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A U.S. State-level Analysis of the Presidential Election in 2016: IQ, Race, and Well-being Emerge as Mutually-Suppressed Predictors

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Abstract

I report U.S. state-level relationships between measures of race, IQ, other well-being variables (e.g., income, health), and the results of the 2016 U.S. presidential election. Based on prior research (Pesta & McDaniel, 2014), I predicted first that IQ and race would be relatively unrelated to election results in bivariate analysis. Instead, a mutual suppression effect was expected, such that IQ would more strongly predict election outcomes when controlling for race, and vice versa. The predicted pattern appeared; so too did mutual suppression effects between racial composition and most but not all other measures of state well-being (i.e., religiosity, crime, education, health, and income) used here. The suppression patterns consistently revealed that after adjusting for racial composition, blue states were smarter and more prosperous than were red states. I conclude that at the aggregate level of the U.S. state, conservatism (as measured here by the state percent of votes cast for Trump) is inversely related to IQ and other measures of well-being.

Keywords: Intelligence, IQ, Race, Well-being, Presidential elections, Red-states / blue-states

1 Introduction

In America, a "blue state" is one whose residents reliably vote Democrat, while a "red state" is one whose residents mostly vote Republican. My primary focus here is on whether blue states are smarter than red states. I use the percent of residents who voted for Donald Trump in the 2016 U.S. presidential election as the measure of state blueness / redness, and I employ Mcdaniel (2006) estimated IQ scores as the measure of state intelligence.

Secondarily, since U.S. state-level IQ scores vary strongly with other important variables (e.g., income, health), I am also interested in whether blue states have higher levels of average "well-being." Pesta et al. (2010) (see also Kirkegaard (2015)) showed that at the level of the U.S. state, almost all measures (i.e., "subdomains") of well-being are intrinsically intercorrelated. Specifically, they found that the subdomains of intelligence, religiosity, crime, education, health, and income covaried so strongly that a general factor of state "well-being" could be derived. The general factor of well-being (and, separately, many of its individual sub-domains) then predicted other important political, social, and economic outcomes (Pesta et al., 2010). Most relevant to the present study, well-being predicted U.S. presidential election outcomes for the years 2000, 2004, 2008, and 2012 (Pesta & McDaniel, 2014). In sum, although I am primarily interested in IQ as the predictor measure, I also present analyses employing the five other sub-domains of well-being.

Third, even at the U.S. state level, IQ and race / ethnicity covary strongly. But, race has been a surprisingly poor predictor of state-level election outcomes, regardless of whether the presidential candidate was Black or White. For example, the percent of state residents who were Black or Hispanic correlated only .08 and .14 with votes cast for Barack Obama in the 2008 and 2012 presidential elections, respectively (Pesta & McDaniel, 2014). These correlations, however, increased substantially when controlling for state IQ (Pesta & McDaniel, 2014). I am therefore also interested in whether state racial composition, by itself, or in conjunction with other variables, predicts state-level results of the 2016 U.S. presidential election.

In sum, here I report how measures of U.S. state racial composition, IQ, and five other measures of

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well-being (i.e., religiosity, income, education, health, and crime) predict results of the 2016 presidential election. Based on Pesta & McDaniel (2014), I expect these measures will predict better when entered together in regression equations, versus when entered alone. Of specific interest, I predict that race and IQ, and then race and the other well-being variables will mutually suppress each other, as further described below.

1.1 Suppression Situations

In multiple regression, a suppression situation exists when an independent variable's predictive power extends beyond that indicated by its bivariate correlation with a dependent variable (Conger, 1974). The classic example was perhaps provided by Horst (1941), who tried to predict pilot success in a training program from measures of mechanical, numerical, spatial, and verbal ability. In the bivariate sense, the first three ability variables correlated with pilot success; whereas, verbal ability did not. When all four predictors were included in the model, verbal ability now strongly predicted pilot success. The suppression effect occurred because verbal ability was requisite for pilot trainees to read the instructions and the items on the tests (Horst, 1941).

