Still One Drop of Blood?
The New Rules of Ethnoracial Classification in the U.S.

Ariela Schachter[1], René D. Flores[2], and Neda Maghbouleh[3]

September 18, 2018

Keywords: race and ethnicity, racial classification, survey experiments

[1] Department of Sociology, Washington University in Saint Louis.
[2] Department of Sociology, University of Chicago.
[3] Department of Sociology, University of Toronto.

ABSTRACT

What are the rules governing ethnoracial classification in the United States today? While the U.S. historically has relied on ancestry and hypodescent to police boundaries between Whites and Blacks, diversity driven by post-1965 immigration and rising intermarriage has led to both growing numbers of ethnoracial categories and rising ambiguity about where individuals fall within them. Additionally, despite the alleged primacy of ancestry in the U.S., there is suggestive evidence that social and cultural cues like social class and family name may also shape perceived race. The growing ambiguity in ethnoracial boundaries coupled with copious evidence of the continuing significance of race/ethnicity has led to calls for research on observer classification. To address these calls, we use a unique paired conjoint survey experiment with a nationally-representative sample of 1,500 non-Hispanic White respondents to identify the biological and socio-cultural traits that shape ethnoracial classification as White, Black, Hispanic, Native American, Middle Eastern (MENA), and Asian. Our findings point to the importance of both biological and cultural signals, depending on the ethnoracial category in question, and complicate the idea of a 'one drop rule'. We explore the implications of our findings for discrimination and racial inequality, state ethnoracial categories, and sociological research on race/ethnicity in the United States.

An extended abstract…a work in progress.

INTRODUCTION

Throughout American history few conditions have been as consequential as one's race/ethnicity. Historically, racial classification—that is, how people are racially categorized by others—determined whether individuals experienced freedom or slavery (Davis 1991), citizenship or deportation (Haney-Lopez 1996). Today, few scholars debate the continuing centrality of race/ethnicity in shaping individual experiences. Nevertheless, most contemporary research on ethnoracial boundaries focuses on *self-identification* rather than external *classification*, perhaps because that is how measures of race/ethnicity are typically collected in government data and surveys. Yet, perceived race remains especially important for individual life chances as it shapes how we are treated by others (Feliciano 2016; Telles and Lim 1998).

Complicating the study of perceived race/ethnicity are deep disagreements over whether and how the 'rules' of ethnoracial classification have changed. Traditionally U.S. ethnoracial boundaries have followed the hypodescent rule, which stipulated that 'one drop' of African blood made a person "Black" (Davis 1991). But the growing diversification of the U.S. population may be redrawing pre-existing ethnoracial boundaries as Latinos, Asians, Middle Easterners, and individuals of mixed ancestries occupy ambiguous places in the U.S. racial system (Alba, Beck and Sahin 2018; Bonilla Silva 2004; Maghbouleh 2017; Schachter 2014). Additionally, though ancestry has long been considered the foundation of racial classification in the U.S., there is suggestive evidence that social and cultural cues like class background and family name may also shape perceived race (Flores 2019; Freeman et al. 2011; Garcia and Abascal 2015; Penner and Saperstein 2008; Saperstein and Penner 2010; 2012). The growing ambiguity in ethnoracial boundaries coupled with copious evidence of the continuing significance of race/ethnicity (Pager, Western and Bonikowski 2009) has led to calls for research on observer classification (Gans 2012; Roth 2016). We heed these calls by conducting the first systematic study of the contemporary rules of ethnoracial classification in the U.S.

We ask: how important are biological cues like ancestry and skin color in shaping ethnoracial classification? Can social and cultural traits like language, class, or religion also shape perceived race? While we pay special attention to the boundaries of 'White' and 'Black' given their historical and continued significance in U.S. society, we also expand traditional research on ethnoracial classification schemas to explore and directly compare the norms governing classification as Latino, Asian, MENA (Middle Eastern/North African), and Native American. This allows us to assess whether biological or socio-cultural cues are more important for some ethnoracial categories than for others.

To address these questions, we use a unique paired conjoint survey experiment on a nationally-representative sample of 1,500 non-Hispanic White U.S. residents. Respondents viewed randomly assigned profiles of hypothetical individuals that listed several dimensions of race/ethnicity, including genetic ancestry and skin color, but also traits like religion and language, and were asked to classify each profile. By analyzing the classification of 15,000 fully randomized individual profiles, we can identify ethnoracial boundaries that are widely shared by non-Hispanic Whites—who, as members of the most privileged group in U.S. society, have the most power to shape and maintain the rules of ethnoracial classification (Gans 2012; Roth 2016). We thus use micro-level data patterns to unearth evidence of shared, macro-level boundaries.

In our preliminary analysis (detailed below), we find that ancestry and skin color overwhelmingly determine who is classified as White and who is classified as Black. But we find little evidence supporting the 'one drop' rule: some amount of Sub-Saharan African ancestry does not preclude classification as White. Moreover, when presented with conflicting ethnoracial cues, observers tend to rely on *skin color* rather than ancestry to determine classification as White or Black. We also find that cultural signals, including names, language, and religion, in addition to ancestry and skin color, are used to decide one's classification as Native American, MENA, and Asian. Interestingly, we find little evidence of ancestry or skin color effects on classification as Hispanic, which is perhaps a reflection of the heterogeneity of this group. Instead, socio-cultural cues powerfully shape Hispanic classification. Lastly, we find no evidence that social class has an independent effect on ethnoracial classification for any group.

The potential implications of our findings are widespread. Most importantly, our results suggest that the rules of ethnoracial classification in the United States have shifted. Rather than focusing on ancestral blood as the one drop rule stipulated, our findings point to the importance of skin color, especially in deciding who is viewed as 'White' and who as 'Black.' In line with recent work on the stratifying effect of skin color on African American life chances, (Monk 2018) we find the U.S. system of racial classification may be more similar to Latin America, which has long been characterized as a skin-color-based system in contrast to the ancestry-based system in the U.S., than previous work suggests (Bonilla-Silva 2004; Sue 2017). And while we find more muted skin color effects for other ethnoracial categories, we suspect that rather than there being limited physical or, in the words of Omi and Winant (2015) 'ocular' dimensions to these categories, it may be the case that other aspects of phenotype, such as physical stature, facial hair, and/or ethno-religious attire may be more consequential than skin color in determining classification outside of the White-Black binary, an issue which future research must address. Altogether, our findings offer novel insight into how everyday people ethnoracially classify others across a range of characteristics that have historically constituted "race/ethnicity" in the U.S. By specifying which characteristics matter and how for six different groups, the findings complicate what we know about how race/ethnicity is ascribed or observed, with significant implications for the content and shape of ethnoracial categories as assigned by the state and, ultimately, as reflected in American sociology.

