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So What "*Should*" We Use? Evaluating the Impact of Five Racial Measures on Markers of Social Inequality

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Abstract

In recent years, researchers have increasingly noted the malleability of racial boundaries across time, context, and life course. Although this research has advanced our knowledge of the maintenance and perceptions of racial groups, it has introduced a new question: If we are attempting to best capture the actual variation in racial inequality, how should we operationalize race? Using the 2006 wave of the Portraits of American Life Study, a national-level, in-home survey with extensive race measures and oversamples of Blacks, Hispanics, and Asians, the authors identify five ways that race can be and to varying degrees is operationalized: census, combined race/ethnic, pentagon, triracial, and skin tone measures. Using the Vuong non-nested model tests, the authors compare the effectiveness of these five measurements in predicting three measures of social inequality: household income, education, and self-rated health. The authors find that overall, Hollinger's ethnoracial pentagon is best able to capture existing inequality. Thus, for scholars attempting to understand variation in contemporary racial inequality, this research suggests that scholars should use five monoracial categories: White, Black, Hispanic, Native American and Asian.

Keywords

race, racial inequality, quantitative studies, measurement, racial classification

Research in the United States undeniably demonstrates persistent racial inequalities on various measures of socioeconomic status and quality of life (Bobo and Thompson 2010; Hall and Crowder 2011; Lewis 2003; Oliver and Shapiro 1995; Royster 2003; Saperstein and Penner 2013; Williams and Sternthal 2010). However, how we measure "race" is complex, contextual, time bound, and theoretically and often politically based (Lopez 1996; Mora 2014; Nobles 2000; Roth 2012). Thus, race scholars, social activists, and journalists are presented with the challenge of simultaneously illuminating the social construction of racial categories while demonstrating their real consequences. For instance in recent months, the Black Lives Matter movement has stressed the need for racial equity, particularly for Blacks. Simultaneously, the revelation that an NAACP activist, Rachel Dolezal, is transracial (born into a White family but identifies as Black) reinvigorated the question—who is *Black*? These concurrent conversations illuminated the tension between activists fighting for equality while desiring to nuance the public's understanding of racial categories.

Multiple scholars do an excellent job of diving into these complexities and exploring how the malleability of racial categories actually further solidifies racial inequalities (Bonilla-Silva 2004; Roth

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2012; Saperstein and Penner 2013). Yet the truth is that every article on racial inequality does not have the space to both explore multiple race operationalizations and present findings regarding race's influence on social outcomes. Given this reality, most quantitative scholars often default to the operationalizations of race available in their data sets. As a result, the important and vast research on the contextual and changing nature of racial categories is typically ignored in studies of racial inequality. Building on the work of race scholars who have illuminated the complexities of racial classifications, the present study is a quantitative research note that compares five proposed operationalizations of race and empirically examines which best captures the variation in contemporary income, educational, and health inequalities. Thus, we are not attempting with this research to replace work on the social construction of race or suggesting that researchers should not make theoretically driven decisions about how they operationalize race. Instead, we are standing on the shoulders of such research and using it to inform scholars on how they might operationalize race in examinations of U.S. contemporary inequality.

THEORETICAL BACKGROUND

Historically, race was perceived as an undeniable, innate, and biologically driven classification of humans into distinct, hierarchically ordered categories. Social scientists now argue that this conception itself, and not biology, is what created race (Smedley and Smedley 2012). Nonetheless, the prevalence and duration of this belief across centuries has resulted in ongoing social inequalities. But because the categories are socially constructed, they continue to mutate (Khanna 2011; Morning 2009; Obasogie 2014; Saperstein and Penner 2013). Thus, no one can identify "true" racial classifications, because they do not exist. We can, however, illuminate which operationalizations of race at one point in time are most associated with inequality. To do so, we first review common operationalizations of race and social outcomes theorized to be stratified by race.

Five Common Measures of Race

The most common measure of race in the United States is the *census measure*. This measure includes seven categories: White, Black, Asian, Native Hawaiian and Pacific Islander, Native American/American Indian, Other, and Two or More Races. Its popularity derives from the fact that is required on a majority of government forms, and many surveys use it to ensure that their samples correlate with the racial proportions found in the decennial census. The U.S. Census Bureau works closely with social scientists to maintain an operationalization of race that reflects the contemporary understanding of race in the population. Yet any major change must be approved by Congress, meaning that this operationalization of race does not change as quickly as racial classifications. In fact, currently the Census Bureau is undertaking studies to explore whether "Hispanic" should be added as a racial category (Compton et al. 2012).

Since the 1960s, when Hispanic/Latino ethnicity was first proposed, there has been debate regarding if the Hispanic/Latino ethnicity question should be combined with the race question or remain a separate question (Mora 2014). Recent research has demonstrated that the U.S. public conceptualizes Hispanic as a distinct race (Frank, Akresh, and Lu 2010; Golash-Boza and Darity 2008; Roth 2012; Saperstein and Penner 2013). Hence, many social scientists have adopted a *combined race/ethnic measure*. This measure is the same as the census measure but adds an eighth category: "Hispanic." In this operationalization of race, all Hispanic respondents, no matter their racial identification, are categorized as one unified group. For example, Black Dominicans are included in the Hispanic category rather than the Black category.

Other researchers agree with the use of Hispanic as a racial category but argue the general public does not differentiate among all eight of the combined race/ethnic categories (Hollinger 2006; Smedley and Smedley 2012). Specifically, categories such as multiracial, Native Hawaiian/Pacific Islander, and Other are not perceived as distinct classifications. Instead, Hollinger (2006) argued that U.S. residents categorize humans into ethnicities (e.g., Italian, Mexican), each of which they associate with one of five monoracial categories—White, Black, Hispanic, Asian, or Native American. Hence, he called this the ethnoracial *pentagon measure* and suggested once people categorize others into these five groups, they unconsciously or consciously treat them accordingly, meaning that social inequalities fall along these same lines.

