UNVEILING THE COSMIC RACE: SKIN TONE DISPARITIES IN LATIN AMERICA

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Abstract

Could physical traits drive racial inequalities rather than ethnoracial identities? This paper investigates descriptive skin tone-based disparities across 25 Latin American countries. Using a nine-tone color palette, darker skin tones correlate with lower household income per capita, fewer years of schooling, and a 2 percentage point decrease in upward educational mobility. The direct and indirect skin tone disparities persist after bounding the estimates for unobserved heterogeneity. The skin tone gradients are present across different ethnoracial and gender groups and vary widely across countries. Oaxaca-Blinder decompositions suggest that discrimination likely drives a substantial portion of these gaps.

Keywords: Race, Skin tone, Intergenerational mobility, Inequality, Discrimination, Identity.
JEL: J15, J62, J71, O54, Z13.

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1 Introduction

Economic inequalities are not colorblind. Traditional race-related studies in economics often rely on broad ethnoracial categories such as "White," "Black," "Asian," or "Latino," which may not adequately capture the nuances of racial disparities. These "census-style" categories (Loveman 2014; Monk 2022) might obscure the distinct disparities arising from physical traits.

This issue is particularly pronounced in Latin America, where the majority of the population identifies with 'melting pot' ethnoracial identities such as *'Mestizos'* (mixed-race descendants of European and Indigenous populations) and *'Mulatos'* (mixed-race descendants of European and African populations) (Dixon and Telles 2017; Martínez Casas et al. 2019; Telles and Martínez Casas 2019). Baptized as *'La Raza Cósmica,'* or the 'Cosmic Race,' intellectuals like José Vasconcelos celebrated this racial hybridism, viewing it as possessing the unique virtue of "the ability to blend different races possessing different qualities" (Knight 1990). The 'Cosmic Race' is both a fact and a myth: while racial mixture was more the rule than the exception in Latin America, the myth persists that this mixture has eradicated racial inequalities.

This paper explores whether racial inequalities are driven by physical traits, specifically skin tone, rather than ethnoracial identities. I provide novel descriptive evidence on skin tone gaps across 25 countries in Latin America. Using data from the Latin American Public Opinion Project's (LAPOP) AmericasBarometer survey, I compile a unique dataset that includes skin tone measures using the Project on Ethnicity and Race in Latin America (PERLA) palette (Dixon and Telles 2017; Telles and Martínez Casas 2019), as well as information on ethnoracial identities, income, human capital accumulation, and educational intergenerational mobility (IM).

First, I present descriptive statistics on the extent and composition of the 'Cosmic Race.' Out of the 25 Latin American countries studied, in 15 the majority of the population indeed defines themselves as Mestizos. However, these broad ethnoracial identities conceal substantial phenotypical heterogeneity when measured by skin tone. While individuals identifying as Black or White tend to have darker or lighter skin tones, respectively, there is significant variation within these categories. This is especially true for Mestizo and Indigenous identities. Thus, not isolating physical phenotypical traits from other ethnoracial social identities might lead to underestimating or veiling racial inequalities.

Next, I provide descriptive evidence on skin tone gaps in income. On a skin tone scale from one (lightest) to nine (darkest), a marginal increase in darker skin tone correlates on average with a 4% decrease in household income per capita. These estimates control for fine within-country location, cohort, gender, and mother's educational attainment as a proxy for parental status. The results are robust to alternative measures of income or consumption. Following the partial identification literature (Bontemps and Magnac 2017; Lewbel 2019; B. Kline and Tamer 2023), I employ Cinelli and Hazlett (2020) bounds and demonstrate that the skin tone gaps in income remain negative and statistically significant even when accounting for unobserved confounders three times as strong as mothers' educational attainment.

I also find significant skin tone gaps in human capital accumulation and educational intergenerational mobility (IM). Holding constant mothers' educational attainment, darker skin tones correlate with fewer years of schooling. Furthermore, the probability of achieving higher educational attainment relative to one's mother, or experiencing upward absolute educational mobility, decreases with darker skin tones, although relative mobility is not systematically different. Specifically, a marginal increase in darker skin tone is associated with a 2 percentage point decrease in upward educational mobility. These gaps remain robust against unobserved heterogeneity as large as three times the effect of mothers having tertiary education. These results indicate that disparities arise even before entering the labor market and potentially persist across multiple generations.

Lastly, after accounting for differences in human capital, employment status (i.e., working, unemployed, etc.), salary status (i.e., self-employed, employed in the private sector, etc.), and location, a marginal increase in darker skin tone correlates with a decrease in household income per capita of 3.35%. These estimates remain negative and significantly different from zero, relative to confounders as strong as twice the estimate of respondents' years of schooling on income. These results underscore systematic skin tone gaps across countries with different historical and institutional settings around race.

I explore the heterogeneous effects by ethnoracial identity and gender. Consistent with the argument that the Mestizo identity veils racial inequalities, within such ethnoracial identity, skin tone correlates with lower income and human capital accumulation. While there are no statistically significant differences in income gradients by ethnoracial identity from the mean, the gradient for human capital accumulation is steeper for White males and Indigenous females. Within those identified as Black, skin tone appears less salient than the identity itself in human capital accumulation. Additionally, there is substantial heterogeneity in skin tone gaps across different countries, even after accounting for within-country location. In some countries, the skin tone gaps are more pronounced, suggesting that local contexts and histories of racialization play a crucial role in shaping these disparities.

In the final section, I explore discrimination, in its broadest sense, as a potential mechanism explaining the skin tone gaps. Using a Oaxaca-Blinder decomposition (Ñopo 2008), I show that around 72% of the skin tone disparities in human capital and income cannot be attributed to differences in observable characteristics. Additionally, I provide suggestive evidence that darker-skinned individuals have a higher probability of reporting experiences of discrimination in schools, public spaces, or by government officials. Measuring discrimination in observational data is challenging without exogenous variation (Guryan and Charles 2013; Huber 2015; Bertrand and Duflo 2017), making it difficult to determine whether it is taste-based (Becker 1957), statistical (Arrow 1971; Phelps 1972), systemic (Bohren, Hull, and Imas 2022), or due to other subtle forms of discrimination. However, the systematic skin tone gaps in upward educational mobility, human capital, and income are challenging to explain without considering preferences over certain phenotypical traits, particularly skin tones. This suggests that some form of racial discrimination is likely a contributing factor (Rose 2023).

This paper contributes to two main strains of literature. First, it contributes to the literature on racial disparities. Most studies have primarily focused on substantial racial disparities in the United States (Cook and Logan 2020; Lang and Spitzer 2020; Arnold, Dobbie, and Hull 2021, 2022; Derenoncourt and Montialoux 2020; Derenoncourt 2022; P. Kline, Rose, and Walters 2022; Derenoncourt et al. 2024). However, racial inequalities are also significant in other regions with shared historical experiences of slavery and segregation. In Latin America, ethnoracial identities determine disparities in the labor market and educational attainment (Ferreira and Gignoux 2011; Ñopo 2012; Arceo-Gomez and Campos-Vázquez 2014; Botelho, Madeira, and Rangel 2015; Card et al. 2018; Arceo-Gómez and Campos-Vázquez 2019; Derenoncourt et al. 2021).

Specifically, this paper contributes to the constructivist literature on race (Rose 2023), which is closely related to stratification economics (Darity 2022), and the literature on colorism (Bodenhorn 2006; Hersch 2006; Goldsmith, Hamilton, and Jr. 2007; Diette et al. 2015; Dixon and Telles 2017; Hernández-Trillo and Martínez-Gutiérrez 2021; Monk 2021; Abramitzky et al. 2023; Adukia et al. 2023; Solís, Güémez, and Campos-Vázquez 2023). This paper presents further evidence of skin tone penalties using a sizable sample of individuals across multiple Latin American countries (Bailey, Saperstein, and Penner 2014; Ayala-McCormick 2021). These countries may have very different racialization histories and categorizations, but we can uniformly measure income and human capital differences by skin tone. Moreover, I show the strength of the effects relative to unobserved heterogeneity, thereby bounding the skin tone penalties.

Second, this paper contributes to the growing literature on intergenerational mobility (IM). Building on theories of the intergenerational transmission of inequalities (Becker and Tomes 1979; Durlauf 1996; Piketty 2000), there is increasing interest in the empirical study of IM in the U.S. (Solon 1992; Black and Devereux 2011; Corak 2013; Chetty et al. 2014, 2020; Deutscher and Mazumder 2023; Mogstad and Torsvik 2023; Ray and Genicot 2023; Davis and Mazumder 2024) and other regions (Neidhöfer, Serrano, and Gasparini 2018; Alesina et al. 2021; Barone and Mocetti 2021; Berman 2022; Munoz Saavedra 2022; van der Weide et al. 2023; Kenedi and Sirugue 2023; Salgado and Castillo 2023; Genicot, Ray, and Concha-Arriagada 2024). In the absence of administrative records, recent studies have turned to harmonized public opinion surveys to study IM. As highlighted by Alesina et al. (2021) and van der Weide et al. (2023), exploring educational IM offers certain advantages. Concerns related to measurement error in educational attainment are relatively lower compared to income or consumption measures. Furthermore, unlike income or consumption, human capital accumulation remains relatively constant throughout the lifecycle, reducing methodological complexities in its estimation. Alesina et al. (2023) study differences in IM between religious groups in Africa, and Asher, Novosad, and Rafkin (2024) show that caste groups determine upward mobility in India. This paper incorporates how the endowments, skin tone, of social groups, ethnoracial identities, directly affect social mobility by finding substantial skin tone gaps in absolute educational IM for 25 countries in Latin America. This extends previous evidence of skin tone gaps in IM, which was previously limited to Mexico (Campos-Vázquez and Medina-Cortina 2019; Monroy-Gómez-Franco and Vélez-Grajales 2021; Monroy-Gómez-Franco 2022).

This paper also relates to the literature on social identities (Akerlof and Kranton 2000; Hoff and Stiglitz 2016). Consistent with the conceptual framework of choosing one's identity proposed by Shayo (2020), and similar to Darity, Mason, and Stewart (2006)'s argument, I show evidence that phenotypical traits, particularly skin tone, shapes stated ethnoracial identities. While identities directly shape labor market outcomes (Oh 2023), this paper contributes to the literature by demonstrating that attributes or qualities could directly affect human capital accumulation and income independently of social identities. Moreover, this paper touches on the literature on national identities or nation-building (Shayo 2009; Sambanis and Shayo 2013; Almagro and Andrés-Cerezo 2020; Depetris-Chauvin, Durante, and Campante 2020; Rohner and Zhuravskaya 2023). In the context of salient and shared national identities in Latin America, I show one collateral effect of nation-building: veiling racial inequalities through a shared ethnoracial identity.

The rest of the paper is structured as follows. Section 2 describes the context. Section 3 introduces the data and Section 4 presents the empirical strategy. Section 5 presents the results on skin tone gaps across Latin American countries and discusses possible mechanisms. Section 6 concludes.

2 Context

Race is socially constructed rather than biologically determined (Jablonski 2021a; Darity 2022; Rose 2023). Sociologists argue that racial conceptions are often based on physical characteristics or phenotypical traits, while ethnicity pertains to cultural traits. The long-term co-evolution of culture, genes, and environment explains differences in pigmentation (Henrich 2016; Jablonski 2021b), with skin tone being a key, but not the only, element of race (Sen and Wasow 2016).

In pioneering 'imagined communities' (B. Anderson 1983), 19th-century Latin American nation-states often embraced the ethnoracial identity of mestizos or mulatos, denoting mixed-race descendants from European, Indigenous, and African populations (Dixon and Telles 2017; Martínez Casas et al. 2019; Telles and Martínez Casas 2019). Unlike the United States, where race was defined primarily by descent, Latin America's racialization relied largely on phenotypic appearance and skin color shades (Dixon and Telles 2017).

This section presents a general and brief context on the racial question in Latin America. Its aim is to provide an overview of how phenotypical traits and ethnoracial identities matter. It does not account for the vast and important historical and institutional settings across and within countries defining race. There is extensive literature in sociology, anthropology, and history with more detailed overviews and debates around these issues, both across the Americas and for specific case studies and countries (Graham 1990; Loveman 2014; Wade 2015; Tenorio-Trillo 2017, 2023; Telles and Martínez Casas 2019; Risério 2023; Ang and Islas Weinstein 2024).

Colonial Period. The encounter among Indigenous populations, European conquerors, and Africans brought as enslaved people led to early miscegenation across the continent. Colonial empires actively constituted social groupings through legal and administrative means, as reflected in the casta paintings of New Spain, which depicted the complex social arrangements of colonial times (Loveman 2014; Katzew 2005).

The colonial caste system was a multifaceted legal and political arrangement. Indigenous populations often had communal property rights, while mestizos occupied an intermediate status but were not fully accepted by either Spaniards or Indigenous groups. Enslaved Black people and their descendants faced harsh legal restrictions. Whites born in Europe (peninsulares) held the most prestigious positions, whereas those born in the Americas (Creoles) had slightly lesser status. Despite its rigidity, the caste system allowed for some flexibility, as individuals navigated and manipulated their racial classifications for economic or legal benefits (Graham 2013; Loveman 2014).

Racial disparities in colonial Latin America were shaped by a combination of social, economic, and racial factors, even before formal racial theories emerged. The intersection of race and class was a defining feature of social stratification (R. D. Anderson 1988; McCaa, Schwartz, and Grubessich 1979).

Nation-States Formation up to the 20th Century. Following independence in the early 19th century, Latin American states underwent significant changes regarding race. Nation-building processes and the dissolution of the colonial caste system led to new national identities. However, liberal ideologies of individual freedom clashed with the caste system, leading to its formal abolition in many new republics (Loveman 2014). Despite these changes, racial and ethnic classifications persisted in everyday life, with whiter individuals generally enjoying higher social status. This period also saw the emergence of racial theories in the late 19th century, which further justified these disparities (Graham 1990).

In the late 19th and early 20th centuries, some Latin American countries, such as Argentina, Uruguay, and Chile, attempted to whiten their populations through European immigration (Helg 1990). Others, like Mexico and Brazil, embraced mestizo and mulato identities, promoting national unity through a mixed-race narrative. This mestizaje ideology became a cornerstone of national identity, emphasizing the cultural and racial blending unique to Latin America (Knight 1990). Prominent intellectuals like Franz Boas, Gilberto Freyre, and José Vasconcelos challenged scientific racism and celebrated racial mixing, or the 'Cosmic Race,' as a national strength (Knight 1990; Skidmore 1990). This ideology served as a counter-narrative to racial segregation in the United States and Nazi Germany's racial hatred, presenting a more inclusive vision of racial and ethnic integration.

Race Today. Today, the mestizo or mulato identity remains prevalent in Latin America, yet racial inequalities persist through phenotypical traits and ethnic disparities. Lighter skin tone individuals often have better socio-economic outcomes, and various forms of racism continue in everyday life (Krozer and Gómez 2023). Despite historical and anecdotal evidence of these disparities, only recently have social sciences developed methodologies to measure ethnic and racial identities systematically (Telles and Martínez Casas 2019).

The discussion of race has re-emerged in Latin America, criticizing mestizaje (Telles and Martínez Casas 2019; Ang and Islas Weinstein 2024), with responses to those critics pointing out its advantages over other racial narratives (Risério 2023; Tenorio-Trillo 2023). The region's historical experience with racial mixing and identity formation offers valuable insights into addressing racial inequalities globally. Understanding the nuances of Latin American racial dynamics through phenotypical traits can inform broader discussions on race disparities in other regions.

