Unveiling the Cosmic Race: Racial Inequalities in Latin America*

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Abstract

This paper provides evidence of the welfare consequences of racial discrimination at the individual and racial inequality at the country levels in Latin America. Latin American countries built their national identities through a 'melting pot' ethnic figure: the *'Cosmic Race'* or the mixed-race descendant from the European, Indigenous, and African populations. However, *mestizaje* identity veiled income inequalities between racial groups. Using LAPOP AmericasBarometer data, I compile information on skin tone and proxies for income for nearly 100 thousand individuals across Latin American countries during the last decade. The purpose of the paper is twofold. In the first part, I use Spatial First Differences to provide causal estimates of the racial income gap: out of an eleven-color palette, every darker skin tone has at least 8 percent less monthly income per capita. I also use Oaxaca-Blinder decompositions to provide causal evidence that racial discrimination is the main mechanism driving the racial gap: two-thirds of the latter is due to racial discrimination, with substantial heterogeneity between countries. In the second part of the paper, I estimate newly racial inequality measures at the country level. Countries with higher income inequality between racial groups have worse economic development: a one percent increase in the ratio of racial over total income inequality correlates with a decrease of nearly 4 percent in GDP per capita. The results suggest that, besides justice or reparations, progressive policies on income or wealth can diminish racial inequalities and improve aggregate welfare.

Keywords: Race, Inequality, Economic Development, Discrimination.
JEL: *D3*, *J15*, *J71*, *O12*, *O54*, *Z13*.

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1 Introduction

Inequalities lie beyond class struggle. Besides income, wealth, occupation, or educational attainment, other dimensions also explain the distributive conflict: gender, race, ethnicity, religion, nation, or other social identities (Akerlof and Kranton 2000; Chakravarty 2015; Fleurbaey and Schokkaert 2011; Piketty 2020; Shayo 2009). Most economic literature studying inequalities has mainly relied on interpersonal comparisons of income or wealth, weighting little attention to the latter dimensions. Not surprisingly, economics remarkably understudies ethnic and racial inequalities compared to other social sciences, like sociology and political science: by 2020, the share of race-related publications in economics was nearly 2% (Advani et al. 2021).

Nonetheless, recent events showed the salience of racial inequalities: in 2020, the murder of George Floyd in the US was followed by mass mobilizations like Black Lives Matter denouncing racial discrimination and disparities.[1] Soon after, movements in other latitudes denounced other forms of ethno-racial disparities: the Commission on Race and Ethnic Disparities in the United Kingdom provoked controversy;[2] the old debate on the lack of racial statistics renewed relevance in the French public debate.[3] Furthermore, movements denounced the 'invisible' racism on blacks, brown-skinned, and indigenous in many Latin American countries.[4]

This paper studies racial inequalities in Latin America. Latin America is one of the most unequal regions in the world: even when income inequality decreased in the last two decades due to higher educational attainment and better oriented social policies (Lustig, Lopez-Calva, and Ortiz-Juarez 2016), overall income and wealth inequality are still high in absolute terms and relative to other regions and countries (De Rosa, Flores, and Morgan 2020). Moreover, the region is one of the most diverse, both racially and ethnically. The latter matters since, alongside an extractive elite, race and ethnicity are also central dimensions shaping income and wealth inequalities (Sánchez-Ancochea 2021).

However, there is a relevant challenge in studying racial inequalities, usually ignored by economists. The latter is to disentangle inequalities across a cultural dimension and physical phenotype. Sociologists argue that *race* or *racialization* are physical characteristics or phenotypes that can define group membership, while *ethnicity* membership is often based on cultural characteristics (Telles and Martínez Casas 2019). Most ethno- or race-related studies account for differences between broad ethnic categories as "White," "Black," "Asian," "Indigenous," or "Latino," which can describe both phenotype and cultural characteristics simultaneously. To overcome the challenge, I compile a data set of repeated cross-sections with representative information on skin tone, self-reported broad ethnic categories, and income for nearly 100 thousand individuals in more than 25

[1] See https://www.economist.com/leaders/2021/05/22/race-in-america.

[2] See https://www.bbc.com/news/uk-56585538.

[3] See https://www.economist.com/leaders/2020/11/21/a-lack-of-data-on-race-hampers-efforts-to-tackle-inequalities.

[4] See https://elpais.com/sociedad/2020-06-08/el-racismo-invisibilizado-en-america-latina-alza-la-voz.html.

countries for the last decade. I use the AmericasBarometer Survey data from the Latin American Public Opinion Project (LAPOP), which includes the color palette of the Project on Ethnicity and Race in Latin America (PERLA). I exploit such data with two overreaching goals.

