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*Descriptive Finding*

# Race, color, and income inequality across the Americas

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# Race, color, and income inequality across the Americas

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## Abstract

**BACKGROUND**
Racial inequality in the U.S. is typically described in terms of stark categorical difference, as compared to the more gradational stratification based on skin color often said to prevail in parts of Latin America. However, nationally representative data with both types of measures have not been available to explicitly test this contrast.

**OBJECTIVE**
We use novel, recently released data from the U.S. and 18 Latin American countries to describe household income inequality across the region by perceived skin color and racial self-identification, and examine which measure better captures racial disparities in each national context.

**RESULTS**
We document color and racial hierarchies across the Americas, revealing some unexpected patterns. White advantage and indigenous disadvantage are fairly consistent features, whereas blacks at times have higher mean incomes than other racial populations. Income inequality can best be understood in some countries using racial categories alone, in others using skin color; in a few countries, including the U.S., a combination of skin color and self-identified race best explains income variation.

**CONCLUSIONS**
These results complicate theoretical debates about U.S. racial exceptionalism and methodological debates about how best to measure race. Rather than supporting one measure over another, our cross-national analysis underscores race's multidimensionality. The variation in patterns of inequality also defies common comparisons between the U.S. on the one hand and a singular Latin America on the other.

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## 1. Introduction

In the Americas, the United States has long been considered unique in terms of race relations – primarily for its norm of hypodescent, which erased mixed-race classifications and assigned black status to anyone with any apparent African ancestry (Davis 1991). At the other end of the stylized regional spectrum are Latin American countries characterized by large mestizo populations and national efforts to promote "whitening" (Schwartzman 2007; Telles and Garcia 2013). Scholars have contrasted these racial schemes as defined, respectively, by ancestry versus phenotype (Nogueira 1985; Davis 1991) and as associated with contrasting systems of racial stratification – racial versus color hierarchies (Skidmore 1993; Bonilla-Silva 2004).

It is also possible that, instead of being the bases for different race paradigms, categorical race and skin color are best viewed as two distinct dimensions of the same race construct. Recent research suggests their utility as analytic concepts may vary across contexts (Ñopo, Saavedra, and Torero 2007; Villarreal 2010; Roth 2010; Telles and Steele 2012; Loveman, Muniz, and Bailey 2012); hence, the appropriateness of using one measure or the other, or both, is an empirical question. However, until recently data limitations have prohibited an explicit comparison of these two approaches in the U.S. versus Latin America. Now, for the first time, nationally representative data including both self-identified race and perceived skin color is available in the U.S. and in similar recent surveys across Latin America. We use these data to provide fresh insight into cross-national patterns of racial inequality by comparing the degree to which per capita household income varies along these two dimensions of race in the United States and 18 countries in Latin America.

## 2. Data and methods

Our data are from the 2012 General Social Survey (GSS) in the United States (Smith et al. 2013) and the 2012 AmericasBarometer (AB) survey in Latin America. In both surveys, interviewers rated respondent skin color after concluding their interview using similar 10-point (GSS) or 11-point (AB) scales with visual color referents. Respondents provided their racial identification using national categorization schemes. Household income is self-reported in national currencies using a list of 25 (GSS) and 16 (AB) intervals.

We first graph mean per capita household income values for each point on a country's skin color scale and for each category of its national racial categorization scheme that includes 30 cases or more. Hence, some countries register fewer color points; in others, small racial populations are not included. Skin color category five serves as our benchmark in each country; we present all other average incomes in relation to the value for that mid-range color point.

To examine whether racial self-identification or skin color best accounts for income inequality in each country, we predict logged per capita household income using the same measures presented in our descriptive analysis. These models use ordinary least squares regression with interviewer fixed effects. Supplementary analysis using household-size adjusted household income (dividing by the square-root of household size) yielded similar results.

In parallel fashion to Figure 1, our regression results are intended to highlight the overall observed level of income inequality. Hence, we do not control for factors through which racial inequality might be mediated or reproduced in a given setting. Those considerations, such as education and region, are important for the purposes of identifying intervening factors, but our aim in this study is not to isolate the country-specific mechanisms through which racial inequalities arise. Rather, we lay the groundwork for such analyses by determining the extent to which skin tone and/or self-identified race best characterize economic inequality across the Americas. To this end we compare three models: one with skin color alone, one with racial categories alone, and one that contains both perceived skin color and self-identification.

In order to discern the preferred of our three models, we focus on the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), where lower values indicate better fit. AIC generally favors complexity over parsimony, whereas BIC penalizes additional model parameters more heavily. We follow Raftery (1995) in determining the strength of evidence in favor of the most parsimonious model, ranging from "weak" (BIC difference of 2 or less) to "very strong" (BIC difference of 10 or more). When the BIC difference is less than two we conclude that the two models fit equally well for our purposes. (See Appendix for full details on data and measures.)