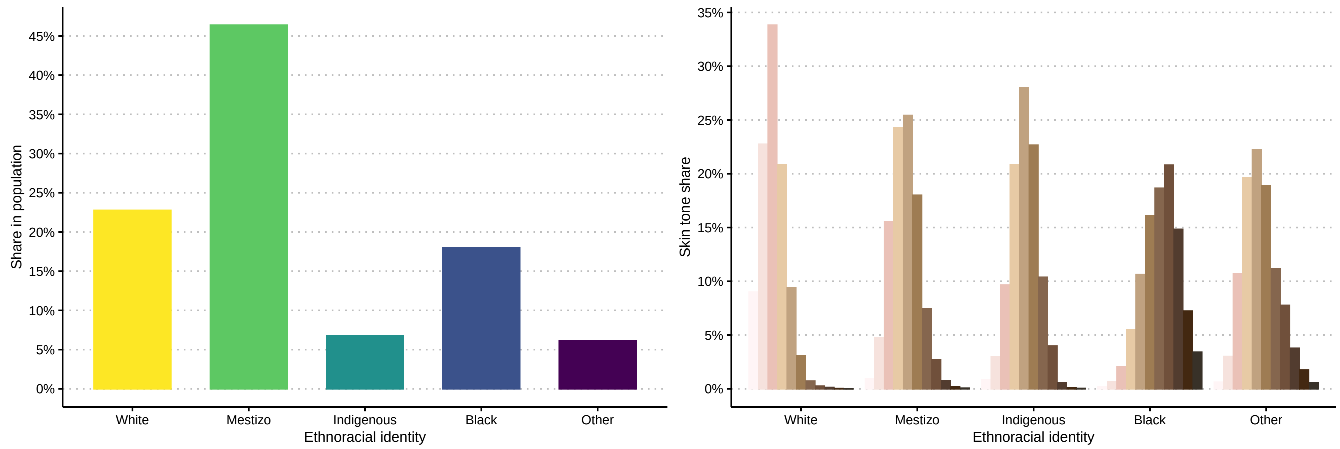
3 Data

To study phenotypical disparities across Latin American countries, I leverage a comprehensive dataset that examines both ethnoracial identity and phenotypic dimensions. This dataset originates from the Latin American Public Opinion Project's (LAPOP) AmericasBarometer survey. The survey is conducted biennially in most countries across the Americas, employing a standardized questionnaire and utilizing stratified, nationally representative samples of voting-age adults (LAPOP 2024).

Ethnoracial Identities. LAPOP's dataset encompasses a broad range of ethnoracial identities, including White, Mestiza, Mulata, Afro, Indigenous, and other categories (e.g., Asian, Arab, among others). Given the relatively small sample size for the Mulata category, I combine it with the Mestiza category for analysis. Figure 1 panel (a) shows the distribution of ethnoracial identities across all countries.

Consistent with the mestizaje narrative, 45% of the population defines themselves as Mestiza or Mulata. Approximately 22% self-identify as White, and another 18% as Black or Afro. Only 6% identify as Indigenous, and another 6% belong to other ethnoracial groups. Most countries in the Caribbean have a majority of the population defining themselves as Black. In Argentina, Chile, Costa Rica, and Uruguay, the majority identifies as White. However, in any other country, the Mestizo identity represents the majority (Figure A.1).

Skin Tone. Besides measuring ethnoracial identities, LAPOP has implemented the Project on Ethnicity and Race in Latin America (PERLA) palette as part of their questionnaire. This scale ranges from 1 to 11, with 1 denoting the lightest skin tone and 11 the darkest. During interviews,



(a) Ethnoracial identities

(b) Skin tone share by ethnoracial identity

Figure 1: Ethnoracial identities and skin tone

Notes: Based on LAPOP waves 2012, 2014, and 2016/2017. In both panels, the x-axis shows the ethnoracial identity self-declared by the respondent. The y-axis in panel (a) shows the ethnoracial sample share. The y-axis in panel (b) shows the skin tone share by ethnoracial identity. Skin tone is measured by enumerator.

enumerators are discreetly instructed to annotate the respondent's skin color, referencing the PERLA palette, without revealing the guides to the respondents (Dixon and Telles 2017; Telles and Martínez Casas 2019).[1] The PERLA scale serves as a proxy for perceived skin tone rather than a direct measure of skin color.

Broad ethnoracial categories obscure the immense phenotypic heterogeneity that exists within them. Figure 1 panel (b) shows the skin tone distribution by ethnoracial group. Most individuals who self-identify as White have light skin tones, while most individuals who identify as Black or Afro have dark skin tones. The majority of individuals defining themselves as Mestizo, Indigenous, and Other have medium or brown skin tones. However, each ethnoracial identity exhibits substantial skin tone heterogeneity. Finally, there is also vast variation in skin tone both between and within countries (Figure A.2).

Assuming the skin tone proxies correctly phenotypical traits, these descriptive patterns are consistent with Darity, Mason, and Stewart (2006) and Shayo (2020) endogenous identity framework: individuals choose their ethnoracial identity based on their attributes, such as individual skin tone, and the prototypical attributes of their reference group, such as the mean ethnoracial skin tone. Moreover, they are also consistent with the constructivist approach on race (Rose 2023). Note, however, that racial identification is also historty and location dependent (Dahis, Nix, and Qian 2019).

[1] Solís, Güémez, and Campos-Vázquez (2023) show that, holding fixed an outcome of interest, skin tone correlations remain stable if the latter is measured by: 1) the individual self-declaring their skin tone, 2) the enumerators' measure, and 3) colorimeters. To help control for potential enumerator biases in recording skin tone, most LAPOP waves also incorporate information on the self-reported skin tone of the enumerator, alongside their gender.

To measure racial gaps by physical attributes rather than identity, I use the PERLA skin tone measure as my main treatment variable. Note, however, that skin tone is not the only physical trait related to race affecting economic outcomes: other attributes such as eye and hair color (Solís, Güémez, and Campos-Vázquez 2023), or height (Vogl 2014), also shape ethnoracial identities and relate to economic outcomes. Moreover, there are other physical traits unrelated to race that also shape economic outcomes, such as obesity (Macchi 2023), and perceived beauty (Hamermesh and Biddle 1994). Using objective skin tone measures, as well as eye and hair color, Solís, Güémez, and Campos-Vázquez (2023) show that skin tone still predicts socioeconomic status. As such, skin tone still works as a salient cue of race.

Sociodemographics. LAPOP data also encompass additional sociodemographic data. My primary focus centers on the survey waves featuring the most comprehensive set of information, specifically those from 2012, 2014, and 2016/2017. This encompassing dataset includes a range of demographic variables, such as age, gender, years of schooling, occupational status, marital status, religion, and geolocation, which is determined by strata within municipalities.[2] Additionally, the dataset provides retrospective information on respondents' mothers' education. As my dependent variables, I use two proxies of household income, years of schooling to measure human capital, and absolute and relative educational IM measures.

Household Income. To proxy for a continuous measure of income, I rely on self-reported monthly household income brackets. Initially, I calculate the median value of each bracket to represent the monthly household income in the local currency of the respective country. Subsequently, I divide this continuous household income measure by the household size and convert it to a daily rate, yielding an approximate measure of daily income per capita. I apply the 2019 Purchase Parity Power rates provided by the World Bank to convert the local currencies.

As an alternative measure of household income, I construct a household asset index. Following McKenzie (2005), I use information on the composition of household assets and construct a normalized index using Principal Component Analysis. The household assets include television, fridge, washing machine, microwave, telephone, cellphone, computer, number of cars, motorcycles, access to drinking water at home, and bathroom at home. There is a positive correlation between daily household income per capita and the constructed asset index: a one standard deviation increase in the household asset index correlates with a 16.5% increase in household income per capita (Figure A.3).

Educational IM. I leverage the retrospective information on respondents' mothers' educational attainment provided by LAPOP. I construct absolute and relative measures of educational IM following van der Weide et al. (2023) to ensure comparability. First, I create educational measures

[2]The geographic location levels, ranging from coarser to finer granularity, include: country, within-country region, state/province, municipality, and within-municipality strata. In a given wave, the average number of observations per within-municipality stratum is 6.15, with a standard deviation of 2.16. Therefore, the within-municipality stratum serves as the smallest available geographical unit for analysis.

for respondents and their mothers in line with UNESCO's International Standard Classification of Education (ISCED): (i) less than primary (ISCED 0), (ii) primary (ISCED 1), (iii) lower secondary (ISCED 2), (iv) upper secondary or postsecondary non-tertiary (ISCED 3–4), and (v) tertiary (ISCED 5–8).

Second, I create absolute and relative mobility measures. As explained by Genicot, Ray, and Concha-Arriagada (2024), absolute measures reflect individual changes in economic standing independent of changes in others' positions, while relative measures focus on changes in comparative standings. To measure absolute mobility, I construct a dummy variable equal to one if respondents have a higher educational category than their mothers, with tertiary education being the benchmark if the mother has tertiary education. To measure relative mobility, I follow Chetty et al. (2014), ranking respondents and their mothers by birth cohort and country to determine their percentile in the years of schooling distribution.

While LAPOP data only measures mothers' educational attainment, there is educational persistence, as mothers' educational attainment predicts respondents' years of schooling (Figure A.4). Moreover, my educational attainment measures (respondents' and mothers' years of schooling) and IM estimates (absolute and relative mobility) are robustly correlated with those by van der Weide et al. (2023), who use Latinobarometro as their data source (Figure A.5). Finally, consistent with Neidhöfer, Serrano, and Gasparini (2018) patterns, intergenerational mobility is rising throughout cohorts in Latin America (Figure A.6).

Sample. My final sample using LAPOP data comprises over 86,000 individual observations from twenty-six countries across the Americas, with household income per capita observed for 63% of the sample. I exclude respondents younger than 21 years old or still enrolled in school, except those who have completed upper secondary education and are 21 years or older. Table A.1 shows the descriptive statistics across the sample and by skin tone.

One relevant point to underline is that disparities in observable characteristics between adjacent skin tones tend to be relatively less pronounced. For instance, when comparing PERLA skin tone one and two, which represent the two lightest skin tones, differences in education, household size, occupational status, geographical sorting, and even mother's education are nearly negligible. This pattern holds for most pairs of adjacent skin tones. Consequently, relatively similar skin tones might serve as more suitable counterfactuals when analyzing differences than comparing the extremes of the lightest and darkest skin tones.

4 Empirical strategy

I estimate the skin tone gaps on income, human capital, and educational IM for countries in Latin America using the following specification:

$$y_{ic} = \delta_c + \sum_{k=2}^{9} \alpha_k \cdot 1[\mathit{Skin\ tone}_i^k] + \mathbf{X}i\text{'}\Gamma + \varepsilon ic \tag{1}$$

where y_{ic} is an economic outcome (i.e., income, years of schooling, absolute educational mobility) of individual i interviewed in a given cluster c. The right-hand side of specification (1) includes the terms $1[\mathit{Skin\ tone}_i^k]$, which are dummies equal to one if individual i has PERLA skin tone k, where $k = 2$ is the second lightest skin color and $k = 9$ is the darkest.[3] The base of comparison is the lightest skin tone, PERLA color one.

Specification (1) also accounts for cluster fixed effects, δ_c. A cluster c is the interaction between within-municipality strata (the smallest geographical unit), year, and enumerator's identification number.[4] Finally, $\mathbf{X}_i$ is a vector of controls.

I employ OLS to estimate specification (1) for household income per capita, years of schooling, absolute educational mobility, and educational percentile. Since many observations report zero income, I follow Chen and Roth (2023) and use a log-transformation to handle these zero values, shutting off the extensive margin. I cluster standard errors at the within-municipality strata times year times enumerator and use LAPOP sample weights to make results comparable across countries and waves.

4.1 Partial identification and bounds

The parameters of interest are $\sum_{k=2}^{9} \alpha^k$, which capture the skin tone gap on economic outcomes for each PERLA skin tone k. Skin tone offers an advantage over ethnoracial categories or dummies as it allows for marginal variation in the cues or perceptions of one dimension of race (Table A.1). However, several challenges arise in point identifying these parameters.

The first challenge is potential measurement error in assessing skin tone. Since skin tone is recorded by the enumerator, there is the possibility of bias introduced by the enumerator's preconceptions or the socio-economic status of the respondent (Roth, Solís, and Sue 2022). The term δ_c accounts for this issue. This interaction allows for the comparison of individuals living in the same geography, being interviewed in the same year, and by the same enumerator.

[3] Given the small sample size for the darkest skin tone, I top code the skin tone greater than 9 as skin tone 9.

[4] In a given within-municipality stratum and year, typically one to three enumerators are involved. To distinguish between enumerators, I use an interaction between the within-municipality strata times year fixed effect and the enumerator's skin tone and gender, which serves as a proxy for enumerator-specific characteristics. This interaction helps identify individual enumerators within the data.

The second issue is omitted variable bias (OVB). It is likely that unobserved factors correlate both with skin tone and adult economic outcomes. As these unobserved factors most likely correlate positively with skin tone and negatively with adult economic outcomes, estimates from specification (1) are likely biased upwards in absolute terms.

Finally, another relevant challenge is included variable bias (IVB). Some observable characteristics might also be affected by skin tone (Guryan and Charles 2013), or, in the causal mediation analysis framework, they are mediators in the causal pathway of skin tone on economic outcomes (Huber 2015; Celli 2022). For instance, within households, early childhood capital accumulation may differ among siblings with different skin tones (Rangel 2015; Abramitzky et al. 2023). Additionally, evidence suggests racial biases in grading at basic education levels against black students (Botelho, Madeira, and Rangel 2015), and youth aspirations might decline due to the influence of phenotypical traits stereotypes (Campos-Vázquez and Medina-Cortina 2017). Thus, when studying income gaps, the inclusion of human capital might create IVB. In specification (1), the vector $\mathbf{X}_i$ includes observed covariates that serve as good or clean controls (Angrist and Pischke 2008). Therefore, I control for gender, age, and the mother's education as a proxy for parental socio-economic status. These variables were fixed when skin tone was determined.

Under point identification, α^k estimates represent correlations without a causal interpretation. However, consistent with the partial identification literature (Bontemps and Magnac 2017; Lewbel 2019; B. Kline and Tamer 2023), we can learn something about skin tone disparities under the current cross-sectional nature of the data and in the absence of exogenous shocks. More specifically, we can learn if skin tone has any effect on income, human capital accumulation, and upward absolute educational mobility using bounding approaches.

I employ Cinelli and Hazlett (2020)'s bounding approach. Unlike other sensitivity procedures (Altonji, Elder, and Taber 2005; Oster 2019; Diegert, Masten, and Poirier 2022; Masten and Poirier 2023), Cinelli and Hazlett (2020) offers a parametrization of omitted variable bias based on partial R^2. This approach allows us to evaluate the strength of association between confounders and both the treatment and the outcome, all without assumptions about the functional form of the treatment assignment mechanism or the distribution of unobserved confounders. I establish bounds for skin tone estimates with respect to an observed characteristic that correlates with both skin tone and economic outcomes: mothers' education. As such, we can learn the strength of the skin tone gaps relative to unobserved factors as strong as mothers' education.

5 Results

This section first presents descriptive skin tone gaps in income, years of schooling, and educational IM. Then, I use bounds to discuss the direct and indirect effects of skin tone on income. Finally, I show heterogeneity by ethnoracial group, ethnoracial majority, gender, and country.

5.1 Descriptive skin tone gaps

Income. There exists a systematic negative correlation between skin tone and income. Figure 2 panel (a) illustrates the saturated skin tone estimates on household income per capita, while accounting for fine geographic fixed effects, year fixed effects, enumerator fixed effects, gender, age, and mother's education. Each coefficient in the figure represents the income gap relative to the lightest skin tone, accompanied by their respective confidence intervals. For instance, individuals with PERLA skin tone 4 have, on average, 14% less income than those with the lightest skin tone; individuals with the darkest skin tones have 25% less income.

