Shades of Race:
How Phenotype and Observer Characteristics Shape Racial Classification

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Although race-based discrimination and stereotyping can only occur if people place others into racial categories, our understanding of this process, particularly in contexts where observers categorize others based solely on appearance, is limited. Using a unique dataset drawn from observers' assessments of photos posted by White, Black, Latino and multiracial on-line daters, this study examines how phenotype and observer characteristics influence racial categorization and cases of divergence between self-identities and others' classifications. I find that despite the growth in the multiracial population, observers tend to place individuals into monoracial categories, including Latino. Skin color is the primary marker used to categorize others by race, with light skin associated with Whiteness, medium skin with Latinidad, and, most strongly, dark skin with Blackness. Among daters who self-identify as Black along with other racial categories, those with dark skin are overwhelmingly placed solely into a Black category. These findings hold across observers, but the proportion of photos placed into different racial categories differs by observers' gender and race. Thus, estimates of inequality may vary depending not only on *how* race is assessed, but also on *who* classifiers are. I argue that patterns of racial categorization reveal how the U.S. racial structure has moved beyond binary divisions into a system in which Latinos are seen as a racial group in-between Blacks and Whites, and a dark-skin rule defines Blacks' racial options.

Racial classification has become more complex as the size of populations not clearly categorized in Black or White terms has grown through immigration and intermarriage. Latinos and multiracials are the fastest growing segments of the U.S. population. Latinos made up more than half of the U.S. population growth from 2000 to 2010 alone, and are expected to double in size by 2050 (Stepler & Brown, 2015). From 2000 to 2010, the population identifying as more than one race grew by 32 percent, faster than any single-race population (N. A. Jones & Bullock, 2012). Unlike most Blacks and Whites, the way Latinos and multiracials self-identify racially often does not correspond with how others categorize them (Brunsma, 2006; Herman, 2010; Itzigsohn, 2009; Roth, 2012). How do individuals come to categorize others? And why might others' categorizations differ from racial self-identities? While much of the literature examines this second question from the perspective of racial *identification,* fewer studies have examined the process through which individuals place others into racial categories (for exceptions – see Roth 2012; Telles 2002). Yet because racial categorization must occur before racial discrimination, this process fundamentally contributes to racial inequality.

The process of racial categorization provides insight into the racial structure in the U.S. and the place of different racial groups in it. Scholars recognize that the U.S. racial structure, previously characterized primarily by a Black/White divide, is changing, but they disagree on how. Some argue that the U.S. racial structure continues to be dominated by binary divisions between Blacks and non-Blacks (Lee & Bean, 2007); (Yancey, 2003). Others argue for a more complex racial system in which Latinos are recognized as a racial group in-between Blacks and Whites, with inequality highly dependent on phenotype (Bonilla-Silva, 2004; Roth, 2012). How observers assign race can shed light on the changing racial structure in at least three ways. First, whether the categories of Black and White continue to be used most frequently to assign race, or whether mixed racial categories are also used often, suggests either a rigid or more flexible structure. Second, if particular phenotypic markers are often used to classify individuals as Latino, it suggests that Latinos are seen as a race, like Whites and Blacks. Third, if markers such as dark skin are used to place individuals who self-identify differently into the Black racial category, while the classifications of other groups are not as phenotype-dependent, it suggests that Black continues to be the most stigmatized category.

Understanding how racial categorization differs from self-identification also has implications for the measurement of race. Studies suggest that the Census and surveys should include a measure of perceived race to more adequately assess race to monitor discrimination (Roth, 2010). However, we do not have a strong understanding of how much different observers agree or disagree in their racial assessments, which phenotypic characteristics are used to assign race, and how observers' own characteristics shape racial classifications, all of which would affect how racial questions should be designed and who should collect such data.

I examine racial categorization, and how it differs from self-identification, by drawing on data from observers' assessments of the race and phenotypic characteristics of photos posted on an online dating website. This context, in which daters posted their photos in order to attract a date, and outside observers classified their race, mirrors a real-life process: under the default search method for Match.com and other online dating websites, members enter a desired gender and age and are presented with a group of photos. Since race remains a symbolic boundary (Roth, 2012), racial categorization likely factors into whether profiles are selected for more in-depth readings; thus, racial classification has implications for date, and ultimately mate, selection. Such cursory classifications, based on physical appearance and little else, are similar to many other real-life situations in which we see disparate treatment by race, such as encounters with police, doormen, or salespeople. Within this context, I build upon existing research on racial categorization in several ways. First, while existing studies focus on one group, such as Latinos or multiracials, I examine how racial classification differs from self-identification for those who identify as White, Black, Latino or any of these in combination with other races. Second, while current studies only consider observed race, I include measures of phenotypic characteristics, allowing me to assess their role in shaping racial classification. Third, unlike most research that relies on one interviewer's assessment of race, I include multiple observers' assessments of race. This allows me to examine how much observers agree on the racial categorizations of different self-identified racial groups and the role of observers' gender and race in shaping racial classifications.

BACKGROUND

Racial Classification, the U.S. Racial Structure, and Racial Inequality

As suggested above, the process through which individuals are placed into racial categories by others

may shed light on racial inequality and the changing U.S. racial structure. First, while some scholars suggest that Latinos are an ethnic group assimilating into Whiteness (Yancey 2003), others argue that Latinos are increasingly seen *as* a race situated in-between Whites at the top of the racial hierarchy and Blacks at the bottom (Bonilla-Silva, 2004). If indeed, the "United States racializes Latinos" (Cobas, Duany, & Feagin, 2009), this would be reflected in observers using particular phenotypic characteristics to classify individuals *as* Latino. Second, how multiracial people are perceived by others can reveal whether the U.S. racial structure is changing to a more flexible system in which it is possible to belong to multiple racial groups, or whether multiracial individuals ultimately must blend into existing monoracial groups.

Third, understanding how appearance relates to racial categorization may shed light on the continued salience of the one-drop rule. It is widely accepted that, historically, individuals in the United States with any known African ancestry have been categorized as Black (Davis, 1991). However, recent research suggests the one-drop rule was not always strictly enforced, as status distinctions between mulattos and Blacks were meaningful during the turn of the 20th century (Saperstein & Gullickson, 2013). In the contemporary U.S. context, the operation of a strict one-drop rule has also been questioned (Campbell, 2007; Roth, 2005). While the one-drop rule ultimately depends upon ancestry knowledge, how phenotype matters in the application of the rule is important because, in many contexts, phenotype is used *as* an indicator of ancestry. If dark skin is strongly associated with Black classification, while any one phenotypic marker is less consequential in the classification of other groups, it suggests that Black continues to be a uniquely stigmatized minority group with the least flexible racial options. At the same time, if some individuals who self-identify as Black or part-Black, such as those with lighter skin tones, are not classified as Black, it suggests that only some segments of the self-identifying Black population are subject to this stigmatization. While future studies that include observers' knowledge of ancestries would be more definitive, divergence by skin tone suggests a loosening of the one-drop rule since historically even light-skinned individuals with other stereotypically Black physical features were categorized as Black (Davis 1991).

Understanding how observers place individuals into racial categories, and when that diverges from self-identified race, has further implications for understanding inequality. Existing research has established the role

of phenotype in shaping stratification *within* racial groups. For example, self-identified Blacks with more stereotypically Black phenotypes are treated more negatively (see Maddox, 2004 for a review), and darker-skinned Latinos and Blacks have worse criminal justice outcomes and lower incomes (Blair, Judd, & Chapleau, 2004; Hunter, 2005; Telles & Murguia, 1990). However, existing research does not consider that those with less stereotypical features may benefit from others classifying them as members of another racial group. By showing how phenotype shapes racial categorization, this study highlights a potential mechanism through which we see inequality *within* self-identified racial groups.

Racial classification processes also have implications for estimates of inequality *between* racial groups (Saperstein & Penner, 2012).This study adds to a growing body of work that considers the multidimensionality of race by analyzing self and other classifications (Ahmed, Feliciano, & Emigh, 2007; Saperstein, 2006; Telles & Lim, 1998). Previous studies show that racial classification and racial self-identification are differentially associated with outcomes such as income (Bailey, Loveman, & Muniz, 2013; Saperstein, 2006; Telles & Lim, 1998) and health (C. P. Jones et al., 2008). For example, Jones et al (2008) find that racial classification by others matters more for determining health status than self-identified race. This implies that Latino-White health disparities are under-estimated using standard racial self-identification measures. Understanding how phenotype shapes racial classification therefore has implications for racial inequality because it suggests a mechanism – the use of phenotypic markers to assess race – to explain why the disadvantage of Blacks relative to other racial groups may be more pronounced when race is measured as racial classification rather than self-identification.

Self-Identifications vs. Outsider Classifications of Race

Divergences between racial self and other classifications may be accounted for by several different processes. For example, individuals from different countries may have racial understandings that differ (Itzigsohn, 2009; Roth, 2012; Saperstein, 2006). Or, outsiders might mark differences that individuals wish to eliminate, such as when individuals identify as majority group members, but are labeled as minority group members (Ahmed et al., 2007). In a third example, insiders might assert differences that outsiders disregard, such as when mixed-race people resist monoracial labels (Daniel, 2002; Davis, 1991).

Although, theoretically, anyone may experience discrepancies in classification, research in the U.S. has shown that observers' classifications tend to be most congruent with the identifications of Whites and Blacks, and more incongruent with the identifications of self-identified Latinos and multiracials (D. R. Harris, 2002; Herman, 2010). For example, while over 97% of self-identified Blacks and Whites in Saperstein's (2006) study were consistently classified by observers, only 50% of self-identified "others" were. Herman (2010) finds that observers classify almost half of self-identified multiracials into monoracial categories, and that while individuals who identify as part-Black are usually classified as Black by observers, observers were less consistent in classifying non-Black multiracials. In her study of Puerto Rican and Dominican migrants, Roth (2010) finds that many respondents who self-identify racially as Hispanic would be categorized as White or Black based on appearance. Following this literature, *I expect that self-identities expressed in dating profiles will diverge the most from outsiders' classifications among multiracial individuals, followed by Latinos. I also expect that multiracial Blacks will be more likely than other multiracial groups to be placed into a single monoracial category (in this case, Black).* For the same reasons, *I expect observers to disagree the most in classifying those who self-identify multiracially, and I expect the most agreement about who is Black.*

What drives inconsistencies between self and other classifications? While recent work has examined how status markers (e.g. poverty level, education) and demographic characteristics (e.g. age, nativity) relate to inconsistencies between self-identification and other-classification (Ahmed et al., 2007; Saperstein, 2006; Telles, 2002), most existing studies in the U.S. context do not include measures of phenotype. Thus, we know relatively little about how phenotypic characteristics matter in cases where self-identifications diverge from outsider classifications despite the likelihood that in many social settings, appearance is the first and primary marker used to racially classify individuals. One contribution of this study is to assess how particular phenotypic characteristics relate to inconsistencies in self vs. other classifications.

