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# **Socioeconomic Inequality in the US: Ethnicity, Racial Admixture and Environmental Causes**

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## **Abstract**

General socioeconomic factor (S) scores were calculated for US states by SIRE (self-identified race/ethnicity) groups based on 3 indicators. The S factor loadings were generally but not always stable across subgroup analyses and the factor scores were generally stable across factor analytic extraction methods (almost all  $r$ 's  $\approx 1$ ). For Whites, Blacks and Hispanics, there were strong correlations between cognitive ability scores and S factor scores across states ( $r$ 's = .55 to .78;  $N$ 's = 28-50). This pattern also held when all data were analyzed together ( $r$  = .86,  $N$  = 115). Furthermore, the size of the Hispanic-White and Black-White S and cognitive ability gaps strongly correlated across states ( $r$ 's = .62-.69;  $N$ 's = 36-37). Lastly, parasite prevalence did not plausibly explain SIRE gaps in cognitive ability because gaps were *smaller* in more parasite-rich states (combined analysis  $r$  = -.17,  $N$  = 91).

Previously, we looked at the association between overall state-level racial ancestry and overall state-level outcomes. It was found that European ancestry relative to African and Amerindian ancestry was associated with better outcomes. This analysis was extended by looking at the state-level ancestry-outcome associations individually for Black and Hispanic SIRE groups. For Blacks, state-level European and Amerindian admixture was positively associated with better outcomes (mean  $r$ 's = .28 and .27), while African admixture was associated with worse outcomes (mean  $r$  = -.31,  $N$  = 31). For Hispanics, African and European admixture was related to better outcomes (mean  $r$ 's = .36 and .13), while Amerindian admixture was associated with worse outcomes (mean  $r$  = -.40;  $N$  = 24-34). These SIRE specific state-level results were only partially consistent with the overall state-level ones.

Finally, it was found that climatic and geospatial variables did not correlate strongly with cognitive

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ability and S scores when scores were decomposed by SIRE group, but did so at the total state-level, even after statistical control.

**Key words:** inequality, general socioeconomic factor, S factor, USA, United States, states, cognitive ability, IQ, intelligence, NAEP, race, SIRE, group differences, cognitive sociology, sociology of intelligence, ecology of intelligence

## 1. Introduction

In our target article (Fuerst & Kirkegaard, 2016) in *Mankind Quarterly* we examined the relationship between estimated racial admixture, cognitive ability and socioeconomic outcomes across sovereign nations of the Americas as well as across first-level administrative divisions (states, departments, etc.) within 4 nations (USA, Mexico, Colombia and Brazil). Generally, we found strong correlations ( $r$ 's .5-.8) between European ancestry, cognitive ability and S. One glaring exception to this pattern was the relationship between European ancestry and socioeconomic outcomes in the US. For this country, the zero-order correlation between European ancestry and S was comparatively low at .39; moreover, when cold weather and latitude were included in regression and path models, the relation became moderately to strongly negative (Fuerst & Kirkegaard, 2016). In Fuerst and Kirkegaard (Fuerst & Kirkegaard, 2016), we noted that further research was needed for this country. Two commenters, Leon (2016) and Pesta (2016) presented new US analyses. In line with previous research Leon (2016) and Pesta (2016), looked at total state outcomes, a practice which is problematic given interstate ethnic differences. In this paper, we attempt to gain analytic leverage by decomposing state-level outcomes by major self-identified race/ethnicity (SIRE) groups.<sup>3</sup>

## 2. Data sources

### 2.1. S-factor scores

Measure of America (<http://www.measureofamerica.org/>) publishes analyses as well as socioeconomic datasets for US states, counties and other divisions (<http://www.measureofamerica.org/download-agreement/>). As in the case of a previous study (Kirkegaard, 2015), we downloaded the dataset covering US states. We used the 2010 data as this was the most recent. Because we wished to analyze outcomes by SIRE groups by state, we were restricted to the following variables:

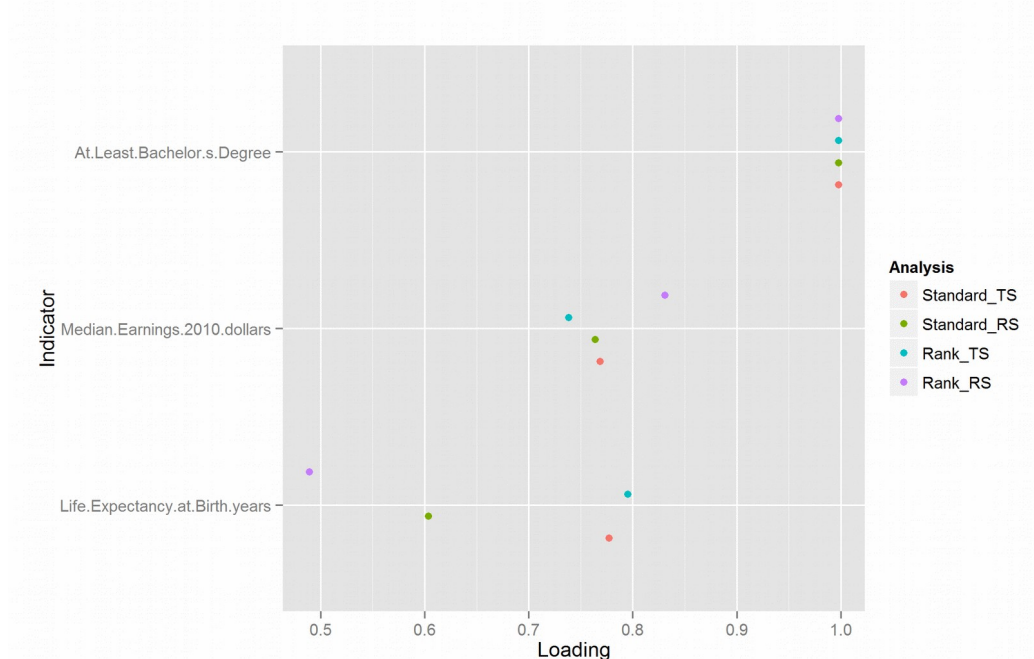
1. Human Development Index [American Human Development Index]
2. Life Expectancy at Birth (years)
3. Less Than High School (%)

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<sup>3</sup> The term *race* is a polyseme. In this paper, we are interested in two meanings: one, self-identified race/ethnicity (SIRE) and, two, biogeographic ancestry. While SIRE is a social identity, biogeographic ancestry is a description of relative genetic relatedness. Owing to centuries of admixture along with social and political whims, the two meanings often do not or do not neatly correspond. For instance, many members of the SIRE group Blacks/African Americans have substantial non-(West) African biogeographic ancestry (discussed in more detail below). In this paper, we will use the term *race* to refer to biogeographic ancestry, in line with traditional usage, and we will use the acronym *SIRE* to refer to the social identities. Sometimes we will use the following abbreviations for SIRE groups: Blacks/African Americans = B, Whites Americans = W, Asian Americans = A, Hispanic/Latino Americans = H and Native Americans = NA. For more details, see Fuerst (2015).