The coefficients at the top of the table indicate the difference between adjacent skin tones, or marginal effects, along with the linear combination test adjusted q-value (M. L. Anderson 2008). Notably, skin tone penalties on income become evident during the transition from lighter to brown skin tones, with a secondary but less pronounced shift from brown to darker skin tones. In this context, the Average Marginal Effect (AME) denotes the mean difference between adjacent skin tones, weighted for the number of observations in each skin tone. On average, a marginal increase in darker skin tone correlates with a 4% decrease in household income per capita.

Table B.1 shows non-saturated OLS estimates using the continuous skin tone measure, adding one control at a time. Consistent with recent evidence on the place-based effects on income (Card, Rothstein, and Yi Forthcoming), half of the variation between household income per capita and skin tone can be explained by the cluster fixed effects. Although the saturated specification estimates depict a non-monotonic correlation between skin tone and income, Figure 2 panel (a) shows in the top-right side that the AME does not differ from the non-saturated OLS estimate (Table B.1, Column 6), with a hypothesis test p-value of 0.882.

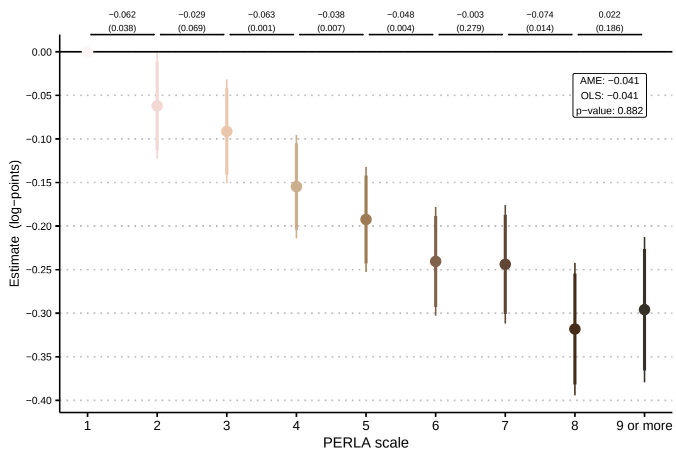
These patterns are consistent using alternative proxies of household income or consumption. Figure 2 panel (b) presents the skin tone estimates for the household asset index. The AME implies that a marginal increase in darker skin tone correlates with a 0.06 decrease in the household asset index. Consistent with the previous dependent variable, the AME is indistinguishable from the linear non-saturated OLS estimate.

Human capital. Before assuming a direct effect of skin tone on income, it's essential to explore the disparities in human capital accumulation. Panel (c) in Figure 2 illustrates the correlations between skin tone and years of schooling. Table B.2 shows non-saturated OLS estimates.

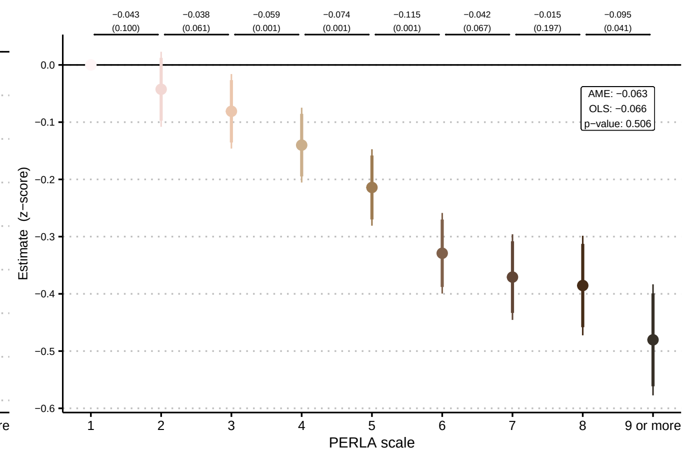
The gaps in human capital accumulation among skin tones exhibit a non-monotonic pattern similar to that observed in income gaps. These differences translate to an AME of 0.05 standard deviations between each adjacent skin tone, not statistically different from the linear non-saturated OLS estimate. The mean years of schooling is 9.92, equivalent to secondary education or ISCED level 2. The standard deviation in the sample is 4.27. Thus, holding constant the mother's educational attainment, the estimates imply that individuals with the darkest skin tones have, on average, 1.5

fewer years of schooling.

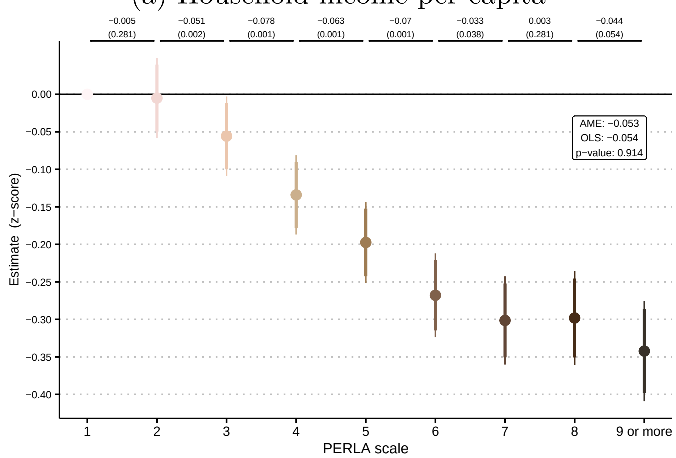
These results suggest darker skin tones accumulate less human capital compared to their lighter-skinned peers, holding constant mothers' educational attainment. The results imply that income disparities between skin tone groups could be partly attributed to variations in human capital accumulation, which is shaped during childhood or adolescence stages (Heckman and Mosso 2014).



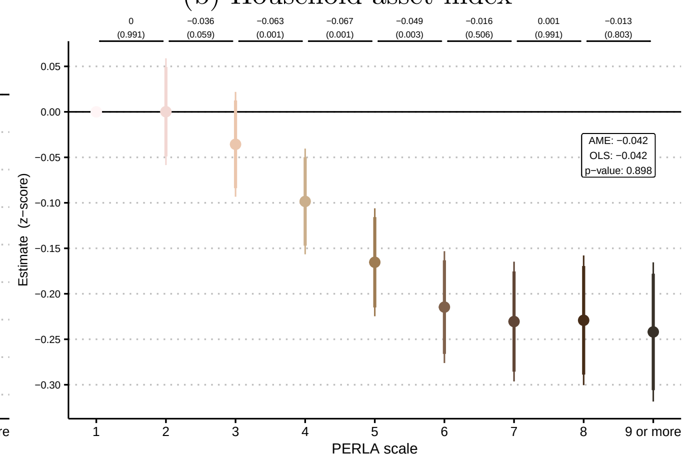
(a) Household income per capita



(b) Household asset index



(c) Years of schooling



(d) Absolute upward educational mobility

Figure 2: Skin tone disparities

Notes: The x-axis shows the skin tone measure: the PERLA color palette including scales from 1 to 9, top coding skin tones above 9 given their small share. The y-axis in panel a) shows the log-points estimate for housheold income per capita. The y-axis in panel b) shows the z-score estimate for household asset index. The y-axis in panel c) shows the z-score estimate for respondents years of schooling. The y-axis in panel d) shows the z-score estimate for respondents absolute mobility (indicator variable equal to one if respondents' have strictly higher educational category than mothers if mothers do not have tertiary, or with tertiary education if the mother has tertiary). The specifications includes a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. The specifications also controls for sex, age, and mothers' ISCED education level. Thin (thic) error bars show 95% (90%) confidence intervals at the cluster level. On top of each figure, the horizontal lines show the difference in estimates between adjacent skin tones or marginal and the respective linear hypothesis adjusted q-value in parenthesis using Anderson (2008). The labels in the top-right represent the weighted Average Marginal Effect, or the marginal effects between adjacent skin tones mean, the linear non-saturated OLS estimate, and the p-value testing the equivalence of these coefficients.

Educational IM. Do individuals with darker skin tones accumulate less human capital with respect to their mothers? In other words, do they have less upward educational mobility? To examine variations in educational IM among different skin tone groups, I first analyze absolute upward mobility gaps. Panel (d) in Figure 2 shows the saturated regression of skin tone on the probability that the respondent achieved a higher educational level than their mother. Conditional on the mother's educational attainment, on average, individuals with darker skin tones have 0.02 percentage points or 0.04 standard deviations less probability of experiencing upward mobility. Table B.3 shows non-saturated OLS estimates. Note that the absolute upward educational mobility estimates replicate the years of schooling ones, indicating that educational persistence is stronger for individuals with darker skin tones.

Are there skin tone differences in relative educational IM? I study the correlation between the respondents' educational rank and their mothers' educational rank, modifying specification (1) to follow Chetty et al. (2014) and Chetty et al. (2020):

$$y_{ic} = \delta_c + \sum_{k=2}^{9} \alpha_k \cdot 1[\mathit{Skin\ tone}_i^k] + \sum_{k=2}^{9} \beta_k \cdot \mathit{Mother's\ education\ ranki} + \mathbf{X}i\text{'}\Gamma + \varepsilon ic \tag{2}$$

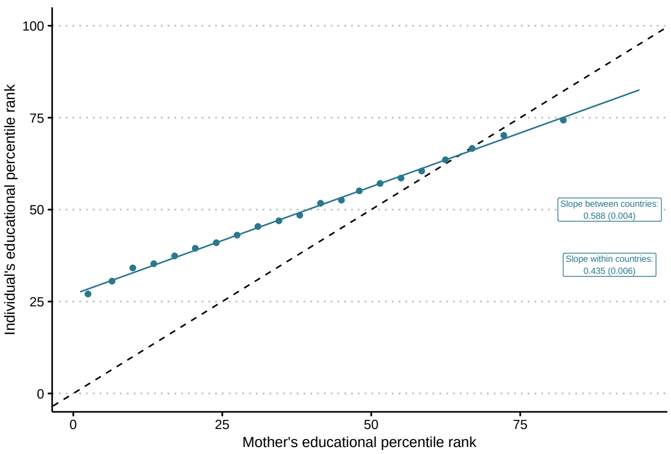
where yic is the educational percentile rank of individual i interviewed in a cluster c. The term $\mathit{Mother's\ education\ rank}_i$ represents the mother's educational percentile rank of individual i. The remaining terms are the same as in specification (1).

Note that individual i's adult outcomes are a function of their parents' socio-economic status, proxied by the mother's educational attainment, $\mathit{Mother's\ education\ ranki}$, allowing for variation between skin tones rather than racial categories as in Chetty et al. (2020). For each outcome, $\sum k = 2^9 \alpha^k$ captures the skin tone gap in economic outcomes for each PERLA skin tone k. Namely, it represents the mean outcome of an individual of skin tone k whose mother has an educational rank of $\mathit{Mother's\ education\ rank}_i = 0$. When analyzing the educational percentile rank, α^k captures the skin tone absolute educational rank mobility; β_k measures the skin tone rate of relative mobility (Chetty et al. 2020).

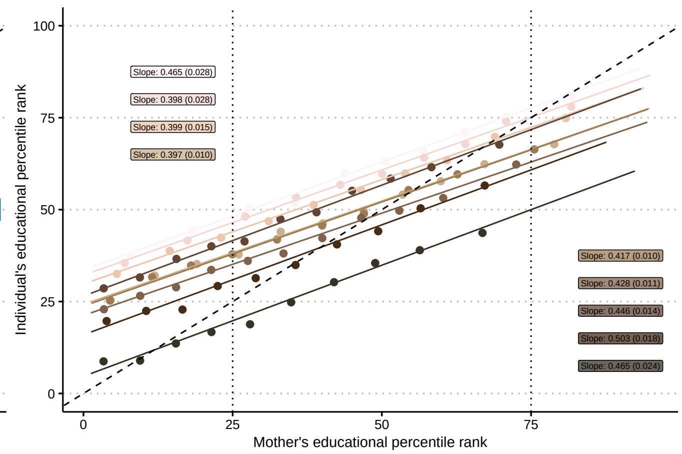
Figure 3 panel (a) displays a binscatter representing the relationship between the respondent's educational percentile rank and their mother's educational percentile rank. When considering country fixed effects, year fixed effects, age, and gender, the rank-to-rank correlation, or the average relative IM coefficient, is 0.58. After incorporating fine geographical fixed effects, thereby accounting for sorting within the country, enumerator fixed effects, age, and gender, the rank-to-rank correlation reduces to 0.43, which remains statistically significant at conventional levels. There is substantial heterogeneity by country. Figure B.1 shows the educational IM rank-to-rank binscatters and relative coefficients by country.

In Figure 3 panel (b), I present the educational relative IM estimates categorized by skin tone groups. The lightest and the darkest skin tones have the highest rates of educational persistence, around 0.465, while the other skin tone groups exhibit lower relative mobility estimates, around 0.40 (see Figure B.2 for inference on the differences between skin tone groups' relative IM estimates).

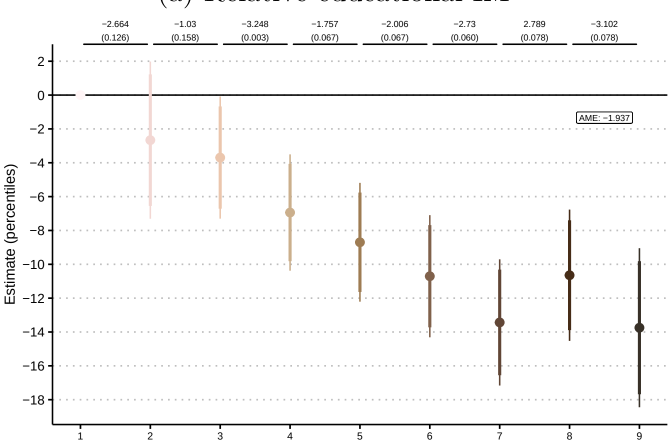
However, the most significant gaps between skin tone groups are in absolute mobility. Specifically, for a given mother's educational percentile rank, darker skin tones exhibit lower absolute mobility. Panels (c) and (d) in Figure 3 illustrate the absolute IM gaps at the 25th and 75th mother's educational percentile rank. At each mother's educational percentile rank, I compute the expected child percentile rank using the absolute and relative estimates for each skin tone. I obtain the gap's mean and standard deviation



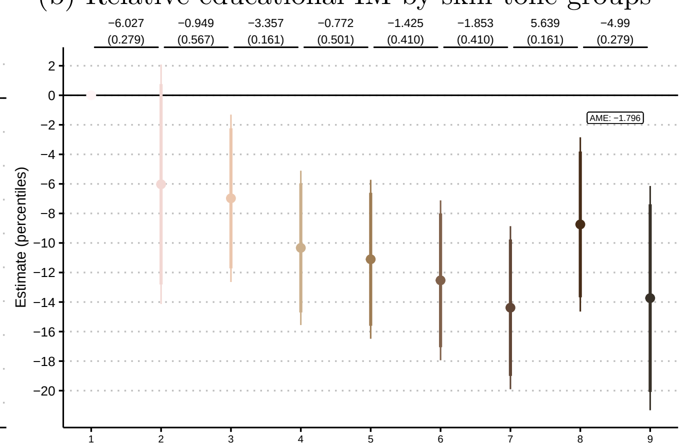
(a) Relative educational IM



(b) Relative educational IM by skin tone groups



(c) Absolute IM skin tone gaps at pct. 25



(d) Absolute IM skin tone gaps at pct. 75

Figure 3: Educational intergenerational mobility (IM)

Notes: Panels a) show educational intergenerational mobility (IM) relative estimates for the complete sample. Panel b) shows the IM relative estimates by skin tone group. The x-axis shows the mother's educational percentile rank. The y-axis shows the children or respondent educational percentile rank. Labels in panel a) show the relative educational IM correlations between contries and within country. Labels in panel b) show the relative educational IM within country by skin tone group. Within country and skin tone specifications includes a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Panel c) and d) show the absolute educational IM gaps for each skin tone evaluated at the 25th and 75th mother's educational percentile rank, respectively. The x-axis shows the skin tone group. The y-axis shows the gap estimate in percentiles. Thin (thic) error bars show 95% (90%) bootsrapped confidence intervals using Rubin (1981). On top of each figure, thehorizontal lines show the difference in estimates between adjacent skin tones and the respective linear hypothesis adjusted q-value in parenthesis following Anderson (2008).