# 3. Results

## 3.1 Skin color inequality

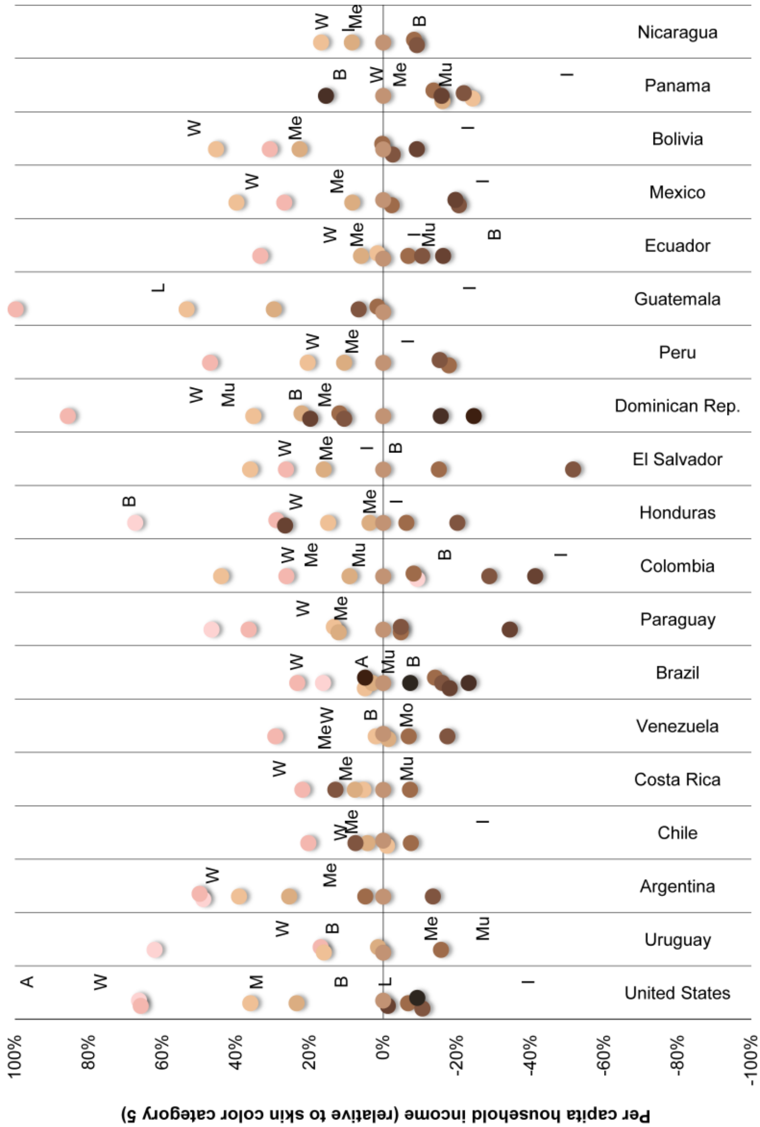
In most countries there is a relatively linear relationship between perceived skin color and per capita household income: lighter colors are associated with higher incomes, and darker colors with lower incomes (see Figure 1 and Table A1). For example, Paraguayans with the lightest color have incomes 47% greater, on average, than those in color category five, while Paraguayans with the darkest skin color have incomes 36% less. Overall, results are consistent with a tendency toward color hierarchy across the region, but the degree to which specific skin colors are associated with advantage or disadvantage varies considerably across countries. The largest gaps between the lightest color category and the mid-range category (suggesting extreme light-skinned elitism) are in the Dominican Republic and Guatemala. At the other end of the spectrum, results from El Salvador and Colombia reveal stark disadvantages for those with the darkest skin tones. In some countries such as the United States and Bolivia we find substantial clustering at different points in the color distributions, suggesting that each step along the color scale is not always equally consequential.

Several countries – including Panama and Honduras – appear to complicate the traditional notion of color hierarchy. Panamanians with the darkest skin color have the highest mean income, while those with the lightest skin color that registers in our sample have an average income 25 percentage points lower than the medium color category. The unusually high ranking of dark skin in Panama and Honduras underscores the importance of understanding country-specific histories of how color interacts with social status. The relative advantage of darker skin in these contexts follows in part from selective West-Indian (Afro-Antillean) migration for jobs involving large-scale, transnational enterprises, including the Panama Canal Company and the United Fruit Company (Andrews 1997; Guerrón-Montero 2006). These contrasting cases aside, the overarching pattern is that color hierarchy is a significant aspect of inequality across the Americas, and the United States is no exception.

### 3.2 Self-identified racial hierarchy

Figure 1 (and Table A2) also demonstrates the advantage of white racial group membership across the region. Whites have the highest mean incomes in 14 of the 18 countries that include a white racial category. (Guatemala did not include a white response option, and a non-white population ranks above whites in the U.S., Venezuela, Honduras, and Panama.) Both Colombia and Brazil exemplify categorical racial inequality characterized by white advantage. In Colombia, whites top the hierarchy, followed in order by mestizos, mulattos, blacks, and indigenous. In contrast, in the United States, self-identified Asian Americans – and Asian Indians, in particular – have the highest per capita household incomes, despite having an average skin color darker than self-identified whites (3.2 compared to 1.7 on the 10-point color scale).