Still other researchers posit the United States is becoming similar to Latin America, where individuals' skin tones and phenotypes are used to identify racial classification. Specifically, Eduardo Bonilla-Silva (2004) put forth the *triracial measure*, which includes the categories White, Honorary White, and Collective Black. He argued that U.S. residents use a combination of physical appearance and ethnic heritage to categorize individuals into three distinct groups. Bonilla-Silva suggested that contemporary and future racial inequalities will fall among these three groups. Other scholars, such as Lynn (2008), agree with Bonilla-Silva's assertion that racial classifications are increasingly based on individual appearance but disagree that people are then placed into three distinct categories. Instead, some operationalize race on the basis of *skin tone*. Investigation into the socioeconomic inequality within racial groups on the basis of skin tone provide initial evidence that racial inequalities in the United States might vary on a phenotypical spectrum (Golash-Boza and Darity 2008; Hill 2002; Hochschild 2007; Hunter 2002; Keith and Herring 1991; Villarreal 2010).

All five of these measures of race—census, combined race/ethnic, pentagon, triracial, and skin tone—have theoretical bases, and each has its role in the study of race. Nevertheless, in the present study we are interested in which of these measures best captures contemporary inequality. Thus, we now examine racial inequalities.

Racial Inequalities

Multiple mechanisms perpetuate inequalities between racial groups. In the United States currently, three mechanisms are particularly potent. First is overt discrimination, which is when influential professionals such as employers, school teachers, and doctors make assumptions about individuals' abilities or diagnoses on the basis of racial stereotypes (Lewis 2003; Pager 2003; Royster 2003). The second mechanism is inherited disadvantage, when historical discrimination is passed down through material inheritance, such as knowledge of educational institutions and access to quality health care (Jackson 1985; Oliver and Shapiro 1995). The third and final mechanism is racial residential and educational segregation that has enabled unequal appreciation of home values and access to unequal educational resources and quality food and recreation (Lareau and Goyette 2014; Massey and Denton 1993; Sampson 2012; Sharkey 2013).

To illuminate what operationalization of race best captures variation across social outcomes, we choose three outcomes that are influenced by all three mechanisms. The first outcome we consider is income. As mentioned above, income is influenced by employers' overt racial discrimination in hiring, firing, and wage compensation decisions (Pager 2003; Royster 2003). Moreover, income is also influenced by inheritance and appreciation of housing values, which depend on past discrimination and neighborhood location (Jackson 1985; Oliver and Shapiro 1995; Sharkey 2013). The second outcome, education, is similarly influenced by overt discrimination in the classroom (Lewis 2003). Additionally, educational outcomes are influenced by school resources and parents' knowledge of educational systems, which in turn are often determined by residential neighborhood and parent's access to education. Finally, we examine health. Health is also influenced by overt discrimination from doctors as well as parents' health and neighborhood access to supermarkets and exercise facilities (Williams and Sternthal 2010), among other factors.

DATA AND METHODS

Finding a data set that has enough information regarding respondents' heritages and phenotypes to enable us to compare the various racial measurements is no easy task. Fortunately, the 2006 wave of the Portraits of American Life Study (PALS; n = 2,610), a national-level, in-home survey with extensive race measures and oversamples of Blacks, Hispanics, and Asians, is well served for the purposes of this study.[1] Below we explain how each of our race measurements are operationalized.

Operationalization of Racial Measurements

Census measure. In the PALS data, there is no variable that matches the census definition of race as White, Black, Asian, Native Hawaiian and Pacific Islander, Native American/American Indian, Other, and Two or More Races. However, it can be easily derived. Respondents were first asked to self-identify as White, Black, Hispanic, Asian American, Native Hawaiian and Pacific Islander, Native American/American Indian, Mixed Race, or Other. Then, Hispanic respondents were asked if they considered themselves White, Black, Asian American, Native Hawaiian and Pacific Islander, Native American/American Indian, or Other. So the census race variable is retrospectively created by taking those who identified as Hispanic and assigning them the race they selected during the follow-up question. Hispanic respondents who did not choose a category but chose their own responses were then coded to match the categories provided. For example, if they said "Mixed Race," "Black and Puerto Rican," or "Mulatto" they were coded as Multiracial. If they answered, "Brown," "Mexican," "Latino/Hispanic," et cetera, they were coded as "Other." For the demographic breakdown of the PALS sample, see Tables 1A and 1B.

Table 1A. Descriptive Statistics of Racial Measurements (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Triracial		Skin Tone	
White	0.5665	White	0.4851	White	0.4963	White	0.5017	*Mean*	0.29
Black	0.2086	Black	0.2032	Black	0.2090	Honorary White	0.2881	*SD*	0.32
Asian	0.0694	Hispanic	0.1958	Hispanic	0.2094	Collective Black	0.2102		
Pac. Islander	0.0050	Asian	0.0686	Asian	0.0783				
Nat. Amer.	0.0140	Pac. Islander	0.0050	Nat. Amer.	0.0070				
Mixed Race	0.0279	Nat. Amer.	0.0050						
Other	0.1086	Mixed Race	0.0233						
		Other	0.0140						

Note. Pac. Islander = Pacific Islander. Nat. Amer. = Native American.

Table 1B. Descriptive Statistics of Dependent Variables (n = 2,579).

Variable	Mean (*SD*)
Household income	\$52,322 (\$43,252)
Education (years)	13.2 (2.5)
Self-rated health[a]	3.43 (1.14)

[a]Health was rated by respondents on a scale ranging from 1 to 5 on which 5 represents "excellent" health and 1 represents "poor" health.

Combined race/ethnic measure. For this measure we used the first question on race in PALS, which asks respondents to identify as White, Black, Hispanic, Asian American, Native Hawaiian and Pacific Islander, Native American/American Indian, Mixed Race, or Other.

Pentagon measure. PALS also provides the pentagon measure in the public data set. Self-identified White, Black, Hispanic, Asian, or Native American monoracial respondents are assigned to their corresponding categories. Following the historical precedent of the Census Bureau, respondents who identified as Native Hawaiian and Pacific Islander were coded as Asian. Respondents who identified as multiracial were asked which of their multiple racial groups they most closely identified with. They were then recoded as belonging to that racial category.[2] Respondents who identified as "Other" were asked to specify their racial identification. Using their open-ended responses, these respondents were then classified into one of the five monoracial categories. For example, respondents who wrote "Italian" were coded as White. Six respondents gave multiple heritages, and one multiracial respondent reported identifying equally with all indicated racial groups. For these seven respondents, their listed ethnicities, surnames (maiden and married), skin tone, eye color, and areas of residence, as well as the racial makeup of their six closest friends, were used to assign them to one of the five monoracial categories.