Phenotype and Racial Classification

While phenotypic differences are often employed in most definitions of race[1], how particular phenotypic characteristics are used to categorize individuals into racial categories is often not clear-cut. Wade

(1993) criticizes racial theorists' tendency to take physical differences for granted, arguing that we must recognize the historical processes through which only certain physical markers have been racialized. Moreover, race is generally constructed as a set of discrete categories, but phenotypic characteristics occur along a continuum. How phenotypic characteristics are employed in categorizing individuals, and which markers are most salient, is especially unclear in the case of multiracials and Latinos.

Few studies have examined the role of phenotypic characteristics in shaping how individuals racially classify others. Studies of multiracial individuals' *self*-identifications have confirmed appearance is important, but most have only examined outsiders' perception of their race, rather than particular phenotypic characteristics (Brunsma & Rockquemore, 2001; Herman, 2004). Experiments with morphed photos or photos of real biracial people have found that, consistent with the one-drop rule, Black-White biracials are more frequently categorized as Black than White (Halberstadt, Sherman, & Sherman, 2011; Herman, 2010; Ho, Sidanius, Levin, & Banaji, 2011; Peery & Bodenhausen, 2008). However, one recent study found that Black-White biracials are more likely to be classified as White than Black (Chen & Hamilton, 2012). These divergent findings may stem from the actual phenotypic features in the photographs, which were not assessed.

Research on racial awareness and categorization has found that hair, nose, lips and skin color variation are all used to classify photos as Black (Alejandro-Wright, 2013; Blair & Judd, 2011). However, studies suggest that skin color is the most important criterion used to assign race (Brown, Dane, & Durham, 1998). For example, Alejandro-Wright's research (2013) shows that, at least among children, skin color is the dominant criterion used to place others into racial categories, so much so that photos of medium or lighter-skinned Blacks are often classified as non-Black. While providing valuable insights, these studies are limited to experimental settings and have only examined the role of phenotype in categorizations as Black.

Limited research has assessed the role of phenotypic characteristics in classifications as Latino or multiracial, although experimental research has shown that, with considerable agreement, subjects do identify a stereotypical "Latino" appearance (Wilkins, Kaiser, & Rieck, 2010). One experimental study showed that ambiguous faces with curly hair were more often classified as Hispanic than Black (MacLin & Malpass, 2001). Moreover, fieldwork by Roth (2010: 1297) suggests that people recognize a Latino racial type

characterized by "brown skin color and/or a mixture of European and African features." Similarly, studies suggest that self-identified Latinos with light skin recognize that they are seen as less authentic than their darker-skinned Latino counterparts (Hunter, 2005; Jimenez, 2004).

I extend prior research by considering how skin colors, nose and lip shapes, and hair types influence racial categorization generally, and I also consider the role of body type, since research suggests that body types are racialized, with heavier bodies more accepted among Latinos and Blacks than among Whites (Glasser, Robnett, & Feliciano, 2009). *I expect skin color will be the most important phenotypic characteristic shaping racial classification, with the strongest association between dark skin and Black classification. Medium skin will be associated with Latino classification, and light skin with White classification.* While skin color may be the most salient phenotypic marker, *I also expect that those with stereotypically Black characteristics, such as full lips, broad noses, and kinky or braided hair, will be more likely to be classified as Black, while those with thin lips, narrow noses, and straight hair will be more likely to be classified as White.* Finally, *I expect non-dark-skinned individuals with characteristics that do not conform to one racial type, such as those with light skin and kinky hair, to be mostly classified as mixed or other.*

Different Observers and Observer Characteristics

Most studies that include measures of perceived racial classification have relied on the reports of one observer, implicitly assuming that different observers vary little in their racial assessments. However, how much observers agree in their racial categorization of others may depend upon the extent to which observers share a common culture, and this may vary by historical and geographic context. For example, in his study of racial categorization in Puerto Rico, Gravlee (2005) finds a high degree of consensus among observers in contrast to a prior study in the Brazilian context (M. Harris, 1970). In the U.S. context, Roth (2012) argues people are increasingly adopting a Hispanicized U.S. racial schema, in which Latinos are considered a racial group. If this racial schema is widely adopted, we would expect a high level of agreement among observers from different racial backgrounds in their use of the Latino racial category.

However, observer characteristics, such as race and gender, may also influence classification. Social psychological literature offers two competing hypotheses about the influence of observers' race on their

classification of others. On the one hand, some argue that individuals are biased towards excluding others as members of their own group because of a desire to maximize their in-group's distinctiveness (Castano, Yzerbyt, Bourguignon, & Seron, 2002; Leyens & Yzerbyt, 1992). On the other hand, racial categorization may be shaped by familiarity, such that individuals are more likely to recognize a range of phenotypes as members of their in-group (Chen & Hamilton, 2012; Willadsen-Jensen & Ito, 2006). While some studies of particular subpopulations have found no effects of observer characteristics on racial classification (Herman, 2010), Harris (2002) finds evidence consistent with the latter theory: White, Asian, and multiracial individuals were more likely to classify photos as members of their in-group. However, Black observers were no more likely than others to classify photos as Black, which might be attributed to a tendency for all observers to perceive photos with any trace of African ancestry as Black (Harris 2002: 13). Harris's study is limited because it is based on photos pre-selected to be racially ambiguous. Nevertheless, based on this research and the theory that familiarity shapes a tendency towards in-group classifications, *I expect Whites will be more likely to categorize others as White and Latinos more likely to categorize others as Latino*. Given the historic operation of the one-drop rule for Blacks and the corresponding norm that those with any discernable African ancestry be categorized as Black, *I expect racial classification as Black will not vary by observers' race.*

Gender may also shape classification, since women are more likely to identify as multiracial (D. R. Harris & Sim, 2002) and have more liberal racial attitudes (Johnson & Marini, 1998; Schuman, 1997). Harris (2002) finds that women are more likely to classify others in complex ways (ie: as multiracial), which he argues stems from women's socialization to think more about others. However, others have not found gender differences in racial classification (Herman, 2010; Roth, 2012). Based on this limited research, *I expect that gender will not shape racial categorization except that women will be more likely to categorize others as multiracial*.

In sum, although race-based discrimination and stereotyping can only occur if people place others into racial categories, our understanding of this process is limited in important ways, particularly for Latinos and multiracials, two of the fastest growing segments of the U.S. population. While prior research suggests that these two groups experience the most dissonance between how they self-identify and how they are classified

by others, questions remain about how they, and other self-identified groups, are placed into racial categories when observers rely solely on appearance. This study addresses several questions by examining how observers categorize a sample of photos taken from online dating profiles: 1) How much do observers agree in their racial classifications of photos of daters who self-identify as White, Black, Latino, or one or more of these categories? 2) How does racial classification by others differ from self-identification for these groups? 3) What is the role of phenotype (skin color, nose and lip shapes, hair type, body type) in racial categorization? 4) How do observers' race and gender affect racial categorization?

DATA AND METHODS

This study relies on data collected from Internet dating profiles posted on Match.com, one of the leading Internet dating websites, with over 1.6 million active subscribers (Anon "IAC Reports Q1," 2011), between April 2011 and June 2011. Random, stratified samples of profiles from people seeking opposite-sex dates, living within 50 miles of Los Angeles, Chicago, Atlanta or New York City, and self-identifying as Black, White, or Latino[2] were collected, including those who identify with more than one racial group (whom I term "multiracial"). These metropolitan areas allow for regional diversity (West, Northeast, Midwest and South), and variation in racial/ethnic diversity[3]. Research assistants randomly selected two hundred profiles for each race/gender/region combination and coded all of the demographic information the daters provided (such as age and self-identified race)[4]. Later, 5 male and 24 female undergraduates coded only the photographs (see Appendix Table 2)[5]. Each coder was randomly given from 300 to 1700 profiles and each profile was coded by at least seven observers. The coders were explicitly instructed *not* to look at any parts of the profile except for the photograph(s).[6]

Measures

Self-Identified Race

In the "About You" section of the dating profile, daters could choose from a set of categories that included White/Caucasian, Latino/Hispanic, Black/African descent, Pacific Islander, Native American, Asian, East Indian, Middle Eastern, and Other to describe themselves. Daters could check more than one box. This study only includes daters who selected White, Black, or Latino. I re-coded self-identified race into a set of

nine categories: White only, Black only, Latino only, Black/White, Black/Latino, Latino/White, Black/Others (those who identify as Black and any other combination of racial categories), White/Others (those who identify as White and any other combination of non-Black categories), and Multiracial Others (any other combination).

Observed Race

Observers were asked to mark their best guess of the dater's race based on their photograph(s), and were given the options: White/Caucasian, Asian[7], Latino/Hispanic, Black/African-American, other, and "don't know". Coders were further instructed that "other" included multiracial groups, and were asked to write in the other race or races if they selected this category. When selecting "other," observers most frequently wrote in multiracial classifications, such as Black/White or Latino/White, although categories such as Indian or Middle Eastern were also used. In assigning race, observers may have relied on self-presentations of cultural identities (as expressed through clothing, hairstyle, etc…), in addition to phenotypic characteristics (Roth, 2012). Racial classifications may also be affected by social status cues (Freeman et al., 2011). Because each profile was coded by 7 observers, the final observed race variable used as a dependent was based on the category observed by at least 60% of the observers[8]. Cases in which over 60% of observers did not agree on a category were placed into a residual ambiguous/mixed category, and cases with less than three valid responses were dropped, which brought the analytical sample down to 4676 from 4681[9].