**Figure 1: Skin color and race inequality in income across the Americas**




*Source*: United States – 2012 General Social Survey; all others – 2012 AmericasBarometer.
*Notes*: The mean per capita household income of skin color category five serves as the reference (0%) for each country. Skin color points are shaded to match the category number on the color scales. Racial categories are denoted by letters – W = white/blanca, B = black/negra, A = Asian/amarela, M = multiracial (US only), L = Latina (US only) or Ladina (Guatemala only), Me = Mestiza, Mo = Morena, Mu = Mulata, I = Indígena/American Indian. Countries are arranged according to the percent of the sample that falls into the lightest 3 skin color categories (highest to lowest). Only race and color categories with 30 or more respondents are reported.

Samples included sizeable black populations in ten countries, yet self-identified blacks are at the bottom of the hierarchy in just four: Brazil, Ecuador, El Salvador, and Nicaragua. In Ecuador, black racial disadvantage appears especially deep, with average household incomes 36 percentage points lower than Ecuadorians of medium skin color, and well below the indigenous and mulatto categories. In five other countries, the United States, Venezuela, Uruguay, Colombia, and the Dominican Republic, blacks are in positions of disadvantage compared to whites, but have higher incomes than some other racial populations. In Panama and Honduras, blacks rank at the top, as was also suggested by the color measure. In most cases, though, the experience of blackness is one of distinct disadvantage in comparison to whites.

The indigenous category is typically found at the bottom of the racial hierarchy, occupying the lowest position in 9 of the 12 countries with large enough indigenous populations to analyze. This includes the United States, where the extreme disadvantage of self-identified, monoracial American Indians often goes unacknowledged in large national studies of inequality, due to their small numbers and segregation from much of the population (Snipp and Saraff 2011).

Finally, 17 out of the 19 countries include at least one explicit mestizo or “mixed race” category. In most cases, mestizos are disadvantaged compared to whites but have higher mean incomes than any other racial category. The exception is Venezuela where mestizos earn slightly more on average than whites. The relative advantage of mixed-race populations may reflect whitening strategies in Latin America, in which higher status individuals try to distance themselves from blackness and indigeneity (Schwartzman 2007). Notably, in the U.S. racial hierarchy the position of the multiracial category – people who gave two or more responses to the GSS race question – is similar to the general pattern of mestizos throughout Latin America.

### 3.3 Comparing color and self-identification

Table 1 lists goodness of fit statistics for our models regressing household income on skin color, on categories of racial identification, and on both measures simultaneously. Looking first at BIC (privileging parsimony), in 11 of the 19 countries the variation in household income is better explained by differences in skin color than by self-identified race or a combination of self-identified race and skin color. In Colombia and Uruguay the models with both race categories and skin color fit as well as the models with color alone. In three countries – the United States, Ecuador, and Guatemala – models that include both racial identification and skin color provide the best account for observed variation in income, even when privileging parsimony.

**Table 1: Comparing BIC and AIC across models by country, GSS and AB**

| Country | Model | BIC | AIC |
|---|---|---|---|
| U.S. | perceived color | 10269 | 10263 |
| | self-identification | 10223 | 10192 |
| | combined | **10206** | **10169** |
| Uruguay | perceived color | **2841** | 2836 |
| | self-identification | 2847 | 2831 |
| | combined | **2841** | **2820** |
| Argentina | perceived color | **1982** | 1977 |
| | self-identification | 1988 | 1983 |
| | combined | 1984 | **1975** |
| Chile | perceived color | **2586** | 2581 |
| | self-identification | 2602 | 2592 |
| | combined | 2594 | **2579** |
| Costa Rica | perceived color | 2332 | 2327 |
| | self-identification | **2322** | **2313** |
| | combined | 2330 | 2315 |
| Venezuela | perceived color | **1637** | **1632** |
| | self-identification | 1645 | **1631** |
| | combined | 1650 | **1631** |
| Brazil | perceived color | 2881 | 2876 |
| | self-identification | **2871** | **2855** |
| | combined | 2876 | **2855** |
| Paraguay | perceived color | **3323** | **3318** |
| | self-identification | 3342 | 3337 |
| | combined | 3330 | 3320 |
| Colombia | perceived color | **3197** | 3192 |
| | self-identification | 3204 | 3184 |
| | combined | **3198** | **3173** |
| Honduras | perceived color | **2715** | 2710 |
| | self-identification | 2718 | 2703 |
| | combined | 2717 | **2696** |
| Salvador | perceived color | **3034** | 3029 |
| | self-identification | 3066 | 3051 |
| | combined | 3037 | **3018** |
| Dom. Rep. | perceived color | **3241** | 3236 |
| | self-identification | 3255 | 3240 |
| | combined | 3253 | **3232** |

**Table 1: (Continued)**

| Country | Model | BIC | AIC |
|---|---|---|---|
| Peru | perceived color | **2553** | **2548** |
| | self-identification | 2566 | 2555 |
| | combined | 2564 | **2549** |
| Guatemala | perceived color | 2844 | 2839 |
| | self-identification | 2764 | 2759 |
| | combined | **2742** | **2732** |
| Ecuador | perceived color | 3232 | 3227 |
| | self-identification | 3224 | 3219 |
| | combined | **3222** | **3217** |
| Mexico | perceived color | **2726** | 2721 |
| | self-identification | 2735 | 2725 |
| | combined | 2732 | **2717** |
| Bolivia | perceived color | **5367** | 5362 |
| | self-identification | 5390 | 5379 |
| | combined | 5373 | **5355** |
| Panama | perceived color | 2936 | 2932 |
| | self-identification | **2872** | **2851** |
| | combined | 2879 | 2853 |
| Nicaragua | perceived color | **3434** | **3429** |
| | self-identification | 3453 | 3437 |
| | combined | 3455 | 3434 |

*Note*: The smallest BIC and AIC statistics, indicating the best model fit, are noted in bold. When the difference between two or more models was less than 2, we concluded the models fit equally well and bolded each.