(Very abbreviated!) BACKGROUND

U.S. ethnoracial boundaries, rooted in African slavery, have long been characterized as rigid (Sue 2017). In contrast to other regions of the world like Latin America where physical traits like skin color shape racial classification (Telles and PERLA 2014), in the U.S. ancestry has historically determined who is classified as either "black" or "white." The hypodescent rule, which was codified into law, stipulated that a single drop of African blood made a person "black" (Davis 1991). However, some scholars argue that the rules of ethnoracial classification are now in flux (Alba 2018; Gans 2012). The post-1965 immigration waves, originating mostly from Asia and Latin America, have complicated the old U.S. White/Black racial binary. These groups do not fit neatly into either White or Black categories (McDermott 2018). Further, their offspring often marry native Whites, giving rise to a growing multiracial population. Scholars are unsure how multiracials will come to be classified by the White majority and/or whether the hypodescent rule will apply to them (Alba 2018; Bratter 2018 and 2007; Roth 2005). Some claim that their descendants will be accepted as "white", particularly if they are light skinned and middle class (Alba 2018; Lee and Bean 2010). However, others envision a different future, in which some Latinos and Asians continue to be racialized as "non-white" (Bonilla-Silva 2010). The racial status of other groups like Native Americans and Middle Easterners also seems uncertain though evidence is more limited (Maghbouleh 2017; Snipp 2003; Snipp, Eschbach and

Supple 1998). Further, though race in the U.S. has been historically considered ancestry-based, individuals may increasingly be using skin color and other physical markers to determine race as the number of individuals with mixed ancestry grows (Dixon and Telles 2017; Monk 2016).

Indeed, despite the alleged primacy of ancestry in the U.S., there is some evidence that social and cultural factors may also shape perceived race including class background (Freeman et al. 2011; Penner and Saperstein 2008; Saperstein and Penner 2010; 2012), names and language (Garcia and Abascal 2015; Roth 2010), religion (Maghbouleh 2017), and even romantic partners (Flores 2019). This work suggests that the rules of ethnoracial classification may be becoming more flexible, moving away from ancestry as the sole racial/ethnic criterion.

At the same time, even as the social and cultural underpinnings of perceived race are increasingly recognized, biological cues of race may actually be growing in importance (Morning 2014). The advent of mass-market DNA (genetic) tests, which purportedly provide scientific and objective indicators of one's ancestry, may be strengthening more essentialist, biologically-based understandings of ethnoracial categorization (Roth 2018; Nelson 2016).

We explore these tensions by directly comparing signals of ancestry, skin color, social class and cultural heritage on ethnoracial classification as White, Black, Latino, Native American, Middle Eastern, and Asian, all within the same research design.

RESEARCH DESIGN

Prior research on racial classification uses surveys that include interviewer-assessed race (e.g., Penner and Saperstein 2008; Saperstein and Penner 2010; 2012). While this approach has yielded valuable insights, it is limited in that only one interviewer is typically observing each survey respondent, and each survey respondent-interviewer interaction is distinctly shaped by the content of the survey (including the respondent's home and neighborhood). We do not know whether another observer would classify the respondent's race/ethnicity in the same way, or even if the interviewer would make the same classification in a different setting or under a different set of circumstances (Feliciano 2016; Harris 2002). Feliciano (2016) improves on this by tasking multiple trained observers to classify a unique data set of online daters' photos, and finds that there is important variation in ethnoracial classification across observers. However, online daters are not representative of the U.S. population and their photos have been intentionally selected for a specific purpose—finding a romantic partner—which may impact how individuals appear in the photos. Moreover, photos include many potential confounding signals like class background or attire that may influence classification decisions, leaving it unclear exactly which factors are driving categorization.

Instead of relying on interviewers or submitted photos, we use an original survey experiment to tease apart the independent and interactive effects of multiple dimensions of race/ethnicity on classification. We use a conjoint, or multidimensional choice, experimental design because it lets us compare the effects of multiple ethnoracial signals on classification simultaneously (Flores and Schachter 2018; Hainmueller, Hopkins, and Yamamoto 2014; Schachter 2016). Our profiles of hypothetical individuals vary along several dimensions, including genetic ancestry test results (GAT), skin color, first name, religion, language spoken at home, and occupation. For each treatment category we selected a range of levels meant to capture the diversity of the U.S. population (see Table 1 below for a full list of treatments). While prior studies have examined some of these traits individually or in small groups, we believe that ours is the first to consider all of them simultaneously, in an experimental context, with many observers.

[Table 1 about here]

Using this approach we can identify the independent (casual) effects of each our treatments, net of all of the other traits included in the experiment. Critically, the conjoint design allows us to directly compare effect sizes and also consider how our treatments interact with one another and with observer characteristics. Using actual pictures of people may have been a more realistic signal of race than our approach; however, our randomization schema has strong internal validity—we can precisely compare the independent impact of each dimension of race included in the experiment—and by conducting our experiment as part of a national survey with 1,500 distinct participants, we also gain generalizability. In particular, our design allows us to isolate the effect of skin color, an aspect of physical appearance long considered to be a key element of race (Flores and Telles 2012; Telles and PERLA 2014), without having to worry about other physical confounders like hair texture, nose shape, eye color, etc. We thus view these methods as complements of, rather than substitutes for, one another.

In the experiment respondents read a short passage that introduced the task by saying "We are interested in studying how people classify the race/ethnicity of others…." (see Design Appendix). To make respondents more comfortable with the task, the introduction stressed that there were no correct answers. Respondents were then presented with two randomly assigned profiles and asked, *"How would you classify these [U.S.-born citizens/immigrants]* [4] *?* Respondents were presented with the six proposed U.S. Census 2020 ethnoracial categories [*White; Black; Native American; Hispanic; MENA; Asian*] (Office of Management and Budget

[4] The experiment contains a separate, independent randomization of whether the profiled individual is described as a US citizen or immigrant. We will explore these differences in future work. All results reported here average across these two conditions.

2016) and instructed to select just one category for each profiled individual.[5] Our experimental design capitalizes on the Census Bureau's internal 2015 Content Test Analysis Report on Race and Ethnicity ("NCT"), which presented the Office of Management and Budget (OMB) with the above six "optimal" categories for improved accuracy and reliability (US Census Bureau 2017). At time of writing, the OMB has declined to move forward with the six suggested 2020 categories. We recode these responses into six dummy variables, one per category, which we use as our dependent variables in all analyses.

In conjoint designs profiles are typically presented in randomly assigned pairs even when they are not being explicitly compared to one another, as is the case in our experiment, because the presentation of pairs makes the task more interesting and maximizes respondent engagement, yielding more accurate estimates (Hainmueller et al. 2015). Additionally, evaluation of repeated profiles is standard in conjoint experiments and is used to increase statistical power (Bansak et al. 2017). In our experiment each respondent repeated the task 5 times, classifying 10 individual profiles in total.