Phenotypic Characteristics

Observers were provided a visual guide of hands with different skin colors and were asked to mark the number, from 1(very light) to 10(very dark), corresponding to the hand closest in color to the dater's skin color in their photo(s).[10] I averaged the responses across all the observers of each profile (see Appendix Table 1 for descriptive statistics). Because preliminary analyses showed this variable was non-linearly associated with racial categorization, I recoded average skin color into a set of three categories, light, medium, and dark, first by dividing average skin color into thirds, based on the distribution. However, under that coding, no cases with dark skin were coded White and no cases with light skin were coded Black. Thus, I widened these categories just enough so that skin color was distributed across all racial classifications, which was necessary in order to run multivariate analyses. Findings therefore *underestimate* the effect of dark and light skin colors.

Using a visual nose shape guide created for this study,[11] observers coded the daters' noses as narrow, medium or broad (or don't know)[12]. Similarly, using a visual lip shape guide and visual hair type guide, observers coded the daters' lips as thin, medium or full (or don't know) and the daters' hair types as straight, wavy, curly, braids, kinky, or don't know[13]. The final variable for each of these measures was based on the category observed by at least 60% of the observers; the categories braids and kinky were collapsed due to small sample sizes and similar effects. Cases in which over 60% of observers did not agree on a category were placed into a residual "mixed" category, along with a retained "missing" category for those cases in which there were less than three valid responses.

Although observers did not code for body type, it was often visible from the photos. I therefore rely on daters' self-described body types as a proxy for observed body type. Daters could decline to answer or select from one of the following categories to describe their body types: slender, about average, athletic and toned, heavyset, a few extra pounds, or stocky. I collapsed the heavyset, few extra pounds, and stocky answers to distinguish between average, slender, athletic/toned, and heavy body types.

Observer Characteristics

Observers were asked to code their race and were given the options, White/Caucasian, Asian, Latino/Hispanic, Black/African-American, and Other and instructed that if they self-identified with more than one racial group, they should use Other and write in the groups.[14] From these data, I created measures of the percent White, percent Asian, percent Latino, and percent Black who coded each profile. Observers were similarly asked whether they identified as male or female. I created a measure of the percentage of females who coded each profile. Appendix Table 2 shows the distribution of gender and race across the 29 coders. I note that this study is highly influenced by female observers, since only five male observers participated.

Control Variables

Observers also coded their assessment of the quality of the photograph(s) in terms of how clearly they could view the respondent's appearance. Responses ranged from 1 (poor quality, unclear) to 5 (excellent quality, extremely clear). I averaged the responses across observers to create the photo quality variable.

Using measures taken from the daters' profiles, I also controlled for the gender and age of the daters. The daters' ages ranged from 18-86 with a mean age of 33. Female gender is coded 1 and male 0.

Analytic Strategy

The analysis proceeds as follows. First, I descriptively show how much observers agree on the racial categorizations of the nine monoracial and multiracial groups in the sample, and how self-identification varies by observer classification. Second, I present results from a multinomial regression model, highlighting the effects of particular phenotypic characteristics on racial categorization. Third, through the presentation of predicted probability graphs based on multinomial regression results, I show how phenotype, especially skin color, affects divergence between self and observer classifications. Finally, I present a series of graphs from the multinomial models showing how the race and gender of observers affects racial classification.

FINDINGS

Observer Categorizations and Self-Identities

Table 1 shows how much different observers agree on the racial categorizations of daters from various self-identified groups. Consistent with my hypothesis, observers agree the most about who is Black, followed by who is White: self-identified Blacks were classified by 97% of observers as Black, on average, and self-identified Whites were classified by 92% of observers as White, on average. In contrast, observers agreed less about who is Latino: only about 80% of observers on average classified self-identified Latinos as Latino; the relatively large standard deviation (.26) indicates more profiles with less agreement. The next most common category self-identified Latinos are placed in is White (a mean of 11% of observers), followed by Black (a mean of 5% of observers). Conversely, an average of 6% of observers view self-identified Whites as Latino and only an average of 2% of observers view self-identified Blacks as Latino.

[TABLE 1 ABOUT HERE]

As expected, observers tend to agree more when viewing photos of self-identified monoracials than self-identified multiracials. However, observers agree on the race of *some* multiracials to a much greater extent than others. For example, an average of 77% of observers classified Black/Latinos as only Black. On the other

hand, observers disagree the most when viewing photos of those who self-identify as White/Others: an average of 57% view these individuals as White, 25% as Latino, 15% as Other, and 3% as Black.

Table 2 examines divergences between self-identities and observer classifications by classifying individuals according to the racial group into which over 60% of observers placed them. Among monoracial self-identified groups, we see the least divergence between observer and self-classifications among those who self-identify as Black, 98% of whom are viewed by most observers as Black as well. Among those who self-identify as White, 93% are viewed by most observers as White, while 6% are seen as ambiguous/ other. As expected, self-identified Latinos experience more divergence than Whites or Blacks: 11% are viewed as ambiguous or other by most observers, while 5% are viewed as White and 3% as Black.

[TABLE 2 ABOUT HERE]

Consistent with my hypothesis and previous research (Herman 2010), those who self-identify as more than one racial group experience more divergence in observers' classifications because they are usually placed into a monoracial category. Also consistent with my expectation, daters who self-identify as Black and one or more racial groups are usually placed in the monoracial Black category by others; this ranges from 59% of Black/Whites viewed as only Black to 74% of Black/Latinos viewed as only Black. In contrast, daters who self-identify as White and one or more non-Black racial groups experience more divergence in how they are viewed by others. For example, while 48% of those who identify as White/ Latino are viewed as Latino, 30% are viewed as ambiguous or other, and 22% are viewed as White only. The most common classification for those self-identified as White/Others is White (48%), followed by ambiguous or other (33%).

How Phenotype Shapes Racial Categorization

Table 3 reports average marginal effects based on multinomial regressions of racial categorization that control for age, gender, photo quality and observer characteristics (full model available upon request). The marginal effects are based on predicted probabilities, and highlight the net *change* in the average probability of being viewed as White, Black, Latino or mixed/ambiguous from one value or category of the independent variable to another. The hypotheses regarding the importance and direction of skin tone effects are all supported. We see that, of all the phenotypic characteristics, skin color is the most robustly significant and of

the largest magnitude in predicting who is classified as White, Black or Latino.[15] For example, compared to those with light skin, the probability that daters with medium skin tones are classified as White is 34 percentage points lower, while the probability that those with dark skin are perceived as White is 50 percentage points lower. In contrast, the probability that a dater with medium skin is observed as Black is 8 percentage points higher than for a dater with light skin. Most strikingly, the probability that a dater with dark skin vs. light skin is viewed as Black is 76 percentage points higher. Those perceived by most observers as Latino are most likely to have medium skin tones: the predicted probability of Latino classification for a dater with medium skin vs. light skin is 24 percentage points higher. The probability of Latino classification is 23 percentage points lower for those with dark skin vs. light skin.

[TABLE 3 ABOUT HERE]

I find some support for the hypothesis that other phenotypic characteristics shape racial classification. Nose shape does not affect racial categorization, and the effects of most other traits are small, although usually in the expected direction. The probability of White categorization is 16 percentage points lower for daters with full lips than for those with ambiguous/mixed lip shapes. To a much lesser extent, those with medium lip shapes are also less likely to be perceived as White, while those with thin lip shapes have a five percentage point higher probability of White classification. Those with straight hair are more likely to be categorized as White, while the probability that those with braids or kinky hair are classified as White is 30 percentage points lower than for those with mixed hair types. Finally, athletic and toned bodies are positively associated, and heavier body types negatively associated, with White classification.

Dark skin is overwhelmingly the phenotypic characteristic most associated with Black classification, but lip shapes and hair type have significant effects. Those with thin lips have an 11 percentage point lower probability than those with mixed lip shapes of Black classification, while those with full lips have an 11 percentage point higher probability. Those with straight hair are slightly less likely, and those with braids or kinky hair are more likely, to be perceived as Black as compared to daters with mixed hair types.

Latino classification, in addition to being strongly associated with medium skin tones, is also associated with medium lip shapes. Body type also matters slightly in categorizing Latinos: the probability of

Latino classification is three percentage points lower for those with athletic bodies and three percentage points higher for those with heavy body types (compared with average body types).

Finally, few phenotypic characteristics were associated with daters whose race was not agreed upon by observers or who were viewed as multiracial or another race. The two exceptions are that those with full lips have a 14 percentage point higher probability of being perceived ambiguously and those with braids or kinky hair have a 30 percentage point higher probability of being perceived ambiguously.

While Table 3 clearly shows that skin color is the major criterion observers draw upon to place others in White, Black, or Latino categories, it does not show how individuals with stereotypically Black features but light skin are categorized, nor how those with European-associated features but dark skin are categorized. Consistent with the hypothesis that those with lighter skin but stereotypically Black features would be classified as mixed or other, the top panel of Figure 1 shows that those with light skin but full lips and braids/ kinky hair (the two phenotypic characteristics aside from skin tone most associated with Black classification) are overwhelmingly categorized as Mixed or Other: the predicted probability of Mixed/Other classification is .74 as compared with .15 for Black classification and .11 for Latino classification; no individuals with these traits are predicted to be classified as White. In contrast, the bottom panel shows that about half of those with dark skin but European features (thin lips, straight hair) are categorized as Black, while 28% are categorized as Latino and 22% as Mixed/Other. Moreover, a closer look at these data reveal that the average skin color of the dark-skinned individuals with thin lips and straight hair who are categorized as Black is actually much higher than for those placed in the Latino or Mixed/Other category (5.66 vs. 4.32). Thus, these findings show that while light skin alone is not enough to categorize someone as White, dark skin is used as the primary marker of Black classification even among those with stereotypically White features.

FIGURE 1 ABOUT HERE

How Phenotype Shapes Divergent Self and Observer Classifications

While the previous analyses considered what phenotypic characteristics were associated with observers' categorizations of race, I now return to the question of divergence between self and other classifications. Figure 2 shows, for those who self-identify monoracially and biracially, how phenotype shapes

divergent (and convergent) classifications by comparing the predicted probabilities of racial classification as White, Black, Latino or Mixed across (1) a model that does not control for phenotypic characteristics, (2) a model that controls for nose, lip, hair, and body types only, and (3) a model that also controls for skin color (full model 3 shown in Appendix Table 3).