4. At Least High School Diploma (%)
5. At Least Bachelor's Degree (%)
6. Graduate Degree (%)
7. School Enrollment (%)
8. Median Earnings (2010 dollars)
9. Health Index
10. Education Index
11. Income Index

Of these, 1 and 9-11 were aggregate variables calculated from the others; as such, they were of little interest because we wanted to compute our own aggregate. Variables 2 and 8 were independently useful, but 3-7 were all education related and strongly overlapped. To avoid possible general factor contamination/coloring (Jensen, 1998, p. 85; Kirkegaard, In review), we selected only one of these, number 5. This left us with variables 2, 5 and 8. There are multiple ways one can extract S factors from the present data. We begin by analyzing the values for all states (N = 50). We do this because we want to know how well the S factor scores extracted from 3 indicators correlate with those extracted from 81 variables (Kirkegaard, 2015). We also analyze the SIRE state data as units in one analysis (N=154). Results are shown in Figure 1.



*Figure 1: S factor loadings for total states and SIRE states analyses. Standard (interval) and rank-order data.*

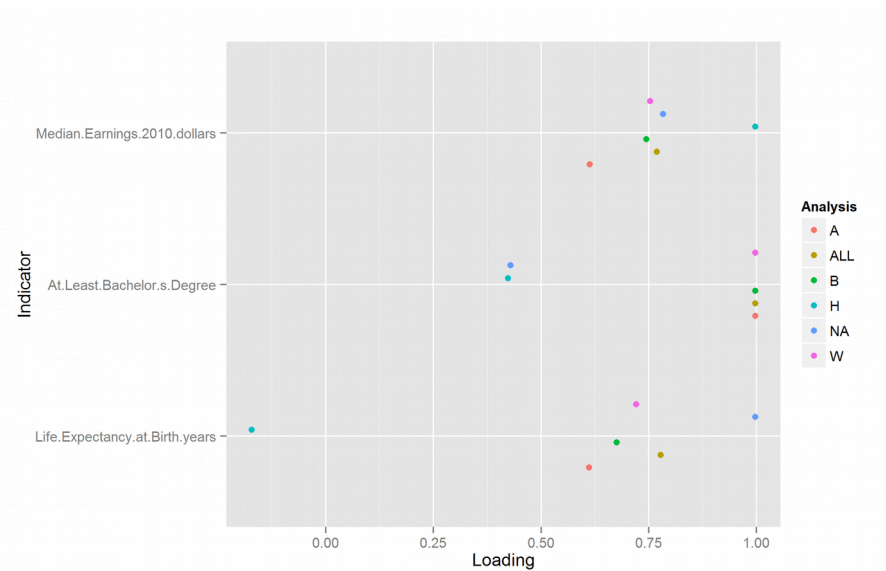
As expected, all variables have positive loadings. However, the loading of life expectancy was somewhat unstable being about .2-.3 lower for the SIRE state data. The educational variable had a loading of ~1, even when using ranked data. The correlations between the different total state S factors

are shown in Table 1. While not near unity, the correlation between the 3 and 81 variable S-factor scores was very strong. The interval and rank order versions were correlated near unity, so it should not matter much which method is used.

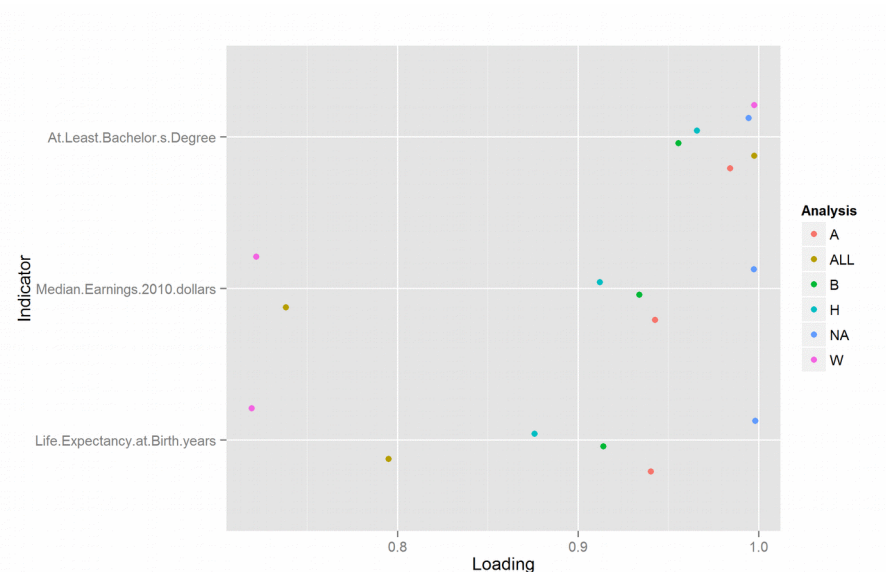
Var	S_3indi	S_3indi_rank	S_81indi
S_3indi		50	50
S_3indi_rank	0.979		50
S_81indi	0.876	0.871	

*Table 1: Intercorrelations between total state S factors. Unweighted correlations below the diagonal, pairwise N's above.*

One can split the dataset by SIRE groups and analyze each subset. Such an analysis can show if the structure of S is different for the different SIRE groups. Results are shown in Figures 2 and 3.



*Figure 2: S loadings for SIRE states by SIRE. Interval data.*



*Figure 3: S loadings for SIRE states by SIRE. Rank data.*

With the interval data, life expectancy with regards to Hispanics is a clear outlier with a loading below 0. However, this phenomenon disappears when using rank data. Still, with rank data, there was some instability, though all loadings were between .7 and 1. Due to the somewhat unstable factor loadings, it is worth examining the cross method correlations between factor scores by SIRE. These are shown in Table 2.

	S_ALL	S_B	S_A	S_H	S_NA	S_W	Srank_ALL	Srank_B	Srank_A	Srank_H	Srank_NA	Srank_W
S_ALL		37	28	28	11	50	50	37	28	28	11	50
S_B	0.743		26	24	7	37	37	37	26	24	7	37
S_A	0.252	0.09		22	6	28	28	26	28	22	6	28
S_H	0.396	0.002	0.209		7	28	28	24	22	28	7	28
S_NA	-0.228	-0.242	0.204	-0.464		11	11	7	6	7	11	11
S_W	0.888	0.757	0.032	0.34	-0.275		50	37	28	28	11	50
Srank_ALL	0.979	0.761	0.169	0.352	-0.214	0.872		37	28	28	11	50
Srank_B	0.735	0.985	0.092	-0.001	-0.166	0.749	0.757		26	24	7	37
Srank_A	0.225	0.103	0.967	0.175	0.23	-0.014	0.15	0.113		22	6	28
Srank_H	0.372	-0.012	0.2	0.982	-0.375	0.312	0.308	-0.012	0.145		7	28
Srank_NA	-0.216	-0.186	0.176	-0.535	0.972	-0.271	-0.202	-0.109	0.215	-0.424		11
Srank_W	0.895	0.751	0.035	0.318	-0.423	0.982	0.894	0.749	0.003	0.273	-0.415	

Table 2: Cross SIRE state and cross-method correlations. Correlations below the diagonal, N's above.