5.2 Bounding skin tone estimates

I employ Cinelli and Hazlett (2020) bounding approach to analyze the robustness of the skin tone estimates, specifically their sign, to unobserved heterogeneity. I bound the continuous linear skin tone estimate relative to a clean control: an indicator of whether the mother had tertiary education. This allows me to determine how strong the correlation between unobserved heterogeneity and both skin tone and the variable of interest must be to explain away my estimates.

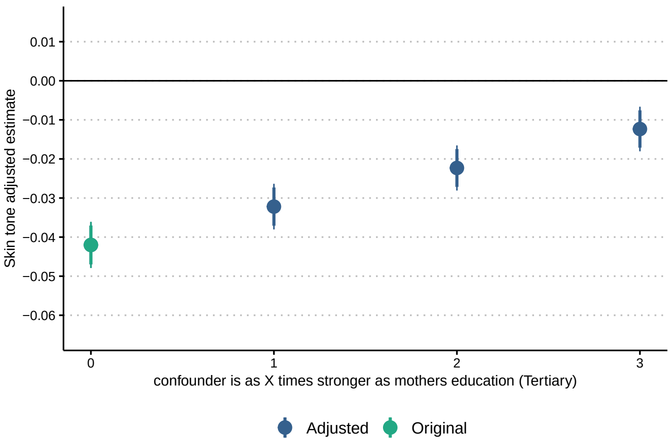
First, I bound the absolute educational upward mobility estimates. Figure 4 panel (a) shows the original and adjusted skin tone estimates on upward mobility, measured as the probability that the respondent has higher educational attainment relative to their mother. The original estimate suggests that a marginal increase in darker skin tone correlates with a decrease of 0.04 standard deviations in the probability of experiencing upward mobility. If the respondent's mother had tertiary education, there is a 0.75 standard deviation lower probability that the respondent experienced upward educational mobility (Table B.3, Column 6). I find that an unobserved covariate correlated with both skin tone and absolute educational upward mobility would need to be more than three times as strong as the estimate of mothers having tertiary education to explain away the skin tone effect on upward mobility.

Consistently, I find that marginal increases in darker skin tones correlate with a decrease of 0.05 standard deviations in years of schooling (Table B.2, Column 6). Figure 4 panel (b) shows that the skin tone estimates are robust to unobserved heterogeneity that is more than three times as large as the estimate of mothers having tertiary education, which is correlated with an increase of 0.73 standard deviations in years of schooling. Thus, skin tone is robustly and systematically correlated with lower human capital accumulation.

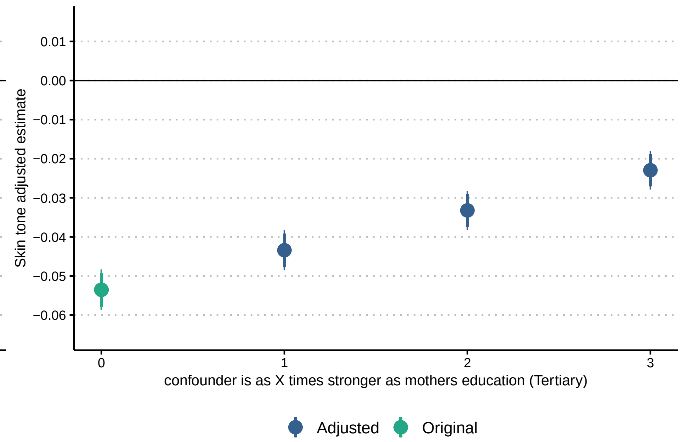
Then, I bound the direct and indirect effects of skin tone on income. The negative estimates of skin tone on income are also robust to unobserved heterogeneity. Without accounting for differences in human capital accumulation or other variables themselves affected by skin tone, Figure 4 panel (c) shows that the skin tone estimates on household income per capita remain negative and statistically significant. This robustness holds against confounders that are more than three times as strong as the estimate of mothers having tertiary education, which in this specification is correlated with an increase of 43.3% in household income per capita.

When including the respondent's human capital and other covariates that might also be influenced by skin tone, such as ethnoracial identity, occupational status, salary status, marital status, and religion, the linear skin tone estimate still shows a significant effect. Specifically, a marginal increase in darker skin tone correlates with a 3.3% decrease in household income per capita, even after controlling for the respondent's years of schooling (Table B.1, Column 8). In contrast, each additional year of schooling for the respondent correlates with a 4.6% increase in household income per capita. Figure 4 panel (d) demonstrates that the skin tone estimates on household income per capita remain negative and significantly different from zero, even when accounting for confounders as strong as twice the estimate of years of schooling on income.

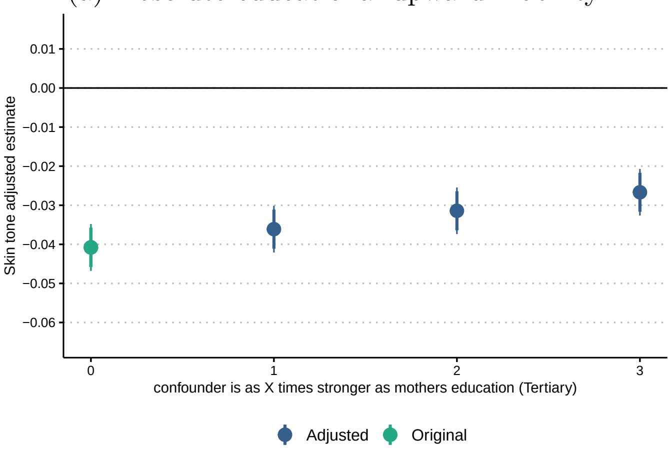
Together, while these results are not point-identified, they imply there are systematic skin tone penalties to educational upward mobility, human capital accumulation, and income.



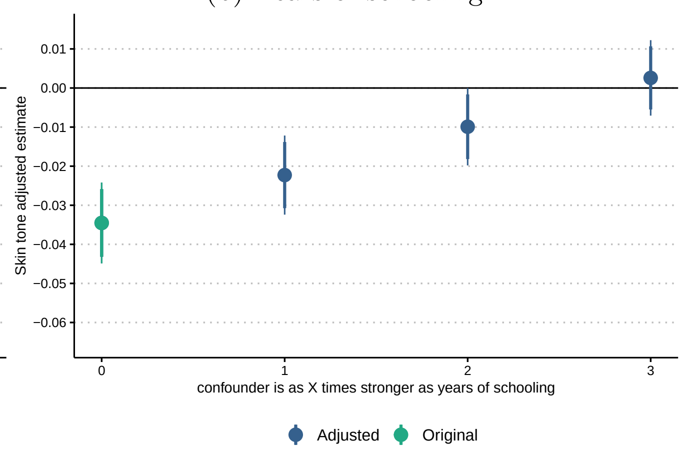
(a) Absolute educational upward mobility



(b) Years of schooling



(c) Household income per capita



(d) Household income per capita (*unclean* controls)

Figure 4: Bounding skin tone estimates

Notes: Bounded adjusted estimates using Cinelli and Hazlett (2020). The x-axis shows the size of the unobserved heterogeneity relative to the benchmark covariate. For panels a), b), and c), the benchmark covariate is the indicator if mother achieved tertiary education. For pabel d) the benchmark covariate is respondent's years of schooling. The y-axis estimate for the dependent variable of interest. For panels a) and b), the estimate is in z-score. For panels c) and d) the estimate is in log-points. All specifications control for sex, age, and mothers' ISCED education level, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Specification in Panel d) aditionally controls for years of schooling, ethnoracial identity, occupational status (i.e. working, unemployed), salary status (i.e. self-employed, owner, worker in private sector, etc.), marital status (i.e. married, single, divorced, etc.), and religion. Thin (thic) error bars show 95% (90%) confidence intervals.

5.3 Heterogeneity

I explore the identity and gendered heterogeneous effects of skin tone penalties on human capital accumulation and income.[5] Then, I study the heterogeneous effects by country. All specifications

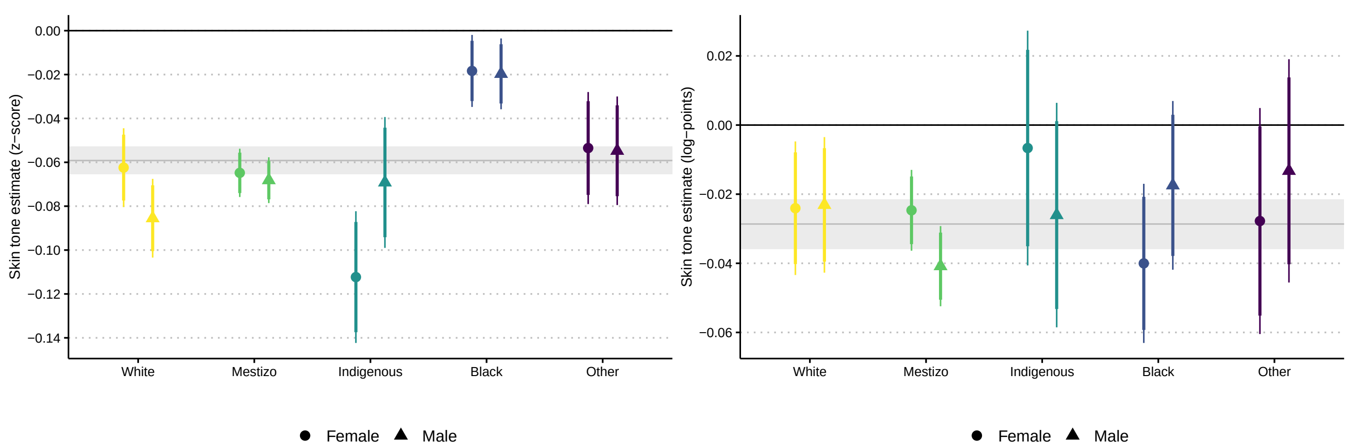
[5]Absolute upward mobility estimates closely follow those of years of schooling.

account for age, sex, and cluster fixed effects, thus comparing individuals living in the same geography, being interviewed in the same year, and by the same enumerator.

Figure 5 panel (a) shows the skin tone estimates on human capital accumulation by ethnoracial identity and gender. Most ethnoracial identities and gender skin tone estimates do not differ from the pooled estimate, represented by the grey line, and its confidence interval, represented by the grey area. However, I find that the skin tone gradient on years of schooling is stronger for males self-identified as White, and especially for females identified as Indigenous. For every darker skin tone, Indigenous women have 0.11 standard deviations fewer years of schooling.

In contrast, individuals identified as Black have a lower skin tone gradient on years of schooling. This is driven by the fact that the constant term for the Black ethnoracial identity is correlated with a decrease of at least 0.2 standard deviations (Figure B.3 panel (a)). Thus, within those identified as Black, skin tone seems less salient than the identity itself.

After controlling for the respondent's years of schooling, skin tone gradients on household income per capita between ethnoracial identities and gender do not vary statistically from the mean pooled estimate, as shown in Figure 5 panel (b). However, consistent with the argument that the Mestizo identity veils racial inequalities, within such ethnoracial identity skin tone correlates with lower income and human capital accumulation.



(a) Years of schooling

(b) Income

Figure 5: Skin tone estimates heterogeneity by ethnoracial group and gender

Notes: The x-axis shows the ethnoracial group. The y-axis shows the skin tone estimate for the dependent variable of interest. For panel a) it represents the z-score on years of schooling. For panel b) it represents the log-points on household income per capita. The gray line represents the mean estimate pooling across ethnoracial identities. The gray area represents the 95% confidence intervals for the mean estimate pooling across ethnoracial identities. All specifications control for sex, age, and mothers' ISCED education level, ethnoracial group, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Panel b) controls for respondent's years of schooling. Thin (thic) error bars show 95% (90%) confidence intervals. The constant term associated with each ethnoracial identity and gender is shown in Figure B.3.

Finally, I explore the heterogeneity by country. These patterns provide suggestive evidence that skin tone gaps are phenomena that extend beyond certain countries, and thus prevail across different historical and institutional settings, but heterogeneity is crucial to better understand the possible policies to address these inequalities.

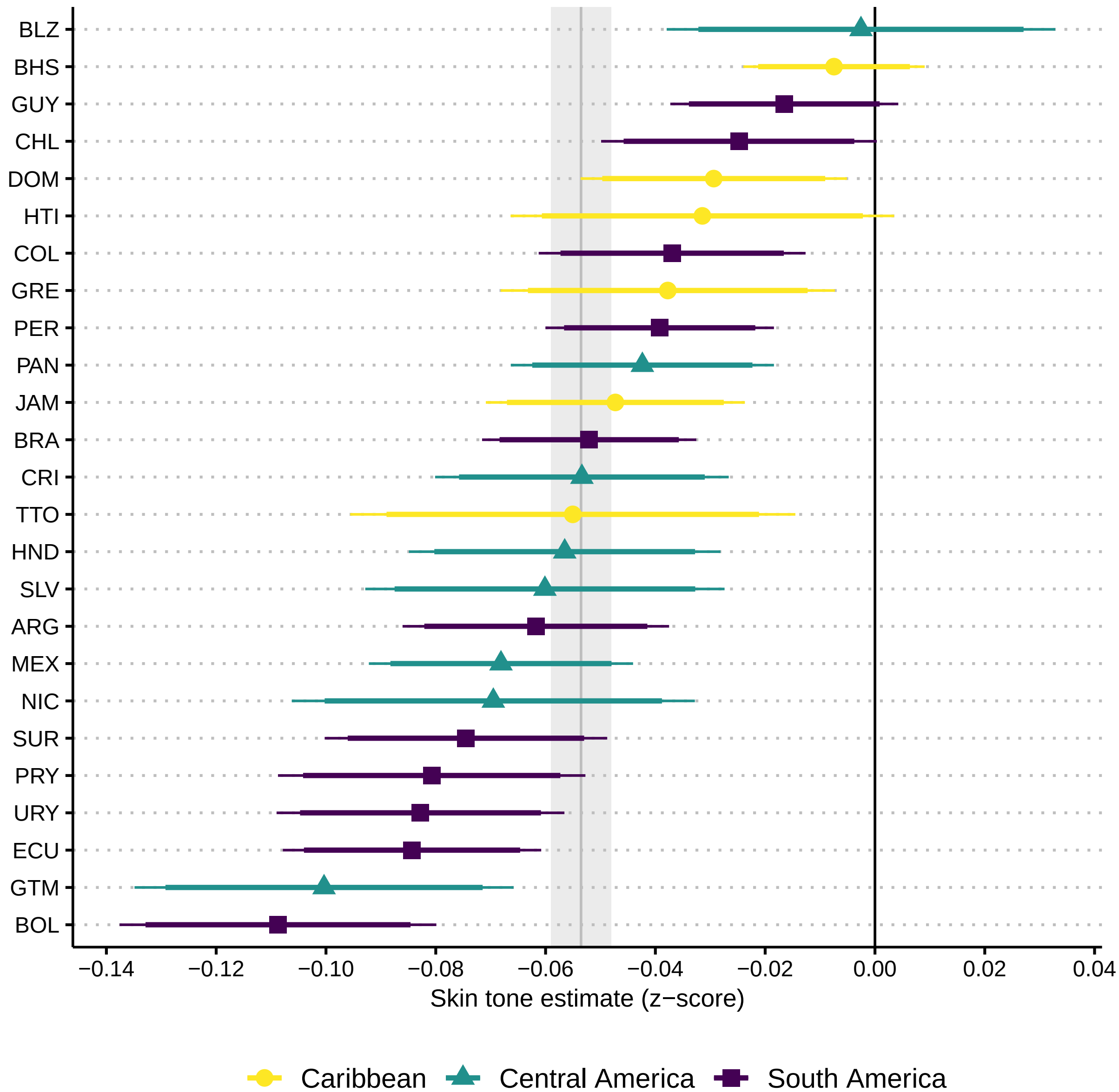


Figure 6: Hetrogenous skin tone effects on human capital by country

Notes: The x-axis shows the skin tone estimates on years of schooling in z-scores. The y-axis shows the country ISO 3-digit codes. The y-axis show self-declared ethnoracial identities shares. The gray line represents the mean estimate pooling across countries. The gray area represents the 95% confidence intervals for the mean estimate pooling across countries. Specifications control for sex, age, and mothers' ISCED education level, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator.