In the more complex case, reciprocal / mutual suppression occurs when both independent variables are inversely related to each other, but relatively unrelated to the dependent variable (Cohen & Cohen, 1983; Pandey & Elliott, 2010; Tzelgov & Henik, 1991). For example, and as previewed above, Pesta & McDaniel (2014) analyzed U.S. state-level data for the four presidential elections held between 2000 and 2012. They discovered that in bivariate analyses, IQ and race (i.e., percent Black or Hispanic) correlated inversely with each other, but near zero with any election's result. However, when both IQ and race appeared in the same regression equation, robust mutual suppression effects emerged. IQ now strongly predicted election results when controlling for race, and race now strongly predicted election results when controlling for IQ. The pattern of suppression was such that higher state IQ predicted votes cast for Democrats; so too did the percent of state residents who were Black or Hispanic. These effects appeared in all four presidential elections.

The mutual suppression effects resulted from state-level inverse relationships between IQ and race, but positive relationships between IQ and liberalism (i.e., votes cast for democrats). That is,

1. Whiter states were smarter on average, but
2. smarter states voted Democrat on average, and
3. Democratic states had fewer Whites (i.e., more Blacks or Hispanics) on average.

This covariance pattern created strong, mutual suppression effects when predicting the past four presidential elections.

1.2 Political orientation and IQ

A mixed literature exists on the relationship between political orientation (i.e., liberalism / conservativism) and IQ. It is also complicated by the fact that different researchers look at different levels of analyses (e.g., people, versus the U.S. states), or they use different proxies for what constitutes political orientation (e.g., votes cast for conservatives or liberals, party affiliation, surveys measuring political attitudes, etc.).

Nonetheless, Rindermann et al. (2012) reported that IQ was highest for center-right political orientations (as measured by a survey; see also, Woodley (2010). Some older studies also show this pattern. Katz (1990) found that conservative beliefs (i.e., adherence to right wing views) correlated positively with WAIS performance-scale IQ. Martin & Ray (1972) likewise reported positive correlations with IQ and an instrument measuring conservatism / authoritarianism.

More recently, a meta-analysis (Onraet et al., 2015) showed lower cognitive ability for people high in right-wing ideological attitudes. Carl (2014a,b) presented data indicating higher cognitive ability for people who identify as Republican. Ganzach (2016), however, showed that Carl (2014a,b)'s effects disappear when controlling for race.

Conversely, some studies find that higher IQ predicts more liberal attitudes (Deary et al., 2008; Schoon et al., 2010). In particular, Stankov (2009) reported that "Conservative Syndrome (CS)" correlated inversely with cognitive ability, both in a large sample of individuals, and at the aggregate-level across 73 nations.

Conservative Syndrome (Stankov, 2007, 2009) is a latent trait capturing some of the variance in scales measuring attributes like personality, attitudes, values, and norms. Examples of traits possessed by people scoring high on CS include "religious," "moderate," "self- disciplined," "polite," and "obedient." People scoring high on CS also have personalities that are high in Conscientiousness, but low in Openness (see Stankov (2007, p. 300)).

Interestingly, Stankov (2007) hypothesized that:

> The data at the national level are consistent with the assumption that there exists a common dimension, perhaps best understood as an affluence / poverty dimension that is the source of aggregate-level differences. This latent dimension is defined

in terms of GDP and other macroeconomic measures (p. 303).

The affluence / poverty dimension Stankov (2009) refers to seems to parallel the U.S. well-being nexus postulated by Pesta et al. (2010). This hypothesis could be supported by showing that a more recent measure of conservatism (i.e., votes cast for the U.S. Republican presidential candidate in 2016) correlates with U.S. state IQ and the various other sub-domains of well-being.

1.3 Political orientation and U.S. State IQ

In addition to Pesta & McDaniel (2014), two other studies exist which looked at U.S. state-level relationships between IQ and liberalism / conservatism. Kemmelmeier (2008) found an interaction such that cognitive ability was lower for conservative states with high political involvement, but higher for conservative states with low political involvement. In a different vein, Pesta et al. (2010) correlated their well-being measures (described above) with various state-level variables thought to measure liberalism / conservatism. Consistent with Stankov (2009)'s hypothesis about the cause of Conservative Syndrome, both the well-being component scores, and the sub-domain scores, correlated moderately-to-largely with state measures of liberalism / conservatism. Examples of these criterion variables included the percentage of residents who owned guns; were atheist; or were in same-sex households. Likewise, state minimum wage, and mean teacher salary correlated positively with the well-being variables.