We are especially concerned with the italicized numbers. Despite the variation in loadings, the scores were very strongly correlated across methods. This is expected because of the strong intercorrelations of the variables in general. Because interval data are generally to be preferred and because the scores were so highly correlated, we used the interval scores for the remaining analyses despite the odd loading of life expectancy in the case of Hispanics. This loading is possibly related to the so-called Hispanic paradox, which is the finding that Hispanics generally live longer than Whites, despite being socioeconomically (and cognitively) worse off (Ruiz, Steffen, & Smith, 2013).

As a robustness check, we extracted the S factor scores using all combinations of extraction methods and scoring methods using the R *fa()* function (Revelle, 2015). No method variance across any of the datasets was detected (i.e., all correlations were near or at unity).

The distributions of the states S scores by SIRE groups are shown in Figure 4.

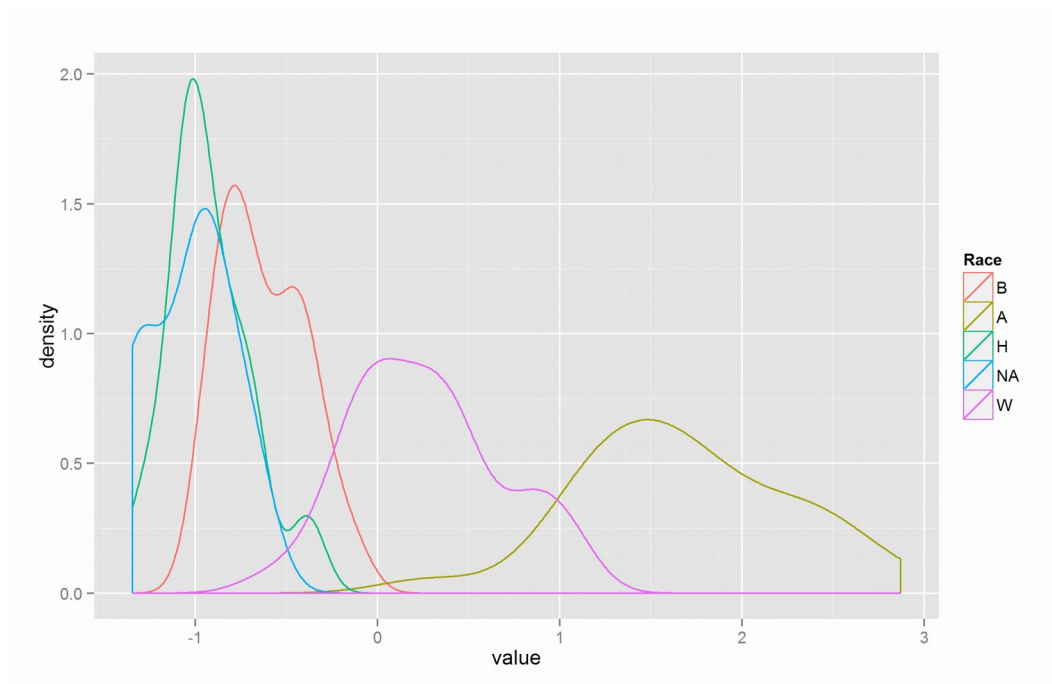


Figure 4: Empirical density plot of distributions of SIRE states.

The three lowest scoring groups are concentrated around -1 to -.5, while Asians are far ahead, even of Whites. There is substantial overlap between Blacks and Whites. Descriptive statistics are shown in Table 3. We note that Whites and Asians have much higher standard deviations than the other groups. Why is not clear.

Statistic / SIRE	Blacks	Asians	Hispanics	Native Americans	Whites
mean	-0.624	1.678	-0.924	-1.030	0.266
sd	0.231	0.582	0.230	0.235	0.413

Table 3: Descriptive statistics for S by SIRE.

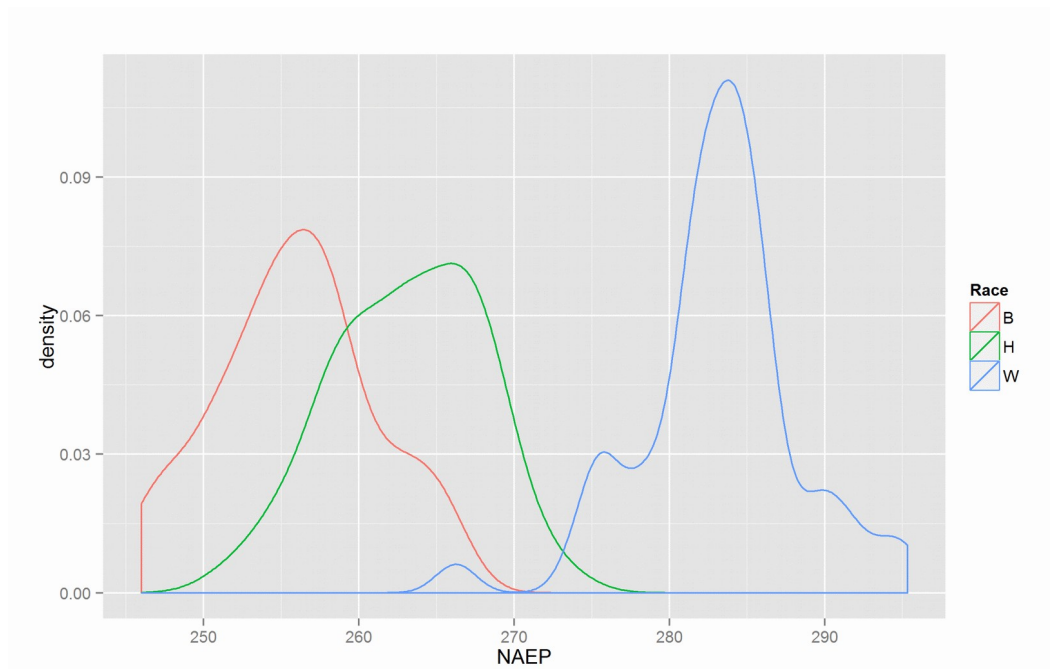
## 2.2. Cognitive scores

There are presently no published, publicly available US IQ scores decomposed by state and SIRE groups. As such, we used The National Assessment of Educational Progress MAIN (MAIN-NAEP)'s math and reading scores as an index of cognitive ability<sup>4</sup>. We used the results from 8<sup>th</sup> graders for years 2011 and 2013. The use of achievement scores was justified because it has been shown that at the aggregate-level, scholastic test scores correlate very strongly with standard IQ test scores (Lynn & Vanhanen, 2012; Rindermann, 2007). One could alternatively use university and/or graduate entrance exam test (e.g., SAT and ACT) scores, but these scores are less representative of state populations (McDaniel, 2006). The NAEP online explorer provides percentages of test takers by SIRE group. This is potentially important because, owing to, for example, migration and population age structure, the SIRE composition of test takers can markedly differ from the overall SIRE composition of a given state. Many states had missing data for the percentages of some of the smaller SIRE groups (e.g.

4 Accessed as: <http://nces.ed.gov/nationsreportcard/naepdata/>

Pacific Islanders in Connecticut). We filled in these cases with 0's.

Figure 5 shows a density plot of state cognitive ability by SIRE groups.