First, I study the racial income gap and its underlying mechanisms at the individual level. More specifically, I estimate the skin tone effect on monthly household income per capita using Spatial First Differences (SFD) (Druckenmiller and Hsiang 2018). SFD exploits the spatial dimension of the data and purges unobserved heterogeneity that biases the estimates. The effect is unambiguously negative: a darker skin tone has at least 7 percent less monthly income per capita, out of a color palette with eleven tones. To test whether the gap is driven by racial discrimination, I combine SFD with an Oaxaca-Blinder decomposition for continuous variables (Ñopo 2008b), which allows having a precise estimate of racial discrimination. On average, between 50% and 70% of the racial gap can be attributed to race discrimination, with substantial country-specific heterogeneity. Consistent with the race discrimination hypothesis, individuals with darker skin tones report higher discrimination behavior against them.

In the second part of the paper, I estimate new measures of racial inequality –income inequality between racial groups– at the national level using skin tone rather than the conventional broadly defined ethnic categories. I use the Mean Log Deviation decomposition (Foster and Shneyerov 2000) to measure income inequality within and between components for skin tone groups. Then, I compute the inequality ratio between racial groups to the total inequality measure. Firstly, consistent with historical and anecdotal evidence, I show that countries with a high share of the 'mestizo' population have a higher racial gap. Furthermore, using cross-country variation for the last decade and controlling for time-invariant characteristics and common-shocks trends, I find that higher ratios of racial inequality over total income inequality correlate to a lower GDP per capita. Along with the ethnic-inequality results (Alesina, Michalopoulos, and Papaioannou 2016), higher racial inequality in income hinders economic development.

This paper contributes to three economics literature strains. Firstly, this paper is related to the ethno-racial disparities literature. There is growing literature on the black-white gap on income, wealth, years of schooling, segregation, health outcomes, and economic opportunities in the United States (Chetty et al. 2020; Cook, Logan, and Parman 2016; Derenoncourt and Montialoux 2020; Logan and Parman 2017). Economic race-related studies mainly focus on the US due to the historical experience of slavery, segregation, discrimination, and wealth inequality (Cook and Logan 2020). Nevertheless, racial inequalities are also salient in other countries and regions, some with historical experiences of slavery and segregation.

During the last two decades, scholars have compiled extensive evidence studying how ethno-racial components determine economic outcomes in Latin America. For instance, there is literature on the ethno-racial disparities in the labor market and wages (Arceo-Gomez and Campos-Vazquez 2014; Arceo-Gómez and Campos-Vázquez 2019; Card et al. 2018; Campos-Vázquez 2020; Garavito et al. 2013; Ñopo, Saavedra, and Torero 2007; Ñopo 2012), educational attainment (Botelho, Madeira,

and Rangel 2015; Telles and Steele 2012; Telles and Martínez Casas 2019), social mobility (Campos-Vázquez and Medina-Cortina 2019; Monroy-Gómez-Franco and Vélez-Grajales 2020; Solís, Güémez Graniel, and Lorenzo Holm 2019), as well as access to the financial sector (Hernández-Trillo and Martínez-Gutiérrez 2021).[5]

Most of the previous literature focuses on a single country, like Brazil, Mexico, or Peru. Also, there is little comparability on the measures of ethnicity and race since their meaning and understanding changes country by country. Lastly, there is no single methodology for the studies, but a mix of descriptive statistics, regression analysis, structural estimations, decomposition techniques, and not many experimental and quasi-experimental designs. While some present historical, anecdotal, and descriptive statistics, they do not address endogeneity concerns of the estimates.[6] Thus, this paper contributes with evidence of the racial gap in Latin America using skin tone measures, a sizable sample of individuals across multiple countries, and a comparable methodology with a more credible research design.

Precisely, the paper's second contribution is to exploit SFD research design and combine it with Oaxaca-Blinder decomposition to provide causal estimates of racial discrimination. Economics understand discrimination when members of a minority group *are treated differently (less favorably)* than members of a majority group with *identical productive characteristics* (Altonji and Blank 1999; Lang and Spitzer 2020; Ñopo 2012). The latter definition implies that ethno-racial disparities are not due to discrimination as long as two individuals are *differently productive*. Classic studies in labor economics used the Oaxaca-Blinder decomposition to study differences in earnings between groups, for instance, racial groups (Fortin, Lemieux, and Firpo 2011). The component that captures differences in earnings that observable average characteristics cannot explain is usually attributed to discrimination. However, in cases where the researcher cannot control for relevant unobserved characteristics that correlate with the group treatment and the outcome, the discrimination component also captures all the potential effects of differences in unobserved variables (Jann 2008).

