects the research results and interpretations of the authors alone and may not reflect the opinions or views of the NIH or ABCD consortium investigators. The ABCD data repository grows and changes over time. The ABCD data used in this report came from Version 3.01. The raw data are available at https://nda.nih.gov/edit_collection.html?id=2573.
Additional support for this work was made possible from supplements to U24DA041123 and U24DA041147, the National Science Foundation (NSF 2028680), and Children and Screens: Institute of Digital Media and Child Development Inc. NDA waved the requirement of creating a NDA data project (NDA, Oct 26, 2022).

References

- A'Hearn, B., Baten, J., & Crayen, D. (2009). Quantifying quantitative literacy: Age heaping and the history of human capital. *The Journal of Economic History*, *69*(3), 783-808.
- Baten, J., Benati, G., & Ferber, S. (2022). Rethinking age heaping again for understanding its possibilities and limitations. *The Economic History Review*, *75*(3), 960-971.
- Baten, J., & Nalle, S. (2022). Age Heaping and Life Course Reckoning. *Vierteljahrschrift für Sozial-und Wirtschaftsgeschichte*, *109(*3), 337-350.
- Baten, J., & Juif, D. (2014). A story of large landowners and math skills: Inequality and human capital formation in long-run development, 1820–2000. *Journal of Comparative Economics*, *42*(2), 375-401.
- Bates, D., Maechler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H.,... & Grothendieck, G. (2009). Package 'lme4'. URL http://lme4.r-forge.r-project.org.
- Braveman, P. A., Arkin, E., Proctor, D., Kauh, T., & Holm, N. (2022). Systemic And Structural Racism: Definitions, Examples, Health Damages, And Approaches To Dismantling: Study examines definitions, examples, health damages, and dismantling systemic and structural racism. *Health Affairs*, *41*(2), 171-178.
- Berry, B. (1969). *The Education of American Indians, a Survey of the Literature*. Prepared for the Special Subcommittee on Indian Education of the Committee on Labor and Public Welfare, United States Senate, February 1969.
- Blum, M., & Krauss, K. P. (2018). Age heaping and numeracy: Looking behind the curtain. *The Economic History Review*, *71*(2), 464-479.
- Bruce, M. (1940). Factors affecting intelligence test performance of whites and Negroes in the rural South. *Archives of Psychology*, *36*, (252).
- Chaitanya, L., Breslin, K., Zuñiga, S., Wirken, L., Pośpiech, E., Kukla-Bartoszek, M.,... & Walsh, S. (2018). The HIrisPlex-S system for eye, hair and skin colour prediction from DNA: Introduction and forensic developmental validation. *Forensic Science International: Genetics*, *35*, 123-135.
- Colman, A. M. (2016). Race differences in IQ: Hans Eysenck's contribution to the debate in the light of subsequent research. *Personality and Individual Differences*, *103*, 182-189.
- Erikson, C. E., Dent, R. B., Park, Y. H., & Luo, Q. (2022). Historic redlining and contemporary behavioral health workforce disparities. *JAMA Network Open*, *5*(4), e229494-e229494.
- Ferguson, G. O. (1916). *The psychology of the Negro: An experimental study* (No. 36). Columbia University.
- Ferguson, G. O. (1919). The intelligence of Negroes at Camp Lee, Virginia. *School and Society*, *9*, 721–726.
- Flynn, J. R. (2019). Reservations about Rushton. *Psych*, *1*(1), 35-43.
- Francis, G., & Kirkegaard, E. O. (2022). National Intelligence and Economic Growth: A Bayesian Update. *Mankind Quarterly*, *63*(1).
- Fryer, R. (2014). 21st century inequality: The declining significance of discrimination. *Issues in Science and Technology*, *31*(1), 27-32.
- Fox, J. & Weisberg, S. (2018). *An R Companion to Applied Regression*. Sage
- Fuerst, J. G., Hu, M., & Connor, G. (2021). Genetic ancestry and general cognitive ability in a sample of American youths. *Mankind Quarterly*, *62*(1).
- Fuerst, J. G. R., Kirkegaard, E. O., Piffer, D. (2021). More research needed: There is a robust causal vs. confounding problem for intelligence-associated polygenic scores in context to admixed American populations. *Mankind Quarterly*, *62*(1), 151–185.
- Fuerst, J., & Kirkegaard, E. O. (2016). Admixture in the Americas: Regional and national differences. Mankind Quarterly, 56(3), 255.
- Fuerst, J. G., Lynn, R., & Kirkegaard, E. O. (2019). The Effect of Biracial Status and Color on Crystallized Intelligence in the US-Born African–European American Population. *Psych*, *1*(1), 44-54.
- Garth, T. R., & Garrett, J. E. (1928). A comparative study of the intelligence of Indians in United States Indian