FIGURE 2 ABOUT HERE

For classification as White, we see few divergences regardless of lip, nose, hair or body shape, as Models 1 and 2 predict that over 90% of self-identified Whites are classified by others as White. However, Model 3 shows that this high level of convergence is largely due to both self-identified and other-identified Whites tending to have lighter skin colors. The probability that self-identified Whites with *medium* skin tones (Model 3) are seen as White declines to .63. Few who self-identify as Black only, Black/White or Black/Latino are classified as White, even controlling for all phenotypic characteristics. In addition, the small percentage of self-identified Latinos who are classified by others as White (about 4%) have lighter skin tones, as the predicted probability declines to almost zero for those with medium skin tones (Model 3). Similarly, skin color appears to be the strongest marker used to place those who self-identify as White *and* Latino in the monoracial White category. In this case, the predicted probability of White categorization is .21 overall, declines to .17 once other phenotypic characteristics are considered, and declines to only .03 for those with medium skin.

We see a much greater likelihood of divergence between self-identity and observer classification as Black than White, due to the high probability that anyone who self-identifies as Black/White or Black/Latino will be classified solely as Black. For example, we see that the overall predicted probability of Black classification for a dater who self-identifies as Black/ Latino is .76 (Model 1). The predicted probability of Black classification declines to .65 once lip, nose, hair, and body type characteristics are considered, but then declines to only .08 once only those with medium skin tones are considered; thus, this divergence between self and observer classifications is mostly driven by skin color. We see a similar pattern for those who self-identify as Black and White, and even for the few Latinos who are categorized as Black.

The third and fourth panels of Figure 2 show that medium skin tones are associated with classifications as Latino, and, to a lesser extent, with mixed classifications. The predicted probability that self-

identified Whites are classified by others as Latino is less than .02, and controlling for other phenotypic characteristics does not change this finding (Models 1 & 2). However among self-identified Whites with medium skin tones, the probability increases to .12. Similarly, while the predicted probability that self-identified monoracial Blacks are viewed by others as Latino is less than .01 (Models 1 & 2), among those with medium skin colors, this rises to .14. As we saw earlier, self-identified Latinos experience more divergences in outsider classifications: the predicted probability of concordant classification is .84, even with phenotypic characteristics other than skin color considered (Model 1 & 2). However, among self-identified Latinos with medium skin tones, the probability of convergence climbs to .92. Daters who self-identify as Black/Latino are not very likely to be categorized as only Latino overall (.08, Model 1), but this is much more likely for those with medium skin tones (.42, Model 3). About half of daters who self-identify as Latino/White are likely to be classified by others as only Latino (.51, Models 1 & 2), and this rises to .71 among those with medium skin tones.

Finally, the last panel shows that inconsistent classification or classification as other/multiracial is more common among self-identified Whites and Blacks with medium skin tones (model 3). This is also the case for Black/Latinos and Black/Whites. Most strikingly, while the predicted probability of inconsistent or other/multiracial classification for those who self-identify as Black/White is .33, when phenotypic characteristics including skin color are considered, we see the likelihood of multiracial or ambiguous classification rises to .66.

Overall, these findings illustrate how phenotype, especially skin color, shapes divergent racial classifications: because light skin is associated with Whiteness, dark skin with Blackness, and medium skin with Latinidad, individuals whose self-identities do not match these phenotypic associations are more likely to experience discordant classification from outsiders. While additional analyses (not shown) show that these relationships do not change by observer, observers' characteristics may also shape racial categorization.

How Observer Characteristics Shape Racial Categorization

Figure 3 shows how the percentage of women who coded each profile affects the predicted probability of racial categorization. Contrary to the hypothesis that gender would not relate to monoracial categorizations,

photos coded by more women are more likely to be categorized as White: all else equal, the probability of White classification for photos coded by all men is .18 compared with .34 for photos coded by all women. While observers' gender appears to matter little in terms of categorization as Black, women are significantly less likely to categorize daters as Latino, as the probability of Latino classification for photos viewed by only men is .45, but is only .20 among photos coded by all women. Photos are also slightly more likely to be coded as multiracial/other or in divergent ways when viewed by more women.

FIGURE 3 ABOUT HERE

Figure 4 shows predicted probabilities of racial categorization by the percentage of White, Black, Latino and Asian coders. Contrary to my hypothesis, I find no evidence that observers are more likely to classify others as in-group members. The likelihood of White categorization does not vary by the percentage of White, Latino, or Asian observers, but as Black observers increase, classification as White declines. As expected, the likelihood of classification as Black does not vary across observers. However, the probability of Latino classification increases slightly with the percentage of Asian observers, from .21 with zero Asian observers to .25 with 60% Asian observers. Finally, the percentage of Black observers also positively relates to the probability of ambiguous or inconsistent classification, which is only .08 with zero Black observers, and rises to .19 with 60% Black observers. While these findings should be viewed with caution given the small number of observers in the sample (see Appendix Table 2), overall, these finding are consistent with previous research suggesting that observer effects matter little in terms of classification as Black but more in terms of classification as Latino and White (Harris 2002). In addition, these findings suggest that Black observers differ the most from other racial groups in how they racially classify others.

FIGURE 4 ABOUT HERE

DISCUSSION AND CONCLUSION

Through an analysis of observers' classifications of photos posted on the dating website Match.com, this study provides insight into the factors that shape racial categorization in contexts in which observers classify based only on appearance. It is in this type of context that individuals are most likely to experience being perceived differently than how they self-identify. Indeed, consistent with previous research, I find that

despite the growth in self-identified multiracials, observers tend to place others into monoracial categories (Harris 2002b; Herman 2010). Observers use skin color to categorize others as White, Black *or* Latino, suggesting that the U.S. racial structure is moving towards a classification system in which Latino is viewed as a race. However, the association between dark skin and Blackness is the strongest, suggesting the fewest racial options for dark-skinned individuals.

The online dating environment may influence the findings here because how individuals self-identify and how others racially classify them are driven by social forces (Campbell, 2007; Campbell & Rogalin, 2006). Many self-identified monoracial Blacks may actually be of mixed ancestry, but choose a Black identity based on how they are perceived (Bratter, 2007; Brunsma & Rockquemore, 2001). However, racial self-identities are often employed strategically (Saperstein, 2006), and in this context, individuals might be more likely to state multiple racial identities if they hope to attract dates from diverse racial backgrounds. Daters' choice of photos is also likely driven by a desire to present themselves in a particular way, perhaps with cues to their racial identity (Roth, 2010). Since people often engage in self-presentation strategies, it would be worthwhile to assess how self-presentation and self-identities shift in different contexts, such as in an interview for a job or graduate school.

In the context of this study, patterns of consistencies between observers' classifications and self-identifications are revealing. Racial classifications are most consistent for self-identified monoracial Blacks and Whites. Observers agree the most about who is Black, and self-identified monoracial Blacks are *almost always* categorized by others as Black (98%). The few cases of divergence are driven by skin color (non-dark-skinned Blacks categorized as non-Black, Figure 2). Consistent with previous research, I find that the majority of those who self-identify as Black *and* other racial backgrounds are classified by others as only Black (Herman 2010). While physical characteristics such as hair type and lip shape influence classification, skin tone is the primary marker. Dark skin is such a powerful marker of Blackness that self-identified multiracial Blacks who do not have dark skin are more likely to be classified as multiracial or ambiguous than as monoracial Black (Figure 2), and even dark-skinned daters with stereotypically European features are usually categorized as Black only (Figure 1). While not definitive because I lack ancestry information, these findings

suggest a shifting away from the one-drop rule, which previously defined anyone with a drop of African ancestry, visible or not, as Black (Davis, 1991). My findings are consistent with recent research suggesting some flexibility historically in who was subject to the one-drop rule (Saperstein & Gullickson, 2013). Here, we see that in terms of self-identity, many individuals who appear Black to others do not accept the one-drop rule, asserting other racial self-identities in addition to Black. In terms of classification, only those with dark skin, the phenotype most associated with Blackness, are classified by most others as Black, suggesting a *dark-skin rule* rather than a one-drop rule in contexts where racial classifications are made based on appearance alone. While this means greater flexibility and fluidity in racial classifications for some with Black ancestry, at least in some contexts, it also suggests that regardless of self-identity, dark-skinned individuals ultimately have no racial options: they are viewed and treated as Black (Waters, 2001).

While self-identified Latinos experience more divergence in outsider classification than self-identified monoracial Whites and Blacks do, over 80% are classified consistently *as* Latino. In addition, observers use particular phenotypic characteristics, mainly a medium skin tone, but also medium lip shapes and heavier body types, to categorize photos as Latino. These findings challenge the idea that because Latinos often identify as White on the Census, they are "becoming White" (Patterson, 2001; Yancey, 2003). Instead, it appears Latinos are increasingly "racialized": observers think of Latinos, like Blacks, as a group with a singular racial appearance (Cobas et al., 2009). Moreover, that observers from varied racial groups similarly use the same phenotypic features to classify Latinos suggests a shared cultural understanding of Latinos as a racial group in-between Whites and Blacks (Gravlee 2005; Roth 2012). However, the appearance-based cues as to who is Latino are also less clear-cut than for Blacks or Whites, as observers disagree more in their categorizations of self-identified Latino photos. Moreover, that those who identify as Latino/White are more likely to be categorized as White than those who identify as Black/White suggests more flexible racial options for multiracial Latinos[16] than multiracial Blacks. However, this is explained by varying phenotypes as non-dark-skinned Black/Whites are just as likely as Latino/Whites to be categorized as White (Figure 2).