Given review of the literature, I predict that in bivariate analysis,

1. U.S. state IQ will correlate only weakly with 2016 presidential election results;
2. so too will U.S. state racial composition. However, in multiple regression analysis,
3. a strong, mutual suppression situation will emerge such that IQ will correlate inversely with presidential election results (i.e., percent Trump); whereas, race (i.e., percent White) will correlate positively.
4. Finally, I predict the same pattern of mutual suppression will exist with race and the other well-being variables.

Namely, with race controlled, state religiosity, crime, health, and income will become even stronger predictors of the election (and vice versa). I exclude state-level education in my predictions, as it failed to emerge as a strong suppressor variable in Pesta & McDaniel (2014). Thus, race adjusted, I predict that religiosity and crime should correlate positively with percent Trump; whereas, IQ, health, income, and global well-being should correlate negatively.

2 Method

2.1 Measures

The population was the 50 U.S. states, and the primary dependent measure was the percent of votes cast for Donald Trump within each state. I coded the percentages from CNN (*Presidential Results*, 2016). To avoid redundancy, I analyzed data only on percent Trump, as these values correlated -.94 by U.S. state with percent Clinton. Race data for each state were retrieved from the U.S. Census. Variables included the percent of residents in each state (in 2015) who were White, Black, or Hispanic (U. S. Census, 2016)[1]. Consistent with Pesta & McDaniel (2014), I also created a composite variable (percent Black or Hispanic) that was the sum of state residents who were either Black or Hispanic.

The well-being variables were derived from Pesta et al. (2010), and included U.S. state- level measures of IQ, religiosity, crime, education, health, and income, plus a global well-being composite score resulting from principal component analysis (PCA) of these six, sub-domains. State IQ scores originally came from Mcdaniel (2006), who estimated them from public school achievement test scores. Religiosity was created with state-level data measuring fundamentalist religious beliefs (e.g., "My holy book is literally true;" "Mine is the one true faith"). Crime was derived from burglary, murder, rape, and violent crime rates, as well as the number of inmates per capita, in each state. Education included the percentage of state residents with college degrees, and the percentage of the labor force in jobs related to science, technology, engineering or mathematics. Health contained a set of variables ranging from infant mortality to the incidence of obesity, smoking, and heart disease by U.S. state. Finally, Income was composed of variables including: income per capita, disposable income per capita, percent of families in poverty, and percent of individuals in poverty (see Pesta et al. (2010), for complete descriptions of these variables, together with their values by U.S. state).

2.2 Analyses

My analyses first involved calculating bivariate correlations for all variables coded in this study. Regarding

[1] The U.S. Census codes race and Hispanic as separate variables such that Hispanics may be of any race. I defined Hispanic as any self-identified Hispanic regardless of race, and I defined Blacks as non-Hispanic Blacks.

predicted relationships with percent Trump: IQ and race should show little to no correlation; whereas, the five well-being variables should correlate with percent Trump in ways that replicate Pesta & McDaniel (2014). Tests with bivariate analyses are less important than are tests for the existence of suppression effects.

In multiple regression, suppression exists when the beta weight for a variable alone in an equation increases when entered together with some other variable (see, e.g., Cohen & Cohen (1983); Tzelgov & Henik (1991)). Tests for suppressor variables here involved a series of multiple regressions, each initially including just two independent variables (due to strong multicollinearity—see, e.g., Pesta et al. (2010)). I predicted that the beta weights for IQ and then the well-being variables would increase considerably after controlling for race, and vice versa. In the first set of regressions, IQ was entered together with percent White only, then percent Black only, then percent Hispanic only, and then percent Black or Hispanic only. Based on results of these analyses, twelve more regressions were run, each using a single well-being variable and either percent White, or percent Black or Hispanic (i.e., the key race variable used by Pesta & McDaniel (2014)), as predictors of percent Trump. Finally, additional regressions and a PCA were ran—results of which appear mostly in the supplementary materials file[2]—in an attempt to address why IQ, race adjusted, predicted the results of the 2016 U.S. presidential election.