In Brazil, Panama, and Costa Rica we find that racial identification alone provides an equal or better account of inequality, even when we privilege complexity (using AIC). This finding for Brazil is consistent with claims that color gradations among nonwhites are less important than the categorical divide between whites and nonwhites for understanding racial stratification (Silva 1985, but see Telles and Lim 1998). In Panama, categorical racial divisions were explicitly cultivated in the Canal Zone and by the United Fruit Company (Andrews 1997; Craft 2008); the latter also influenced racial dynamics in Costa Rica (Andrews 1997: 16–18). These results echo previous research suggesting that focusing only on racial categories in the U.S. misses an important dimension of inequality, while privileging gradational color distinctions in Latin America would do the same (c.f. Telles and Murgia 1990; Monk 2013).

A closer examination of the U.S. illustrates this point (see Table 2). The model that includes only skin color estimates that each one-point increase on the color scale (i.e., from light to dark) is associated with an 11% decline in per capita household income. The model that compares mean income differences by self-identified race indicates that blacks, multiracial Americans, Latinos, and American Indians all have significantly lower household incomes than whites, with disparities on the order of 39% to 66%. In the combined model a significant (8%) income penalty per color category remains, and the inclusion of skin color explains nearly all of the difference in mean income between blacks and whites in the United States, and nearly one-third of the gap between whites and Americans who report multiple races.

**Table 2: Income inequality in the United States**

| | Perceived color only | Self-id only | Combined |
|---|---|---|---|
| Skin color scale | -0.116*** | - | -0.084*** |
| | (0.012) | | (0.023) |
| *Racial categories* | | | |
| Black (non-Latino) | - | -0.530*** | -0.152 |
| | | (.075) | (0.140) |
| Asian (non-Latino) | - | -0.000 | 0.123 |
| | | (.121) | (0.128) |
| Multiracial (non-Latino) | - | -0.498*** | -0.356** |
| | | (0.114) | (0.103) |
| American Indian (non-Latino) | - | -1.086*** | -.988*** |
| | | (0.270) | (.270) |
| Latino | - | -0.650*** | -0.534*** |
| | | (0.071) | (0.079) |
| Constant | 9.988*** | 9.882*** | 10.024*** |
| | (0.033) | (0.017) | (0.042) |
| Observations | 3,645 | 3,645 | 3,645 |
| BIC | 10,269 | 10,223 | **10,206** |
| AIC | 10,263 | 10,192 | **10,169** |

*Source:* General Social Survey, 2012.
*Notes:* Results from three separate ordinary least squares regression analyses on logged per capita household income. Standard errors shown in parentheses. All models include interviewer fixed effects and estimates are weighted to account for sampling and non-response. Both BIC and AIC statistics favor the combined model, as noted in bold.
* p<.05 ** p<.01 *** p<.001

Nevertheless, Latinos and American Indians remain categorically disadvantaged in the U.S. even when differences in skin color are taken into account. Supplemental models (not shown) confirm that immigrants do not drive this result for Latinos, and controlling for education does not erase the gap between self-identified Latinos and whites. Thus, the disadvantaged position of Latinos in the U.S. racial hierarchy is not well explained by skin color, education, or recent migration.

## 4. Conclusion

Researchers have long debated the contours of racial inequality in the Americas, with disagreements over whether inequality is structured by rigid categorical divides or by color continua, and even whether race is the right concept to describe the social order in some regions (Degler 1971; Skidmore 1993; Banton et al. 2012). However, until recently most of this scholarship focused on race using a singular lens. Research advocating a multidimensional approach to measuring race has produced theoretical insight in Latin America and the U.S. (Telles and Lim 1998; Saperstein 2006, 2012; Bailey, Loveman, and Muniz 2013). Using this approach and newly available data with both perceived skin color and self-identified race, we show that although all 19 countries in our study are racially stratified, they vary in the extent to which one dimension of race or another most structures a country's social inequality. The reasons why a particular measure of race might be more salient in a particular country then become important questions for future research and should facilitate cross-country comparison.

Shifts in racial understandings and demography across the Americas also increase the need for a more flexible, multidimensional approach to racial classification. In the last two decades Latin American policymakers, census bureaus, and scholars of inequality are turning to the more categorical language of race (Santos 2005; Bailey 2008; Paschel 2010; Loveman 2014). At the same time the United States has adopted mixed-race classification and has grown ever more diverse through immigration. Some have speculated these changes will lead to color lines and socioeconomic divides in the United States that will look more variegated and "Latin American-like" (Bonilla-Silva 2004: 931; Lee and Bean 2007; Lichter 2013). The use of multiple dimensions of race will be important in tracking possible shifts in color lines or changes in classification schemes, and will provide a more nuanced comparative lens on racial inequality.