*Figure 5: Empirical density distributions for cognitive ability for SIRE states.*

We see a substantial overlap between Black and Hispanic scores, as would be expected given the magnitude of differences between between these groups (for example: Roth, Bevier, Bobko, Switzer, & Tyler, 2001). There is, however, almost no overlap between these and the white distribution (the outlier is West Virginia). Table 4 shows the descriptive statistics.

Statistic / SIRE	Blacks	Hispanics	Whites
Mean	255.876	263.103	283.151
SD	5.108	4.765	5.178

*Table 4: Descriptive statistics for cognitive ability by SIRE.*

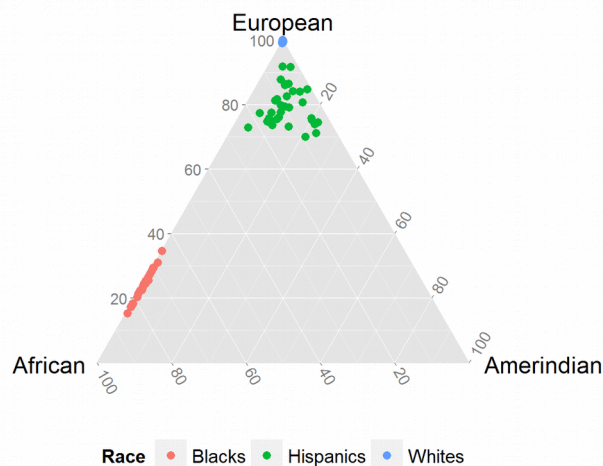
### 2.3. Within SIRE racial admixture data

Within SIRE racial admixture data was copied from Bryc et al. (2015) who obtained the results by analyzing customer data from the personal genomics service 23andMe (<https://www.23andme.com/>). The data is problematic because it is from a self-selected group; it is unknown how this self-selection influences the admixture estimates. Since among Blacks and Hispanics, European ancestry is positively correlated with SES and since interest in genomic testing and a willingness to purchase a test-kit (at 100-200 USD) probably correlates with SES, Blacks and Hispanics participants were probably, to some degree, indirectly selected for European ancestry (Fuerst & Kirkegaard, 2015). Additionally, for Blacks and Hispanics, data is lacking for many states and for other states is based on small sample sizes.

Bryc et al. showed ternary plots for individual admixture (their Figure S4) but they did not show one for the state-level data. They did, however, report the state admixture percentages by SIRE group in



table form (their Table S2), from where we obtained them. Figure 6 shows a ternary plot of racial admixture for states by SIRE group.



*Figure 6: Ternary plot of the three main sources of genomic admixture in SIRE states. Plot based on assigned admixture only.*

One can see that Blacks lie on a line between the African and European clusters with close to no Amerindian admixture. As Whites are almost entirely European (top corner), owing to the trivial variation in ancestry, admixture analysis would provide meaningless results. Hispanics are mostly European, but show non-trivial African and European admixture. Table 5 shows basic descriptive statistics for each SIRE group and their admixture percentages.

SIRE/race	n	mean	sd	median	mad	min	max
<i>Blacks</i>							
African	31	0.74	0.04	0.74	0.03	0.64	0.83
Amerindian	31	0.01	0.00	0.01	0.00	0.00	0.01
European	31	0.23	0.04	0.24	0.03	0.15	0.34
Other	31	0.02	0.00	0.02	0.00	0.01	0.03
Total	31	0.98	0.00	0.98	0.00	0.97	0.99
<i>Hispanics</i>							
African	34	0.09	0.05	0.08	0.06	0.01	0.22
Amerindian	34	0.10	0.05	0.09	0.03	0.04	0.21
European	34	0.73	0.07	0.72	0.05	0.57	0.90
Other	34	0.08	0.05	0.07	0.03	0.02	0.34
Total	34	0.92	0.05	0.93	0.03	0.66	0.98
<i>Whites</i>							
African	50	0.00	0.00	0.00	0.00	0.00	0.01



Amerindian	50	0.00	0.00	0.00	0.00	0.00	0.00
European	50	0.99	0.00	0.99	0.00	0.98	1.00
Other	50	0.01	0.00	0.01	0.00	0.00	0.02
Total	50	0.99	0.00	0.99	0.00	0.98	1.00

Table 5: 23andMe based racial admixture estimates by SIRE group. *Mad* = adjusted median absolute deviation.

As noted by Bryc et al. (their section: *Aggregating Local Ancestry Information*), the estimates do not generally add up to exactly 1. This is because the researchers adopted a conservative approach which left unassigned some admixture. We created two additional variables “Other” and “Total”, where the latter refers to the sum of the *assigned* admixture and the former refers to the residual. Inspecting the table makes it clear that Hispanics have substantial unassigned admixture (mean = 8%). Figure 7 shows a histogram of total assigned admixture by SIRE group and state.

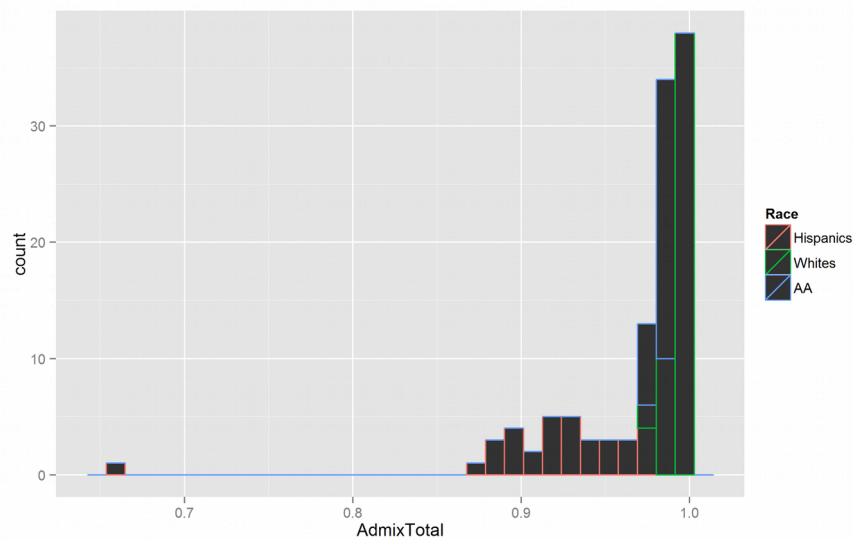


Figure 7: Histogram of total assigned admixture.

The far outlier is Hawaii, where presumably a large chunk of the missing admixture is Pacific Islander/Hawaiian/Asian. The presence of substantial missing admixture for Hispanics problematizes interpretations of admixture x outcome results.

## 2.4. US states climatic data

Sources are given in our target article (Fuerst & Kirkegaard, 2016).