We hired YouGov, an established internet polling firm, to conduct a survey of 1,500 self-identified non-Hispanic White respondents, in July of 2018. The survey was constructed to be a nationally-representative sample of U.S. adult non-Hispanic Whites using YouGov's proprietary advanced matching algorithm (Rivers 2007). Because each respondent evaluated 10 profiles, our total number of observations is 15,000. Before the experiment was fielded we received approval from the Washington University in St. Louis Institutional Review Board (ID 201612013). Before we analyzed the data, we registered the research design and analysis plan at Evidence in

[5] In pretesting we checked whether results varied if we allowed respondents to select more than one category; they do not. Results available from authors upon request.

Governance and Politics (EGAP), an online repository of social science experiments and observational studies (ID 20180815AA).

Despite the complex-sounding design, estimating treatment effects from a conjoint design follows the same logic as a factorial experiment, comparing any two treatment levels to one another while averaging across all other treatments in the experiment. For example, we can estimate the effect of speaking Spanish compared to English (two of the categories of our language treatment) on being classified as "White" by simply comparing the average rates of White classification for all profiles assigned the Spanish treatment and all profiles assigned the English treatment, regardless of any of the other treatment values. Put another way, because all other treatments are orthogonal (by design) to the language treatment, we can ignore them. Formally, these treatment effects are called Average Marginal Component Effects (AMCEs), a name which notes that effects in conjoint designs are conditional on all other treatments included in the experiment. AMCEs can be efficiently estimated using an OLS model but treatment effects are not model dependent (Hainmueller et al. 2014). We use STATA's "cluster" command to estimate Eicker-Huber-White standard errors, which adjust for clustering within respondents, in all analyses.

PRELIMINARY FINDINGS

Table 2 displays our main findings. In each column, we present results for each ethnoracial category: White, Black, Native-American, Hispanic, MENA, and Asian. The first model shows that biological traits are the most important factors that predict white categorization, but socio-cultural cues also play a role. We find that the more European ancestry, the more likely our respondents classified a profile as *White*. Small amounts of non-European ancestry (i.e. 10%)

did not significantly reduce White classification (relative to having 100% European ancestry). Interestingly, despite our expectations based on the one drop rule, African ancestry was not treated differently by our respondents compared to other non-European ancestries: its negative effect on White categorization was similar to others. In other words, what mattered was the amount of European ancestry, and not what it was mixed with. In contrast, having only 50% European ancestry did reduce White categorization by about 20 points, but again we find that the penalty is similar regardless of the other ancestry.

[Table 2 about here]

Skin color was also a powerful predictor of White classification. Only the first three colors of our palette were regarded as "White" by our respondents. After this point we observe a drop off point as the medium skin tones (4 to 6) resulted in a strong reduction in White classification (-22 points). As expected, the darkest skin tones, 7 to 10, had an even larger negative effect (-31 points).

At the same time, some socio-cultural cues also influence White categorization. In contrast to prior work (Penner and Saperstein 2008; Saperstein and Penner 2010; 2012), we find that class background, captured as occupational status, had no effect on whiteness. Indeed, occupational status was not a significant predictor for any of the ethnoracial labels we examined. Nevertheless, as Table 2 shows, other traits like names, religion, and language did have a (small) effect. All non-Anglo names had a negative effect on perceived whiteness (including Spanish names, which are of European origin). Such effect was small (-4 points), but statistically significant at conventional levels. In addition, all religions except for Catholicism, Protestantism, and Judaism had a small, negative effect on White categorization. This suggests that non-Judeo Christian religions have become racialized as non-White in the U.S. Lastly, speaking any non-

European language but also Spanish significantly reduced perceived whiteness. The fact that speaking this Western European language (Spanish) has a negative effect on White categorization highlights the degree of racialization that Latinos have encountered and points at the uniqueness of the U.S. context. In contrast, having a German mother tongue actually increases White categorization relative to speaking English, perhaps because the German language has not significantly spread outside of Europe. This might make it a less ambiguous marker of European ancestry than widely spread colonial languages like English, Spanish, or French.

Black categorization, displayed in the second column, is also strongly shaped by ancestry and skin color, and, to a lesser extent, socio-cultural markers. As expected, African ancestry is positively correlated with perceived blackness. Holding every other trait constant, having 100% African ancestry increases Black categorization by 18 points (relative to having 100% European ancestry). Skin color is also a powerful predictor of blackness. The darkest skin tones (6-10) increase Black categorization by 35 percentage points relative to the lightest (1-3).

Similar to whiteness, some socio-cultural traits also have a modest effect on perceived blackness. Interestingly, neither occupational status nor religion affect Black categorization. However, having a stereotypically African-American name like DeShawn or Lakisha has a small positive effect on Black classification (3 points) net of all other traits. Lastly, all languages have a small negative effect on perceived blackness relative to speaking English. Despite the sizable numbers of Spanish-speaking Afro-descendants in the U.S. and across the world, speaking Spanish was also a negative predictor of perceived blackness, which explains why some Caribbean Latinos emphasize Spanish speaking practices and cultural identities in order to avoid being classified as Black (Portes and Rumbaut 2001).

Native American classification is shown in column 3. We find that signaling ancestry from native groups from the U.S. as well as from Mexico strongly increased classification as native. Having full Cherokee/Navajo and Mixtec/Mayan ancestry increased classification as "Native American" by 67 and 58 points, respectively. This was a surprising finding to us since we had included native groups from Mexico since we thought they might signal "Hispanic" classification among some of our respondents, but that was not the case.

We also find that skin color is a much weaker predictor of Native American classification than for either White or Black categories. While medium skin tone increases of Native American categorization by 2 points, dark skin tones decreases such categorization by 2 points. We also find a small positive effect of Native names and a small negative effect of two religions: Muslim and Hindu. In contrast, speaking a Native American language was a powerful predictor increasing of Native American classification by 20 points. Interestingly, despite the fact that many Native American groups in the American continent speak Spanish, such language actually slightly decreased of Native American classification by 2 points.

Hispanic classification, listed in column 4 of Table 2, was the most elusive one in our study. Biological cues of ancestry or skin color had the weakest effects on this ethnoracial category. Instead, cultural traits were more important. More specifically, we find that none of the ancestry cues we used, which are the standard ones used by commercial GAT companies like 23andMe, triggered Hispanic classification in the minds of our non-Hispanic White respondents. This was the case for both the European cues and even for the Native American labels from Mexico (Mayan and Mixtec) we included in our ancestry treatments. This could suggest that our respondents may share the official U.S. Census definition of Hispanic as being an ethnic label and not a racial one tied to specific ancestries. Alternatively, it could mean that some respondents may believe that there is a specific "Mexican" or "Latin American" ancestry that is neither European nor Native American, even if such belief has no scientific basis. In addition, skin color was not an important predictor of Hispanic categorization, suggesting that for our respondents Hispanics can be of any color.

We also find that neither occupational status nor religion are important predictors of Hispanic classification. Nevertheless, two cultural markers proved more important. Having a Spanish name (+6 points) and speaking Spanish (+18 points) significantly increased Hispanic classification. The surprising lack of importance of biological cues for Hispanic categorization and the importance of cultural ones suggest that our respondents may believe "Hispanic" is more of a cultural category rather than a racial one. Alternatively, it could mean that cultural markers have become racializing cues in the case of Hispanics.