This study, while not representative, draws on a much wider and more current sample of adult photos than other studies (D. R. Harris, 2002; Herman, 2010; Roth, 2012), allowing multiple observers to draw on the

same information to assess race. However, individuals have more visual information to draw on in-person (Tskhay & Rule, 2013), and future research might consider whether the role of phenotype in racial categorizations in person differs from that in photos. In addition, while I include more observers than most previous studies (29), all were undergraduates at one college campus[17] and the number of Black and male observers was small (see Appendix Table 2). Despite these limitations, the findings here support previous research suggesting that the relationships between self-identification and racial classification, and phenotype and racial categorization, do not vary substantially by observers' race or gender (Herman 2010). However, I do find observers' characteristics influence assessments of race to a limited degree, although often not in clear-cut ways. For instance, photos coded by more women were more likely to be coded as White and less likely to be coded as Latino. To the extent that Whites are at the top of the American racial hierarchy, this finding could reflect women's tendency to be more racially inclusive (Johnson & Marini, 1998; Schuman, 1997). Also, in contrast to existing theories and research, I found no clear indications that observers were more or less likely to classify others as members of their racial in-group (D. R. Harris, 2002). However, Asian observers were slightly more likely to categorize photos as Latino. I speculate that relative newcomers to the American racial hierarchy (most Asian observers were children of immigrants[18]) may tend to perceive more people as racial others as a way to elevate their own status, consistent with previous research showing Asians are more likely than Whites to exclude Latinos as possible dates (Robnett & Feliciano, 2011). Finally, Black observers were less likely to categorize photos as White and more likely to code them as other or multiracial, leading to more disagreement in the classifications of photos coded by more Blacks. These findings suggest that Blacks see race in more complex ways than other racial groups. However, consistent with previous research, Black observers are no more or less likely to classify others as Black (D. R. Harris, 2002), suggesting the pervasiveness of the *dark-skin rule* discussed earlier. While these findings should be interpreted cautiously due to the small and select observer sample, especially since most observers were women, they suggest that the proportion of people racialized in different ways depends on who is classifying.

Ultimately, racial categorization matters because of its implications for inequality. Numerous studies, mainly of Blacks but also of Latinos, have shown that individuals who have physical features that are most

typically associated with their race are perceived more negatively (Maddox, 2004). I suggest that part of the process through which differential treatment results may be that individuals with non-stereotypical features are perceived to be members of other racial groups. Thus, the way most U.S. surveys and the Census collect race data –self-identity–is problematic for monitoring inequality and discrimination, and surveys should collect skin tone and perceived race data (Roth 2010). Moreover, while the relationships between self-identity, phenotype and racial categorization may be similar across observers, future research should investigate whether our estimates of inequality vary depending not only on *how* race is assessed (self vs. other classifications), but also on *who* the classifiers are. Surveys that collect racial classification relying on one person's assessment should consider that observers' characteristics and perspective. In addition, while initial racial assessments in many contexts, such as encounters with police and salespeople, may be based on phenotypic markers, additional information available in other contexts or with continued interaction also likely affects classification, such as ethnic names (see Hilliar & Kemp, 2008), ancestry, local racial composition, and class background. Future research should investigate how racial classification varies across different contexts, how the presence of additional information interacts with phenotypic markers, and how racial classification processes shape inequality.

ENDNOTES

[1] For example, in their popular textbook, Cornell and Hartman (1998) define a race as "a human group defined by itself or others as distinct by virtue of perceived common physical characteristics that are held to be inherent" (p24).

[2] Although the larger study collected profiles of self-identified Asians and same-sex daters, due to resource limitations, observers only coded the photos of self-identified Latino, White, and Black opposite-sex daters. We focused on coding the photos of Latinos, Whites, and Blacks who date the opposite sex because previous research shows divergent outcomes for those viewed as members of these three groups ((Feliciano & Robnett, 2014) and we expected fewer self-identified Asians would be placed in these categories. The racial categorization of Asians is an important area for future research.

[3] Since a specific aim of the larger project was to examine diversity among Latinos, we deliberately chose cities with varied Latino ethnic compositions (ie: Los Angeles contains the largest Mexican-origin population, while New York contains the largest Puerto Rican population). Including other metropolitan areas, such as San Francisco, might have yielded a larger sample of multiracial individuals. However, New York, Los Angeles, and Chicago are the cities with the largest numbers of persons identifying with more than one race on the Census (Jones and Bullock 2012).

[4] Unlike other dating websites that only show profiles based on potential "matches" generated from computer algorithms, Match.com allows individuals to search through all profiles. Thus, profiles are available to anyone who creates an account by providing an email address and password. Within each race/gender/region group, research assistants downloaded the first 200 profiles sorted by when daters joined the site so that researchers' own profiles did not affect what profiles they were exposed to. Duplicate profiles were eliminated.

[5] Undergraduate coders were recruited from various lower-division sociology undergraduate classes at a research university in Southern California through email requests. The coders are similar demographically to the student body at this university in which about half of the students are Asian and less than 2% are Black (see Appendix Table 2).
[6] We believe that, for the most part, coders did not look at the information on the profiles because the coding was completed quickly. However, we cannot rule out the possibility that one or more of the coders did consult the profile texts on occasion. The profiles contain the dater's self-identified race/ethnicity and other characteristics (such as age and relationship status), blurbs about themselves and what they are looking for, and characteristics they are looking for in a date (such as race/ethnicity, education level). Each dater also chose a unique username and wrote a headline to describe him/ herself. Usernames, in some cases, contain information that might reveal their self-identified race/ethnicity such as ethnic nicknames or explicit references to race. If so, this would bias the coding in the direction of more daters being categorized consistently with the daters' own self-identity. However, few daters' usernames or headlines made reference to race and a search through a random sample of profiles showed that even those whose usernames or headlines suggested a racial/ethnic identity were categorized differently if their physical characteristics did not match the stereotypical characteristics of that race/ethnicity. For example, I found profiles with usernames containing Spanish first names coded Black (only), and profiles that referenced "Black" coded Other/mixed.
[7] We included Asian as an option to avoid potentially biasing the responses. Since the coders were not told the self-identifications of the photos they were given, and many of the observers self-identified as Asian themselves, we did not want to inadvertently reveal that the photos only included self-identified Whites, Blacks, or Latinos.
[8] Substantive findings do not change if I use the more stringent cut-off of 75%. However, using the 75% cut-off yields more empty cells in bivariate analyses of self-identification and observer classification, and observer classifications and skin color, which limits the use of multivariate analyses. I therefore chose the more flexible 60% cut-off.
[9] Of these five missing cases, two self-identified as White, one as Black, and two as Latino.
[10] The skin color scale was created for the New Immigrant Survey and is available online: http://nis.princeton.edu/downloads/NIS-Skin-Color-Scale.pdf (Massey and Martin 2003).
[11] All visual aids are available upon request.
[12] Nose shapes were difficult to match to the guide in photos that were not taken at a direct angle, results in 25% coded "don't know."
[13] Hair types were often not discernible because daters were bald, wore hats, or had very short haircuts; thus, 17% were coded "don't know."
[14] Only four of the 29 coders identified as "Other;" two identified with two racial groups (White and Latino, Black and Latina), and two identified as Middle Eastern.
[15] Because previous work has shown that race affects how observers assess skin tone (Hill 2002), I considered whether the fact that the same observers coded skin tone and race would bias my results. However, I found the same substantive results regardless of whether I only examined profiles coded by particular racial groups. Moreover, I did not find, as others have, that Whites coded Blacks as having darker skin tones than Blacks did. This may be because, unlike those studies, here, observers were not aware of the self-identified race of the dater. It is also likely that, as previous research has shown, assessments of phenotypes and race co-occur; thus, if an observer views a photo as Black, they rate their skin color darker (MacLin and Malpass 2001).
[16] In the absence of data on ancestry and/or parents' racial background, it is impossible to know whether Latinos who identify as Latino and White are multiracial in the sense of having parents from different backgrounds or whether they are following official U.S. Census classification schemes in which Latinos are an ethnic group and White is their race.
[17] The student observers all attended a University in which Asians are the largest racial group, followed by Latinos and Whites, with only a very small Black population.
[18] While we did not ask observers about their parents' place of birth, we know from the campus demographics that most Asian students are children of immigrants.

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Table 1. How Much Does Observer Agreement on Racial Categorization Vary by Self-identified Race?

	Mean Percentage of Observers Who View Person as…								
Self-Identified Race	White		Black		Latino		Other[a]		N
White	92.08	(.17)	0.34	(.05)	6.21	(.14)	1.35	(.06)	1458
Black	0.32	(.05)	97.11	(.11)	1.66	(.08)	0.88	(.04)	1336
Latino	11.26	(.21)	5.48	(.17)	79.73	(.26)	3.46	(. 09)	1158
Black/White	14.34	(.23)	66.55	(.34)	14.97	(.20)	4.14	(.08)	42
Black/Latino	0.28	(.02)	76.75	(.28)	17.98	(.25)	4.99	(.09)	102
Latino/White	36.02	(.31)	1.53	(.07)	57.70	(.30)	4.76	(.08)	213
Black/Others[b]	9.13	(.23)	72.30	(.37)	11.96	(.22)	6.61	(.14)	221
White/Others[b] (non-Black)	56.73	(.38)	2.76	(.15)	25.37	(.31)	15.13	(.27)	93
Multiracial Others[b] (non-Black, non-White)	11.82	(.22)	11.44	(.26)	62.11	(.31)	14.62	(.24)	53

Notes: standard deviations in parentheses.

[a] Other includes Other, Asian, and more than one race

[b] Others includes Other, Native American, Pacific Islander, Middle Eastern, East Indian, Asian, and three or more races

Table 2. Variation in Observer Classification by Racial Self-identification

	Over 60% of Observers View Person as…					
Self-Identified Race	White	Black	Latino	Mixed[a]		
					Total	N
White	92.73	0.21	1.23	5.85	100%	1458
Black	0.22	98.05	0.52	1.2	100%	1336
Latino	4.84	3.11	81.43	10.62	100%	1158
Black/White	2.38	57.14	4.76	35.71	100%	42
Black/Latino	0.00	73.53	7.84	18.63	100%	102
Latino/White	21.60	0.00	48.36	30.05	100%	213
Black/Others[b]	5.88	71.04	5.43	17.65	100%	221
White/Others[b] (non-Black)	48.38	3.23	15.05	33.33	100%	93
Multiracial Others[b] (non-Black, non-White)	7.55	9.43	60.38	22.64	100%	53

Notes: [a] Mixed includes the residual category for profiles in which less than 60% of observers agreed on race (n=382), and cases in which over 60% viewed as Other (n=3) or Asian (n=19)