Out of 25 countries, only Belize, the Bahamas, Guyana, and Haiti do not have statistically significant skin tone penalties on human capital accumulation (Figure 6). Chile has a small but statistically significant negative skin tone gradient on years of schooling. Among the remaining countries, only Ecuador, Guatemala, and Bolivia have a skin tone gradient on human capital

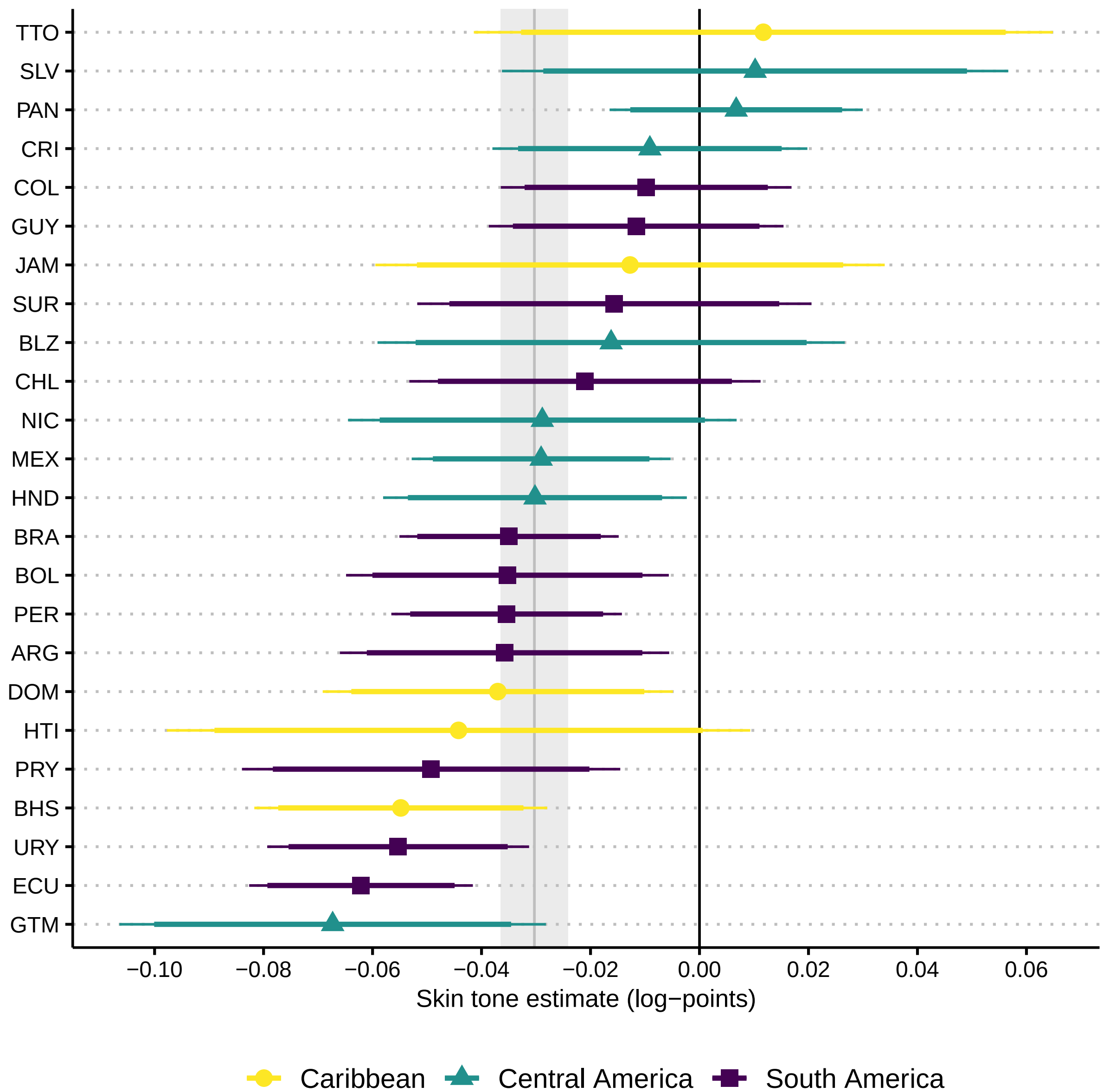


Figure 7: Hetrogenous skin tone effects on income by country

Notes: The x-axis shows the skin tone estimates on household income per capita in log-points The y-axis shows the country ISO 3-digit codes. The y-axis show self-declared ethnoracial identities shares. The gray line represents the mean estimate pooling across countries. The gray area represents the 95% confidence intervals for the mean estimate pooling across countries. Specifications control for sex, age, respondent's years of schooling, and mothers' ISCED education level, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator.

accumulation that is statistically greater in absolute terms relative to the pooled mean estimate.

After controlling for human capital gaps, almost half of the countries in the sample have negative and statistically significant skin tone penalties on income (Figure 7). In Central America, Mexico, Nicaragua, and especially Guatemala exhibit skin tone penalties on household income per capita after controlling for differences in human capital. In the Caribbean, while the skin tone gaps in human capital are small or not statistically significant, there is a negative correlation between skin tone and income in the Dominican Republic and the Bahamas. Finally, in South America, Brazil, Bolivia, Peru, and Argentina exhibit similar skin tone penalties on income, while the estimates for Paraguay, Uruguay, and Ecuador are larger in absolute terms.

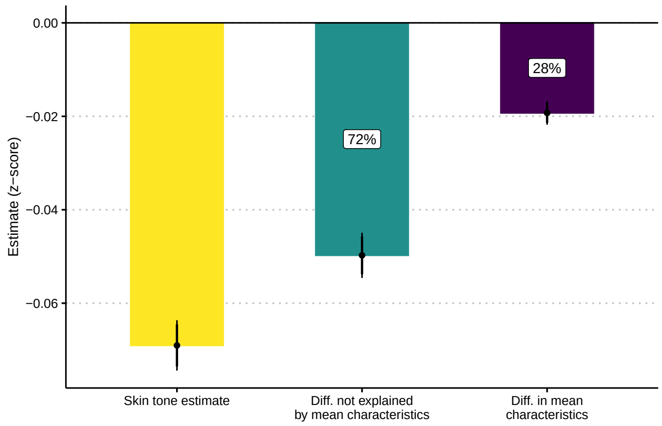
5.4 Potential mechanisms: skin tone discrimination

In this section, I provide suggestive evidence on how discrimination, in its broadest sense, partly explains the human capital and income gaps between skin tone groups.

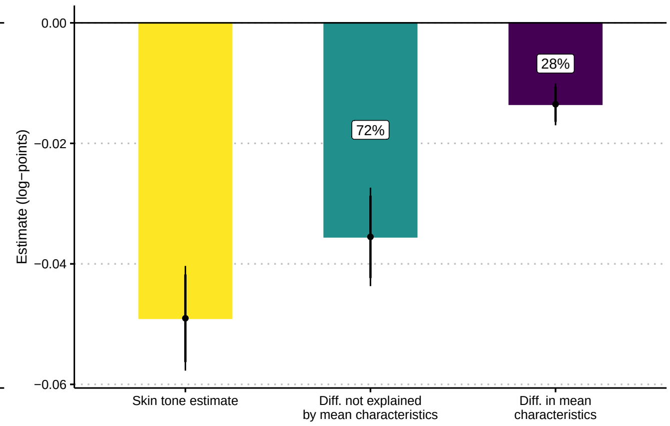
If discrimination or preferences over skin color are salient cues at early childhood stages, the interaction with other mechanisms such as aspirations (Campos-Vázquez and Medina-Cortina 2017) and beliefs about the labor market (Angeli, Matavelli, and Secco 2024; Ruebeck 2024) could potentially further explain the human capital and income gaps. Note, however, that absent exogenous variation, it is difficult to discern the magnitude of discrimination (Guryan and Charles 2013), or whether it is taste-based (Becker 1957), statistical (Phelps 1972), systemic (Bohren, Hull, and Imas 2022), or other subtle forms of discrimination (Angeli, Matavelli, and Secco 2024; Buchmann, Meyer, and Sullivan 2024; Roussille 2024; Ruebeck 2024). Moreover, there are other sources of disparities not taken into account, such as skin tone gaps in health (Aguilar-Gomez, Cárdenas, and Díaz 2024).

First, I decompose the skin tone gaps in human capital and income using a Oaxaca-Blinder (OB) decomposition for continuous variables (Ñopo 2008). Figure 8 panel (a) shows the OB decomposition for human capital. The linear skin tone estimate on years of schooling, after demeaning by cluster fixed effects, is almost 0.07 standard deviations (Table B.2, Column 4). Once including the interactions of skin tone with age, gender, and mother's educational attainment, 72% of the correlation cannot be attributed to differences in mean characteristics. In other words, 72% of the skin tone estimate on years of schooling cannot be explained by location, age, gender, and mother's educational attainment, but rather by a combination of discrimination and unobservable characteristics. Note that these gaps are present before entering the labor market.

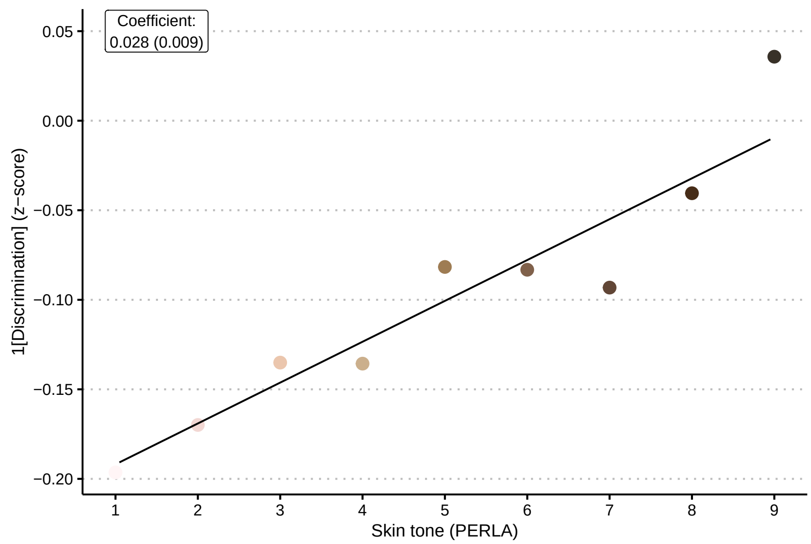
Figure 8 panel (b) shows the OB decomposition for household income per capita. The linear skin tone estimate on income, after demeaning by cluster fixed effects, and including a set of bad controls as years of schooling, occupation status, salary status, among others is 0.049 log-points. Consistently, 72% of the skin tone estimate on household income per capita cannot be explained by the mean characteristics of each skin tone (Table B.1, Column 8). Thus, skin tone gaps and potentially skin tone discrimination play a role once individuals enter the labor market.



(a) OB Decomposition: Human capital



(b) OB Decomposition: Income



(c) Skin tone and discrimination

Figure 8: Potential mechanisms: Discrimination

Notes: Panels a) and b) show Oaxaca-Blinder (OB) decomposition for contunous variables following Ñopo (2008). Panel c) shows the coniditional binscatter on self-reported having suffered discrimination on skin tone. For panels a) and b), the x-axis shows the skin tone esstimate and the two OB decomposition estimates: the first one is the difference in the dependent variable not explained by mean characteristics; the second component is the difference in the dependent variable explained by mean characteristics. For panels a) and b), the y-axis shows the estimates in z-scores and log-points, respectively. The label shows the OB component share out of the total skin tone estimate. For panel c), the x-axis shows the skin tone measure: the PERLA color palette including scales from 1 to 9, top coding skin tones above 9 given their small share. The y-axis shows the residualized probability of declaring have suffered discrimination at the school, public spaces, or by government officials. The specifications controls for sex, age, and mothers' ISCED education level, and includes a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. The label in the top-left shows the estimate and standard error.

The last suggestive evidence favoring discrimination as one of the main mechanisms driving the skin tone gaps is the correlation between self-reported experiences of discrimination and skin tone. Figure 8 panel (c) shows the binscatter of the residualized probability of declaring having suffered discrimination at school, in public spaces, or by government officials. After controlling for location, sex, age, and both mothers' and respondents' education levels, a marginal increase in darker skin tone correlates with a 0.03 standard deviation higher probability of suffering discrimination. The correlation is robust to unobserved heterogeneity as three times as large as the correlation between age and reporting discrimination (Figure B.4).

6 Conclusion

Broad ethnoracial identities can veil racial inequality. In this paper, I examine economic disparities based on skin tone across 25 Latin American countries, focusing on income, human capital accumulation, and educational intergenerational mobility. Even accounting for the diversity of historical and institutional contexts regarding race, the results reveal significant penalties associated with darker skin tones, showing a consistent negative correlation with household income, years of schooling, and upward educational mobility across all of Latin America. These disparities persist even after controlling for various factors, including geographic and demographic variables. Using a bounding approach, I demonstrate that the skin tone effects are robust to substantial unobserved heterogeneity.

This paper is a stepping stone for a necessary research agenda. Given the results on the heterogeneous effects by ethnoracial identity, gender, and country, future research should aim to better understand the context-specific or local forms of these inequalities shaped by phenotypical traits. This is especially true given the different historical and institutional contexts, compared to the United States, finding similar skin tone penalties. Moreover, consistent with the suggestive evidence that discrimination might explain the skin tone gaps, future studies should investigate the specific drivers, including the exact types of mechanisms and forms of discrimination (i.e., direct discrimination, systemic discrimination, the marriage market, network effects, etc.) that shape these gaps.

This paper can offer relevant guidelines for policy. From a theoretical perspective, the results suggest that, since skin tone is fixed and there is little room for behavioral responses, 'tagging' (Akerlof 1978; Alesina, Ichino, and Karabarbounis 2011; Piketty and Saez 2013) could potentially serve as a redistributive policy. However, given the high-stakes political economy implications of such alternatives, we need realistic policy measures to overcome racial disparities at early stages. One possibility is affirmative action policies (Mello 2022, 2023). Consistent with Chetty et al. (2020), given that relative mobility is similar for all skin tone groups, reducing skin tone disparities requires policies that address these gaps in children's outcomes conditional on parental educational investment, through changes in schooling or the childhood environment.