In contrast, we find that both biological *and* cultural cues are important factors for classification as Middle Easterner or North African (MENA). Table 2, column 5, shows that MENA ancestry powerfully predicts MENA classification. Having 100% MENA ancestry increased MENA categorization by 40 points. Skin color was also a significant predictor. Respondents seem to have a normative image of MENA individuals as light brown as the medium skin tones (4 to 6) significantly increased MENA categorization by 8 points net of all other traits (dark skin increased it by 4 points relative to having light skin).

Cultural cues were also important predictors of perceived MENA status. Being Muslim (+8), Hindu (+6), and to some extent Jewish (+2) increased MENA classification relative to being Protestant. In addition, having a common Middle Eastern name (+6) and speaking Arabic (+18 points) were important predictors. Interestingly, speaking any other language reduced

MENA classification relative to speaking English (with the exception of German, perhaps because of the sizable population of German Turks).

Lastly, Asian categorization was also activated by both biological and cultural cues. Results can be seen in Column 6, Table 1. 100% Asian ancestry increased Asian classification by 60 points relative to having full European ancestry. Similarly, having 50% Asian ancestry and either 50% European or 50% African ancestry increases Asian classification by 30 and 19 points, respectively. Skin color has a weaker effect on Asian categorization. Only a dark skin tone results in a small penalty (-5 points).

Cultural cues are also important in shaping perceived Asian status. We find that using a common Asian name (+6 points) and speaking Korean (+18 points) were positive predictors of Asian categorization, net of all other traits. In contrast, religious cues had a small effect. Practicing Hinduism (+3 points) and Buddhism (+3 points) moderately increased Asian classification.

EXTENSIONS AND PLANNED NEXT STEPS

While these preliminary results demonstrate the value of our experimental design, there is much to explore in our results beyond the independent effects of each treatment on ethnoracial classification. Specifically, before the PAA conference we plan to test for interactions between our treatments and respondents' characteristics, and among our treatments. Testing for heterogeneous effects by respondent background will allow us to examine, for example, whether respondents who grew up in the South, which has a long history of strong enforcement of the one drop rule, rely more on ancestry in their racial classification of Blacks and Whites. We also plan to test whether there are differences based on Whites' educational background, partisanship, or previous exposure to genetic ancestry testing. These analyses will deepen our understanding of how much (if any) variation there is among Whites in how they understand the rules of ethnoracial classification in the United States.

We also plan to test for interactions among our treatments. For example, we plan to test whether cultural cues like speaking a non-English language or practicing a non-Christian religion are more consequential for darker-skinned individuals. And we have uncovered some preliminary evidence of interaction effects between two of our key treatments: ancestry and skin color, which we intend to explore in more detail before the PAA conference. In our preliminary analysis we specifically looked for evidence of what happens when these two key physical/biological signals of race/ethnicity give conflicting signals by isolating our analysis to profiles that were assigned the '100% European Ancestry' treatment and the '100% Sub-Saharan African' treatment. (We plan to expand this analysis to other key single and mixed ancestries before the PAA conference.) By interacting ancestry with skin color, we are able to test whether the effects of these ancestries on classification depend on skin color, and vice-versa.

[Figures 1 and 2 here]

The results of this analysis is reported in Figures 1 and 2, above. Starting on the right-hand side of Figure 1, we can see that when profiles have light skin *and* a 100% European ancestry, they are classified as White over 70% of the time. In contrast, as we move from left to right across the graph, we see that when a profile with 100% European ancestry has a medium skin tone (levels 4-6), their probability of White classification drops to about 40%. While this remains the single most common classification for 100% European profiles, almost 30% of profiles with pure European ancestry but medium colored skin are instead classified as Middle Eastern (MENA). Finally, on the far left side of Figure 1 we see that for profiles with dark skin (levels 7-10), even when they are assigned 100% European ancestry, a majority of the time (about 50%) they are classified as Black, and their odds of White classification are close to zero. While in reality most individuals with dark skin may be unlikely to have a 'purely' European ancestry, these theoretically important combinations help us understand just how powerful skin tone is in resolving conflicting signals of ethnoracial classification.

Figure 2 reveals a similar pattern. Starting from right to left on the graph this time, we see that profiles with dark skin and 100% Sub-Saharan African ancestry are overwhelmingly classified as Black (around 70% of the time). In contrast, profiles with medium skin tone and 100% Sub-Saharan ancestry are almost as likely to be classified as Black (about 40%) as they are to be classified as Middle Eastern (about 35%). Finally, on the far left side of figure 2 we see that respondents do not agree on how to classify profiles with the lightest skin colors and African ancestry. We again see that MENA is a common classification for these individuals (about 30%), but 30% of these profiles are classified as White, and just 20% are classified as Black.

Our results here suggest that when ancestry—in the form of GAT results—does not match with skin color—a more 'ocular' form of race (Omi and Winant 2015), observers tend to privilege skin color. They seem to trust what they can see *more* than the 'science'. These patterns fit with Roth's (2018) finding that self-identification based on GAT results is constrained by individuals' perceptions of whether others would 'see' them as their ancestry results rather than their phenotypic appearance. Our findings also reveal the interesting perception of the Middle Eastern/MENA category as an 'in between' 'brown' group-- rather than Hispanic as much of the literature would suggest. This is a thread we intend to pursue in more detail in our additional analyses.

In sum, despite all the ambiguity, we identify clear patterns and shared rules of ethnoracial classification among our diverse sample of non-Hispanic Whites. First, both ancestry—in the form of GAT results—and skin color, two biological dimensions of race, are critical for classification as White or Black. Yet while ancestry is clearly an important dimension separating White from Black, our results challenge the idea of hypodescent and African exceptionalism. If anything, we find more evidence of a skin tone 'color line' than of a one drop rule. Ancestry and skin color (less so) also matter in shaping other ethnoracial classifications, with the exception of Hispanic classification, which seems to be the most ambiguous category in the minds of our respondents. Cultural signals also matter, although the effects sizes are generally smaller; these cultural signals are especially important for Hispanic, MENA, and Native American classification. These findings have profound implications for understanding how Americans think about race/ethnicity, who is most at risk for different forms of discrimination, and how sociologists study and signal race in their research.

REFERENCES

Alba, Richard. 2018. "What Majority-minority Society? A Critical Analysis of the Census Bureau's Projections of America's Demographic Future." *Socius* 4: doi: 10.1177/2378023118796932.

Alba, Richard, Brenden Beck, and Duygu Basaran Sahin. 2018. "The U.S. mainstream expands -- again." *Journal of Ethnic and Migration Studies* 44(1): 99-117.

Bansak, Kirk, Jens Hainmueller, Daniel J. Hopkins, and Teppeir Yamamoto. 2017. "The Number of Choice Tasks and Survey Satisficing in Conjoint Experiments." SSRN (https://papers.ssrn.com/sol3/papers .cfm?abstract_id=2916951).