3 Results

Across the 50 U.S. States, the mean percent of votes cast for Trump was 50 (SD = 10). This value was 44 (SD = 11) for Clinton, $t(49) = 2.01$, $p = .05$, $d = .57$. Likewise, the state mean percentage of non-Hispanic Whites was 70 (SD = 16); of Blacks, was 10 (SD = 10); and of Hispanics, was 12 (SD = 10). From prior research, state IQ has a mean of 100.3, and a standard deviation of 2.7 (Mcdaniel, 2006). Religiosity, crime, education, health, income, and well-being are Z scores (Pesta et al., 2010).

Table 1 is a correlation matrix of all study variables. As predicted, the bivariate correlation between IQ and percent Trump is near zero (r = -.06). Regarding the race variables, non-significant correlations existed for percent Black (r = .07), and for percent Black or Hispanic (r = .25). Conversely, percent White (r = .42), and percent Hispanic (r = -.38) correlated moderately with votes cast for Trump. These latter effects did not occur in the past four presidential elections (Pesta & McDaniel, 2014). My primary focus here, however, is on whether race and IQ suppress each other when entered together into the same regression equation.

Also in Table 1, all other well-being variables except crime showed moderate to large correlations with percent Trump. These results closely match those found by Pesta & McDaniel (2014). Bivariate correlations, however, are misleading in suppression situations. Looking just at Table 1, it appears that red (i.e., high percent-Trump) states fare no better or worse on IQ than do blue (i.e., low percent-Trump) states. Yet, given the above-described differences in covariance between IQ, race, and voter preference, suppression effects may exist. Table 2 reports analyses regarding the existence of mutual suppression effects for IQ and race.

In Table 2, the beta weight for IQ predicting percent Trump goes from -.06 to -.65 before and after controlling for percent White. Likewise, the beta weight for percent White increases from .42 to .87 in the same comparison. Thus, a mutual suppression situation exists. The situation is robust. When entered alone, IQ (0 %) plus percent White (18 %) sum to explain just 18 % of the variance in percent Trump. Entered together, they explain 41 % (+128 %). Similarly, but not as strong, IQ and percent Black or Hispanic mutually suppress each other. When both variables are in the regression, the IQ beta changes from -.06 to -.36, and the percent Black or Hispanic beta changes from -.25 to -.48.

IQ's beta weight also increases in the regression equation that includes percent Hispanic. Likewise, the beta weight for percent Hispanic goes up nominally, relative to its bivariate correlation in Table 1. Finally, combining IQ and percent Black into a regression equation does nothing to predict percent Trump over and above each's bivariate correlation with the dependent variable.

Summing up the analyses with IQ and race, strong suppression effects exist, but they do not occur for every racial grouping. Only IQ and percent White, and IQ and percent Black or Hispanic, suppress each other. IQ predicts percent Trump only when controlling for percent White (or percent Black or Hispanic). Percent White (or percent Black or Hispanic) predicts percent Trump, especially when controlling for IQ. These results replicate those reported by Pesta & McDaniel (2014) using prior presidential election data. In Pesta & McDaniel (2014), for example, percent Black and IQ also failed to suppress each other in the 2000, 2004, 2008, and 2012 U.S. presidential elections. I therefore used percent White, and then separately, percent Black or Hispanic, as the variables representing race in the regression equations that follow.

Table 3 shows whether suppression effects exist when predicting percent Trump from percent White and

[2] This file contains the raw data, plus regression results where IQ and % White are paired with all possible combinations of the five other well-being variables.