## 3. Analyses

### 3.1. Cognitive ability and S

We now turn to the relationship between cognitive ability and S. Generally, this relationship has been found to be strongly positive ( $r$ 's .5 to .9) across many aggregated datasets (Fuerst & Kirkegaard, 2016;

Kirkegaard, 2014, 2015), but no meta-analysis has yet summarized the results. In our target article, we reported a weighted correlation of .70 for cognitive ability and *S* for the states of the US. Figure 8 depicts the cognitive ability and *S* relation for each SIRE group and for all three groups aggregated together. All datasets show positive relationships as expected, though the slope is somewhat steeper for Whites. Blacks have somewhat higher *S*-factor scores than Hispanics despite having lower cognitive ability scores, thus giving rise to a slight Simpson's paradox (for a discussion of Simpson's paradox, see: Kievit, Frankenhuys, Waldorp, & Borsboom, 2013). The relatively low socioeconomic status of Hispanics is probably due, in part, to the fact that many are or are the children of recent low-skill immigrants. Table 6 shows correlations and sample sizes.

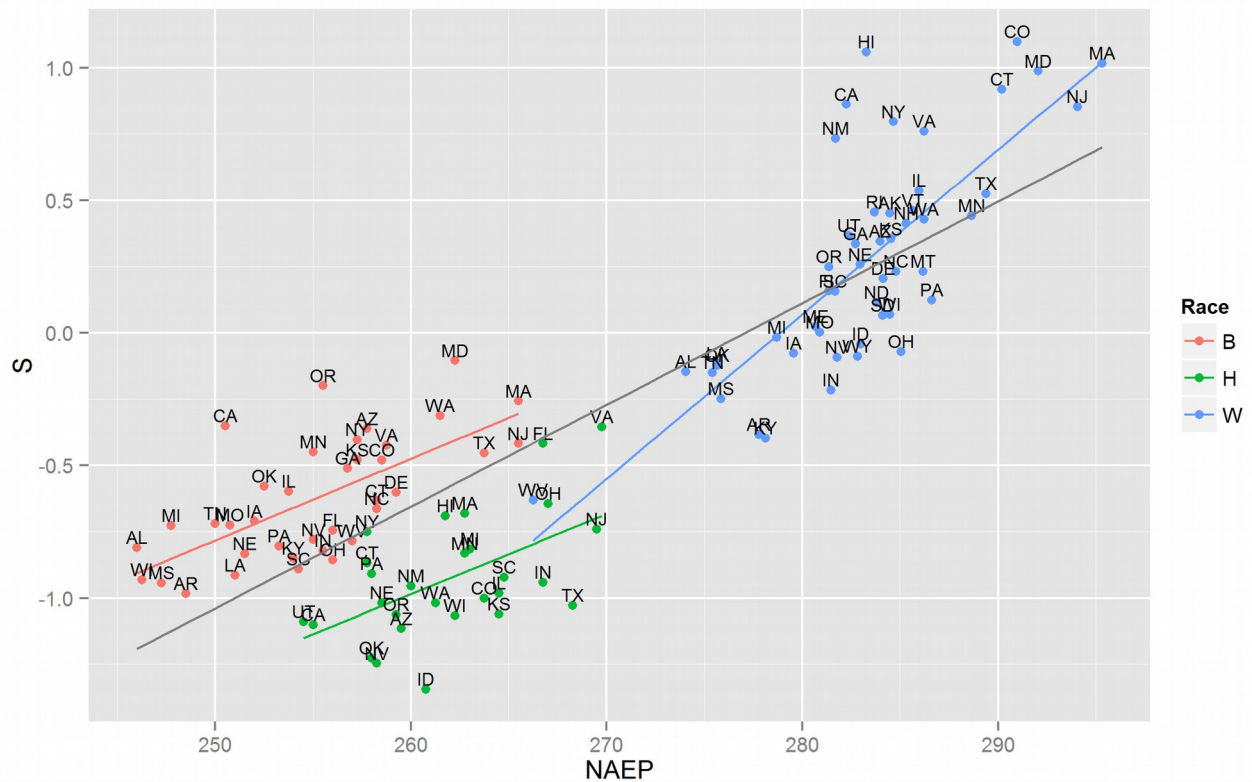


Figure 8: Scatter plot of cognitive ability and *S* by SIRE by state. SIRE groups are marked by colors. The black line is the regression based on all the combined dataset. B = Blacks, H = Hispanics, W = Whites.

Statistic / SIRE	All	B	H	W	Combined
r	0.67	0.67	0.55	0.78	0.86
N	50	37	28	50	115

Table 6: Cognitive ability  $\times$  *S* correlations for total states ("All"), each SIRE state and all SIRE states combined in one analysis.

All correlations are strong and positive. The combined dataset exhibits the strongest correlation, which is expected because the variance is increased as can be seen in the scatter plot. A further finding is that there is almost a positive manifold (i.e., all intercorrelations are positive) for NAEP an S scores by SIRE groups. For instance, in states where Whites are socioeconomically better off, Blacks are smarter ( $r=.566$ ;  $N=37$ ), and vice versa ( $r=.583$ ). The correlation matrix is given in the appendix (see: *NAEP\_S\_cors*).

## 3.2. Cognitive ability and S gaps across states

### 3.2.1. Cognitive ability gaps as a cause of S gaps

Across states there are substantial differences in the magnitude of the gaps between the majority group (Whites) and, respectively, Blacks and Hispanics. Such differences call out for an explanation. If cognitive ability differences cause S differences (the central thesis of cognitive sociology), then S and cognitive ability gaps should be correlated across states. Figure 9 shows the scatter plot. The correlations are strong at .620 ( $N=37$ ) and .692 ( $N=36$ ) for Blacks and Hispanics, respectively. West Virginia (WV) is a clear outlier in terms of the magnitude of the B/W gaps, but it nonetheless falls neatly on the regression line for S-factor and cognitive gaps, as both are near zero.

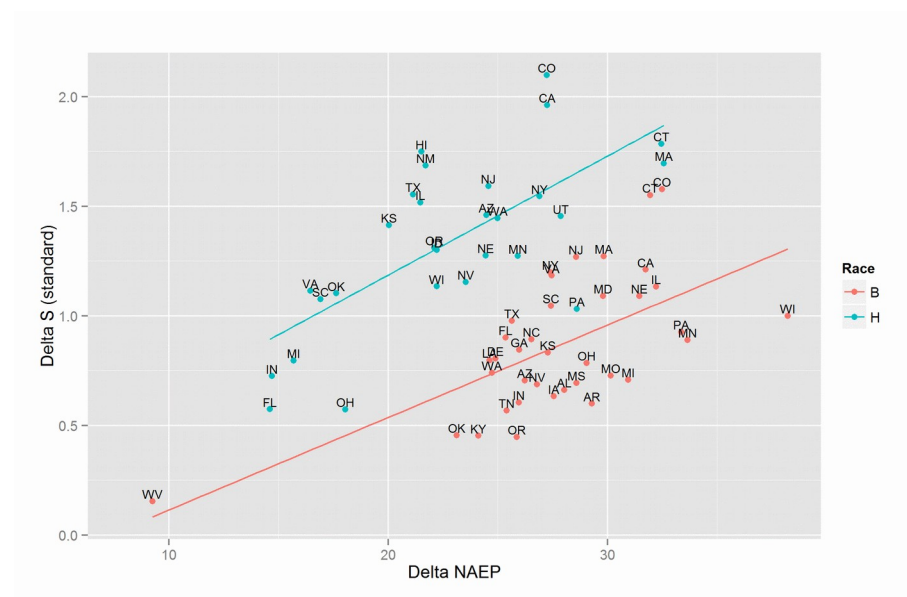


Figure 9: Scatter plot of cognitive ability and S gaps to the White population for Blacks (B) and Hispanics (H).