Triracial measure. Modeling on the basis of Bonilla-Silva's (2004:933) table, we created a triracial variable. Whites of European heritage, New Whites (Russians, Albanians, etc.), and Urban Native Americans were classified as "White," as well as "White" Hispanics, defined as Hispanics with phenotypes of less than 2.5.[3] Japanese, Koreans, Asian Indians, Chinese, Taiwanese, Middle Easterners, Multiracial, Filipinos, and "light-skinned" Hispanics, defined as having phenotypes equal to or between 2.5 and 4.5, were classified as Honorary Whites. Finally, Vietnamese, Hmong, Laotians, Cambodians, Thais, Indonesians, Nepalese, African Americans, West Indians, African immigrants, reservation-bound Native Americans, and "dark-skinned" Hispanics, defined as having phenotypes greater than 4.5, were coded as part of the Collective Black category.

Skin tone measure. The restricted PALS data set includes interviewers' rankings of respondents' skin tone on a scale ranging from 1 (very light) to 7 (very dark).[4] Interviewers went through substantial training and practice to ensure comparability in skin tone ratings across interviewers. We adjusted the ranking to create a continuous variable that ranges from 0 to 1 for ease of model interpretation.[5]

Operationalization of Inequality Measures: The Dependent Variables

Household income. Respondents were asked if their total household incomes before taxes in 2005 were at least $40,000. Depending on their answers, they were given more specific income categories. These questions were combined to create a 19-category scale.[6] Respondents who answered the first question but then refused to provide more specific income information were assigned the mean income levels of their chosen income categories. Thus, those who reported making less than $40,000 in 2005 were assigned to the $20,000 to $24,999 category (67 respondents), and those who reported making at least $40,000 were coded as making $70,000 to $79,999 (48 respondents). There were 165 respondents who did not answer any questions about their incomes. Using regression imputation, we estimated 150 of these respondents' household incomes. All models predicting income were run with and without imputed cases. Imputed cases did not alter the findings but were included so that these observations could be used for the education and health models.[7]

Education. Education in the PALS data is measured as the highest degree completed: less than high school (including General Educational Development certificate), high school diploma, some college, completed bachelor's degree, or completed graduate degree. We used these categories to create a continuous variable of completed years in school.[8]

Self-rated health. Self-rated health has been found to be a highly reliable measure of mortality even compared with more "objective" measures of health (Franks, Gold, and Fiscella 2003; Idler and Angel 1990). Thus, respondents were asked to rank their health on a scale ranging from 1 to 5 on which 5 represents "excellent" health and 1 represents "poor" health.[9]

Control Variables

In addition to race, our dependent variables—income, education, and health—are stratified by personal, familial, and environmental factors. Moreover, these factors vary across racial groups. For example, income is lower among foreign-born individuals, and at this moment in U.S. history, foreign-born individuals are more likely to be Asian or Hispanic than they are to be White. Thus, to ensure that our findings represent differences between the operationalizations of race and not differences in other demographic factors, we follow the well-established practice in the literature of holding personal, familial, and environmental factors constant (Golash-Boza and Darity 2008; Hall and Crowder 2011; Hunter 2002; Keith and Herring 1991; Saperstein and Penner 2013; Williams and Sternthal 2010).[10]

Specifically, we control for three personal factors: female gender,[11] age,[12] and nativity. Additionally, we include two dichotomous familial factors noting if respondents are married and if they have children younger than 18 years old living in their households. Finally, we take into consideration environmental factors. In particular, we include a categorical variable noting if respondents' current residences are in the Northeast, Midwest, South, or West and if they are in rural or metropolitan areas. All models presented include all seven control variables.

Methodology for Comparing Non-nested Generalized Linear Models

Conceptualizing all three of our dependent variables as continuous, we conduct ordered least squares regressions for each of the racial measurements. To evaluate which operationalization provides the best model fit, we use Vuong's (1989) non-nested model selection test. In the social sciences, non-nested model selection is less common, but noting its theoretical utility, scholars have begun using Bayesian statistics or Vuong's test (Clarke 2003). The Vuong test is designed to compare the model fit of overlapping but non-nested models. The specific purpose of the test is to evaluate the effectiveness of particular operationalizations of one variable when all other variables are held constant. Similar to the nested model test, it prefers models that capture the most variation in the dependent variable, yet if two models capture equivalent variation, the tests favor the parsimonious model. The parsimonious model is the one with the fewest categories in the key independent variable. Models and tests were run in R. Signorino and Bernton's command, vuong(), in the "games" package, originally published in January 2014, was used.

RESULTS

Household Income

To begin, we review the relationship between each of the five race measures and household income. Then, using the Vuong test, we explore which of these five models captures more of the contemporary variance in U.S. household income. As expected given previous research, Whites earn more than non-Whites with the exception of Asians

Table 2. Coefficients from Ordinary Least Squares Regression Predicting Household Income (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Triracial		Skin Tone	
Black	−19,746*	Black	−21,908*	Black	−21,646*	Honorary White	−9,670*	Skin tone	−21,638*
Asian	10,731*	Hispanic	−19,622*	Hispanic	−18,202*	Collective Black	−18,698*		
Pac. Islander	9,520	Asian	4,816	Asian	6,304				
Nat. Amer.	−19,620*	Pac. Islander	2,585	Nat. Amer.	−19,922*				
Mixed Race	−9,699*	Nat. Amer.	−33,663*						
Other	−11,532*	Mixed Race	−11,224*						
		Other	4,866						
Intercept (reference: White)	95,853		95,501		95,720		96,830		97,642
R^2	.2301		.2436		.2416		.2154		.2137
Likelihood	−30,852		−30,829		−30,833		−30,876		−30,879

Note. All models include the personal, familial, and environmental controls outlined in the "Data and Methods" section. Coefficients of each control are in the expected direction. For full results, see the Appendix. Pac. Islander = Pacific Islander. Nat. Amer. = Native American.
*$p \leq .05$.

and Pacific Islanders (see Table 2). More specifically, when using the census measure, for Whites living in metropolitan areas in the Northeast who are married and have no children at home and are male, middle aged, and native born, their average household income is $96,000 per year. Blacks who share these same personal, familial, and environmental characteristics make only $76,000 per year, a $20,000 difference. In other words, Whites' household incomes are 26 percent greater than Blacks' even when all personal, familial, and environmental factors are held constant.