Table 1: Correlation Matrix of All Study Variables.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Trump	–	-.94	.42	.07	-.38	-.25	-.06	.58	.10	-.65	-.40	-.53	-.47
2. Clinton		–	-.45	.11	.31	.33	.00	-.54	.00	.53	.23	.50	.36
3. White			–	-.38	-.67	-.80	.68	-.18	-.62	-.13	.39	.01	.37
4. Black				–		-.62	-.50	.58	.62	-.33	-.72	-.27	-.62
5. Hispanic					–	.69	-.34	-.13	.35	-.28	-.06	.05	-.06
6. Black or Hispanic						–	-.64	.32	.73	-.02	-.58	-.16	-.51
7. IQ							–	-.55	-.76	.41	.75	.57	.83
8. Religiosity								–	.51	-.62	-.68	-.72	-.83
9. Crime									–	-.26	-.82	-.42	-.78
10. Education										–	.61	.66	.72
11. Health											–	.63	.92
12. Income												–	.81
13. Well-being													–

Note: Variables 1-6 are percentiles. Variable 7 has a mean of 100.3, and a standard deviation of 2.7. Variables 8-13 are Z scores. A correlation of .28 is significant at p < .05.

Table 2: The Mutual Suppression of Race and State IQ when Predicting Percent Trump.

Variable	B	*SE B*	*B*	R^2
White %				
IQ (-.06)	-2.43	.573	-.652	–
% White (.42)	56.3	10.0	.870	–
				41 %
Black %				
IQ (-.06)	-.105	.625	-.028	–
% Black (.07)	6.18	17.9	.058	–
				00 %
Hispanic %				
IQ (-.06)	-.783	.523	-.210	–
% Hispanic (-.38)	-44.2	13.8	-.449	–
				18 %
Black or Hispanic %				
IQ (-.06)	-1.34	.653	-.360	–
% Black or Hispanic (-.25)	-37.2	13.7	-.476	–
				14 %

Note: Values in parentheses represent the standardized Beta weight for the variable when it alone is entered to predict percent Trump. These values mirror the correlations reported in Table 1.

any of the other (i.e., beside IQ) well-being variables. By itself, religiosity strongly predicts percent Trump (r = .58). Adding percent White into the equation nonetheless results in suppression, as religiosity's beta weight now increases to .67. Likewise, the beta weight for percent White, itself, increases from .42 to .55 in the same equation.

In terms of magnitude, the largest suppression effect in Table 3 exists with crime and percent White. Crime's bivariate correlation with percent Trump is just .10, but this increases to . 59 when controlling for percent White. Likewise, percent White's beta weight changed from .42 to .79 in the two-variable equation. Very strong suppression effects also appear with the global well-being measure, whose beta increases from -.47 to -.72 before and after controlling for percent White. Similar but somewhat weaker suppression effects occur with the health domain of well-being. Finally, suppression effects were absent when percent White and education, and percent White and income, were entered together in regression equations (all three variables, however, correlated with percent Trump in Table 1). The lack of suppression with education was predicted, because it replicates Pesta & McDaniel (2014); whereas, the lack of suppression with income was not.

Table 4 is in some sense a replication of Table 3, as the former uses percent Black or Hispanic to represent race; whereas, the later used percent White. The pattern of suppression is the same across the five well-being variables in each table. Mutual suppression exists with percent Black or Hispanic and religiosity, crime, health, and global well-being, but neither with education nor income.

What happens when race and IQ are entered together with the other well-being variables to predict percent Trump? The answer is clouded by the existence of multi-collinearity, as shown in Table 5.

Here all six well-being variables plus percent White are entered to predict percent Trump. The multiple

Table 3: The Mutual Suppression of State Well-being Variables and Percent White when Predicting Percent Trump.

Well-being Variable	B	*SE B*	*B*	R^2
Religiosity %				
% White (.42)	35.3	5.91	.545	–
Religiosity (.58)	6.90	.921	.674	–
				62 %
Crime %				
% White (.42)	51.2	9.40	.792	–
Crime (.10)	6.00	1.50	5.90	–
				39 %
Education				
% White (.42)	22.5	6.44	.348	–
Education (-.65)	-6.11	1.00	-.606	–
				54 %
Health %				
% White (.42)	44.2	6.84	.683	–
Health (-.40)	-6.70	1.07	-.665	–
				56 %
Income %				
% White (.42)	27.7	6.89	.429	–
Income (-.53)	-5.41	1.07	-.536	–
				47 %
Well-being %				
% White (.42)	44.6	6.20	.69	–
Well-being (-.47)	-7.26	0.97	-.72	–
				63 %

Note: Values in parentheses represent the standardized beta weight for the variable when it alone is entered to predict percent Trump. These values mirror the correlations reported in Table 1.