There are new experimental and reseach designs providing convincing evidence of racial discrimination: audit and correspondent studieson job hiring (Arceo-Gomez and Campos-Vazquez 2014; Avivi et al. 2021; Bertrand and Mullainathan 2004; Hernández-Trillo and Martínez-Gutiérrez 2021; Jacquemet and Yannelis 2012; Kline Evan K Rose Christopher R Walters et al. 2021); studies

[5]Racial components also determine social norms and identities (Campos-Vázquez and Medina-Cortina 2017); electoral preferences (Aguilar 2011; Campos-Vázquez and Rivas-Herrera 2021) and increase the perceptions of racial discrimination (Chong and Ñopo 2008; Ñopo, Chong, and Moro 2009; Trejo and Altamirano 2016).

[6]To my best knowledge, there are few studies on ethno-racial disparities with comparable data and methodology for more tha one Latin American country. Cernat, Sakshaug, and Castillo (2019) do present evidence of measurement error concerns. Ñopo (2012) studies the wage gap between ethnic groups for Bolivia, Peru, Brazil, Guatemala, Paraguay, Chile, and Ecuador, using an Oaxaca-Blinder decomposition with matching techniques (Ñopo 2008a). While Ñopo presents more convincing evidence on the extent of discrimination and differences in endowments to explain the wage gap, the use of broad ethnic categories rather than racial phenotype presents a challenge in countries where the majority of the population can define themselves as the broad ethnic category of *mestizo* or *mulato*.

using historical or natural experiments (Albright et al. 2021; Derenoncourt and Montialoux 2020; Derenoncourt 2021); and new developments on methods also provide causal evidence of racial discrimination (Arnold, Dobbie, and Hull 2021; Hull 2021). But for most cases with cross-sectional data, it is not straightforward to provide causal estimates of racial discrimination.

Spatial First Difference, a novel research desing proposed by Druckenmiller and Hsiang (2018), proves helpful to obtain causal estimates for corss-sectional data. I propose to combiene the SFD research design with with an Oaxaca-Blinder (OB) decomposition for continuous variables (Ñopo 2008b). SFD filters the influence of variables that vary little across space and OB decomposition gauges the differential returns to the analyzed groups, in this case racial groups. I develop the procedure and use LAPOP data to provide causal estimates of racial discrimination in Latin America.

The last contribution of the paper is to the literature studying group-based inequalities and economic development. There is an increasing interest in studying the consequences of group-based inequalities and their potential to explain comparative economic development.[^Closely related to the growing literature studying the historical and cultural patterns shaping economic development (Nunn 2020).] Group-based inequalities matter in comparative development: they can lead to political inequality, discriminatory policies between groups, or inadequate public goods provision (Alesina, Michalopoulos, and Papaioannou 2016). Moreover, group-based inequalities can have persistent effects through intergenerational transmission of cultural traits (Bisin and Verdier 2011), occupational segregation (Bowles, Loury, and Sethi 2014), or spatial segregation (Alesina and Zhuravskaya 2011; Bezin and Moizeau 2017).

Alesina, Michalopoulos, and Papaioannou (2016) use data on nightlights intensity and the location of ethnic and language groups to show that economic inequalities between ethnic groups are correlated with lower economic development at the national level, rather than ethnic diversity by itself (Alesina and La Ferrara 2005). When analyzing specific world regions, Alesina, Michalopoulos, and Papaioannou (2016) find that the negative correlation between ethnic inequality and economic development is not statistically significant for Western Europe and the Americas. A plausible hypothesis is that ethnic inequality is not as salient as racial inequality in Latin America, given the blurry border between ethnicity and race resulting from *mestizaje* politics. Complementing Alesina, Michalopoulos, and Papaioannou (2016), this paper disentangles inequalities across a cultural dimension and physical phenotype and confirms their hypothesis that higher group-based inequalities lead to lower economic development.[7]

In summary, this paper contributes to the ethno- and race-related economic literature in several dimensions. Using the racial dimension rather than the ethnic one, I provide casual estimates of the racial gap and racial discrimination, and show its welfare consequences on aggregate economic development. The rest of the paper is structured as follows. Section 2 reviews the racial question in

[7]Earlier work by Tesei (2014) also computes racial inequality measures for US Metropolitan Areas. However, he uses the broad ethno-racial categories used by the General Social Survey rather than measures of racial phenotype.

Latin America from a historical perspective. Section 3 presents the data. Section 5 estimates the racial-inequality measures at the aggregate level and their relationship with economic development. Section 4 presents the identification strategy and results for the effect of skin tone on monthly income per capita at the individual level and its mechanisms and the heterogeneous effects. Section 6 concludes.