Likewise, Native Americans make on average $20,000 less than Whites, and Multiracials and Others make $10,000 and $12,000, respectively, less than Whites. Conversely, Asians make on average $11,000 more than their White counterparts, and Pacific Islanders make $10,000 more than their White counterparts. With the exception of Pacific Islanders, who make up the smallest proportion of the sample (see Table 1), all coefficients are statistically distinguishable from Whites (see Table 2). For this model and all subsequent models, every control has the expected relationship with income (see Appendix Table A2), thus serving as a check on the validity of the data.

Using the combined race/ethnic measure produces similar results. Blacks, Native Americans, and Multiracials earn less than Whites, while Asians and Pacific Islanders earn more. The main distinction between the combined race/ethnic measure and the census measure is that the White and Other categories in the census measure include Hispanics, whereas in the combined race/ethnic measure, Hispanics have their own distinct classification. Thus, using the combined race/ethnic measure, we find that Hispanics make $20,000 less than comparable Whites, while the Others who are not Hispanic make $5,000 more than their White counterparts. Put another way, what the census measure is unable to illuminate is the considerable income inequality between Whites and Hispanics. Furthermore, removing Hispanics from the White category also increases the differences between Whites and other groups such as Blacks (now a difference of $22,000) and Native Americans (now a difference of $34,000).

A similar pattern emerges when race is operationalized as five monoracial categories, in the pentagon measure. Once again, Blacks, Hispanics, and Native Americans earn less household income than Whites, while Asians earn more household income. Specifically, the average middle-aged, native-born Asian man living in a northeastern metropolitan area who is married with no children has a household income of $102,000, comparable Whites earn $96,000, comparable Blacks earn $74,000, comparable Hispanics earn $78,000, and comparable Native Americans make $76,000. What is distinct about this measure compared with the combined race/ethnic and census measures is that there are no Multiracial, Pacific Islander, and Other categories. The individuals who were previously identified in one of these three groups are recategorized into one of the five monoracial categories. This reclassification does not change the relationship between the racial groups but does reduce the standard errors of the coefficients.

Table 3. Vuong Test Comparing Household Income Models.

	Census	Combined Race/Ethnic	Pentagon	Triracial	Skin Tone
Census		−2.5 (.011)	−4.0 (.000)	1.0 (.310)	0.8 (.410)
Combined race/ethnic	2.5 (.011)		−2.1 (.037)	3.0 (.003)	2.7 (.007)
Pentagon	4.0 (.000)	2.1 (.037)		3.9 (.000)	3.5 (.000)
Triracial	−1.0 (.310)	−3.0 (.003)	−3.9 (.000)		−0.2 (.850)
Skin tone	−0.8 (.410)	−2.7 (.007)	−3.5 (.000)	0.2 (.850)	

Note. The table presents the test statistic and *p* value of the Vuong test comparing the model listed in the row with the model listed in the column. A positive value means that the model in the row is preferred, while a negative value means that the model listed in the column is preferred. To aid readability, if the row model is statistically significantly preferable, the cell has a white background; if the column model is statistically significantly preferable, the cell background is dark grey; and if the models are statistically indistinguishable, the cell background is light gray. Thus, the models whose corresponding rows have the most white cells and columns have the most dark grey cells are most preferable overall.

Turning to the triracial measure, we find that Whites have the highest household incomes, followed by Honorary Whites, who make on average \$10,000 less than Whites, and then Collective Blacks, who make \$19,000 less than Whites. Similarly, when using skin tone of the respondent as the measure of race, those with darker skin tones earn less household income than their lighter skinned counterparts. Specifically, those with the darkest skin tone make \$22,000 less than those with the lightest skin tone.

Although these individual models are informative, the primary question is whether some of these models better capture the differences in household income than others. Using the Vuong test, we can compare each of these five models with every other model. In Table 3, the test statistic and *p* value of each comparison is presented. A negative test statistic denotes that the second model is preferred, while a positive test statistic denotes that the first model is preferred. The test statistic and *p* value of every comparison are displayed in Table 3, with the row measuring the first model and the column representing the second model.

In Table 3, the first row compares the census measure with each of the other models. As indicated by the negative test statistics in the combined race/ethnic and pentagon columns, these two models are preferred to the census measure. That is, when Hispanics are categorized as a distinct group, more of the income inequality in the United States is explained compared with models in which Hispanics are classified as their respective racial groups. Furthermore, the combined race/ethnic and pentagon measures capture more of the income inequality than the triracial and skin tone operationalizations. What distinguishes the combined race/ethnic and pentagon from the triracial and skin tone measures is that the former have distinct categories for Asians, Hispanics, and Native Americans, while the latter use a combination of ethnic heritage and physical features to place individuals on a spectrum. Thus, the finding that the combined race/ethnic and pentagon measures are preferable to the triracial and skin tone measures suggests that income inequality does not range on a phenotypical spectrum. Instead, the incomes of Whites, Blacks, Hispanics, Asians, and Native Americans are generally comparable with those of individuals in their own racial groups, even across phenotypes, but distinct from individuals in other racial categories.

Between the combined race/ethnic and pentagon measure, the pentagon operationalization is preferred. What this means is that recategorizing Multiracials, Others, and Pacific Islanders into Hollinger's (2006) five monoracial categories captures the patterns in contemporary income inequality better than treating them as distinct groups. Having examined the five models and their relationships to one another, we now turn to our second outcome variable, education.