Bonilla-Silva, Eduardo. 2004. "From bi-racial to tri-racial: Towards a new system of racial stratification in the USA." *Ethnic and Racial Studies* 27(6): 931-950.

--- 2010. *Racism Without Racists*. Lanham, MD: Rowman & Littlefield.

Bratter, Jenifer. 2007. "Will 'Multiracial' Survive to the Next Generation? The Racial Classification of Children of Multiracial Parents." *Social Forces* 86(2): 821-849.

--- 2018. "Multiracial Identification and Racial Gaps: A Work in Progress." *The ANNALS of the American Academy of Political and Social Science* 677(1): 69-80.

Davis, F. James. 1991. *Who is Black?* University Park, PA: Pennsylvania State University Press.

Dixon, Angela R. and Edward E. Telles. 2017. "Skin Color and Colorism: Global Research, Concepts, and Measurement." *Annual Review of Sociology* 43(1): 405-424.

Feliciano, Cynthia. 2016. "Shades of Race: How Phenotype and Observer Characteristics Shape Racial Classification." *American Behavioral Scientist*. 60(4): 390-419.

Flores, René D. 2019. "Are you the Company you Keep?: Romantic Relationships and Women′s Perceived Race." *Under review.*

Flores, René D. and Ariela Schachter. Forthcoming. "Who are the 'Illegals'? The Social Construction of Illegality in the U.S. *American Sociological Review*.

Flores, René and Edward Telles. 2012. "Social Stratification in Mexico: Disentangling Color, Ethnicity, and Class." *American Sociological Review* 77(3): 486-494.

Freeman, Jonathan, Andrew Penner, Aliya Saperstein, Matthias Scheutz, and Nalini Ambady. 2011. "Looking the Part: Social Status Cues Shape Race Perception." *PLoS ONE* 6(9): e25107.

Gans, Herbert J. 2012. "'Whitening' and the Changing American Racial Hierarchy." *Du Bois Review* 9(2): 267-279.

Garcia, Denia and Maria Abascal. 2016. "Colored Perceptions: Racially Distinctive Names and Assessments of Skin Color." *American Behavioral Scientist* 60(4): 420-441.

Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto. 2015. “Validating Vignette and Conjoint Survey Experiments against Real-World Behavior.” *Proceedings of the National Academy of Sciences* 112(8):2395–2400.

Hainmueller, Jens, Daniel J. Hopkins, and Teppei Yamamoto. 2014. "Casual Inference in Conjoin Analysis: Understanding Multidimensional Choices via Stated Preference Experiments." *Political Analysis* 22(1): 1-30.

Haney-Lopez, Ian. 1996. *White By Law*. New York: NYU Press.

Harris, David R. 2002. “In the Eye of the Beholder: Observed Race and Observer Characteristics." (Research Report No. 02-522). Ann Arbor, MI: Population Studies Center, University of Michigan. Retrieved from https://www.psc.isr.umich.edu/pubs/pdf/rr02-522.pdf .

Lee, Jennifer and Frank D. Bean. 2010. *The Diversity Paradox*. New York: Russell Sage Foundation.

Maghbouleh, Neda. 2017. *The Limits of Whiteness*. Stanford, CA: Stanford University Press.

McDermott, Monica. 2018. "Terminal Identities: The Racial Classification of Immigrants in Late Nineteenth- and Early-Twentieth-century Death Records." *Sociology of Race and Ethnicity* 4(3): 400-416.

Monk, Ellis P. 2016. "The Consequences of 'Race and Color' in Brazil." *Social Problems* 63(3): 413-430.

--- 2018. "The color of punishment: African Americans, skin tone, and the criminal justice system." *Ethnic and Racial Studies*. doi: 10.1080/01419870.2018.1508736.

Morning, Ann. 2014. "Does Genomics Challenge the Social Construction of Race?" *Sociological Theory* 32(3): 189-207.

Nelson, Alondra. 2016. *The Social Life of DNA*. Boston: Beacon Press.

Office of Management and Budget. 2016. "Review and Possible Limited Revision of OMB's Statistical Policy Directive on Standards for Maintaining, Collecting, and Presenting Federal Data on Race and Ethnicity." *Federal Register* 81, September 30.

Omi, Michael and Howard Winant. 2015. *Racial Formation in the United States* (3rd Edition). London and New York: Routledge.

Pager, Devah, Bruce Western, and Bart Bonikowski. 2009. "Discrimination in a Low-Wage Labor Market: A Field Experiment*." American Sociological Review* 74: 777-799.

Penner, Andrew M. and Aliya Saperstein. 2008. "How Social Status Shapes Race." *Proceedings of the National Academy of Sciences* 105(50): 19628-30.

Portes, Alejandro, and Rubén G. Rumbaut. 2001. *Legacies: The story of the immigrant second generation*. Univ of California Press.

Roth, Wendy D. 2005. "The End of the One-Drop Rule? Labeling of Multiracial Children in Black Intermarriages." *Sociological Forum* 20(1): 35-67.

--- 2010. "Racial Mismatch: The Divergence Between Form and Function in Data for Monitoring Racial Discrimination of Hispanics." *Social Science Quarterly* 91(5): 1288-1311.

--- 2016. "The Multiple Dimensions of Race." *Ethnic and Racial Studies* 39(8): 1310-1338.

Roth, Wendy D. and Biorn Ivemark. 2018. "Genetic Options: The Impact of Genetic Ancestry Testing on Ethnic and Racial Identities." *American Journal of Sociology* 124(1): 150-184.

Saperstein, Aliya and Andrew M. Penner. 2010. "The Race of a Criminal Record: How Incarceration Colors Racial Perceptions" *Social Problems* 57(1): 92-113.

Saperstein, Aliya and Andrew Penner. 2012. "Racial Fluidity and Inequality in the United States," *American Journal of Sociology* 118: 676-727.

Schachter, Ariela. 2014. "Finding Common Ground? Indian Immigrants and Asian American Panethnicity." *Social Forces* 92(4): 1487-1512.

--- 2016. "From 'Different' to 'Similar': An Experimental Approach to Understanding Assimilation." *American Sociological Review* 81(5): 981-1013.

Snipp, C. Matthew. 2003. "Racial Measurement in the American Census: Past Practices and Implications for the Future." *Annual Review of Sociology* 29: 563-588.

Snipp, C. Matthew, Karl Eschbach and Khalil Supple. 1998. "Changes in Racial Identification and Changes in the Educational Attainment of America Indians, 1970-1990." *Demography* 35: 35-43.