### 3.2.2. Parasites as a cause of cognitive ability gaps

It has been proposed that parasite prevalence is an environmental cause of US state-level and national differences in cognitive ability (Eppig, Fincher, & Thornhill, 2010, 2011). If one accepts this, one might also propose that group gaps in cognitive ability within countries could be explained by differential parasite exposure. In this model, the lower scoring groups are more exposed to parasites than the higher scoring groups. This leads to a prediction, namely that the group gaps should be larger in the states with higher parasite prevalence rates. We tested this by correlating human parasite prevalence rates with the size of the gaps (as explained above). Figures 10 and 11 shows the scatterplots.

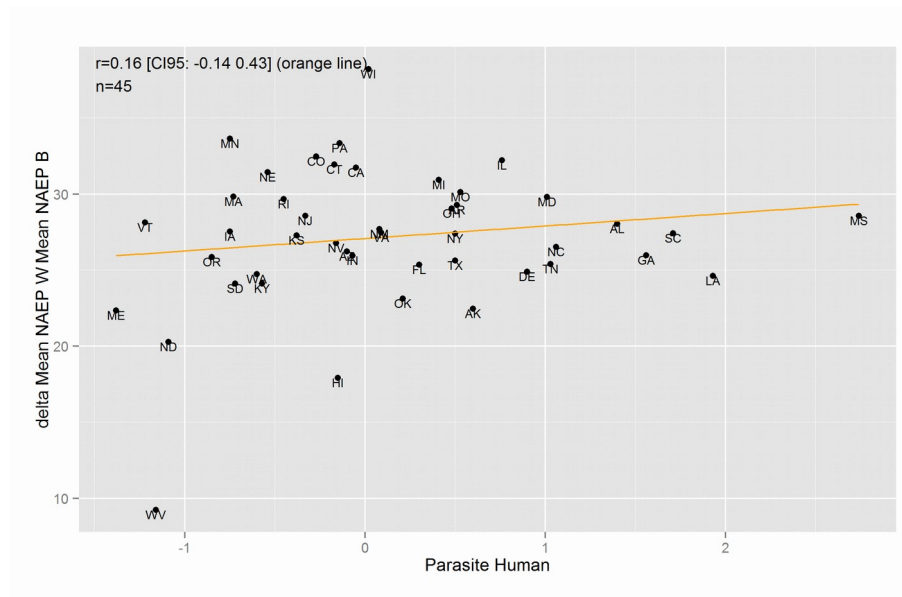


Figure 10: Prevalence of human parasites and White-Black cognitive ability gap by state.

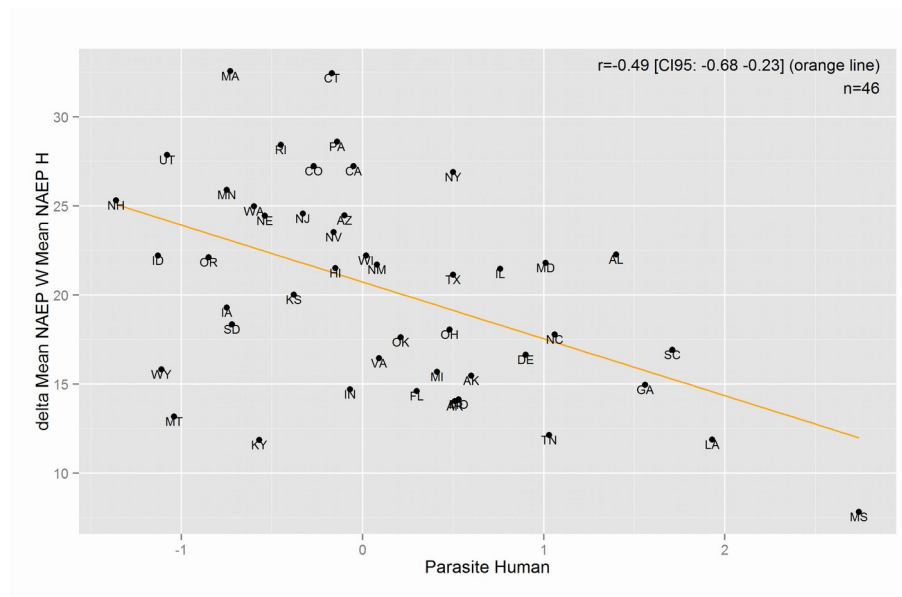


Figure 11: Prevalence of human parasites and White-Hispanic cognitive ability gap by state.

The correlation for the White-Black gaps is slightly positive (with the confidence interval widely overlapping 0) while that for Hispanics is strongly *negative*. If one combines the analyses, the correlation is  $-.17$  [CI95:  $-.36$  to  $.04$ ].

### 3.3. State SIRE composition and cognitive ability

In our target article, we attempted to predict the cognitive ability of the states of the US from their estimated genomic admixture. To create state admixture estimates, we used SIRE admixture estimates in conjunction with 2010 census SIRE state percentages. Since we were interested in the relative effect of European, African and Amerindian ancestry on outcomes we excluded Asian and Pacific Islander SIRE groups from our computations. Based on multiple regressions, we found that using African or

Amerindian ancestry in conjunction with European ancestry offered no incremental validity over using just European ancestry.

Here we rerun the analysis using NAEP test taker percentages for all SIRE groups. We include the state of Hawaii in this analysis, so  $N = 50$ . We carried out multiple regression analyses, testing all possible models ( $N_{\text{models}}=127$ ), with SIRE group percentages as predictors. A number of the models generated senseless results (e.g., all predictors had excessively large negative betas); this problem seems to result when too many SIRE composition predictors are used, probably due to multicollinearity and a lack of free variance. Disregarding them, the top 10 models according to adjusted  $r^2$  are shown in Table 7.

Model #	White	Black	Hispanic	Asian	Native American	Pacific Islander	Mixed	$r^2$ adj
117		-0.600	-0.37		-0.326	-0.426	0.197	0.322
126		-0.601	-0.43	0.227	-0.311	-0.638	0.199	0.318
87		-0.603	-0.384		-0.302	-0.336		0.307
111	0.886		0.216	0.518		-0.433	0.274	0.305
124	0.564	-0.228		0.379	-0.175	-0.480	0.255	0.303
114		-0.604	-0.443	0.221	-0.287	-0.541		0.302
107	0.612	-0.163		0.466		-0.524	0.241	0.301
82	0.701			0.591		-0.576	0.250	0.297
125	0.882		0.220	0.497	-0.091	-0.418	0.284	0.295
108	0.415	-0.315			-0.231	-0.204	0.240	0.294

Table 7: Model statistics for predicting state NAEP scores. Top 10 models by  $r^2$  adj.

We see some familiar patterns: White and Asian percentages are consistently associated with positive betas, while Black, Native American and Pacific Islander percentages are associated with negative ones. The betas for percentage of Hispanics varied depending on the other predictors in the model. The correlation matrix is given in the appendix (see: *NAEP\_beta\_cors*).