Declaration of Generative AI and AI-assisted technologies in the writing process

Statement: During the preparation of this work the author(s) used ChatGPT in order to provide copy-editing for non-native English speakers. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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A Data

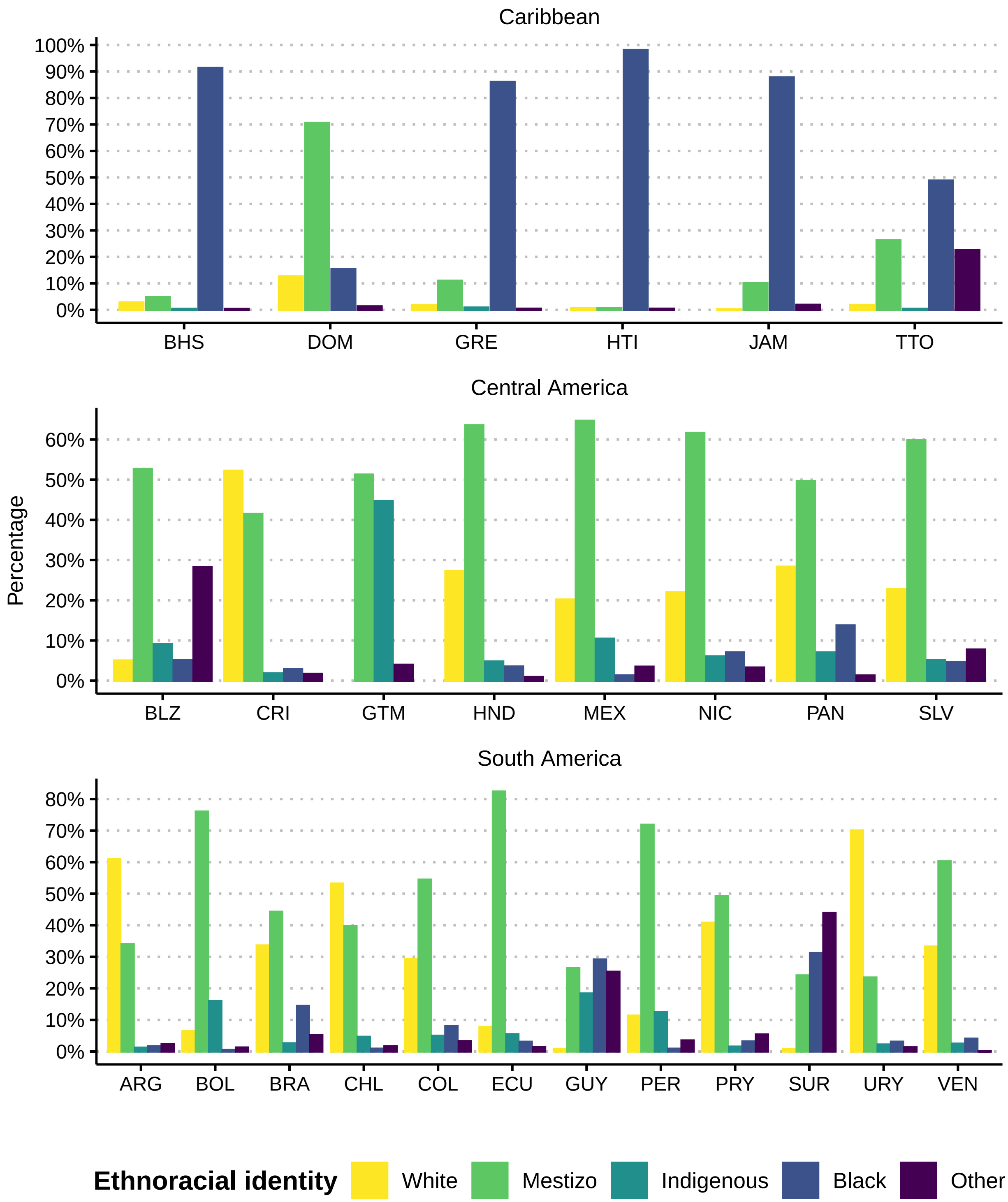


Figure A.1: Ethnoracial identities distributuion by country

Notes: Based on LAPOP waves 2012, 2014, and 2016/2017. The x-axis shows the country ISO 3-digit codes. The y-axis show self-declared ethnoracial identities shares.

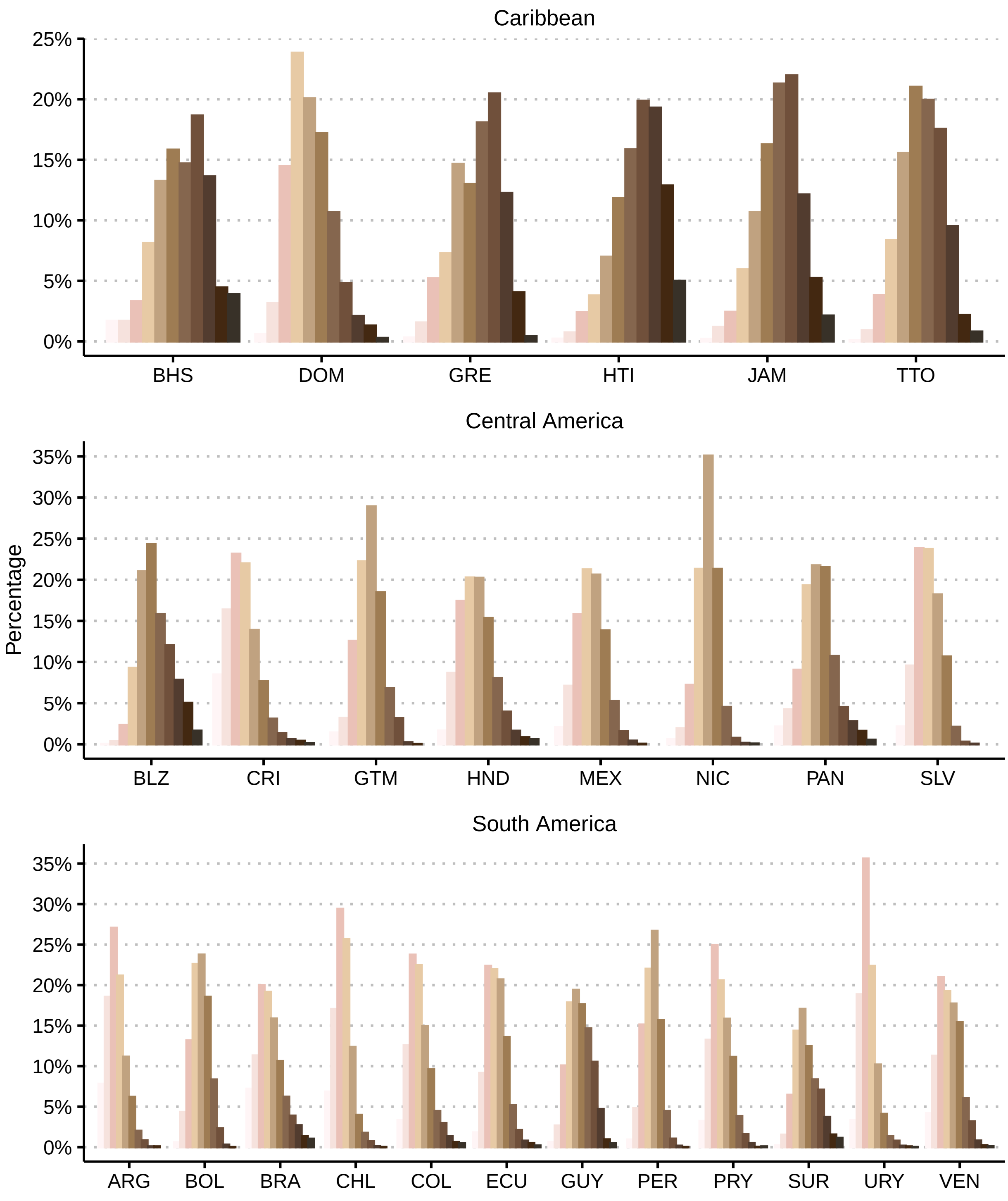


Figure A.2: Skin tone distribution by country

Notes: Based on LAPOP waves 2012, 2014, and 2016/2017. The x-axis shows the country ISO 3-digit codes. The y-axis show the skin tone shares, measured by enumerators.

Table A.1: Summary Statistics

PERLA Skin Tone	1	2	3	4	5	6	7	8	9	10	11	Sample mean
PERLA Palette												
Panel A: *Monthly income per capita (PPP)*												
Percentile 25	146.18	125.33	109.42	91.98	79.89	76.17	75.55	71.11	57.99	42.53	48.75	88.53
Median	262.96	222.01	196.56	167.98	148.88	143.34	150.49	158.64	152.33	117.67	124.18	167.95
Mean	375.47	321.98	286.11	249.30	228.11	227.55	256.15	285.53	286.78	255.63	253.42	260.72
Percentile 75	454.33	402.75	345.76	304.40	271.69	264.50	303.86	351.91	362.41	308.68	330.83	316.24
Panel B: *Demographics*												
Sex = Female (%)	0.57	0.55	0.54	0.52	0.50	0.46	0.46	0.45	0.41	0.42	0.44	0.50
Age	40.62	40.59	39.95	39.33	39.08	39.25	39.04	39.31	39.90	39.51	39.97	39.51
Years of schooling	11.06	10.76	10.45	10.00	9.54	9.34	9.62	9.83	9.78	9.62	9.45	9.92
People per household	3.96	4.01	4.20	4.41	4.60	4.65	4.69	4.66	4.76	4.87	4.80	4.46
Region = Central America (%)	0.33	0.30	0.30	0.35	0.39	0.36	0.25	0.17	0.12	0.17	0.14	0.32
Region = Caribbean (%)	0.04	0.04	0.07	0.11	0.14	0.23	0.40	0.55	0.67	0.66	0.64	0.19
Region = South America (%)	0.62	0.66	0.64	0.54	0.47	0.41	0.36	0.28	0.20	0.16	0.22	0.49
Locality size = Metro area (%)	0.25	0.25	0.25	0.25	0.24	0.26	0.29	0.32	0.31	0.25	0.28	0.26
Locality size = Big city (%)	0.19	0.20	0.19	0.18	0.15	0.13	0.11	0.10	0.10	0.15	0.14	0.16
Locality size = Medium city (%)	0.23	0.19	0.18	0.15	0.14	0.11	0.07	0.04	0.02	0.03	0.03	0.13
Locality size = Small city (%)	0.15	0.15	0.15	0.15	0.15	0.16	0.19	0.19	0.18	0.12	0.13	0.16
Locality size = Rural area (%)	0.01	0.01	0.03	0.04	0.06	0.09	0.15	0.22	0.29	0.32	0.31	0.08
Work status = Working (%)	0.50	0.49	0.49	0.50	0.52	0.53	0.52	0.51	0.50	0.48	0.43	0.51
Work status = Unemployed (%)	0.06	0.06	0.07	0.08	0.08	0.09	0.11	0.14	0.15	0.18	0.20	0.09
Salary status = Self employed (%)	0.37	0.38	0.42	0.43	0.46	0.47	0.42	0.39	0.40	0.38	0.35	0.43
Salary status = Employed public sector (%)	0.16	0.17	0.16	0.17	0.16	0.17	0.19	0.21	0.19	0.21	0.22	0.17
Salary status = Employed private sector (%)	0.41	0.39	0.37	0.35	0.33	0.32	0.35	0.35	0.34	0.35	0.36	0.35
Salary status = Owner (%)	0.06	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.05	0.05	0.06	0.04
Mother's education = Less than primary (%)	0.35	0.36	0.42	0.47	0.50	0.50	0.45	0.39	0.41	0.45	0.47	0.45
Mother's education = Primary (%)	0.24	0.26	0.25	0.22	0.21	0.20	0.21	0.23	0.21	0.21	0.17	0.22
Mother's education = Lower secondary (%)	0.10	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.12	0.12	0.08	0.10
Mother's education = Upper secondary (%)	0.20	0.19	0.16	0.16	0.15	0.16	0.20	0.22	0.22	0.18	0.23	0.17
Mother's education = Tiertiary (%)	0.12	0.10	0.08	0.06	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.06
No. Observations	2309	6886	14669	17440	16660	12691	7113	4887	2658	1141	489	86943

Notes: Based on AmericasBarometer LAPOP data for waves 2012, 2014, and 2016/2017, which include the PERLA skin color palette and all the information on the selected variables. Panel A provides various statistics for the continuous daily income per capita (PPP) measure. Panels B shows the mean values for each respective skin tone group.

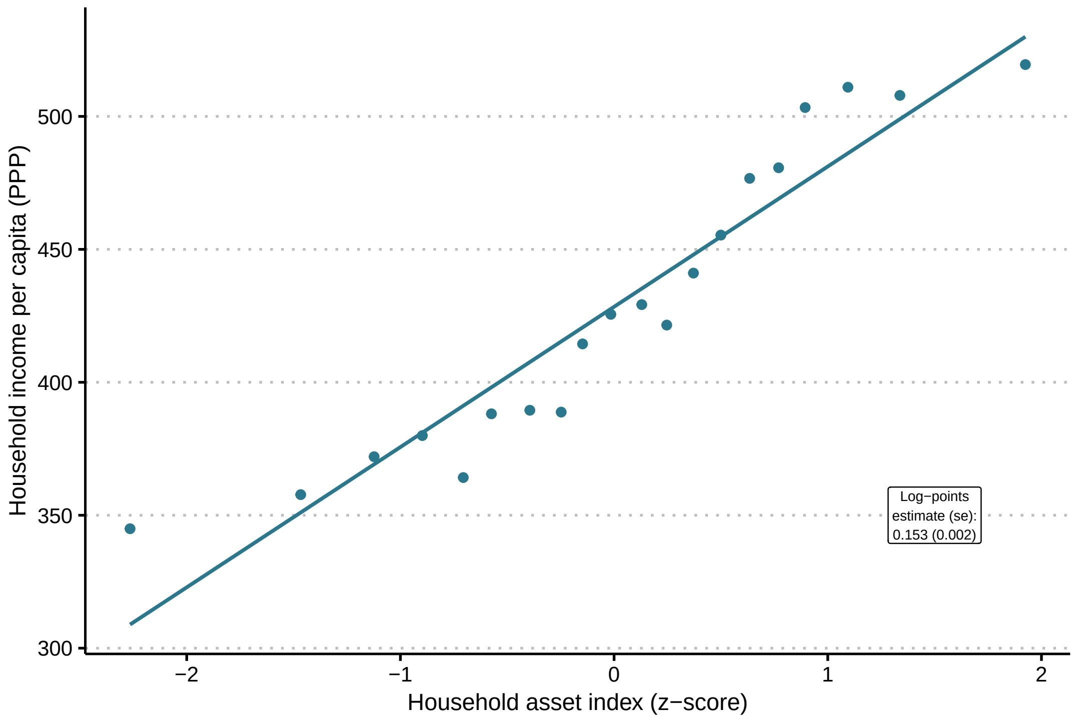


Figure A.3: Household wealth index and income

Notes: The x-axis shows the z-score household asset index. The y-axis shows the household income per capita. The specification includes a country and year FE fixed effect. The label in the bottom-left shows the estimate and standard error in PPP. Number of observations: 54,079. R^2: 0.276.