Table 4: The Mutual Suppression of State Well-being Variables and Percent Black or Hispanic when Predicting Percent Trump.

Well-being Variable	B	*SE B*	*B*	R^2
Religiosity %				
% Black / Hispanic (-.25)	-37.4	8.16	-.479	–
Religiosity (.58)	7.35	1.05	.729	–
				54 %
Crime %				
% Black / Hispanic (-.25)	-52.5	14.6	-.672	–
Crime (.10)	5.90	1.89	.585	–
				22 %
Education				
% Black / Hispanic (-.25)	20.6	8.13	-.263	–
Education (-.65)	-6.62	1.05	-.656	–
				49 %
Health %				
% Black / Hispanic (-.25)	-56.3	9.86	-.720	–
Health (-.40)	-8.23	1.27	-.816	–
				50 %
Income %				
% Black / Hispanic (-.25)	-26.4	8.97	-.338	–
Income (-.53)	-5.90	1.16	-.586	–
				40 %
Well-being %				
% Black / Hispanic (-.25)	-50.9	9.05	.651	–
Well-being (-.47)	-8.03	1.17	.800	–
				53 %

Note: Values in parentheses represent the standardized beta weight for the variable when it alone is entered to predict percent Trump. These values mirror the correlations reported in Table 1.

correlation is .83, yet most of the betas are small, and only religiosity and percent White emerge as significant predictors. Moreover, while no Variance Inflation Factor is greater than ten, three—including IQ—are greater than five. This pattern of co-linearity led Pesta & McDaniel (2014) to report just two-variable regressions.

Regression results including IQ, percent White, and some other number of the other five well-being variables are also hard to interpret. All these analyses appear in the Supplementary Materials file. On balance, these regressions produce inconsistent results, which I attribute to co- linearity. In partial support of this, Table 6 is a PCA including percent Trump, percent White, and all six, well-being variables. The first component is arguably "well-being." Note that percent Trump loads moderately-strongly (-.51) on this component. However, percent White loads only nominally (.370) on the first component, perhaps because of how unsurprisingly the second component captures the covariance between percent White and percent Trump (i.e., Whiter states were Trump states). At any rate, the two components explained 82 % of the variance in the variables included in this PCA, and 83 % of the variance in percent Trump, specifically.

The above PCA, however, comprised the unrotated solution. When rotated obliquely (the components correlated .21 with each other), both IQ (.43) and percent Trump (-.84) load on Component 1, and when rotated orthogonally, IQ (.31) failed to load on Component 1; whereas, percent Trump (-.88) still did. Hence the conclusions change depending on whether the PCA is rotated, and whether the rotation assumes correlated or uncorrelated components. I have no explanation for why this disparity across methods occurred, so the PCA results (testing whether IQ and percent Trump are captured by the same component) should be viewed with caution.

Table 5: Predicting Percent Trump from Percent White and the Six, Sub-domains of Well-being.

Variable	Beta	Variance Inflation Factor
% White	0.49	4.19
IQ	0.15	6.13
Religiosity	0.42	2.68
Crime	0.06	5.27
Education	−0.24	3.08
Health	−0.22	6.76
Income	−0.01	3.45

Table 6: **(Mangler input)** Principal Components Analysis (Unrotated) on the Well-being Variables, Percent Trump, and Percent White.

Variable	Component 1	Component 2
IQ	0.821	0.444
Religiosity	−0.844	0.210
Crime	−0.771	−0.473
Education	0.721	−0.487
Health	0.920	0.111
Income	0.804	−0.302
% Trump	−0.506	0.754
% White	0.370	0.870
(% Variance Explained)	54.8	26.6

4 Discussion

I attempted to predict U.S. state-level results of the 2016 presidential election by using measures of IQ, race, and well-being. Several hypotheses were tested. First, I predicted weak (relative to suppression analyses) bivariate correlations with IQ, race, and percent Trump. This prediction was confirmed, especially for percent Black, and percent Black or Hispanic. These variables did not correlate with percent Trump. Further, although, percent White, and percent Hispanic, both correlated moderately with percent Trump, these effects were weak, relative to those seen when testing for most suppression effects.