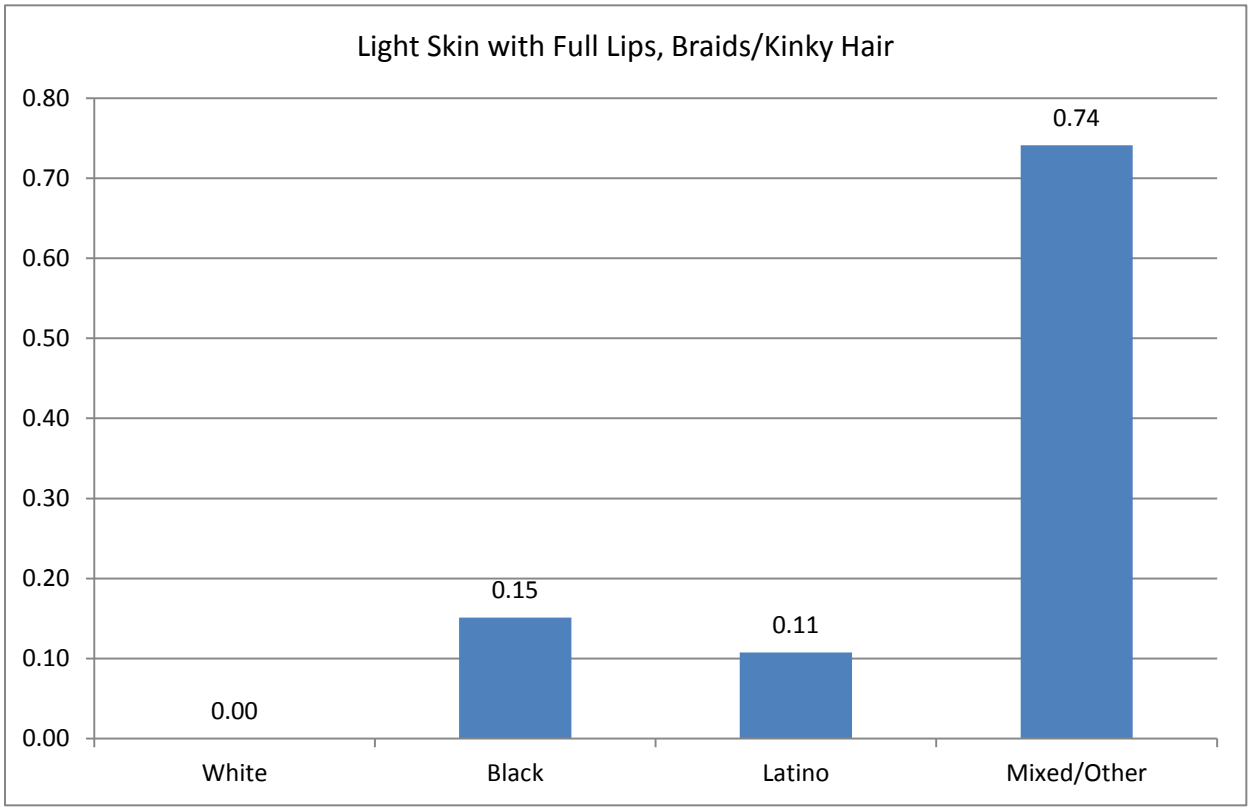
[b] Others includes Other, Native American, Pacific Islander, Middle Eastern, East Indian, Asian, and three or more races

Table 3. Average Marginal Effects of Phenotypic Characteristics on Racial Categorization

	Over 60% of Observers View Person as…							
	White		Black		Latino		Mixed	
Skin Color (reference=light)								
medium	-0.34	***	0.08	***	0.24	***	0.02	
dark	-0.50	***	0.76	***	-0.23	***	-0.03	
Lips (as observed by 60%+, reference=mixed):								
Thin	0.05	***	-0.11	**	0.05	+	0.02	
Medium	-0.03	**	-0.01		0.05	***	0.00	
Full	-0.16	*	0.11	***	-0.08	*	0.14	*
Missing	0.06		0.04		-0.10	*	0.00	
Nose (as observed by 60%+, reference=mixed):								
Narrow	0.01		-0.09		0.03		0.05	
Medium	-0.02		-0.03		0.02		0.04	
Broad	0.02		-0.04		0.05		-0.04	
Missing	-0.03	**	0.01		0.04	**	-0.01	
Hair (as observed by 60%+, reference=mixed):								
Straight	0.03	*	-0.03	**	0.01		-0.01	
Wavy	0.02		0.00		0.00		-0.02	
Curly	-0.05		0.01		0.01		0.03	
Braids or Kinky	-0.30	***	0.06	*	-0.05		0.30	**
Missing	0.02		0.00		-0.02		0.00	
Body type (self-described, reference = average)								
Slender	0.00		0.00		-0.01		0.01	
Athletic and Toned	0.03	**	0.02	*	-0.03	**	-0.02	+
Heavy	-0.02	*	0.01		0.03	*	-0.01	
Missing	-0.03		-0.04	*	0.08	**	-0.01	

Notes: N=4676; Models control for age, gender, photo quality, and observer characteristics
***p<.001, **p<.01, *p<.05, +p<.10

Figure 1. Predicted Probabilities of Racial Categorization for those with Light/Dark Skin and Select Features



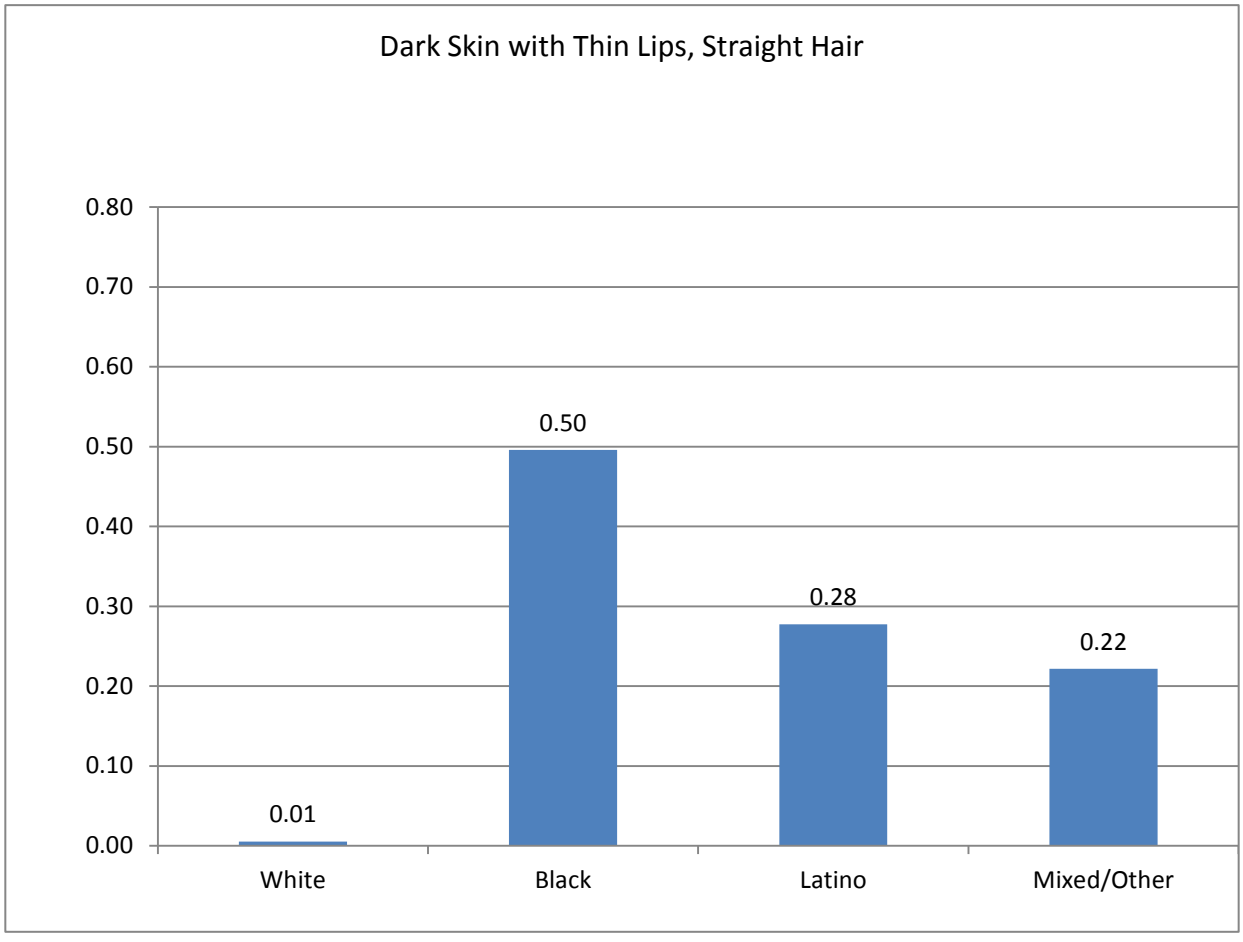


Figure 2. Predicted Probabilities of Racial Categorization, by Self-Identification