Moreover, racial classification in national surveys, and especially in censuses, is becoming more commonplace across the globe (Simon 2012). Our results point to the need for innovative approaches that challenge long-standing assumptions about the structure of racial hierarchies. Data collection efforts that assume a single overarching racial scheme may constrain progress on racial equality by ignoring other salient dimensions of race (Bailey, Loveman, and Muniz 2013). Knowing whether a given context is best characterized by a gradational color hierarchy, categorical racial distinctions, or some combination of the two can promote further understanding of this pervasive and stubborn axis of inequality.

## 5. Acknowledgements

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## Appendix A: Data and measures

This supplement includes additional detail regarding survey design, sample sizes, and coding decisions for both the General Social Survey and AmericasBarometer. We also provide information on the potential for ceiling effects in income in Brazil, the interpretation of results from fixed effect models, and potential issues of endogeneity.

*Survey design and measures: GSS*

The 2012 GSS is a nationally representative probability sample of U.S. adults aged 18 and over and living in households. Since 2010 the biennial survey has employed a rotating panel design that includes a new cross-sectional sample and re-interviews of randomly selected members of the two previous survey waves. Our analyses include the full sample for 2012, which surveyed 4,820 people. Of these, 4,047 were interviewed in person (as opposed to over the telephone) and our final sample size, taking into account missing data on perceived skin color and our other key variables (described below), was 3,645.

For the first time, the 2012 GSS included the interviewer's rating of the respondent's skin color. Interviewers were trained to record the respondent's skin color after concluding their interview, using a 10-point scale. Interviewer field manuals included a color card with 10 circles of varying skin colors, each corresponding to one of the points on the color scale. The color card was not shown to respondents.

GSS respondents were asked to self-identify their race in response to the question: "What is your race? Indicate one or more races that you consider yourself to be." Up to three responses were recorded using the 15 categories used in the U.S. Census. Immediately prior to reporting their race, respondents were asked: "Are you Spanish, Hispanic or Latino/a?" Based on responses to these questions, we recoded respondents into the most commonly used, mutually exclusive racial categories for the United States: non-Hispanic white (N=2,411); non-Hispanic black (N=488); non-Hispanic Asian (N=84); Hispanic, or "Latino," as we refer to it throughout the text (N=424); non-Hispanic multiracial (N=207), and non-Hispanic American Indian (N=32). We dropped all other racial categories that totaled fewer than 30 observations; this included respondents who offered only "Pacific Islander" or "some other race" responses.

In creating mutually exclusive dummy variables for racial self-identification in the United States, we pay careful attention to the grouping of respondents into the Latino, Asian, and multiracial categories. For Latinos, in addition to asking a separate question regarding respondents' Hispanic origin, the 2012 General Social Survey (GSS) also recorded "Hispanic" as a possible race response. All respondents who were recorded as Hispanic on the race question answered yes to the previous question on Hispanic origin, but the reverse was not also true. For example, about half of the respondents in our sample who reported a Spanish/Hispanic/Latino origin identified as white alone on the race question (N=229). Nevertheless, in line with most research on race in the United States, we included anyone who reported a Hispanic origin in our category "Latino," regardless of the race or races they may have also mentioned. Limiting Latinos to only self-identified non-white Latinos does not affect our overall conclusions, as the mean incomes of non-white Latinos are lower than when using our more inclusive definition. The same is true for the mean income of self-identified whites when self-identified Latinos are included, though to a lesser degree because of the larger size of the white category overall. The fact that Latinos tend to be overrepresented among the foreign-born also does not affect our conclusions about the relative ranking of Latinos in the U.S. racial hierarchy. Although 45% of Latino respondents are foreign born in the 2012 GSS, and foreign-born Latinos have lower average income than US-born Latinos, self-identified Latinos remain categorically disadvantaged even when we control for nativity, or when we estimate our models only for U.S.-born respondents (results available upon request).

Among the specific Asian response categories (Asian Indian, Chinese, Filipino, Japanese, Korean, and Vietnamese) only Asian Indian included 30 or more respondents, so we present instead a single racial category, "Asian." The mean per capita household income of $32,000 for "Asians" understates the mean incomes of Asian Indian respondents at nearly $46,000 (N=30), while overstating the incomes of the other Asian origin categories, especially the five Vietnamese respondents who have a mean income under $25,000. It is also worth noting that 74% of self-identified, monoracial Asians in the GSS sample are foreign-born, with per capita household incomes significantly higher on average than their US-born counterparts.

The aggregate category for Americans who gave more than one response to the GSS race question masks similar internal diversity in economic well-being. Nearly half of all multiracial respondents identified as both white and American Indian, while an additional 34 identified as black and American Indian. Black-American Indian respondents have average household incomes most similar to self-identified, monoracial blacks, while the household incomes of white-American Indians are about 15% lower than monoracial whites. However, both of these multiracial populations are better off than their monoracial American Indian counterparts.