Education

As with household income, we first examine the relationships between the five race measures and education and then compare these models' ability to explain educational inequality. Unsurprisingly, the results for the models predicting educational attainment are extremely similar to those for the models predicting household income. As seen in Table 4, using the census measure, on average, Whites in northeastern metropolitan areas who are

Table 4. Coefficients from Ordinary Least Squares Regression Predicting Education (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Triracial		Skin Tone	
Black	−0.9*	Black	−1.0*	Black	−1.0*	Honorary White	−0.7*	Skin tone	−1.1*
Asian	1.7*	Hispanic	−1.5*	Hispanic	−1.4*	Collective Black	−0.8*		
Pac. Islander	0.6	Asian	1.2*	Asian	1.1*				
Nat. Amer.	−1.4*	Pac. Islander	0.1	Nat. Amer.	−1.5*				
Mixed Race	−0.7*	Nat. Amer.	−2.1*						
Other	−0.9*	Mixed Race	−0.9*						
		Other	0.3						
Intercept (reference: White)	14.8		14.8		14.8		14.9		15.0
R^2	.1346		.1612		.1550		.0886		.0890
Likelihood	−5,811		−5,771		−5,780		−5,878		−5,877

Note. All models include the personal, familial, and environmental controls outlined in the "Data and Methods" section. Coefficients of each control are in the expected direction. For full results, see the Appendix. Pac. Islander = Pacific Islander. Nat. Amer. = Native American.
$^*p \leq .05$.

male, native born, middle aged, and married with no children complete 14.8 years of school. In other words, on average, Whites complete 3 years of college. Native Americans with all the same characteristics complete only 13.4 years of school, 1.4 years less than Whites. Others, Blacks, and Multiracials also complete less schooling than Whites, while Pacific Islanders and Asians complete more. As with the household income models, all the coefficients are statistically significant except for Pacific Islanders, and all controls have the expected relationships with education (see Appendix Table A3).

Furthermore, as we saw with household income, when we separate Hispanics into their own category, the differences between comparable Whites and Blacks, Native Americans, and Multiracials increase to 1.0, 2.1, and 0.9 years, respectively. Because Hispanics also have their own category in the pentagon measure, the average years Whites complete in school remains the same at 14.8. Yet the differences among Whites, Hispanics, Native Americans, and Asians change ever so slightly because Multiracials, Pacific Islanders, and Others have been added to these categories. The similarities between the education and income models continue with the triracial and skin tone operationalizations, which demonstrate that darker skinned individuals receive less education than lighter skinned individuals.

Although the results between the income and education models are comparable, this does not necessarily mean that the race operationalization that best reflects income inequality also best reflects educational inequality. We again must conduct tests to make this determination. As seen in Table 5, the census, combined race/ethnic, and pentagon measures are all preferable to the triracial and skin tone operationalizations. That is, the measures that do not distinguish Asians and Pacific Islanders from Hispanics, Native Americans, and Blacks with comparable phenotypes are unable to capture the full range of educational variability across racial groups in the United States. Additionally, the combined race/ethnic and pentagon measures are preferred to the census measure. Again, this suggests that categorizing Hispanics as a distinct category illuminates the current patterns in inequality in the United States.

Once again, we are left with the combined race/ethnic and pentagon models. The test statistic when comparing the combined race/ethnic with the pentagon measure is −0.5, suggesting that the pentagon measure is a better fit. Yet unlike the household income models, the p value for this comparison is .630, suggesting the pentagon model is not statistically distinguishable from the combined race/ethnic model. In short, educational inequality is stratified along the pentagon measure's categories but can also be effectively measured with the combined race/ethnic measure.

Self-rated Health

Finally, we examine racial inequality in self-rated health. As we have done with the previous two outcome variables, we first examine the five models and then compare the ability of each model to

Table 5. Vuong Test Comparing Education Models.

	Census	Combined Race/Ethnic	Pentagon	Triracial	Skin Tone
Census		−3.9 (.000)	−4.1 (.000)	3.8 (.000)	3.6 (.000)
Combined race/ethnic	3.9 (.000)		−0.5 (.630)	6.0 (.000)	5.5 (.000)
Pentagon	4.1 (.000)	0.5 (.630)		6.3 (.000)	5.8 (.000)
Triracial	−3.8 (.000)	−6.0 (.000)	−6.3 (.000)		−0.8 (.440)
Skin tone	−3.6 (.000)	−5.5 (.000)	−5.8 (.000)	0.8 (.440)	

Note. The table presents the test statistic and *p* value of the Vuong test comparing the model listed in the row with the model listed in the column. A positive value means that the model in the row is preferred, while a negative value means that the model listed in the column is preferred. To aid readability, if the row model is statistically significantly preferable, the cell has a white background; if the column model is statistically significantly preferable, the cell background is dark grey; and if the models are statistically indistinguishable, the cell background is light gray. Thus, the models whose corresponding rows have the most white cells and columns have the most dark grey cells are most preferable overall.

capture contemporary racial inequality in health. Using the census measure of race, northeastern metropolitan Whites who are also male, middle aged, native born, married, and childless on average rate their health at 3.89 on a scale ranging from 1 (poor health) to 5 (excellent health). In other words, Whites with these characteristics report health that is approximately very good. Comparable Native Americans on average report good health, a 0.61 lower score than Whites. Although this difference might not seem dramatic, on a five-point scale, a difference of 0.5 is substantively and in this case statistically significant. Holding personal, familial, and environmental factors constant, Blacks also report poorer health than Whites. Unlike the previous two outcome variables, for health, Multiracials, Others, Asians, and Pacific Islanders all report lower levels of health than Whites. Once again, Pacific Islanders are the only group whose differences are not statistically significant (see Table 6). Furthermore, as with the previous two dependent variables, all the control variables have the expected relationships with health (see Appendix Table A4).

As with income and education, when Hispanics are given their own category, the differences between Whites and Native Americans and between Whites and Blacks increase. Likewise, Hispanics, Asians, Multiracials, Pacific Islanders, and Others all have lower health rankings than Whites, yet for Pacific Islanders and Others, these differences are not statistically significant.