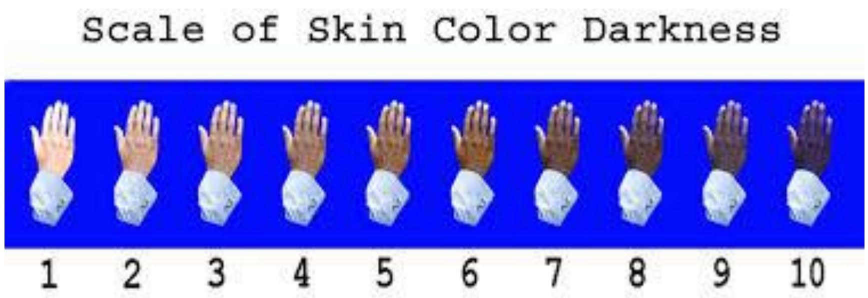
Sue, Christina A. 2017. "U.S. racial and ethnic relations in the twenty-first century: are old divisions prevailing?" *Ethnic and Racial Studies* 40(13): 2210-2217.

Telles, Edward and the Project on Ethnicity and Race in Latin America (PERLA). 2014. *Pigmentocracies: Ethnicity, Race, and Color in Latin America*. Chapel Hill, NC: University of North Carolina Press.

Telles, Edward E. and Nelson Lim. 1998. "Does it mater who answers the race question? Racial classification and income inequality in Brazil." *Demography* 35(4): 465-474.

US Census Bureau. 2017. "2015 National Content Test: Race and Ethnicity Analysis Report." https://www2.census.gov/programs-surveys/decennial/2020/program-management/final-analysis-reports/2015nct-race-ethnicity-analysis.pdf

Table 1. Profile Attributes and Attribute Values

Attributes	Values
Name	Claire, Jake, Pedro, Guadalupe, DeShawn, Lakisha, Tae-min, Soo-jung, Odakota, Lakota, Mohammed, Samaira
Religion	Christian (Protestant), Christian (Catholic), Hindu, Jewish, Muslim, Buddhist, Atheist/Agnostic
Primary Language Spoken at Home	English, Spanish, Korean, Arabic, Navajo, German
Occupation	*Low-status:* Fast Food Cook, Cashier, Home Health Aide *Medium-status:* Real Estate Agent, Food Service Manager, Paralegal *High-status:* Doctor, Sales Manager, Lawyer
Skin Color*	
Genetic Ancestry Test Results	*Single-Ancestries:* 100% European; 100% Asian; 100% MENA; 100% Cherokee/Navajo; 100% Mixtec/Mayan; 100% Sub-Saharan African *Majority-European Ancestries:* 10% Asian, 90% European; 10% MENA, 90% European; 10% Cherokee/Navajo, 90% European; 10% Mixtec/Mayan, 90% European; 10% Sub-Saharan African, 90% European *Majority non-Sub-Saharan African Ancestries:* 10% Sub-Saharan African, 90% Asian; 10% Sub-Saharan African, 90% MENA; 10% Sub-Saharan African, 90% Cherokee/Navajo; 10% Sub-Saharan African, 90% Mixtec/Mayan *European/Non-European Ancestries:* 50% Asian, 50% European; 50% MENA, 50% European; 50% Cherokee/Navajo, 50% European; 50% Mixtec/Mayan, 50% European; 50% Sub-Saharan African, 50% European *Sub-Saharan African/Non-African Ancestries:* 50% Sub-Saharan African, 50% Asian; 50% Sub-Saharan African, 50% MENA; 50% Sub-Saharan African, 50% Cherokee/Navajo; 50% Sub-Saharan African, 50% Mixtec/Mayan *Fully mixed Ancestries:* 20% Sub-Saharan African, 20% European, 20% MENA, 20% Asian, 20% Cherokee/Navajo; 20% Sub-Saharan African, 20% European, 20% MENA, 20% Asian, 20% Mixtec/Mayan

*Each profile was assigned one of the 10 hand images. Images come from Massey and Martin (2003).

Table 2. Treatments Predicting Racial/Ethnic Classification, Average Marginal Component Effects (AMCEs) and (Standard Errors)