Schools and in the public or common schools. *School & Society, 27,* 178–184.

- Garth, T. R. (1933). The intelligence and achievement of mixed-blood Indians. Th*e Journal of Social Psychology,* *4*(1), 134-137.
- Giles, J. (2011). Social science lines up its biggest challenges. *Nature*, *470*(7332), 18-19.
- Goetz, E. (2011). Gentrification in black and white: The racial impact of public housing demolition in American cities. *Urban Studies, 48*(8), 1581-1604.
- Gullickson, A. (2005). The significance of color declines: A re-analysis of skin tone differentials in post-civil rights America. *Social Forces*, *84*(1), 157-180.
- Green, R.F. (1972). On the correlation between IQ and amount of "white" blood. *Proceedings of the Annual Convention of the American Psychological Association,* 7, 285-286.
- Hansen, H. C. (1937). Scholastic achievement of Indian pupils. *The Pedagogical Seminary and Journal of Genetic Psychology, 50*(2), 361-369.
- Hatton, S. (2018). *Preview of the ABCD Study® Data Release 3.0.* Department of Neurosciences, UC San Diego. https://abcdstudy.org/wp-content/uploads/2020/06/ABCD_Release3.0.pdf
- Heeringa, S. G., & Berglund, P. A. (2020). A guide for population-based analysis of the Adolescent Brain Cognitive Development (ABCD) Study baseline data. *BioRxiv*. doi: https://doi.org/10.1101/2020.02.10.942011
- Herskovits, M. J. (1926). On the Relation Between Negro-White Mixture and Standing in Intelligence Tests. *The Pedagogical Seminary and Journal of Genetic Psychology, 33*(1), 30—42.
- Hu, M. (2022). More Evidence of an Association between European Ancestry and g among African Americans: An Analysis of a Nationally Representative Sample of American Youth. *Mankind Quarterly*, *62*(3), 498-507.
- Hu, M., Lasker, J., Kirkegaard, E. O., & Fuerst, J. G. (2019). Filling in the gaps: The association between intelligence and both color and parent-reported ancestry in the National Longitudinal Survey of Youth 1997. *Psych*, *1*(1), 240-261.
- Hunter, W. S., & Sommermier, E. (1922). The Relation of Degree of Indian Blood to Score on the Otis Intelligence Test. *Journal of Comparative Psychology, 2*(3), 257—277.
- Iles, R. E. (1927). Ancestry and IQ. *Social Science*, *2*(4), 382-389.
- Juif, D. T., & Baten, J. (2013). On the human capital of Inca Indios before and after the Spanish Conquest. Was there a "Pre-Colonial Legacy"? *Explorations in Economic History*, *50*(2), 227-241.
- Kirkegaard, E. O., & Piffer, D. (2022). Stability of Italian Regional Intelligence Differences for 150 Years. *Mankind Quarterly, 63*(2).
- Kirkegaard, E.O.W., Wang, M., & Fuerst, J. (2017). Biogeographic Ancestry and Socioeconomic Outcomes in the Americas: A Meta-Analysis. *Mankind Quarterly*, *573*(3):398-427.
- Kirkegaard, E. O., Williams, R. L., Fuerst, J., & Meisenberg, G. (2019). Biogeographic ancestry, cognitive ability and socioeconomic outcomes. *Psych*, *1*(1), 1-25.
- Lasker, J., Pesta, B. J., Fuerst, J. G., & Kirkegaard, E. O. (2019). Global ancestry and cognitive ability. *Psych*, *1*(1), 431-459.
- Loehlin, J. C., Lindzey, G., & Spuhler, J. N. (1975). *Race differences in intelligence*. New York: Freeman.
- Long, J.A. (2020). jtools: Analysis and Presentation of Social Scientific Data. R package version 2.1.0, https://cran.r-project.org/package=jtools.
- Loveman, M. (2007). The US census and the contested rules of racial classification in early twentieth-century Puerto Rico. *Caribbean Studies, 35*(2), 79-114.
- Murray, C. (2021). *Facing reality: Two truths about race in America*. Encounter Books.
- Nisbett, R. E. (2009). *Intelligence and how to get it: Why schools and cultures count*. New York: Norton.
- Office of Management and Budget. (1997). Revisions to the standards for the classification of federal data on race and ethnicity. *Federal Register*, *62*(210), 58782-58790.
- Paschal, F. C., & Sullivan, L. R. (1925). Racial influences in the mental and physical development of Mexican children. *Comparative Psychology Monographs, 3, 14,* 1—76.
- Pérez-Artés, M. C. (2021). *Numeracy Selectivity of Spanish Migrants in Hispanic America (16th-18th Centuries)*. AEHE, Asociación Española de Historia Económica.
- Peterson, J. (1934). Basic considerations of methodology in race testing. *Journal of Negro Education, 3,* 403—410.
- Reardon, S. F., & Ho, A. D. (2015). Practical issues in estimating achievement gaps from coarsened data. *Journal of Educational and Behavioral Statistics, 40*(2), 158-189.
- Revelle, W., & Revelle, M. W. (2015). Package 'psych'. *The Comprehensive R Archive Network*, *337*, 338.
- Roth, W. D. (2016). The multiple dimensions of race. *Ethnic and Racial Studies Review, 39*(8):1310—38.
- Rowe, D. C., & Rodgers, J. E. (2005). Under the skin: On the impartial treatment of genetic and environmental hypotheses of racial differences. *American Psychologist*, *60*(1), 60.
- Ruggles, S., Flood., S., Sobek, M., Brockman, D., Cooper, G., Richards, S. & Schouweiler., M. (2023). *IPUMS USA: Version 13.0* [dataset]. Minneapolis, MN: IPUMS, 2023. https://doi.org/10.18128/D010.V13.0
- Scarr, S., Pakstis, A. J., Katz, S. H., & Barker, W. B. (1977). Absence of a relationship between degree of White