We chose per capita household income as our dependent variable to provide insight into inequality in the resources available to individuals. Although measures like hourly wage (net of overtime pay) can better address issues around discrimination, per capita household income is a better measure for understanding inequality more broadly as it includes differences resulting from factors like assortative mating (Darity and Mason 1998; Schwartz 2010). Household income is self-reported in the GSS using a list of 25 categories that range from "Under $1,000" to "$150,000 and up." Respondents are instructed to answer based on their "total family income, from all sources" for the previous calendar year. We recoded each category to its midpoint, with the exception of the open-ended top category, to which we assigned a value of $160,000 based on the same formula, described below, that we applied to each country in the AmericasBarometer data. (This coding will understate self-identified race or color inequality to the extent that "whites" and lighter skinned Americans are overrepresented in the top category and have incomes substantially greater than $160,000.) We then used the count of persons in the respondent's household to calculate per capita income. Household sizes ranged from 1 to 10 with an average of 2.6 in our sample.

The GSS is designed to be self-weighting at the household level; however, we employ weighted estimates in all of our analyses to account for both non-response and selection based on the number of adults in the household. Unweighted results were substantively similar to those presented here.

*Survey design and measures: AmericasBarometer*

AB is part of the Latin American Public Opinion Project (LAPOP). It is the only cross-national survey of public opinion and behavior that covers the Americas (North, Central, South, and the Caribbean). Our analysis focuses on 18 countries from the following regions: Mexico/Central America, Andean/Southern Cone, and the Spanish-speaking Caribbean. The country surveys are nationally representative, face-to-face samples of voting age adults. Sample sizes are approximately 1,500, with the exception of Bolivia, which was approximately 3,000. The full AB survey has 41,632 observations and includes the United States and Canada. However, those two countries employ a web-based design and did not record skin color; hence we excluded them. In addition, we excluded six other countries whose colonial histories differed significantly from those of Ibero-Latin America and whose official languages are Dutch, English, or French: Suriname, Guyana, Haiti, Jamaica, Belize, and Trinidad & Tobago. Samples in each country were developed using a multi-stage probabilistic design, and were stratified by major regions of the country, size of municipality, and by urban and rural areas within municipalities. We use country-specific weights in all of our analyses; in the countries in which the sample is self-weighted (all but Honduras, Nicaragua, Panama, Bolivia, and Chile) the value of the weight for each case is equal to 1.

The AB color measure is interviewer-rated using an 11-point scale. As with the GSS, interviewers rated respondents after concluding the interview and without showing respondents the skin color scale. Our racial category variable in the AB survey was based on self-identification. Respondents were asked: "Do you consider yourself white, *mestizo*, indigenous, *negro*, *mulatto* or other?" In all countries, the first part of the question ["Do you consider yourself…"] was the same, but the response categories differed according to country schemes. For example, the Brazilian survey used national census categories: white, *pardo* (brown or mixed), *preto* (black), *amarelo* (Asian origin), and indigenous.

The income measure is self-reported using 16 intervals based on each country's currency. Respondents were instructed to answer based on "the total monthly income of this household, including remittances from abroad and the income of all the working adults and children." For each country we assigned midpoint values to the first 15 intervals, and assigned the open-ended top category a value corresponding to the top value of the penultimate category plus half of the penultimate category's range. To calculate per capita income we used the count of persons in the respondent's household.

*Accounting for ceiling effects in income in Brazil*

As noted above, the interval coding of household income, with an open-ended top category, likely results in underestimating racial inequality if whites (or other populations) are overrepresented above the value chosen for the highest income interval. This limitation was potentially magnified in Brazil, where 31% of the sample fell into the final open-ended category for household income. In order to ensure that this did not substantively affect our findings for Brazil we also estimated models (not shown) using that country's personal income measure, in which truncation in the highest category was much less than in household income (only 16% were in the top category). This replication showed that for both household and personal income, BIC confirmed that the model including only self-identified race categories was the better fit to our data for Brazil (results available upon request).

*Interviewer fixed effects models*

All models in the paper include interviewer fixed effects, and take the form:

$$y_{ri} = \beta_0 + \beta_1 x_{ri} + \alpha_i + \varepsilon_{ri}$$

where $y_{ri}$ represents the logged per capita household income of respondent $r$ interviewed by interviewer $i$, $x_{ri}$ represents the independent variables of interest, including either a series of dummy variables for racial categories, a linear term for skin color, or both, depending on the model, and $\alpha_i$ represents fixed effects for each interviewer $i$. Fixed effects models estimate coefficients using the variation that is within the unit indexed by the fixed effect, in this case the interviewer. Computationally, including fixed effects for interviewers is equivalent to subtracting off the interviewer specific mean from each variable in the model. Thus, we are predicting the degree to which a respondent's per capita household income is above or below the mean of all the respondents interviewed by a given interviewer by the degree to which that individual's skin color is above or below the mean of the individuals interviewed by that interviewer. By only making comparison within interviewers, we are in essence estimating the relationship between per capita household income and our independent variables separately for each interviewer, and then taking a weighted average of these estimates. To the degree that some interviewers apply the skin color scale differently than others in a manner that is consistent across respondents (such as recording respondents as being lighter or darker than other interviewers would have recorded the same respondents), including interviewer fixed effects will take these differences into account. We believe that these kinds of perceptual differences in assessing skin color are not driving our conclusions about the contours of economic hierarchy in these countries, as our findings with and without interviewer fixed effects are similar.