	White AMCE	se	Black AMCE	se	Native AMCE	se	Hispanic AMCE	se	MENA AMCE	se	Asian AMCE	se
Name (ref = Claire/Jake)												
Pedro/Guadelupe	-0.04***	(0.01)	0.00	(0.01)	-0.01	(0.01)	0.06***	(0.01)	-0.01	(0.01)	-0.00	(0.01)
DeShawn/Lakisha	-0.03**	(0.01)	0.03**	(0.01)	-0.01	(0.01)	-0.00	(0.01)	0.00	(0.01)	0.01	(0.01)
Tae-min/Soo-jung	-0.04***	(0.01)	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)	0.02	(0.01)	0.06***	(0.01)
Odakota/Lakota	-0.04***	(0.01)	0.01	(0.01)	0.02*	(0.01)	-0.00	(0.01)	0.01	(0.01)	0.00	(0.01)
Mohammed/Samaira	-0.04***	(0.01)	-0.01	(0.01)	-0.01	(0.01)	0.00	(0.01)	0.06***	(0.01)	0.00	(0.01)
Religion (ref = Protestant)												
Catholic	-0.01	(0.01)	0.01	(0.01)	-0.00	(0.01)	0.01*	(0.01)	-0.00	(0.01)	-0.01	(0.01)
Hindu	-0.04***	(0.01)	-0.01	(0.01)	-0.03**	(0.01)	-0.01	(0.01)	0.06***	(0.01)	0.03**	(0.01)
Jewish	-0.00	(0.01)	-0.00	(0.01)	-0.01	(0.01)	0.00	(0.01)	0.02*	(0.01)	-0.01	(0.01)
Muslim	-0.05***	(0.01)	0.01	(0.01)	-0.02**	(0.01)	-0.01	(0.01)	0.08***	(0.01)	-0.00	(0.01)
Buddhist	-0.05***	(0.01)	0.01	(0.01)	-0.01	(0.01)	-0.00	(0.01)	0.02+	(0.01)	0.03***	(0.01)
Atheist/Agnostic	-0.03**	(0.01)	0.01	(0.01)	-0.00	(0.01)	-0.00	(0.01)	0.02	(0.01)	0.00	(0.01)
Language (ref = English)												
Spanish	-0.06***	(0.01)	-0.06***	(0.01)	-0.02**	(0.01)	0.18***	(0.01)	-0.03*	(0.01)	-0.01+	(0.01)
Korean	-0.05***	(0.01)	-0.08***	(0.01)	-0.02*	(0.01)	0.00	(0.00)	-0.04**	(0.01)	0.18***	(0.01)
Arabic	-0.06***	(0.01)	-0.06***	(0.01)	-0.02**	(0.01)	-0.00	(0.00)	0.17***	(0.01)	-0.02***	(0.01)
Navajo	-0.06***	(0.01)	-0.09***	(0.01)	0.20***	(0.01)	0.00	(0.00)	-0.03**	(0.01)	-0.03***	(0.01)
German	0.04***	(0.01)	-0.03*	(0.01)	-0.02**	(0.01)	0.01	(0.00)	0.02	(0.01)	-0.01	(0.01)
Occupation (ref = Low status)												
Medium status	0.01	(0.01)	0.00	(0.01)	-0.00	(0.01)	-0.01+	(0.00)	-0.00	(0.01)	-0.00	(0.01)
High status	-0.00	(0.01)	0.00	(0.01)	-0.00	(0.01)	-0.01*	(0.00)	0.01	(0.01)	0.01	(0.01)
Skin color (ref = Light)												
Medium	-0.22***	(0.01)	0.12***	(0.01)	0.02**	(0.01)	0.01*	(0.00)	0.08***	(0.01)	-0.00	(0.01)
Dark	-0.31***	(0.01)	0.35***	(0.01)	-0.02**	(0.01)	-0.01***	(0.00)	0.04***	(0.01)	-0.05***	(0.01)
Genetic Ancestry Test (ref = 100% European)												
10% Asian, 90% European	-0.00	(0.02)	-0.05**	(0.02)	-0.01	(0.01)	0.00	(0.01)	-0.03	(0.02)	0.09***	(0.02)
10% MENA, 90% European	-0.04+	(0.02)	-0.03	(0.02)	-0.00	(0.01)	-0.01	(0.01)	0.09***	(0.02)	-0.01	(0.01)
10% Cherokee/Navajo, 90% European	-0.02	(0.03)	-0.07**	(0.02)	0.14***	(0.02)	-0.02	(0.01)	-0.02	(0.02)	-0.02	(0.01)
10% Mixtec/Mayan, 90% European	0.00	(0.03)	-0.04+	(0.02)	0.08***	(0.02)	-0.01	(0.02)	-0.03	(0.02)	0.00	(0.02)
10% African, 90% European	-0.04+	(0.02)	0.00	(0.02)	-0.01	(0.01)	-0.01	(0.01)	0.07***	(0.02)	-0.02	(0.01)
50% Asian, 50% European	-0.19***	(0.02)	-0.10***	(0.02)	-0.01	(0.01)	-0.01	(0.01)	0.01	(0.02)	0.30***	(0.02)
50% MENA, 50% European	-0.20***	(0.02)	-0.05**	(0.02)	0.01	(0.01)	-0.03*	(0.01)	0.28***	(0.02)	-0.02	(0.01)
50% Cherokee/Navajo, 50% European	-0.19***	(0.02)	-0.15***	(0.02)	0.43***	(0.03)	-0.03*	(0.01)	-0.04*	(0.02)	-0.02	(0.01)
50% Mixtec/Mayan, 50% European	-0.20***	(0.02)	-0.08***	(0.02)	0.34***	(0.03)	0.00	(0.02)	-0.05*	(0.02)	-0.02	(0.01)
50% African, 50% European	-0.20***	(0.02)	0.08***	(0.02)	-0.00	(0.01)	-0.02*	(0.01)	0.14***	(0.02)	0.01	(0.01)
50% African, 50% Asian	-0.27***	(0.02)	0.03	(0.02)	-0.02	(0.01)	-0.03**	(0.01)	0.09***	(0.02)	0.19***	(0.02)
50% African, 50% MENA	-0.29***	(0.02)	0.04*	(0.02)	-0.03*	(0.01)	-0.03**	(0.01)	0.32***	(0.02)	-0.01	(0.01)
50% African, 50% Cherokee/Navajo	-0.28***	(0.02)	0.03	(0.03)	0.28***	(0.03)	-0.02+	(0.01)	0.01	(0.02)	-0.02+	(0.01)
50% African, 50% Mixtec/Mayan	-0.28***	(0.02)	0.04	(0.03)	0.23***	(0.03)	-0.01	(0.02)	0.05*	(0.02)	-0.02	(0.01)
10% African, 90% Asian	-0.29***	(0.02)	-0.09***	(0.02)	-0.03*	(0.01)	-0.02	(0.01)	-0.03	(0.02)	0.45***	(0.02)
10% African, 90% MENA	-0.26***	(0.02)	-0.02	(0.02)	-0.02	(0.01)	-0.03**	(0.01)	0.35***	(0.02)	-0.02*	(0.01)
10% African, 90% Cherokee/Navajo	-0.31***	(0.02)	-0.11***	(0.02)	0.54***	(0.03)	-0.03**	(0.01)	-0.09***	(0.02)	-0.00	(0.01)
10% African, 90% Mixtec/Mayan	-0.29***	(0.02)	-0.08**	(0.02)	0.44***	(0.03)	-0.00	(0.02)	-0.04*	(0.02)	-0.03*	(0.01)
20-20-20-20-20 (Cherokee/Navajo)	-0.23***	(0.02)	-0.02	(0.03)	0.07***	(0.02)	-0.01	(0.01)	0.15***	(0.03)	0.05**	(0.02)
20-20-20-20-20 (Mixtec/Mayan)	-0.19***	(0.02)	0.01	(0.03)	0.03+	(0.02)	-0.01	(0.01)	0.14***	(0.03)	0.03+	(0.02)
100% Asian	-0.30***	(0.02)	-0.15***	(0.02)	-0.01	(0.01)	-0.04***	(0.01)	-0.09***	(0.02)	0.60***	(0.02)
100% MENA	-0.26***	(0.02)	-0.09***	(0.02)	-0.01	(0.01)	-0.03*	(0.01)	0.40***	(0.02)	-0.01	(0.01)
100% Cherokee/Navajo	-0.30***	(0.02)	-0.21***	(0.02)	0.67***	(0.03)	-0.03*	(0.01)	-0.10***	(0.02)	-0.03+	(0.01)
100% Mixtec/Mayan	-0.31***	(0.02)	-0.13***	(0.02)	0.58***	(0.03)	-0.01	(0.01)	-0.11***	(0.02)	-0.02	(0.01)
100% African	-0.25***	(0.02)	0.18***	(0.02)	-0.02+	(0.01)	-0.03*	(0.01)	0.12***	(0.02)	-0.01	(0.01)
Observations	15,000		15,000		15,000		15,000		15,000		15,000	
R-squared	0.21		0.18		0.33		0.11		0.15		0.30	

Clustered standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05, + p<0. Note: Model controls for whether respondent received "immigrant" or "US citizen" treatments.