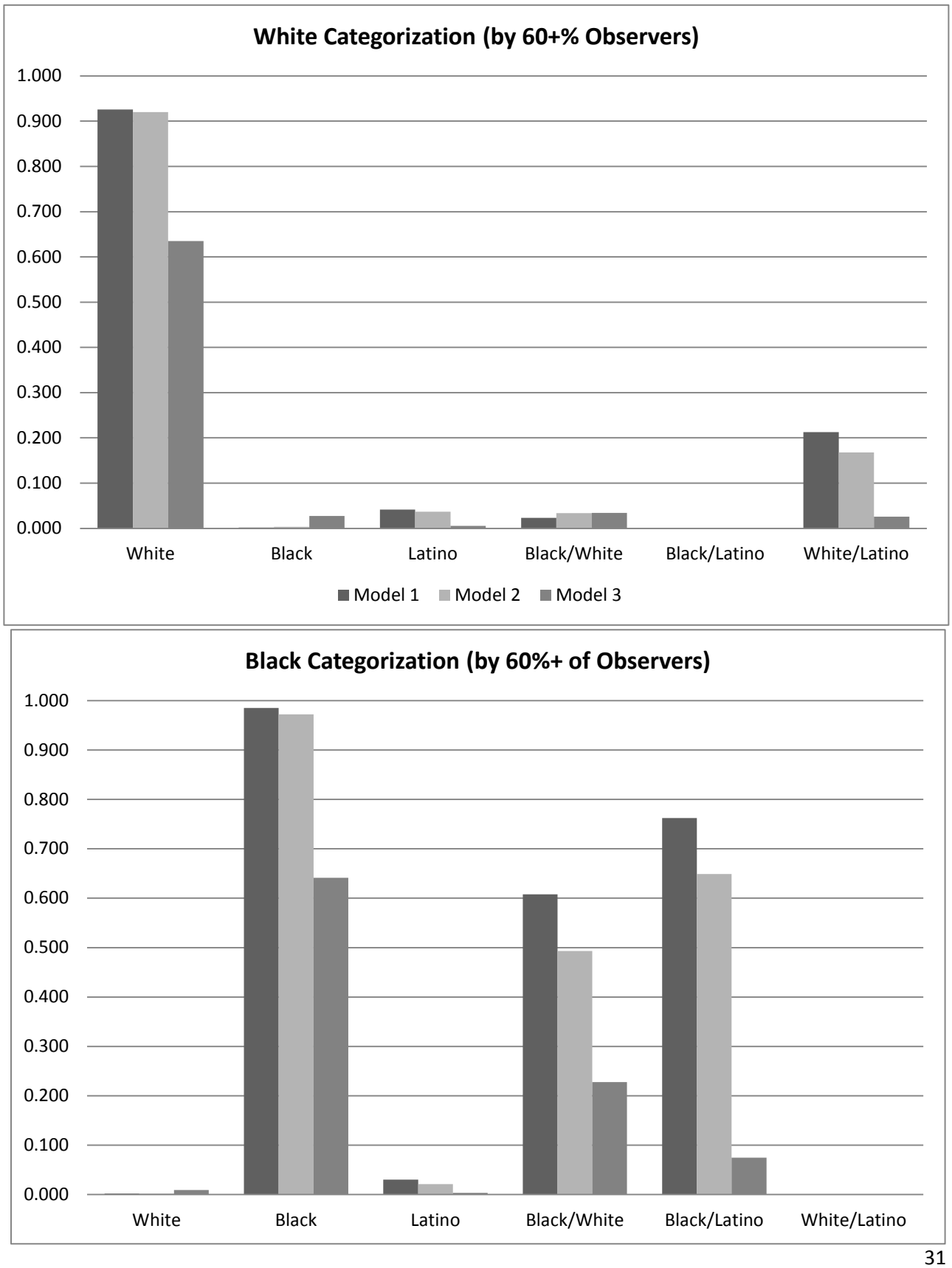
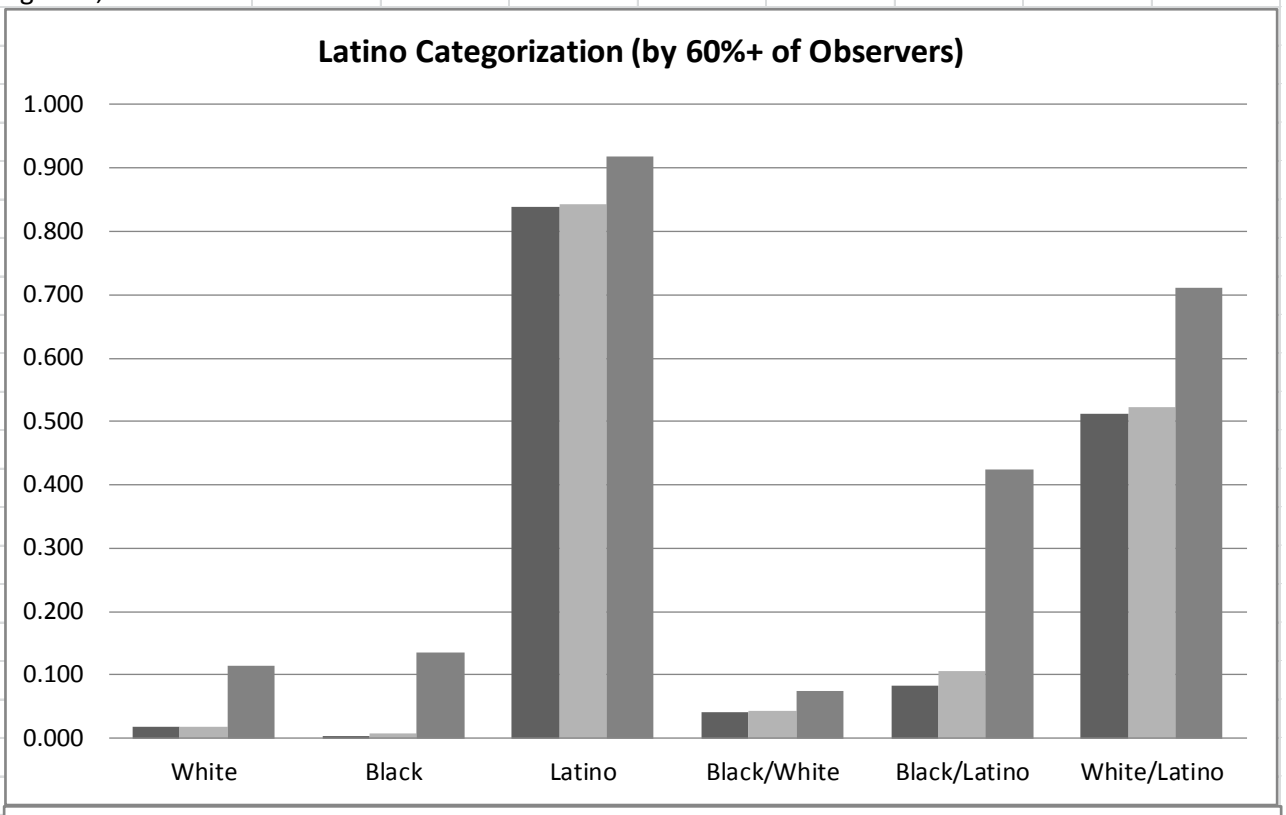
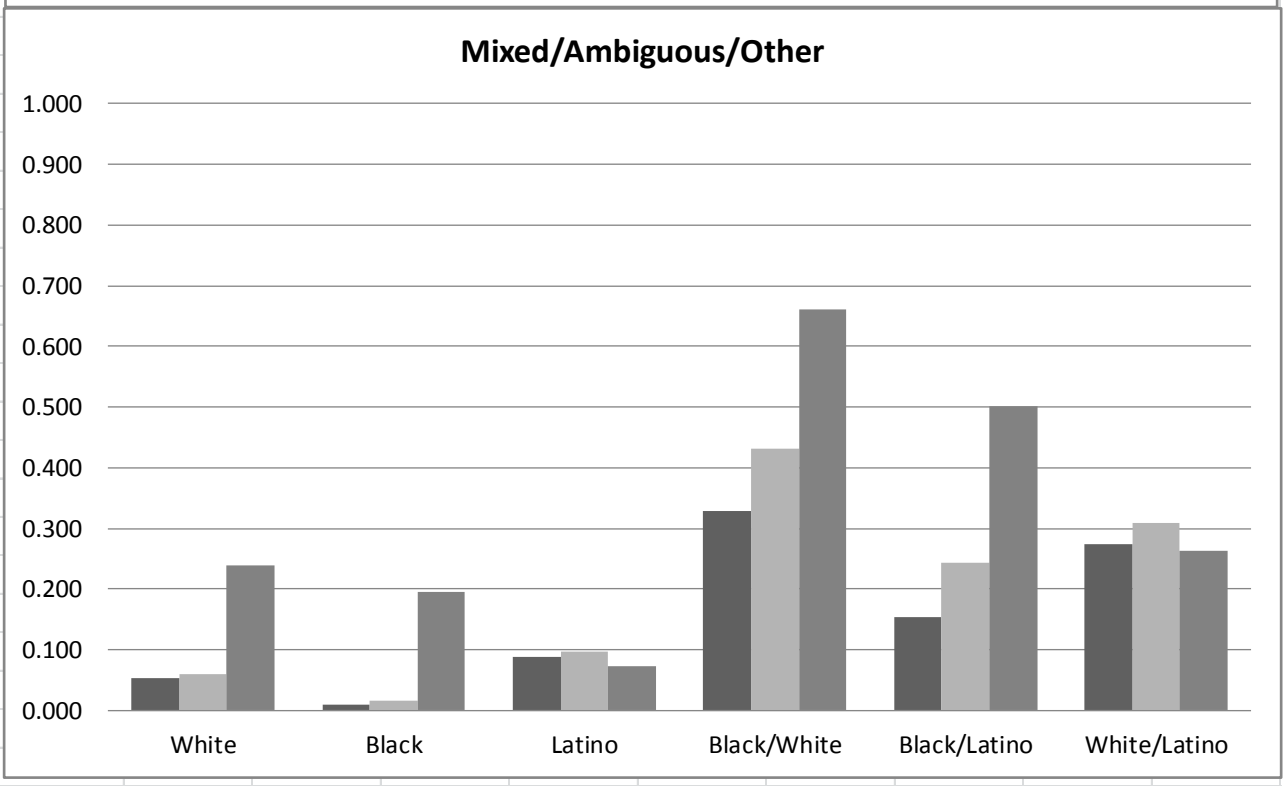


Figure 2, Continued.