Missing data on interviewer identification numbers for both Ecuador and Brazil did pose a challenge for including interviewer fixed effects because 87% and 93% of respondents, respectively, were missing information on interviewer identification number. For these countries we opted to group together respondents who were lacking information about their interviewer, which is analogous to estimating models without interviewer fixed effects for those individuals. BIC statistics with and without fixed effects coincide in strongly indicating self-identification categories as the preferred model in Brazil. In Ecuador the fixed effects models suggest that the combined model fits best, while models without fixed effects favor skin color alone. For most countries the preferred model did not differ depending on whether or not interviewer fixed effects were included. In addition to Ecuador, exceptions included Mexico, Bolivia, and Chile, where the top two models had similar model fits both with and without fixed effects, but one was slightly preferred with interviewer fixed effects and the other slightly preferred without the fixed effects. In the case of Mexico the model without fixed effects favored the more complex “combined” model, while the model with fixed effects favored skin color only; Bolivia and Chile both switched from the “self-identification only” model being favored to a “color only” model (results available upon request).

*Endogeneity*

There is a growing literature that emphasizes the endogeneity of race in understanding social inequality and stratification processes (Villarreal 2010; Schwartzman 2007). This research suggests that not only does people’s race affect their opportunities but people’s life outcomes can also shape how they are perceived racially and how they identify themselves (Saperstein and Penner 2012). This is relevant to our analysis insofar as respondents with higher household incomes, on average, are more likely to self-identify as white (or whichever population is at the top of their country’s racial hierarchy). Similarly, where light skin is associated with success, survey interviewers might be more likely to record better-off respondents as having lighter skin colors than might be recorded using a measurement from a technical instrument, such as photospectrometer.

Given the range of racial identification and color dynamics that we uncover in this study, it seems plausible that the endogeneity of race and socioeconomic status varies across countries. Thus, future research should compare the extent to which self-identified race, perceived skin color, or both, are endogenous to the status attainment process in different places, or vary in the same place at different points in time.

However, for the purpose of this analysis we are interested primarily in describing the state of racial inequality as it is understood in different countries across the Americas. We are not seeking to explain why income inequality is patterned as it is in each country, or in disentangling the degree to which inequality along either dimension of race is endogenous. Rather, we are examining whether countries differ in the extent to which observed variation in per capita household income is more closely linked to a measure of perceived skin color, racial self-identification, or some combination of the two. To the degree that measured income inequality is the result of survey interviewers classifying some people's skin color differently than others based on differences in their social standing, we view this as an interesting and important feature of the relationship between skin color and success that likely has consequences for individual well-being. Put another way, because our goal is to represent the lived experience of racial difference, using what some might consider more subjective measures of race such as perceived skin color and self-identification captures precisely the experience of inequality that we seek to better understand.

## Descriptive tables

### Table A1: Mean per capita household income by country and perceived skin color, in national currencies with sample size in parentheses, 2012.

| Country and currency | Skin Color Scale | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| USA | 27,946 | 27,873 | 22,868 | 20,762 | 16,805 | 15,673 | 15,012 | 16,952 | 15,251 | | |
| Dollar | (1,233) | (1,202) | (466) | (237) | (143) | (104) | (110) | (116) | (34) | - | - |
| Uruguay | 10,102 | 7,291 | 7,238 | 6,318 | 6,232 | 5,255 | | | | | |
| Peso | (34) | (217) | (534) | (317) | (141) | (73) | - | - | - | - | - |
| Argentina | 1,512 | 1,526 | 1,417 | 1,279 | 1,019 | 1,068 | 881 | | | | |
| Peso | (77) | (119) | (245) | (218) | (158) | (139) | (58) | - | - | - | - |
| Chile | | 144,511 | 118,904 | 125,242 | 120,120 | 111,098 | 129,201 | | | | |
| Peso | - | (113) | (423) | (398) | (225) | (98) | (47) | - | - | - | - |
| Costa Rica | | 129,802 | 112,187 | 114,646 | 106,427 | 98,697 | 120,239 | | | | |
| Colón | - | (106) | (274) | (304) | (211) | (88) | (37) | - | - | - | - |
| Venezuela | | 928 | 733 | 708 | 718 | 668 | 593 | | | | |
| Bolívar | - | (83) | (220) | (202) | (168) | (181) | (61) | - | - | - | - |
| Brazil | 521 | 552 | 470 | 461 | 448 | 385 | 376 | 367 | 344 | 470 | 415 |
| Real | (125) | (135) | (208) | (230) | (249) | (181) | (101) | (75) | (44) | (42) | (32) |
| Paraguay | 721,208 | 671,781 | 557,911 | 551,534 | 491,968 | 468,473 | 468,477 | 322,783 | | | |
| Guaraní | (48) | (179) | (204) | (235) | (254) | (250) | (77) | (47) | - | - | - |
| Colombia | 255 | 354 | 404 | 306 | 281 | 258 | 200 | 165 | | | |
| Peso | (43) | (96) | (230) | (340) | (259) | (187) | (68) | (39) | - | - | - |
| Honduras | 2,624 | 2,023 | 1,802 | 1,627 | 1,568 | 1,470 | 1,253 | 1,986 | | | |
| Lempira | (30) | (139) | (223) | (215) | (243) | (211) | (155) | (59) | - | - | - |
| El Salvador | | 93 | 100 | 85 | 73 | 62 | 36 | | | | |
| US Dollar | - | (59) | (246) | (324) | (310) | (257) | (44) | - | - | - | - |
| Dom. Rep. | | 6,869 | 5,004 | 4,521 | 3,700 | 4,139 | 4,092 | 4,432 | 3,122 | 2,790 | |
| Peso | - | (60) | (183) | (249) | (205) | (233) | (168) | (89) | (36) | (33) | - |
| Peru | | 359 | 294 | 270 | 244 | 201 | 207 | | | | |
| Nuevo Sol | - | (32) | (197) | (304) | (383) | (295) | (66) | - | - | - | - |
| Guatemala | | 794 | 610 | 515 | 397 | 404 | 424 | | | | |
| Quetzal | - | (38) | (183) | (269) | (377) | (225) | (31) | - | | - | - |
| Ecuador | | 169 | 129 | 134 | 127 | 118 | 113 | 106 | | | |
| US Dollar | - | (50) | (165) | (285) | (358) | (283) | (125) | (55) | - | - | - |
| Mexico | | 1,442 | 1,589 | 1,232 | 1,137 | 1,111 | 903 | 914 | | | |
| Peso | - | (40) | (136) | (248) | (347) | (277) | (116) | (45) | - | - | - |
| Bolivia | | 592 | 658 | 555 | 452 | 453 | 440 | 411 | | | |
| Boliviano | - | (91) | (265) | (527) | (666) | (574) | (257) | (54) | - | - | - |
| Panama | | | 131 | 145 | 173 | 150 | 135 | 146 | 200 | | |
| US Dollar | - | - | (149) | (202) | (307) | (348) | (170) | (68) | (37) | - | - |
| Nicaragua | | | 1,263 | 1,173 | 1081 | 990 | 982 | | | | |
| Córdoba | - | - | (72) | (353) | (664) | (349) | (66) | - | - | - | - |