Second, I predicted suppression effects with IQ, race, and the other well-being variables as predictors of the 2016 U.S. presidential election. IQ and race clearly and strongly suppressed each other. Controlling for percent White (or percent Black or Hispanic), blue states were smarter than red states. Controlling for IQ, blue states were less White (or more Black or Hispanic) than red states. Likewise, race and most of the other five, well-being variables also suppressed each other. Controlling for race, blue states had even higher levels of global well- being, and health, and even lower levels of crime and religiosity. Controlling for many of the well-being variables, percent White (and percent Black or Hispanic) even more strongly predicted percent Trump.

Spearman (1927) hypothesized the existence of a general factor of intelligence—g— based on his discovery of the positive manifold. The positive manifold refers to the empirical finding that cognitive test scores correlate positively among individuals. Decades later, Jensen (1998) postulated the existence of a "g nexus" to characterize the impressive number of psychological, sociological, and biological variables that co-vary with g (as measured in individuals).

This century, researchers have gone beyond studying just individual differences in intelligence. Instead, a new differential psychology has emerged, focusing on intelligence differences across geo-political subdivisions of individuals. Examples of theses subdivisions include the 50 United States (Pesta et al., 2010), nations across the world (Lynn & Vanhanen, 2002, 2012), north / south differences in Italy (Lynn, 2010), and states / provinces in the Americas (Fuerst & Kirkegaard, 2016).

Studies that feature aggregate-level data produce something akin to both the positive manifold, and the g nexus. Much like correlations between math, verbal, and spatial test scores among individuals, U.S. state values on IQ, crime, health, income, etc., are strongly related. Moreover, these relationships make sense. High state IQ, for example, is associated with lower rates of crime and religiosity, and higher rates of health, income, and education. Pesta et al. (2010) labelled the supposed common cause for these effects "well-being." Kirkegaard (2015) called it the "S" (i.e., socioeconomic) factor.

In this study, I attempted to predict a specific node (i.e., liberalism / conservatism) in the well-being nexus from state rankings on other nodes (i.e., IQ, race, and well-being). Prediction mostly failed when IQ or race alone appeared in the regression equation. When combined, however, each strongly predicted the percent of state residents voting for Trump. Recall that Stankov (2009) hypothesized the existence of a "common dimension, perhaps best understood as an affluence / poverty dimension, that is the source of aggregate-level differences [in conservatism] (p. 303)". A reasonable inference is that this common dimension is well-being, and that well-being partly explains aggregate- (i.e., U.S. state-) level difference in conservatism.

Limitations to the present study include the potential to commit the ecological fallacy (Robinson, 1950). Effects existing with groups of people (i.e., residents of the 50 U.S. states) may not generalize to individuals within groups. One cannot infer from the present data that a liberal individual is likely smarter than a conservative individual. Moreover, studies using aggregate-level data can produce higher correlations than those that use individual-level data for statistical rather than psychological reasons (Ostroff, 1993). Second, neither all measures of race, nor all measures of well-being, showed the predicted suppression effects. For example, U.S. state income and racial composition did not create a suppression situation. Nonetheless, I tested for the existence of 14 possible mutual suppression effects across Tables 2, 3 and 4. Suppression effects existed in eight (57 %) of these tests.

Third, my study contained only 50 observations on each variable. However, these were population parameters representing the entire United States. There are no more cases to add, and none of the analyses above involved estimating population values from some sample. Instead, values for each U.S. state were aggregates, representing variance across millions of people.

In sum, I attempted to predict U.S. state-level results of the 2016 presidential election by using measures of IQ, race, and well-being. Large, mutual suppression effects existed in most cases. Of specific interest, IQ predicted the election only after controlling for race. Similar results occurred with race and most of the other well-being measures. I conclude that blue states are smarter and more prosperous than red states, but that these effects are masked by state racial composition. Moreover, conservativism (i.e., using percent Trump as its proxy) is inversely related to well-being at the level of the 50 U.S. states.

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