Another summary of the results is shown below in Table 8. Here, we show the median and adjusted median absolute deviation (mad) beta for each SIRE predictor. These represent robust (to reduce the influence of the invalid models' betas) alternatives to means and the standard deviations. When analyzed this way, the usual patterns emerge, except that the effect of White% is greater than that of Asian%.

The adjusted multiple R of the best fitting model is .57 (the square root of .322 from model 117), vs. .64 in the target article. Again, we fail to find substantial evidence of incremental validity for predictors beyond an index of European ancestry.

Measure	White	Black	Hispanic	Asian	Native American	Pacific Islander	Mixed
median	0.632	-0.456	-0.224	0.206	-0.068	-0.338	0.136
mad	0.230	0.180	0.266	0.520	0.089	0.451	0.070

Table 8: Summary statistics for model predictors.

### 3.4. Cognitive ability and S gaps across states

A number of environmental factors have been proposed to explain differences in cognitive ability and S between countries and administrative units therein (Eppig et al., 2011; Kanazawa, 2008; León, 2016; León & Burga León, 2014). One study examined cognitive ability, socioeconomic outcomes and temperature for US states and statistically controlled for SIRE composition (Pesta & Poznanski, 2014). We argue that a preferable method is to disaggregated scores by major SIRE groups and to then correlate those scores with the variables of interest. As we have disaggregated cognitive ability and S-factor scores we can conduct this analysis. We also include the total state scores for comparison. Table 9 shows part of the correlation matrix.

	CA_All	CA_W	CA_B	CA_H	S_All	S_W	S_B	S_H
<b>Parasite</b>	-0.581	-0.206	-0.360	0.233	-0.541	-0.084	-0.325	0.265
<b>Lon</b>	0.272	0.079	-0.131	0.127	0.162	-0.099	-0.208	0.438
<b>Lat</b>	0.553	0.278	0.152	0.032	0.461	0.036	0.339	-0.233
<b>Temp</b>	-0.588	-0.286	-0.164	0.010	-0.503	-0.064	-0.203	0.240
<b>Rain</b>	-0.234	-0.199	-0.105	0.120	-0.118	-0.079	-0.331	0.681
<b>Humid_morning</b>	-0.123	-0.255	-0.259	0.198	-0.139	-0.311	-0.358	0.367
<b>Humid_afternoon</b>	0.090	-0.054	0.010	0.112	0.250	-0.035	-0.031	0.425
<b>Sun</b>	-0.281	-0.081	-0.051	-0.181	-0.301	0.019	0.055	-0.383

Table 9: Correlations between cognitive ability, S and environmental variables.

In general, there are often sizable correlations between the outcomes – cognitive and S scores – and environmental variables when looking at the total state scores (e.g., temperature x CA = -.59). However, the correlations are much smaller and the directionality is inconsistent when looking at the disaggregated scores. Results for Hispanics, in Table 9, are often at odds with those for the other two SIRE groups. This possibly owes to migratory related effects (e.g., language bias). The true (statistical) effect of the environmental variables is probably best indexed by the average of these variables' correlation with White and Black outcomes. Parasite prevalence, latitude, and temperature are, for Whites and Blacks, associated with outcomes in the directions noted by Leon (2016) and Pesta (2016), yet the magnitudes of the associations are notably smaller than those based on total state scores. To facilitate comparison with Pesta & Poznanski's (2014) results, we ran the partial correlations for total states scores and the environmental variables controlling for the percentage of Whites (in line with the previously mentioned authors' method). This method of controlling left substantially larger correlations between the environmental variables and the outcome variables (e.g., CA x Temp = -.41). This illustrates, to our minds, that statistical controlling for SIRE percentage does not completely remove the effect of SIRE related differences. The full partial correlation matrix is given in the appendix (see: *Partial\_envIRON\_vars*).

### 3.5. Within SIRE racial admixture, cognitive ability and S

A prediction from the racial model tested by Fuerst & Kirkegaard (2016) is that the scores of Black and Hispanic individuals should positively correlate with the individual's % of European admixture. The

underlying logic applies to state scores too – though, on the state-level, there are more confounds. As mentioned in Section 2.3, the admixture estimates available are questionable, especially in the case of Hispanics, in which case a non-trivial portion of admixture was unassigned. Still, it is worth looking at the associations. Tables 10 and 11 show the correlation matrices for Blacks and Hispanics, respectively.

	<b>African%</b>	<b>Amerindian%</b>	<b>European%</b>	<b>Other%</b>	<b>CA</b>	<b>S</b>
<b>African%</b>	1	0.077	-0.993	-0.416	-0.330	-0.295
<b>Amerindian%</b>	0.077	1	-0.147	0.245	0.185	0.356
<b>European%</b>	-0.993	-0.147	1	0.314	0.298	0.253
<b>Other%</b>	-0.416	0.245	0.314	1	0.338	0.350
<b>CA</b>	-0.330	0.185	0.298	0.338	1	0.671
<b>S</b>	-0.295	0.356	0.253	0.350	0.671	1

*Table 10: African American racial admixture by state and outcome variables. Unweighted correlations. N's 31 for admixture variables and 37 for S x CA.*

	<b>African%</b>	<b>Amerindian%</b>	<b>European%</b>	<b>Other%</b>	<b>CA</b>	<b>S</b>
<b>African%</b>	1	-0.424	-0.206	-0.312	0.276	0.450
<b>Amerindian%</b>	-0.424	1	-0.497	0.161	-0.237	-0.559
<b>European%</b>	-0.206	-0.497	1	-0.655	0.137	0.132
<b>Other%</b>	-0.312	0.161	-0.655	1	-0.229	-0.01
<b>CA</b>	0.276	-0.237	0.137	-0.229	1	0.549
<b>S</b>	0.450	-0.559	0.132	-0.01	0.549	1

*Table 11: Hispanic racial admixture by state and outcome variables. Unweighted correlations. N's 34, 24, 34 for admixture x CA, admixture x S, and CA x S, respectively.*

For Blacks we see the expected findings, namely that more European admixture correlates with better outcomes and African admixture with worse. Amerindian ancestry is also positively correlated with outcomes, but, as shown in Table 5, the variation in Amerindian ancestry among African Americans is trivial ( $M = 0.006$ ,  $SD = 0.002$ ), assuring that any association is likely spurious. For Hispanics, as expected, Amerindian ancestry is negatively associated with outcomes. However, unexpectedly, African ancestry is positively so associated. As shown in Table 5, the standard deviation of African Admixture is about the same as that for Amerindian admixture, so the results are not dismissible on the grounds of low variation. It is possible that the results are biased due to the influence of other variables not included in the analysis. Thus, we used hierarchical regression with plausible predictors to see how the results are affected. We include White cognitive ability as an index of the quality of schools. Table 12 shows the models. We start with a baseline model which shows the zero-order correlation between state-level African admixture and state-level African American cognitive ability. We then add our parasite load variable. This seems to acquire some of the validity of African%, though the relations stays negative. We then add White cognitive ability which turns out to be a strong positive predictor. In models 4a and 4b we try adding a second admixture variable, but they have no incremental validity. We



could not add European% because that would create multicollinearity ( $r_{\text{African\%} \times \text{European\%}} = -0.993$ ).