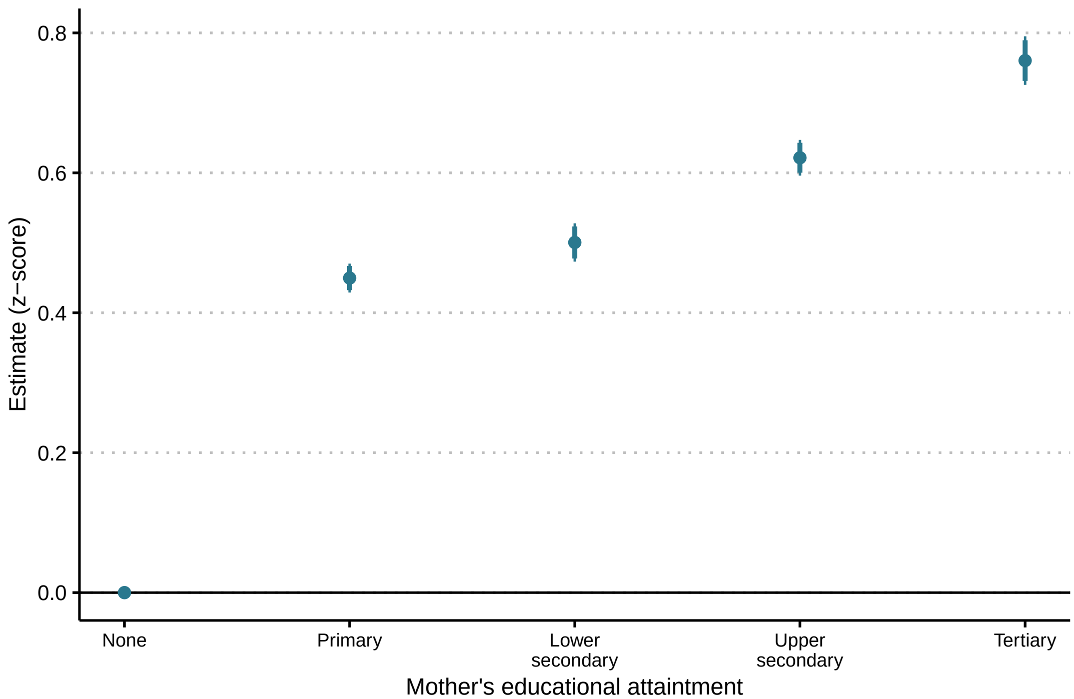
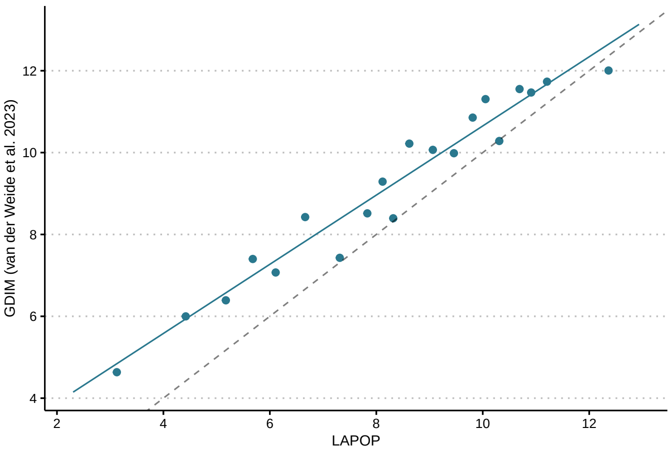
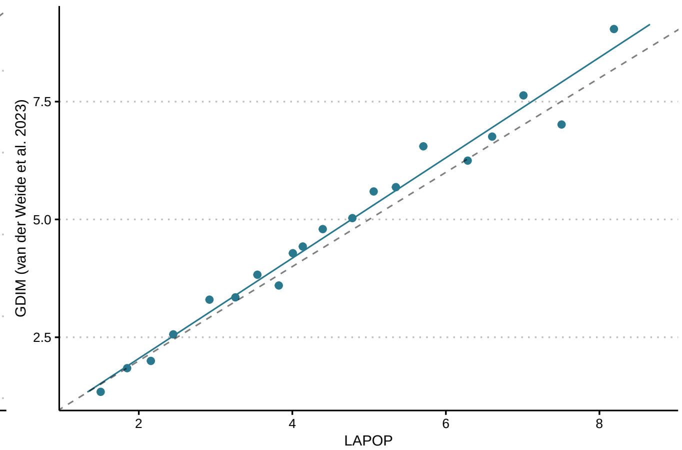


Figure A.4: Educational persistence: Mothers' and respondents' educational attaintment

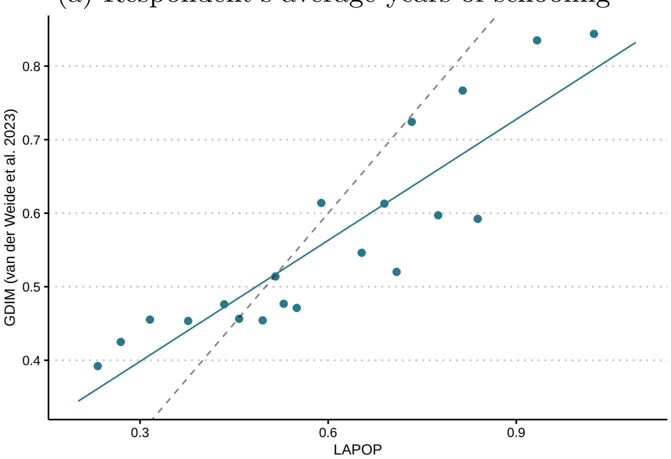
Notes: The x-axis shows the mother's educational attaintment using ISCED categories. The y-axis shows the estimate on standardized respondent's years of schooling. The specification controls for gender and age, and includes a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Thin (thic) error bars show 95% (90%) confidence intervals at the cluster level.



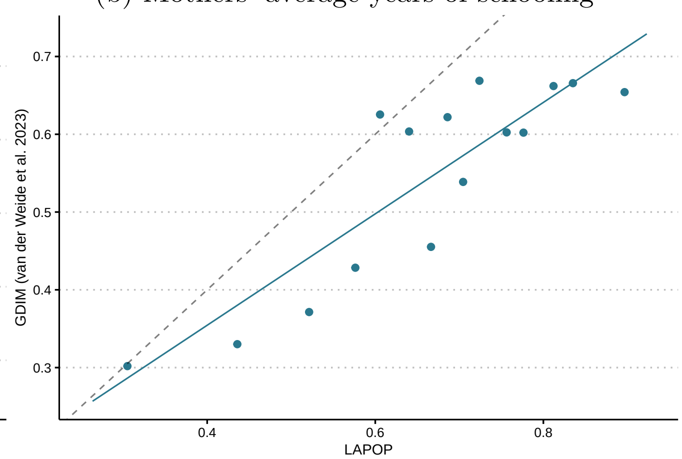
(a) Respondent's average years of schooling



(b) Mothers' average years of schooling



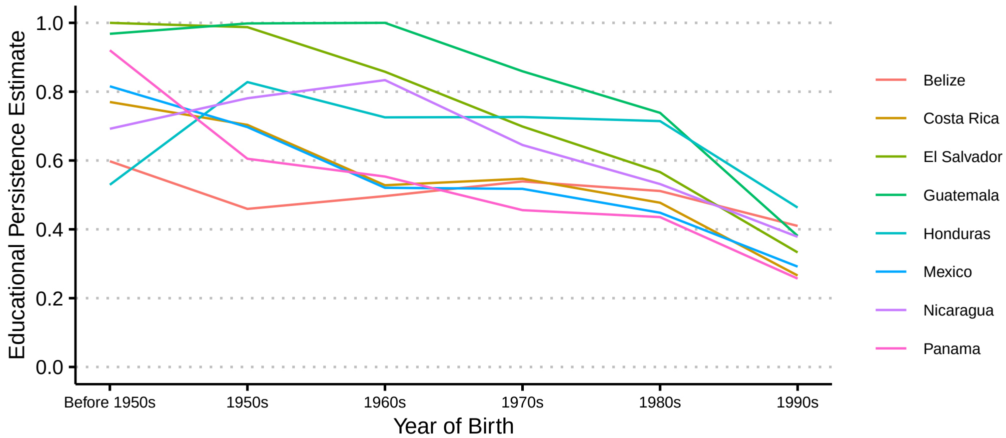
(c) Educational persistence or relative mobility



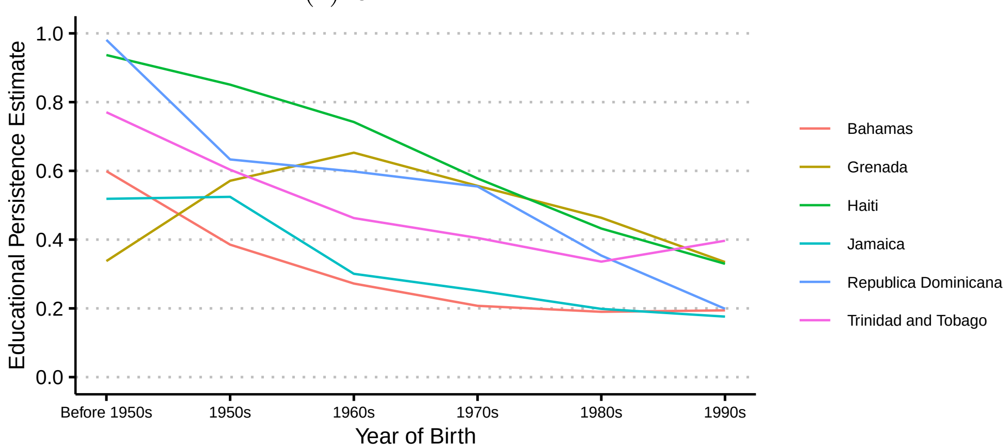
(d) Absolute mobility

Figure A.5: Educational attaintment by sample

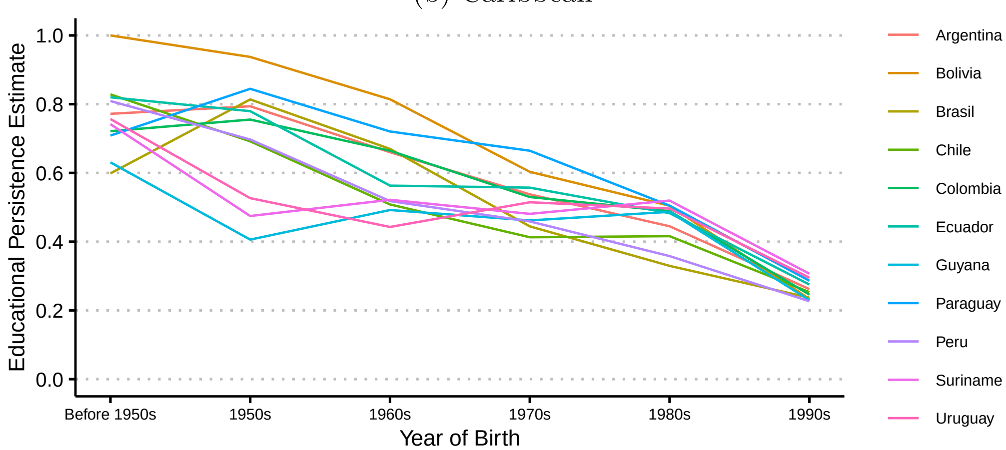
Notes: Estimates by cohort and country. The x-axis shows the estimates according to LAPOP data. The y-axis shows the estimates according to van der Weide et al. (2023) data, based on Latinobarómetro. The dashed lines represent an identity function. Relative mobility estimates by regressing respondents' years of schooling on mothers' years of schooling. Absolute mobility estimates represent share of respondents with strictly higher educational category than parents if parents do not have tertiary, or with tertiary education if either parent has tertiary.



(a) Central and North America



(b) Caribbean



(c) South America

Figure A.6: Educational persitence by cohort and country

Notes: Estimates by cohort and country. The x-axis shows the cohort. The y-axis shows the educational persistence estimates according to LAPOP data. The colored lines represts countries. Educational persistence or relative mobility estimates by regressing respondents' years of schooling on mothers' years of schooling.

B Results

Table B.1: Skin tone gaps: Household income per capita (log-points)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skin tone (PERLA)	-0.097	-0.051	-0.032	-0.035	-0.046	-0.040	-0.030	-0.034
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Age					0.004	0.006	0.008	0.006
					(0.0003)	(0.0003)	(0.0003)	(0.0006)
Gender = Male					0.220	0.208	0.201	0.157
					(0.008)	(0.008)	(0.007)	(0.012)
Mother's education = Primary						0.117	0.037	0.037
						(0.011)	(0.011)	(0.018)
Mother's education = Lower secondary						0.130	0.041	0.043
						(0.016)	(0.016)	(0.024)
Mother's education = Upper secondary						0.214	0.104	0.061
						(0.014)	(0.014)	(0.023)
Mother's education = Tertiary						0.360	0.218	0.167
						(0.022)	(0.021)	(0.032)
Years of schooling							0.046	0.046
							(0.001)	(0.002)
Ethnoracial identity = Mestizo								-0.042
								(0.020)
Ethnoracial identity = Indigenous								-0.106
								(0.036)
Ethnoracial identity = Black								-0.006
								(0.040)
Ethnoracial identity = Other								-0.105
								(0.043)
Country FE × Year FE		Yes						
Within-municipality FE × Year FE			Yes					
Within-municipality FE × Year FE × Interviewer FE				Yes	Yes	Yes	Yes	Yes
Bad or unclean controls								Yes
Dependent variable mean	3.58	3.58	3.58	3.58	3.58	3.58	3.59	3.73
Observations	54,424	54,424	54,424	54,424	54,424	54,424	54,086	28,842
No. Clusters	25,879	25,879	25,879	25,879	25,879	25,879	25,879	18,004
R^2	0.036	0.352	0.623	0.734	0.744	0.748	0.762	0.836
Adjusted R^2	0.036	0.352	0.465	0.493	0.512	0.519	0.545	0.562

Notes: Dependent variable is log-transformation of household income per capita, shutting off the extensive margin following Chen and Roth (2023). Mean monthly household income per capita is 260.74 (PPP). Skin tone stands for the PERLA color palette including scales from 1 to 9, top coding skin tones above 9 given their small share. Clustered Within-municipality × Year × Interviewer standard errors in parentheses. The omitted category in Gender is Female. The omitted category in Mother's education is No education. The omitted category in Ethnoracial identity is White. Bad or unclean controls include: occupational status (i.e. working, unemployed), salary status (i.e. self-employed, owner, worker in private sector, etc.), marital status (i.e. married, single, divorced, etc.), and religion.

Table B.2: Skin tone gaps: Years of schooling (z-score)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Skin tone (PERLA)	-0.050	-0.080	-0.062	-0.069	-0.066	-0.050	-0.068
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Age					-0.019	-0.013	-0.010
					(0.0003)	(0.0003)	(0.0006)
Gender = Male					0.106	0.071	-0.031
					(0.007)	(0.007)	(0.012)
Mother's education = Primary						0.441	0.377
						(0.011)	(0.017)
Mother's education = Lowersecondary						0.488	0.457
						(0.014)	(0.022)
Mother's education = Uppersecondary						0.602	0.545
						(0.013)	(0.021)
Mother's education = Tertiary						0.732	0.741
						(0.018)	(0.027)
Ethno-racial identity = Mestizo							0.100
							(0.018)
Ethno-racial identity = Indigenous							-0.124
							(0.035)
Ethno-racial identity = Black							0.101
							(0.036)
Ethno-racial identity = Other							0.012
							(0.041)
Country FE × Year FE		Yes					
Within-municipality FE × Year FE			Yes				
Within-municipality FE × Year FE × Interviewer FE				Yes	Yes	Yes	Yes
Bad or unclean controls							Yes
Dependent variable mean	9.925	9.925	9.925	9.925	9.925	9.925	9.925
Dependent variable s.d.	4.271	4.271	4.271	4.271	4.271	4.271	4.271
Observations	83,643	83,643	83,643	83,643	83,643	83,643	41,863
No. Clusters	34,936	34,936	34,936	34,936	34,936	34,936	24,448
R^2	0.009	0.113	0.421	0.581	0.639	0.665	0.777
Adjusted R^2	0.009	0.113	0.258	0.281	0.381	0.425	0.463

Notes: Dependent variable is years of schooling. Estimates in z-scores. Skin tone stands for the PERLA color palette including scales from 1 to 9, top coding skin tones above 9 given their small share. Clustered Within-municipality × Year × Interviewer standard errors in parentheses. The omitted category in Gender is Female. The omitted category in Mother's education is No education. The omitted category in Ethnoracial identity is White. Bad or unclean controls include: occupational status (i.e. working, unemployed), salary status (i.e. self-employed, owner, worker in private sector, etc.), marital status (i.e. married, single, divorced, etc.), and religion.