**Table A2: Mean per capita household income by country and race category, in national currencies with sample size in parentheses, 2012.**

| | Racial Category | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Country and currency** | **White/ Blanca** | **Mestiza/ Multiracial** | **Mulata** | **Black/ Negra** | **Indígena/ Am. Indian** | **Morena** | **Latina/ Ladina** | **Asian/ Amarela** |
| USA | 26,681 | 21,570 | | 17,695 | 9,164 | | 15,697 | 32,047 |
| Dollar | (2,410) | (207) | - | (488) | (32) | - | (424) | (84) |
| Uruguay | 7,560 | 5,045 | 4,168 | 6,713 | | | | |
| Peso | (909) | (280) | (35) | (32) | | | - | |
| Argentina | 1,429 | 1,104 | | | | | | |
| Peso | (558) | (396) | - | - | - | - | - | - |
| Chile | 126,347 | 123,201 | | | 80,316 | | | |
| Peso | (827) | (444) | - | - | (36) | - | - | - |
| Costa Rica | 120,514 | 102,746 | 86,352 | | | | | |
| Colón | (574) | (365) | (57) | - | - | - | - | - |
| Venezuela | 783 | 786 | | 699 | | 629 | | |
| Bolívar | (293) | (210) | - | (38) | - | (367) | - | - |
| Brazil | 526 | | 415 | 384 | | | | 447 |
| Real | (496) | - | (632) | (206) | - | - | - | (49) |
| Paraguay | 569,194 | 518,587 | | | | | | |
| Guaraní | (451) | (735) | - | - | - | - | - | - |
| Colombia | 336 | 319 | 282 | 217 | 128 | | | |
| Peso | (379) | (637) | (42) | (101) | (77) | - | - | - |
| Honduras | 1,844 | 1,531 | | 2,555 | 1,417 | | | |
| Lempira | (495) | (719) | - | (59) | (48) | - | - | - |
| El Salvador | 88 | 80 | - | 66 | 72 | | | |
| US Dollar | (259) | (730) | | (35) | (41) | - | - | - |
| Dom. Rep. | 5,352 | 4,061 | 5,032 | 4,356 | | | | |
| Peso | (151) | (766) | (136) | (197) | - | - | - | - |
| Peru | 276 | 250 | | | 213 | | | |
| Nuevo Sol | (114) | (1,013) | - | - | (98) | - | - | - |
| Guatemala | | | | | 280 | | 616 | |
| Quetzal | - | - | - | - | (467) | - | (657) | - |
| Ecuador | 137 | 128 | 103 | 81 | 108 | | | |
| US Dollar | (118) | (1,067) | (52) | (46) | (60) | - | - | - |
| Mexico | 1,472 | 1,210 | | | 760 | | | |
| Peso | (192) | (825) | - | - | (92) | - | - | - |
| Bolivia | 657 | 533 | | | 321 | | | |
| Boliviano | (116) | (1,851) | - | - | (353) | - | - | - |
| Panama | 166 | 155 | 134 | 183 | 76 | | | |
| US Dollar | (374) | (599) | (64) | (183) | (113) | - | - | - |
| Nicaragua | 1,195 | 1,089 | | 909 | 1,115 | | | |
| Córdoba | (326) | (916) | | (90) | (65) | | - | |