Using the pentagon measure, Whites have the same average health as with the combined race/ethnic measure. Native Americans, Hispanics, Asians, and Blacks all still have poorer health than Whites. Using the triracial measure, results show Honorary Whites have the poorest health, followed by Collective Blacks and then Whites. This aligns with the findings from the pentagon measure demonstrating that Hispanics and Asians, who are mainly in the Honorary White category, have poorer health than Blacks, who are primarily in the Collective Black category. Finally, for the skin tone measure, individuals with lighter skin have higher rankings of self-rated health than darker skinned individuals (see Table 6). In summary, the most noticeable difference between these models and the previous models predicting income and education is that instead of having higher scores than Whites, Asians and Pacific Islanders have lower self-rated health than Whites.

Like the previous two dependent variables, the Vuong tests suggest that the pentagon measure captures more of the variation in health than any other operationalization of race. Specifically, the pentagon, triracial, and skin tone measures are all preferable to the census measure (see Table 7). Additionally, the combined race/ethnic measure is also preferable but the difference is not statistically significant. Similarly, the pentagon, triracial and skin tone measures capture more of the variation in self-rated health than the combined race/ethnic measure. Yet only the difference between the pentagon and combined race/ethnic models is statistically significant. Finally, as indicated by the positive test statistics in the row comparing the pentagon measure with the triracial and skin tone measures in Table 7, the pentagon measure captures more of the variation in self-rated health than either of these measures. Yet the differences between

Table 6. Coefficients from Ordinary Least Squares Regression Predicting Self-rated Health (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Triracial		Skin Tone	
Black	−0.20*	Black	−0.24*	Black	−0.24*	Honorary White	−0.31*	Skin tone	−0.30*
Asian	−0.27*	Hispanic	−0.44*	Hispanic	−0.43*	Collective Black	−0.20*		
Pac. Islander	−0.16	Asian	−0.42*	Asian	−0.42*				
Nat. Amer.	−0.61*	Pac. Islander	−0.32	Nat. Amer.	−0.75*				
Mixed Race	−0.35*	Nat. Amer.	−0.89*						
Other	−0.28*	Mixed Race	−0.47*						
		Other	−0.36						
Intercept (reference: White)	3.89		3.89		3.89		3.89		3.89
R^2	.0721		.0798		.0789		.0704		.0668
Likelihood	−3,901		−3,891		−3,892		−3,904		−3,909

Note. All models include the personal, familial, and environmental controls outlined in the "Data and Methods" section. Coefficients of each control are in the expected direction. For full results, see the Appendix. Pac. Islander = Pacific Islander. Nat. Amer. = Native American.
*$p \leq .05$.

the pentagon and these models are not statistically significant. In short, the difference between the pentagon and other measures is less dramatic when considering health inequalities than when examining income or educational inequalities. Nevertheless, the pentagon measure still captures more of the variation in contemporary inequality than any other of the examined measures.

DISCUSSION AND CONCLUSION

Summary of Findings

The fluidity of racial classifications across time and place provides a plethora of theoretical, historical, and empirical work for researchers investigating the construction and maintenance of social categories. Nonetheless, this research note has operated from the assumption that if we are to understand and address racial inequalities, quantitative scholars must have an agreed-upon operationalization of race that reflects contemporary inequality, even if such an operationalization must change over time to capture the fluid nature of race. Our strategy was to examine different measurements of race, gathered from existing literature, and determine which operationalization best captures contemporary variation in social inequality.

After investigating the model fit of five different racial measurements on three different dependent measures of inequality, we conclude that the pentagon measure explains the greatest amount of variation. The pentagon measure is the most consistent and concise operationalization of race for measuring social inequality.

To clarify, investigations into the complexities and malleability of racial boundaries have provided and should continue to provide fascinating and essential findings regarding the social construction of racial categories. Furthermore, the finding that the pentagon measure reflects the current racial stratification should *not* be used as evidence that racial groups are "real" or innate biological categorizations. Instead, this finding is intended to assist researchers' studying contemporary inequalities by encouraging them to use theoretically and empirically sound measures of race rather than defaulting to the operationalization of race in their given data set.

Limitations

Playing the skeptic, perhaps the general finding that the pentagon measure best reflects contemporary inequality is because we did not distinguish among various mixed-race combinations (e.g. White-Black, Asian-White). In other words, it is possible that if Multiracials were classified in specific subgroups, this would help rather than hinder model specification. Although the PALS data do contain information on the specific racial heritages of multiracial respondents, there are not enough respondents in each specific subgrouping to analyze them separately. Yet this is true of the vast majority of nationally representative samples. Thus, unless one's research uses extremely large sample sizes or

Table 7. Vuong Test Comparing Health Models.

	Census	Combined Race/Ethnic	Pentagon	Triracial	Skin Tone
Census		−1.3 (.180)	−3.1 (.002)	−2.5 (.013)	−2.2 (.031)
Combined race/ethnic	1.3 (.180)		−4.3 (.000)	−1.2 (.240)	−0.8 (.450)
Pentagon	3.1 (.002)	4.3 (.000)		0.7 (.470)	0.8 (.450)
Triracial	2.5 (.013)	1.2 (.240)	−0.7 (.470)		0.2 (.830)
Skin tone	2.2 (.031)	0.8 (.450)	−0.8 (.450)	−0.2 (.830)	

Note. The table presents the test statistic and *p* value of the Vuong test comparing the model listed in the row with the model listed in the column. A positive value means that the model in the row is preferred, while a negative value means that the model listed in the column is preferred. To aid readability, if the row model is statistically significantly preferable, the cell has a white background; if the column model is statistically significantly preferable, the cell background is dark grey; and if the models are statistically indistinguishable, the cell background is light gray. Thus, the models whose corresponding rows have the most white cells and columns have the most dark grey cells are most preferable overall.

overrepresentations of multiracial respondents, this study suggests that recategorizing multiracial individuals into monoracial categories is a more effective measure of racial inequality than leaving them in one unified "multiracial" group.

Implications for Future Investigations

This investigation demonstrates that Hollinger's (2006) pentagon measure, which categorizes individuals into five mutually exclusive categories, is best fitted for capturing existing racial inequalities. Although there is some difficulty in classifying people who do not self-select into one of the five categories, the good news for researchers is that most data sets that collect information on race and ethnicity can create the pentagon measure. Furthermore, census data can also be categorized into these five monoracial categories, enabling researchers to continue to use census data to ensure that their samples are nationally representative.