ancestry and intellectual skills within a Black population. *Human Genetics*, *39*, 69-86.

- Shibaev, V. & Fuerst, J. (2023). A Genetically Informed Test of the Cognitive-Colorism Hypothesis. *Natural Systems of Mind*, *3*(1).
- Shuey, A.M. (1966). *The testing of Negro intelligence* (2nd ed.). New York: Social Science Press.
- Sohn, K. (2014). The human capital of black soldiers during the American Civil War. *Economics Letters*, *122*(1), 40-43.
- Szołtysek, M., Poniat, R., & Gruber, S. (2018). Age heaping patterns in Mosaic data. *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, *51*(1), 13-38.
- Thornton, A., & Young-DeMarco, L. (2021). Literacy Among American Indians: Levels and Trends from 1900 to 1930 and Across Birth Cohorts from 1830 to 1920. *Unpublished paper, University of Michigan*.
- Vincenty, N.I. (1930). *Racial differences in intelligence as measured by pictorial group tests with special reference to Puerto Rico and the United States*. Doctoral dissertation, Harvard Graduate School of Education.
- Walsh, S., Chaitanya, L., Breslin, K., Muralidharan, C., Bronikowska, A., Pospiech, E.,... & Kayser, M. (2017). Global skin colour prediction from DNA. *Human Genetics*, *136*(7), 847-863.
- Walsh, S., Chaitanya, L., Clarisse, L., Wirken, L., Draus-Barini, J., Kovatsi, L.,... & Kayser, M. (2014). Developmental validation of the HIrisPlex system: DNA-based eye and hair colour prediction for forensic and anthropological usage. *Forensic Science International: Genetics*, 9, 150-161.
- Warne, R. T. (2020). Continental genetic ancestry source correlates with global cognitive ability score. *Mankind Quarterly*, *60*(3).

Supplementary data: available at https://doi.org/10.32388/CCN648.8

Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.