Model	White CA	Parasites	African%	European%	Amerindian%	Other%	r <sup>2</sup> adj
1			-0.349				0.078
2		-0.388	-0.101				0.109
3	0.555	-0.112	-0.221				0.506
4a	0.551	-0.116	-0.22		0.013		0.487
4b	0.543	-0.109	-0.197			0.066	0.491

Table 12: Hierarchical regression models for African American cognitive ability.

Next we repeat the analysis for Hispanics. Table 13 shows the results.

Model	White CA	Parasites	African%	European%	Amerindian%	Other%	r <sup>2</sup> adj
<i>European% as base</i>							
1				0.121			-0.012
2		0.536		0.168			0.175
3	0.457	0.716		0.321			0.371
4a	0.461	0.687		0.274	-0.092		0.358
4b	0.505	0.809		0.469		0.191	0.372
4c	0.468	0.753	-0.046	0.318			0.351
<i>African% as base</i>							
1			0.245				0.047
2		0.480	0.040				0.139
3	0.355	0.687	-0.075				0.252
4a	0.482	0.791	-0.270		-0.333		0.338
4b	0.374	0.686	-0.127			-0.164	0.261
4c	0.468	0.753	-0.046	0.318			0.351

Table 13: Hierarchical regression models for Hispanic cognitive ability.

We present results using two different bases: European% and African%. This is because the racial model being tested makes relatively clear predictions concerning the expected associations (positive for European and negative for African). We add variables as before. It is worth noting that parasite prevalence has a strong *positive* beta, which is not as expected if parasite burden was lowering the cognitive ability of Hispanics. As before, White cognitive ability is a moderate to strong positive predictor across all models. Of special interest is that European% begins as weakly positive but becomes more strongly positive in the best models, while African% begins as weakly positive but becomes *more negative* in the better models. The full set of models are given in the appendix (see: *NAEP\_A\_models*, *NAEP\_H\_models*).

We now present the regression results for S. These are analogous to those for cognitive ability except

that parasite prevalence is not used as a predictor. Tables 14 and 15 show the results for African Americans and Hispanics, respectively. The results are similar to the cognitive ability ones; specifically, White S is a strong predictor and African% is a moderate negative predictor.

Model	White S	African%	European%	Amerindian%	Other%	r2adj
1		-0.291				0.055
2	0.692	-0.257				0.714
3a	0.671	-0.262		0.059		0.706
3b	0.696	-0.264			-0.018	0.703
4	0.677	-0.276		0.065	-0.032	0.696

*Table 14: Hierarchical regression models for African American S.*

Model	White S	African%	European%	Amerindian%	Other%	r2adj
<i>European% base</i>						
1			0.150			-0.027
2	0.374		0.369			0.039
3a	0.370		0.065	-0.596		0.344
3b	0.364		0.434		0.083	-0.004
4	0.412		-0.281	-0.744	-0.343	0.38
<i>African% base</i>						
1		0.520				0.166
2	0.265	0.555				0.203
3a	0.349	0.287		-0.503		0.397
3b	0.234	0.586			0.071	0.169
4	0.412	0.207		-0.552	-0.126	0.38
<i>Both</i>						
2		0.518	0.142			0.144
3	0.446	0.573	0.401			0.269
4a	0.412	0.327	0.163	-0.440		0.38
4b	0.412	0.801	0.805		0.498	0.38

*Table 15: Hierarchical regression models for Hispanic S.*

For Hispanics, as before, White S is a moderate to strong predictor across all models. Unexpectedly, again, African% is a positive predictor even in the company of other predictors: moreover, the size of the beta is larger than that for European%. The full set of models are given in the appendix (see: *S\_A\_models*, *S\_H\_models*). These results are curious since they suggest that in the Hispanic population African ancestry is more positively associated with outcomes than is European ancestry and, yet, on the national level, self-identifying Black Hispanics perform worse than do self-identifying White

Hispanics. For an illustration of the latter point, 2015 grade 8 NAEP math and reading results are shown below for all Hispanics, Mexicans, Cubans, and Puerto Ricans. Nothing sticks out in these which would account for the lack of a negative association between African ancestry and cognitive ability. Self reported “Black” identify is consistently associated with lower scores across all major Hispanic groups. It is possible that SIRE does not well track ancestry for Hispanics. Or perhaps the African ancestry estimates were off owing to the unassigned admixture. This is a topic which might need to be explored more in the future.

<b>NAEP 2015</b>	<b>Math</b>	<b>Reading</b>
White Hispanic	276	259
White and Black Hispanic	269	254
Black Hispanic	260	242
White Mexican	275	257
White and Black Mexican	268	249
Black Mexican	261	242
White Cuban	280	264
White and Black Cuban	265	244
Black Cuban	256	238
White Puerto Rican	272	262
White and Black Puerto Rican	265	252
Black Puerto Rican	260	244

Table 16: NAEP scores for various Hispanic subgroups.

#### 4. Discussion and conclusion

We found that the state-level cognitive ability x S-factor relation replicated for Blacks, Whites, and Hispanics (Section 3.1). Moreover, across states, the size of B/W and H/W cognitive gaps predicted the size of the respective S-factor gaps (Section 3.2). Replicating previous results, it was found that adding multiple SIRE groups did not substantially increase predictive validity relative to using European ancestry alone (Section 3.3). Environmental factors were found to be less strongly associated, than previously reported, with outcomes when scores were decomposed by SIRE group as compared to

when the statistical effect of SIRE percentages were controlled for (Section 3.4). It was found (Section 3.5) that for Blacks, state-level European admixture was positively associated with better outcomes (mean  $r = .28$ ), while African admixture was associated with worse outcomes (mean  $r = -.31$ ,  $N = 31$ ). For Hispanics, partially contrary to prediction, both African and European admixture were related to better outcomes (mean  $r$ 's =  $.36$  and  $.13$ ), while Amerindian admixture was associated with worse outcomes (mean  $r = -.40$ ;  $N = 24-34$ ). Both sets of results were robust to controls for certain external factors. The reason that state-level African ancestry among Hispanics positively correlates with state-level Hispanic outcomes is unclear, especially in light of the relatively poor performance of self-reported Black Hispanics.

Generally, taken together, the results illustrate how using SIRE decomposed scores can provide analytic leverage when conducting cross-state analyses. It would be interesting to examine the S factor at lower levels of aggregation for the US. Several datasets suitable for this purpose are known to exist: 1) Counties ( $N=3143$ ), 2) Congressional districts ( $N=436$ ), 3) Louisiana parishes ( $N=36$ ), and 4) Metropolitan Areas ( $N=25$ ), all from Measure of America. SIRE composition data is given in the datasets as well, making it possible to conduct crude admixture analyses. While cognitive data are not found in these datasets, cognitive data is known to exist for counties (Barnes, Beaver, & Boutwell, 2013; Boutwell et al., 2013). Furthermore, because some of these datasets are nested inside each other, it is possible to conduct multi-level analyses as well.

## Supplementary material and acknowledgments

R source code, data and the appendix (*appendix.xlsx*) can be found at the project repository at Open Science Framework <https://osf.io/dzqen/files/>.

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