Model 1: includes age, sex, observer characteristics. Model 2: adds nose, lips, hair types Model 3: adds skin color

Predicted Probabilities calculated for women with average age, observer characteristics, and photo quality. Categorical variables set at most common values (nose and lips=mixed; hair=straight, body=average, skin=medium)

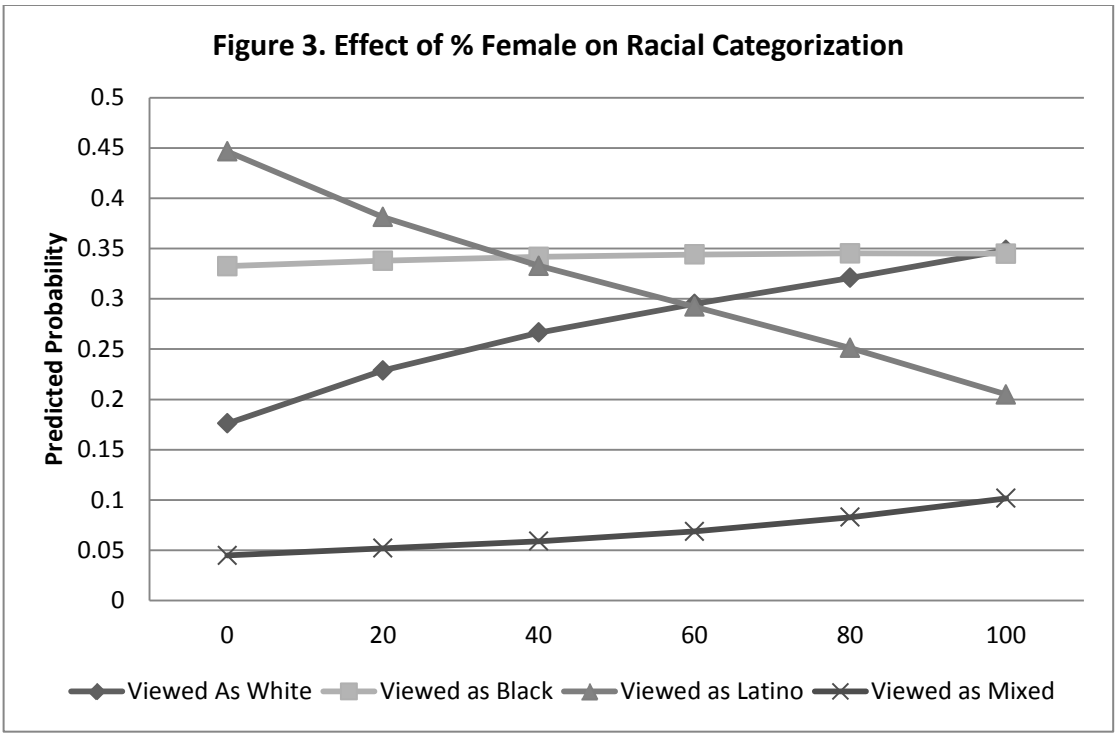
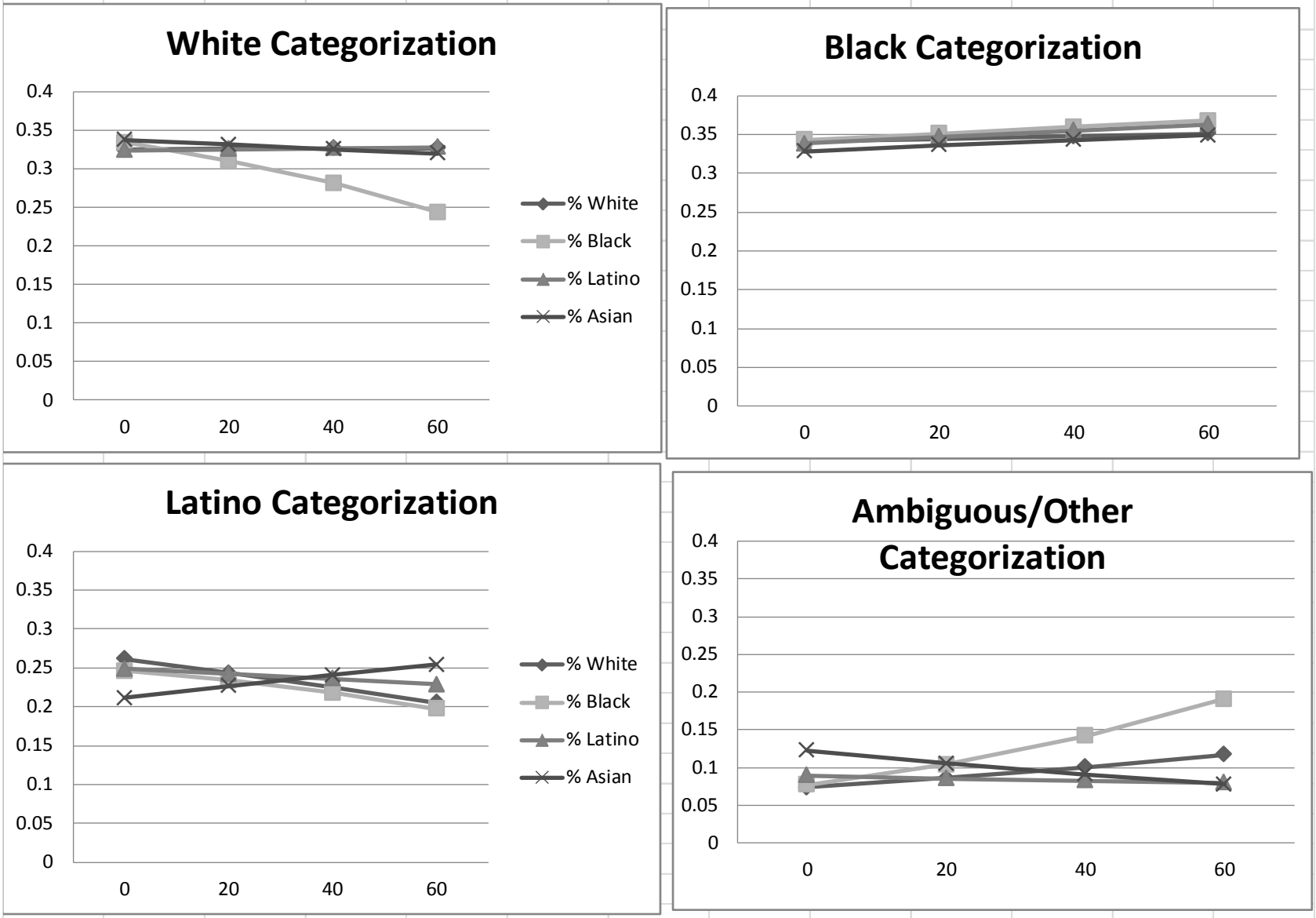


Figure 3. Effect of % Female on Racial Categorization
Predicted Probability
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
20
40
60
80
100
Viewed As White
Viewed as Black
Viewed as Latino
Viewed as Mixed

Figure 4. Effects of Observers' Race on Predicted Probability of Racial Categorizations



Note: Predicted probabilities based on full model in Appendix Table 1.

Appendix Table 1. Means and Percentages of Independent Variables (standard deviations in parentheses)

Body Type (self-described)		
Average	34.67	
Slender	11.48	
Athletic	25.92	
Plus Size	24.66	
Not stated	3.27	
Hair Type (as observed by over 60%)		
Straight	53.57	
Wavy	8.62	
Curly	5.13	
Braids or Kinky	3.15	
Mixed	12.13	
Don't know/Not Visible	17.41	
Nose Type (as observed by over 60%)		
Narrow	4.83	
Medium	8.51	
Broad	4.47	
Mixed	56.01	
Don't know	26.18	
Lips Type (as observed by over 60%)		
Thin	17.64	
Medium	16.08	
Full	12.60	
Mixed	52.69	
Don't know	0.98	
Skin Tone (based on average across observers)		
Light	43.26	
Medium	19.76	
Dark	36.98	
Observers' Characteristics		
Percent Female	82.67	(.10)
Percent White	21.35	(.14)
Percent Black	6.22	(.09)
Percent Asian	41.14	(.18)
Percent Latino	20.74	(.16)
Controls		
Photo Quality	3.57	(.73)
Age of Dater	33.41	(10.89)

Gender of Dater (1=female)	50.27
N	4676.00

Appendix Table 2. Frequency Distribution of Coders' Self-Identified Sex and Race

Race	Sex		
	Male	Female	Total
White	0	7	7
Asian	2	9	11
Latino	2	3	5
Black	1	1	2
Other	0	4	4
Total	5	24	29

Appendix Table 3. Coefficients from Multinomial Regression of Racial Categorization

	Over 60% of Observers View Person as…					
	White (vs. Mixed[a])		Black (vs. Mixed)		Latino (vs. Mixed)	
Controls						
Gender of Dater (1=female)	0.08		1.46	***	0.33	*
Average Photo Quality	-0.12		-0.34	*	0.05	
Age	0.02	*	0.01		-0.01	+
Phenotypic Characteristics						
Skin Tone (reference=light)						
Medium	-2.14	***	2.54	*	0.83	***
Dark	-3.98	***	5.99	***	-0.23	
Lips (as observed by 60%+, reference=mixed):						
Thin	0.84	***	-1.12	+	-0.04	
Medium	-0.06		-0.06		-0.56	
Full	-1.28		1.96	***	0.34	*
Missing	1.17		-0.23		0.29	
Nose (as observed by 60%+, reference=mixed):						
Narrow	0.22		-0.50		-0.44	
Medium	-0.03		-0.81		-0.44	
Broad	1.21		0.56		0.43	
Missing	-0.07		0.47		0.26	
Hair (as observed by 60%+, reference=mixed):						
Straight	0.66	**	-0.63	*	-0.01	
Wavy	0.31		-0.01		0.46	
Curly	-0.42		0.14		0.37	
Braids or Kinky	-10.65		1.22		-1.08	
Missing	0.47		-0.23		-0.37	
Body type (self-described, reference = average)						
Slender	-0.23		-0.33		-0.28	
Athletic and Toned	0.45	*	0.96	**	-0.04	
Plus Size	0.21		0.13		0.27	
Missing	0.00		0.49		0.28	

Self-Identified Race (reference=White only)						
Black	-2.94	***	4.44	***	0.35	
Latino	-3.59	***	0.17		3.26	***
Black/White	-3.94	***	2.19	*	-1.43	+
Black/Latino	-16.96		1.36	*	0.57	
Latino/White	-3.29	***	-14.49		1.73	***
Black/Others[b]	-3.42	***	2.18		0.02	
White/Others[b] (non-Black)	-2.45	***	0.56		0.67	
Multiracial Others[b] (non-Black, non-White)	-3.40	***	-0.03		2.03	***
Observer Characteristics						
Percentage of Female Observers	1.89	*	-1.27		-3.76	**
Percentage of White Observers	-0.60		0.33		-1.83	*
Percentage of Black Observers	-3.61	**	1.58		-1.97	+
Percentage of Asian Observers	-0.10		2.20	+	1.45	+
Percentage of Latino Observers	0.08		2.46	+	-0.29	

N=4676, Pseudo R2 = .74

Notes: ***p<.001, **p<.01, *p<.05, +p<.10

[a] Mixed includes the residual category for profiles in which less than 60% of observers agreed on race (n=382), and cases in which over 60% viewed as Other (n=3) or Asian (n=19)

[b] Others includes Other, Native American, Pacific Islander, Middle Eastern, East Indian, Asian, and 3+ races