Table B.3: Skin tone gaps: Upward educational mobility (z-score)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Skin tone (PERLA)	-0.025	-0.028	-0.019	-0.020	-0.018	-0.038	-0.043
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)
Age					-0.006	-0.013	-0.010
					(0.0003)	(0.0003)	(0.0006)
Gender = Male					0.011	0.054	-0.021
					(0.008)	(0.008)	(0.013)
Mother's education = Primary						0.080	0.046
						(0.011)	(0.018)
Mother's education = Lowersecondary						-0.184	-0.188
						(0.016)	(0.025)
Mother's education = Uppersecondary						-1.07	-1.03
						(0.016)	(0.025)
Mother's education = Tertiary						-0.746	-0.647
						(0.022)	(0.033)
Ethno-racial identity = Mestizo							0.051
							(0.021)
Ethno-racial identity = Indigenous							-0.104
							(0.039)
Ethno-racial identity = Black							0.032
							(0.041)
Ethno-racial identity = Other							-0.010
							(0.044)
Country FE-Year FE		Yes					
Geographic FE			Yes				
Geographic FE-Interviewer's skin tone-sexi				Yes	Yes	Yes	Yes
Dependent variable mean	0.690	0.690	0.690	0.690	0.690	0.690	0.690
Dependent variable s.d.	0.462	0.462	0.462	0.462	0.462	0.462	0.462
Observations	83,643	83,643	83,643	83,643	83,643	83,643	41,863
No. Clusters	34,936	34,936	34,936	34,936	34,936	34,936	24,448
R^2	0.002	0.040	0.284	0.480	0.486	0.561	0.705
Adjusted R^2	0.002	0.039	0.082	0.107	0.118	0.246	0.291

Notes: Dependent variable is absolute upward educational mobility. Estimates in z-scores. Skin tone stands for the PERLA color palette including scales from 1 to 9, top coding skin tones above 9 given their small share. Clustered Within-municipality × Year × Interviewer standard errors in parentheses. The omitted category in Gender is Female. The omitted category in Mother's education is No education. The omitted category in Ethnoracial identity is White. Bad or unclean controls include: occupational status (i.e. working, unemployed), salary status (i.e. self-employed, owner, worker in private sector, etc.), marital status (i.e. married, single, divorced, etc.), and religion.

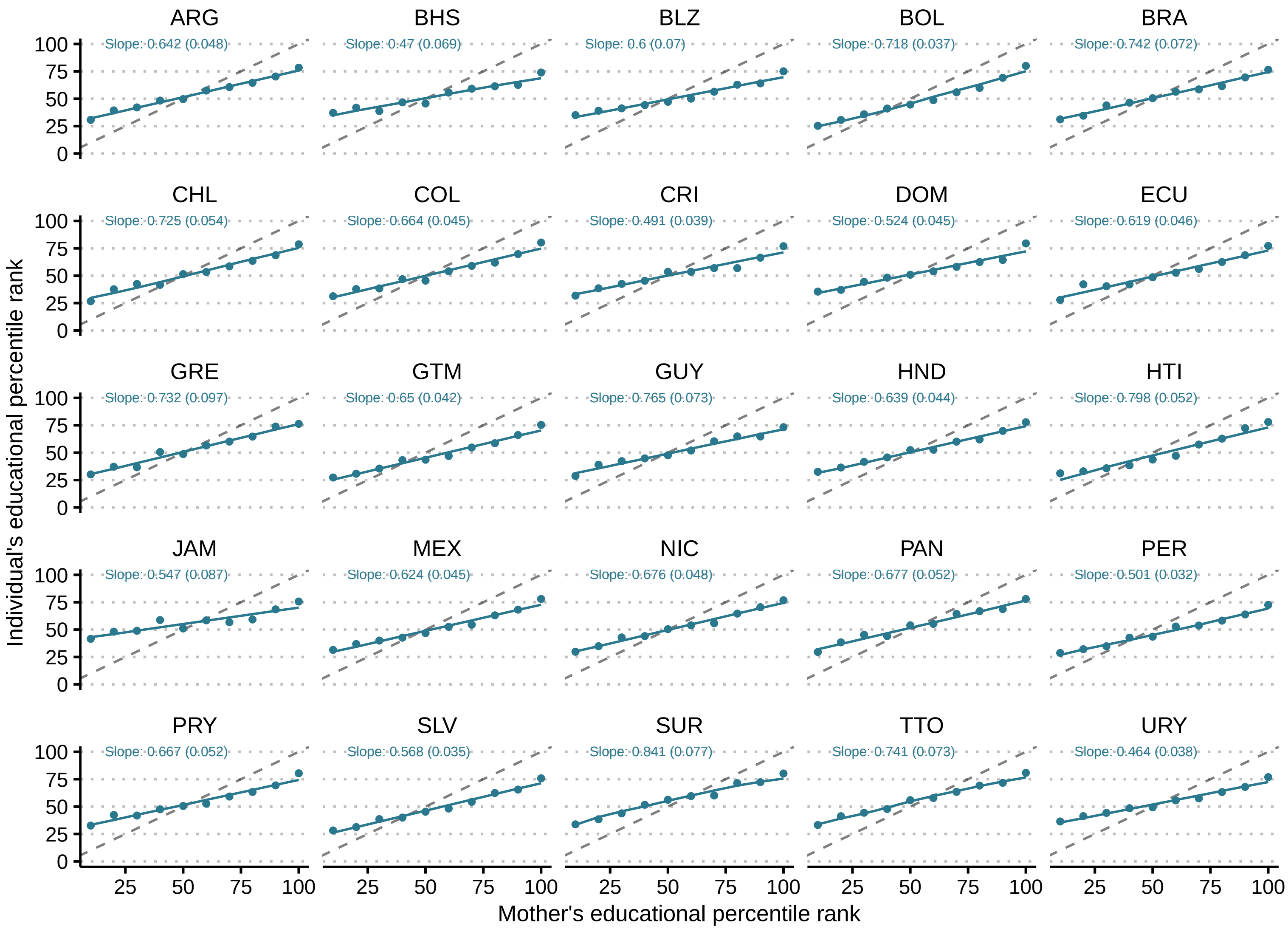


Figure B.1: Relative intergenerational moblity by country

Notes: The x-axis shows mother's educational percentile rank. The y-axis shows respondent's educational percentile rank. The top of each panel shows the country ISO 3-digit codes. The blue labels show the rank-to-rank slope and standard error controling for sex and age.

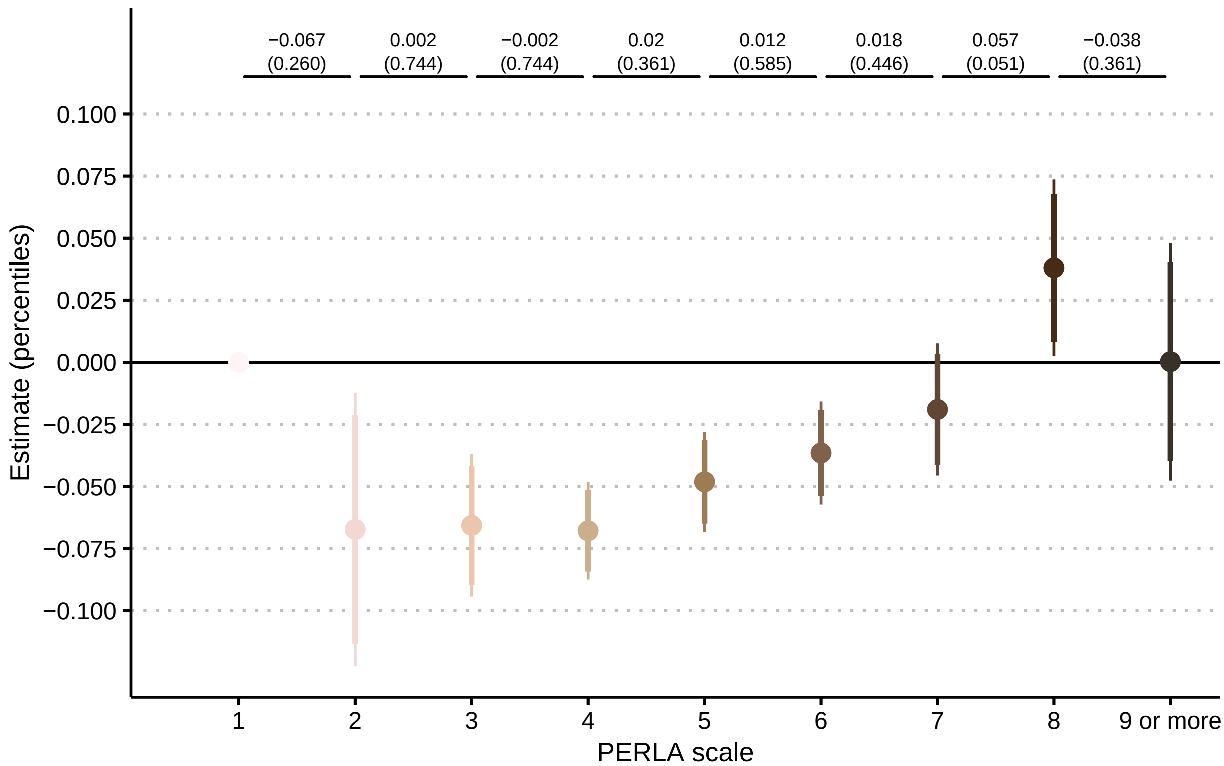
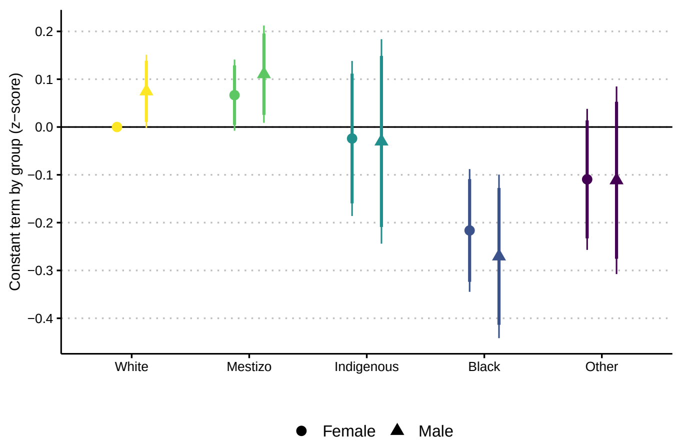
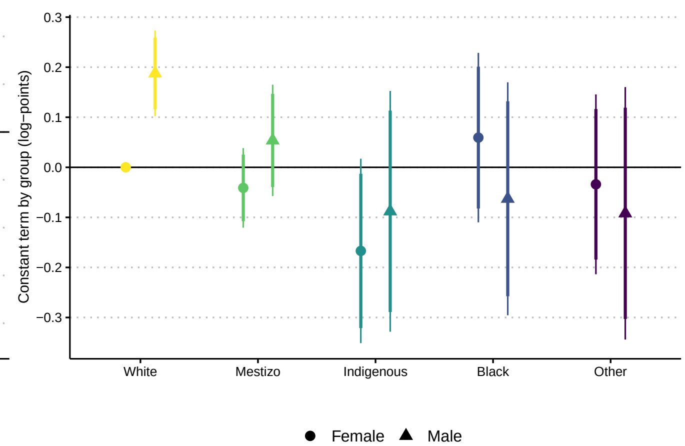


Figure B.2: Relative Educational IM by skin tone

Notes: Relative mobility estimates by skin tone groups. The x-axis shows the skin tone group. The y-axis shows the gap estimate in percentiles. Thin (thic) error bars show 95% (90%) bootsrapped confidence intervals using Rubin (1981). On top of each figure, thehorizontal lines show the difference in estimates between adjacent skin tones and the respective linear hypothesis adjusted q-value in parenthesis following Anderson (2008).



(a) Years of schooling



(b) Income

Figure B.3: Heterogeneity by ethnoracial group and gender

Notes: The x-axis shows the ethnoracial group. The y-axis shows the group or constant term estimate for the dependent variable of interest. For panel a) it represents the z-score on years of schooling. For panel b) it represents the log-points on household income per capita. All specifications control for sex, age, and mothers' ISCED education level, ethnoracial group, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Panel b) controls for respondent's years of schooling. Thin (thic) error bars show 95% (90%) confidence intervals. The heterogenous skin tone estimates by ethnoracial identity and gender are shown in Figure 5.

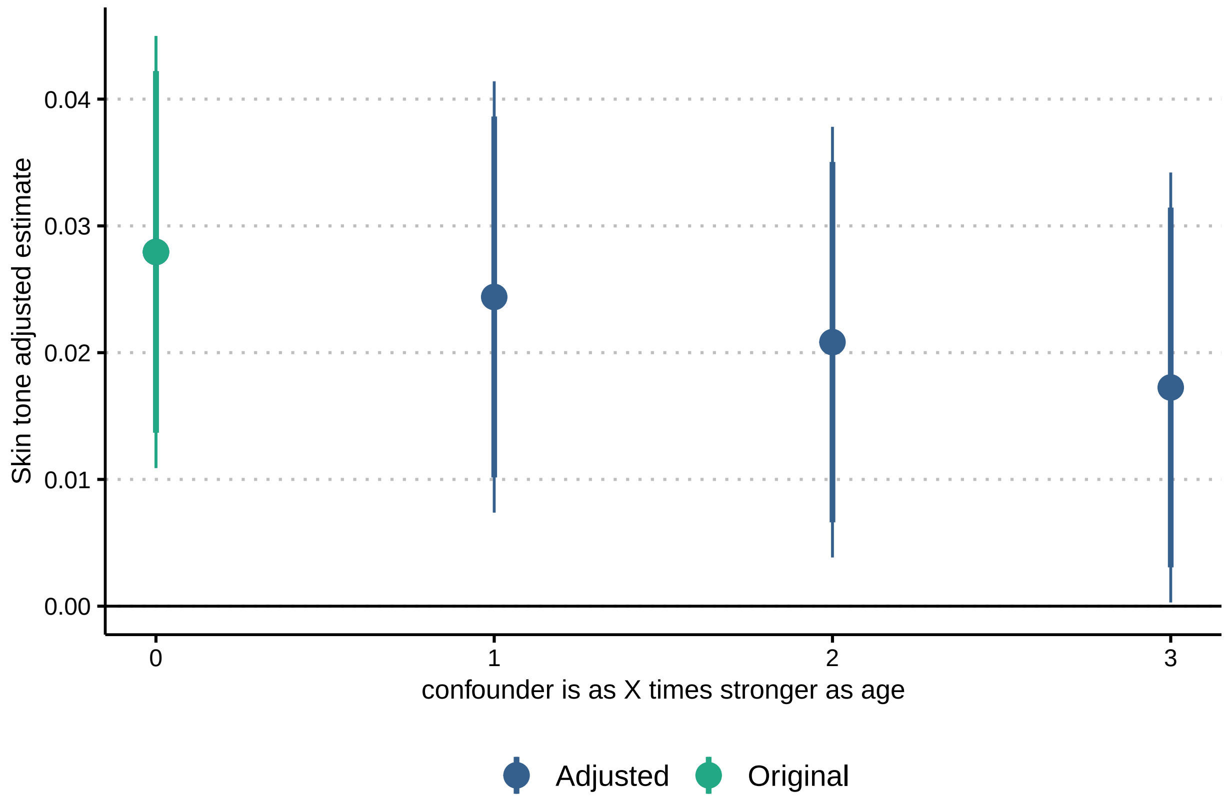


Figure B.4: Skin tone and discrimination: Bounds

Notes: Bounded adjusted estimates using Cinelli and Hazlett (2020). The x-axis shows the size of the unobserved heterogeneity relative to the benchmark covariate: age. The y-axis estimate for the dependent variable of interest in z-score. The specification control for sex, age, mothers' ISCED education level, and respondent's years of schooling, and include a cluster fixed effect. Cluster is the interaction of within-municipality strata, the smallest available geographical unit, and year, and enumerator fixed effects. Thus, cluster FE compare individuals living in the same geography, being interviewed in the same year, and by the same enumerator. Thin (thic) error bars show 95% (90%) confidence intervals.