More research must be done into why the pentagon measure is the most effective in capturing current racial inequality. But for now, the implications of this study for future research are twofold. First, to best capture the contemporary inequality in the United States, researchers should categorize individuals who identify as ethnically "Hispanic" as a distinct category. Second, if researchers are using data that use the census's seven-race measure, then individuals who identify as Native Hawaiian and Pacific Islander, Other, or Two or More Races should be recategorized into one of the five monoracial categories. As was done in this research, information on which of the five monoracial categories individuals most identifies with, their ethnic heritages, and their phenotypes can be used to recategorize them.

Of course, future studies using large sample sizes of Native Hawaiian and Pacific Islanders, Others, and Multiracials need to be conducted to further illuminate best practices for recategorizing these individuals. Yet even without this research, our initial investigations suggest that categorizing multiracial individuals as their racial heritage that is seen as "inferior" on the ethnoracial hierarchy and Native Hawaiian and Pacific Islanders as Asian also captures contemporary inequality patterns. Thus, our study suggests that when possible, quantitative studies on inequality should measure race as consisting of five categories: White, Black, Hispanic, Asian, and Native American.

In the final analysis, the payoffs of doing so are these: (1) for now, researchers have a straightforward means to capture racial inequality; (2) a baseline measurement has been established—in the early 2000s, racial inequalities are best captured with five monoracial categories; and (3) future research can study if the measure that best reflects patterns in social stratification changes over time, and if so, understanding why this is the case will enable much progress in understanding the changing nature of racial inequality in the United States.

APPENDIX A: FULL MODEL TABLES

Table A1. Descriptive Statistics of Control Variables (n = 2,579).

Variable	Mean/Proportion (*SD*)
Personal factors	
Female	0.59 (0.49)
Age (years)	44.21 (16.66)
Foreign born	0.21 (0.41)
Family factors	
Single	0.54 (0.50)
Children in house	0.45 (0.50)
Environmental factors	
Region	
Northeast	0.16 (0.36)
Midwest	0.18 (0.39)
South	0.35 (0.48)
West	0.31 (0.46)
Rural area	0.09 (0.28)

Table A2. Coefficients from Ordinary Least Squares Regression Predicting Household Income Including Controls (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Tri-Racial		Skin Tone	
Race		Race		Race		Race		Race	
Black	−19,746*	Black	−21,908*	Black	−21,646*	Honorary White	−9,670*	Skin tone	−21,638*
Asian	10,731*	Hispanic	−19,622*	Hispanic	−18,202*	Collective Black	−18,698*		
Pacific Islander	9,520	Asian	4,816	Asian	6,304				
Native American	−19,620	Pacific Islander	2,585	Native American	−19,922*				
Mixed Race	−9,699*	Native American	−33,663*						
Other	−11,532*	Mixed Race	−11,224*						
		Other	4,866						
Personal		Personal		Personal		Personal		Personal	
Female	−6,136*	Female	−6,051*	Female	−6,276*	Female	−6,536*	Female	−6,876*
Age	95	Age	77	Age	79	Age	74	Age	87
Age squared	−22*	Age squared	−22*	Age squared	−22*	Age squared	−22*	Age squared	−22*
Foreign	−15,199*	Foreign	−9,426*	Foreign	−9,920*	Foreign	−9,205*	Foreign	−10,606*
Family		Family		Family		Family		Family	
Single	−26,064*	Single	−25,292*	Single	−25,322*	Single	−26,871*	Single	−27,286*
Child	−1,173	Child	−80	Child	−264	Child	−1,718	Child	−1,932
Environment		Environment		Environment		Environment		Environment	
Region		Region		Region		Region		Region	
Midwest	−15,046*	Midwest	−13,594*	Midwest	−13,742*	Midwest	−14,908*	Midwest	−14,298*
South	−13,811*	South	−12,012*	South	−12,268*	South	−14,131*	South	−15,266*
West	−6,061*	West	−4,394	West	−4,801*	West	−4,920*	West	−5,374*
Rural	−17,116*	Rural	−17,902*	Rural	−17,734*	Rural	−17,314*	Rural	−16,570*
Intercept	95,853		95,501		95,720		96,830		97,642
R^2	.2301		.2436		.2416		.2154		.2137
Likelihood	−30,852		−30,829		−30,833		−30,876		−30,879

*$p \leq 0.05$.

Table A3. Coefficients from Ordinary Least Squares Regression Predicting Education Including Controls (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Triracial		Skin Tone	
Race		Race		Race		Race		Race	
Black	−0.9*	Black	−1.0*	Black	−1.0*	Honorary White	−0.7*	Skin tone	−1.1*
Asian	1.7*	Hispanic	−1.5*	Hispanic	−1.4*	Collective Black	−0.8*		
Pacific Islander	0.6	Asian	1.2*	Asian	1.1*				
Native American	−1.4*	Pacific Islander	0.1	Native American	−1.5*				
Mixed Race	−0.7*	Native American	−2.1*						
Other	−0.9*	Mixed Race	−0.9*						
		Other	0.3						
Personal		Personal		Personal		Personal		Personal	
Female	−0.0	Female	−0.0	Female	−0.0	Female	−0.1	Female	−0.1
Age	0.0*	Age	0.0*	Age	0.0*	Age	0.0*	Age	0.0*
Age squared	−0.0*	Age squared	−0.0*	Age squared	−0.0*	Age squared	−0.0*	Age squared	−0.0*
Foreign	−0.6*	Foreign	−0.1	Foreign	−0.1	Foreign	−0.1	Foreign	−0.1
Family		Family		Family		Family		Family	
Single	−0.5*	Single	−0.4*	Single	−0.5*	Single	−0.6*	Single	−0.6*
Child	−0.5*	Child	−0.4*	Child	−0.4*	Child	−0.6*	Child	−0.6*
Environment		Environment		Environment		Environment		Environment	
Region		Region		Region		Region		Region	
Midwest	−0.6*	Midwest	−0.4*	Midwest	−0.5*	Midwest	−0.6*	Midwest	−0.6*
South	−0.4*	South	−0.3*	South	−0.3*	South	−0.5*	South	−0.6*
West	−0.2	West	−0.1	West	−0.1	West	−0.2	West	−0.2
Rural	−0.6*	Rural	−0.7*	Rural	−0.7*	Rural	−0.6*	Rural	−0.6*
Intercept	14.8		14.8		14.8		14.9		15.0
R^2	.1346		.1612		.1550		.0886		.0890
Likelihood	−5,811		−5,771		−5,780		−5,878		−5,877

*$p \leq 0.05$.