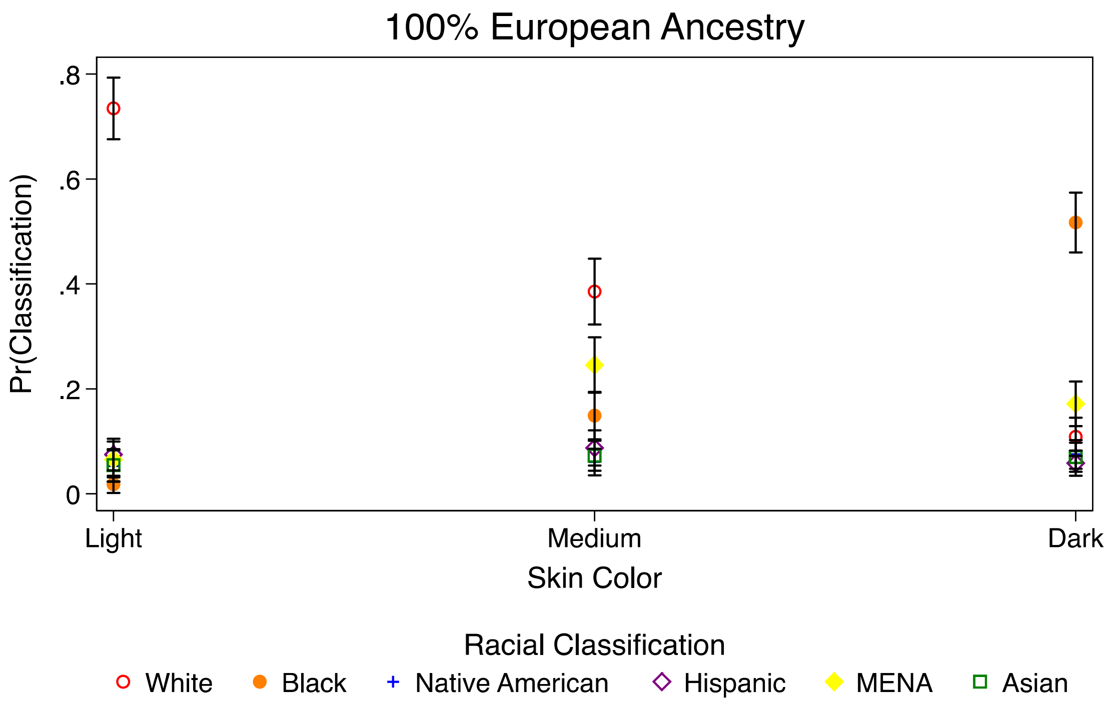


Figure 1. Comparing Racial Classification Probabilities by Skin Color for 100% European Ancestry Profiles

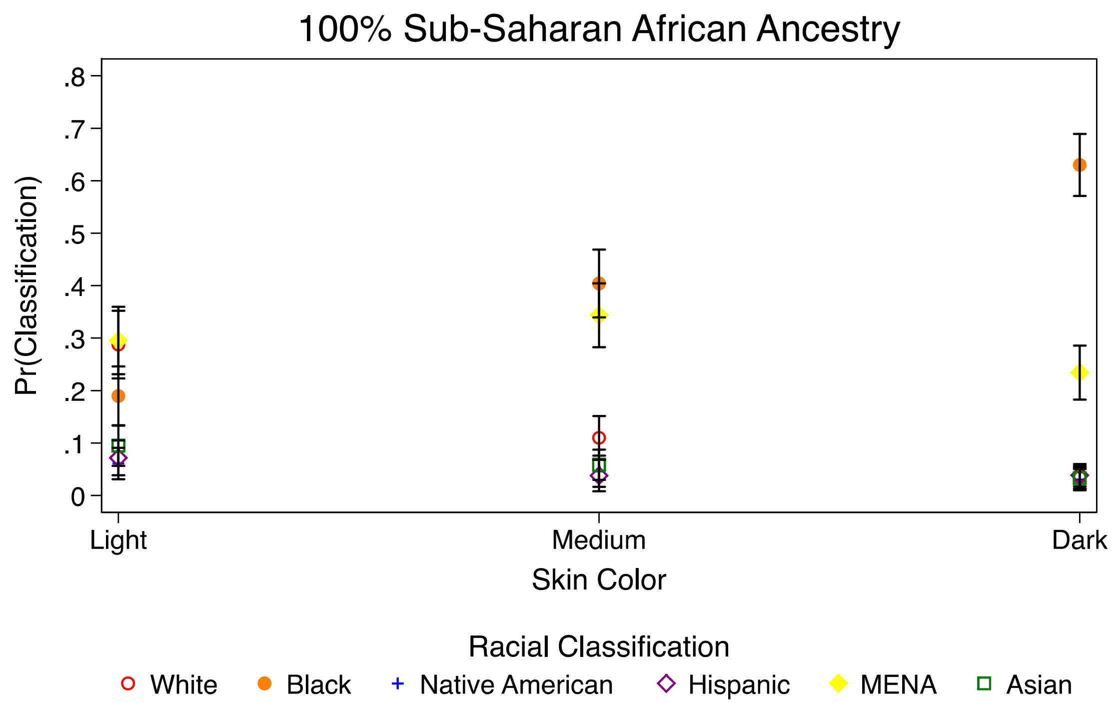


Figure 2. Comparing Racial Classification Probabilities by Skin Color for 100% Sub-Saharan African Ancestry Profiles

Design Appendix

Introductory Text: We are interested in studying how people classify the race/ethnicity of others. You will be presented with pairs of profiles describing different [*U.S-born citizens/ immigrants*] living in the United States. For each pair of profiles, please look at the information carefully, and then indicate how you would classify each person's race/ethnicity. There are no correct or incorrect answers for this, we just want to understand how people make these classifications. Even if you aren't entirely sure, please indicate your best guess about the race/ethnicity of each person.

Dependent Variable: How would you classify these [*U.S.-born citizens/immigrants*]? (please chose the single best category for each individual)

Response Options: White; Black; Native American; Hispanic; Middle Eastern/North African (MENA); Asian

Screen Shot Examples from Actual Survey:

Ex. 1

YouGov

	U.S.-born citizen 1	U.S.-born citizen 2
Genetic Ancestry Test Results	20% Sub-Saharan African, 20% European, 20% Middle Eastern/North African, 20% Asian, 20% Native American (Cherokee)	50% Middle Eastern/North African, 50% European
Skin Color		
Name	Lakota	Samaira
Religion	Christian (Protestant)	Buddhist
Primary Language Spoken at Home	Spanish	Spanish
Occupation	Lawyer	Sales Manager

How would you classify these U.S.-born citizens? (please chose the single best category for each individual)

	White	Black	Native American	Hispanic	Middle Eastern/North African (MENA)	Asian
U.S.-born citizen 1						
U.S.-born citizen 2						

Ex. 2

YouGov

	U.S.-born citizen 5	U.S.-born citizen 6
Genetic Ancestry Test Results	100% Sub-Saharan African	50% Sub-Saharan African, 50% European
Skin Color		
Name	Jake	Soo-jung
Religion	Jewish	Hindu
Primary Language Spoken at Home	Spanish	English
Occupation	Real Estate Agent	Real Estate Agent

How would you classify these U.S.-born citizens? (please chose the single best category for each individual)

	White	Black	Native American	Hispanic	Middle Eastern/North African (MENA)	Asian
U.S.-born citizen 5						
U.S.-born citizen 6						

Ex. 3

YouGov

	Immigrant 3	**Immigrant 4**
Genetic Ancestry Test Results	100% Sub-Saharan African	50% Sub-Saharan African, 50% Asian
Name	Pedro	Tae-min
Primary Language Spoken at Home	Arabic	German
Religion	Christian (Protestant)	Christian (Protestant)
Skin Color		
Occupation	Real Estate Agent	Lawyer