Table A4. Coefficients from Ordinary Least Squares Regression Predicting Self-rated Health Including Controls (n = 2,579).

Census		Combined Race/Ethnic		Pentagon		Tri-Racial		Skin Tone	
Race		Race		Race		Race		Race	
Black	−0.20*	Black	−0.24*	Black	−0.24*	Honorary White	−0.31*	Skin tone	−0.30*
Asian	−0.27*	Hispanic	−0.44*	Hispanic	−0.43*	Collective Black	−0.20*		
Pacific Islander	−0.16	Asian	−0.42*	Asian	−0.42*				
Native American	−0.61*	Pacific Islander	−0.32	Native American	−0.75*				
Mixed Race	−0.35*	Native American	−0.89*						
Other	−0.28*	Mixed Race	−0.47*						
		Other	−0.36						
Personal		Personal		Personal		Personal		Personal	
Female	−0.02	Female	−0.01	Female	−0.02	Female	−0.01	Female	−0.02
Age	−0.02*	Age	−0.02*	Age	−0.02*	Age	−0.02*	Age	−0.02*
Foreign	−0.01	Foreign	0.14*	Foreign	0.14*	Foreign	0.05	Foreign	−0.06
Family		Family		Family		Family		Family	
Single	−0.23*	Single	0.22*	Single	−0.22*	Single	−0.23*	Single	−0.23*
Child	−0.11*	Child	−0.09	Child	−0.09	Child	−0.11*	Child	−0.11*
Environment		Environment		Environment		Environment		Environment	
Region		Region		Region		Region		Region	
Midwest	−0.31*	Midwest	−0.28*	Midwest	−0.28*	Midwest	−0.29*	Midwest	−0.29*
South	−0.19*	South	−0.16*	South	−0.16*	South	−0.17*	South	−0.20*
West	−0.09	West	−0.07	West	−0.07	West	−0.10	West	−0.14*
Rural	−0.16*	Rural	−0.18*	Rural	−0.17*	Rural	−0.16*	Rural	−0.14*
Intercept	3.89		3.89		3.89		3.89		3.89
R^2	.0721		.0798		.0789		.0704		.0668
Likelihood	−3,901		−3,891		−3,892		−3,904		−3,909

*$p \leq 0.05$.

NOTES

1. After imputation, 18 respondents were missing skin tone, an additional 9 were missing income, 1 was missing marital status, 1 was missing age, 1 was missing health, and 1 was missing nativity. After correlation and chi-square analyses were conducted, the variables were deemed missing at random, and the 31 respondents were dropped from the final sample.
2. Because of the historical precedent of identifying all individuals with any Black ancestry as Black, another way of operationalizing multiracial individuals into one of the five monoracial categories would be to categorize them by their racial heritage that is seen as "inferior" on the ethnoracial hierarchy. Analyses using this operationalization were conducted, and no statistical differences between this operationalization and presented results were found. Consistency between these two methods might be a property of the small multiracial sample size.
3. Using PALS in-depth data on skin tone, hair texture, hair thickness, hair color, and eye color, we created a scalar variable that ranged from 1 (European features) to 6 (Afrocentric features). An individual scoring 1 has very light skin, straight and thin blonde hair, and blue eyes, and an individual scoring a 6 has very dark skin, thick and tightly curled black hair, and dark eyes.
4. The interviewer aid for the skin tone scale is available on request.
5. Models were run with skin tone as a continuous variable, a seven-category categorical variable, a three-category categorical variable, and a quadratic variable. Using the Vuong test, we concluded that the continuous operationalization best captured contemporary inequality.
6. These categories are as follows: less than \$5,000, \$5,000 to \$9,999, \$10,000 to \$14,999, \$15,000 to \$19,999, \$20,000 to \$24,999, \$25,000 to \$29,999, \$30,000 to \$34,999, \$35,000 to \$39,999, \$40,000 to \$49,999, \$50,000 to \$59,999, \$60,000 to \$69,999, \$70,000 to \$79,999, \$80,000 to \$89,999, \$90,000 to \$99,999, \$100,000 to \$124,999, \$125,000 to \$149,999, \$150,000 to \$174,999, \$175,000 to \$199,999, and \$200,000 or more. The categories are given the median value in the range to create a continuous income variable.
7. The regression's independent variables were employment status, educational level, major financial crisis in the past three years, nativity, home ownership, and neighborhood safety. The R^2 value of the model was .3931. Fifteen respondents did not have the information necessary for imputation.
8. Less than high school (including General Educational Development certificate) was assigned 10 years, high school diploma was assigned 12 years, some college was assigned 14 years, completed bachelor's degree was assigned 16 years, and completed graduate degree was assigned 18 years. To ensure that the results were not a product of how education was operationalized, additional models were run in which education was defined as a dichotomous variable. The first classified education as either less than high school or high school and more and the second as no college or at least some college. These operationalizations of education did not change any of the substantive results.
9. Similar to the education models, additional health models were run to ensure that the operationalization of health was not affecting results. Once again, dichotomous operationalizations of health did not make large changes to results presented here.
10. Previous research has also included controls for parental factors such as parental education. The PALS data do not contain information on parents, and thus these controls are not included in our models.
11. All PALS respondents identified as either male or female. Thus, gender was operationalized as a dichotomous variable.
12. Age is measured as age when the survey was conducted and included as a continuous variable. Mirroring previous research, the square of age was also included in the income and education models to account for the curvilinear relationship age has with income and education.

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