2 Historical review: The racial question in Latin America

Race and ethnicity have been central dimensions for Latin America, as a region, and within the countries that compose it. As historian Tenorio-Trillo (2017) argues: *"Latin America, from its origins as a concept to this day, has fundamentally been a changing version of a single, enduring, old, and seemingly insurmountable concept: race."*[8] Moreover, within the countries fulfilling the enlisted characteristics, there has been a relatively stable racial order. This section reviews the racial question in Latin America from a historical perspective.

Pre-colonial and colonial period

The encounter of the original population, later labeled as Indians or Indigenous,[9] European conquerors, and populations from Africa, mostly brought as slaves or forced labor, produced an early miscegenation process throughout the continent.[10] Nonetheless, the racial mixture was not unnoticed nor unattended by the colonial empires. As Loveman (2014) argues: *"Through legal and administrative institutionalization of certain categorical divisions and not others, imperial governments in the Americas actively constituted social groupings within the colonized population that came to be perceived as natural groupings."* Figure 1 depicts one of the famous *casta* paintings, representing the everyday life of the different racial and ethnic mixtures in New Spain, nowadays most of Mexico and Central America. During the colonial period, in other contexts of racial apartheid as in Spain, *casta* paintings were a precious art piece due to the exotic representation of a society where the racial mixture was not prohibited but somehow the rule.

Graham (2013) presents a thorough historical overview of the colonial caste system across the continent. Most Indigenous or Indians had a corporate status and communal properties, ensured by the king. Mestizos, the racial mixture of Indigenous and Spanish, lay between white Spaniards

[8] Tenorio-Trillo argues that, besides notions of underdevelopment, violence, corruption, illiberal democracies, political instability, traditionalism, Catholicism, impossible utopias, or backwardness, the Latin prefix responds to the need to distinguish the not Anglo-Saxon region of the continent. *"There would be no Latin America and no Latinos/as without the United States"* (Tenorio-Trillo 2017).

[9] According to Knight (1990) *"The attribution of the Indian identity began, of course, with the Conquest."*

[10] The (re)encounter of the 'New' and 'Old' World begins after 1492, when the Spaniards, led by Columbus, arrived at the shores of the island that nowadays is shared by Haiti and the Dominican Republic. During the XVI century, Spaniards, Portuguese, French, and English dedicated themselves to explore the unknown territories and conquest, sometimes with local allies, pre-colonial societies throughout the continent. For a review of the early stages of the colonial period in the Americas, see Taylor (2013).

Figure 1: Casta Paintings

and Indigenous but were not accepted by both. There was also an important presence of Black slaves, freedmen, and freeborn population in Brazil and coastal areas of Nueva Granada (nowadays Colombia and Venezuela) and the coastal areas of nowadays Mexico, Argentina, and Peru. The mixture of African and European descent, Pardos or free mulattos, had to pay head taxes and were forbidden from marrying whites. Regarding whites or Spaniards, there were those born in Europe, *peninsulares*, and those born in the Americas, Creoles. The first had higher rankings in the most prestigious social positions.

Rather than a strict system, the caste system was a complex legal and political arrangement. As Graham (2013) also explains, in colonial Spanish-America, but also similarly in Brazil, *"the Hapsburg political and economic system had been reinforced by a social structure in which everyone was assigned a fixed position within a multilayered set of social categories (to be sure, always more flexible in practice than in theory)."* The flexibility was a matter of incentives since the caste system was also a tax and legal benefit system. For example, Loveman (2014) describes how some Indigenous wanted to pass for Mestizos to avoid paying tribute, while some Mestizos wanted to pass for Indigenous to escape Inquisition processes.

Even when each group enjoyed certain rights and prerogatives, whiter people were, on average, higher on the social ladder. In sharp contrast, Indigenous and Black were undeniably at the bottom of the caste system. Many Indigenous and Black populations were used for forced labor in

head-tax systems as the *encomienda*, *repartimiento*, *mita*,[11] and later in the plantations or mines as slaves (Loveman 2014). Though it is tempting to argue that racial disparities originated solely as a response to the colonial order, some scholars show evidence that labor disparities based on ethnicity and race can be tracked by pre-colonial social hierarchy and the ability of the local elites to coerce local labor (Arias and Dirod 2014).

Overall, during the colonial period, whiter meant closer to European and thus with higher social status, while there were debates on the human nature of Indigenous and Black populations (Graham 1990). It is not surprising to find more historians arguing how the class-based struggle was not the only salient dimension in colonial Latin America, but its intersection with race and ethnicity (Anderson 1988; McCaa, Schwartz, and Grubessich 1979). However, racial disparities during the pre-colonial and colonial periods were not motivated in racial discrimination behavior or racism, as one understands it nowadays, given that racial theory had its origins until the second part of the XIX century.

XIXth century: States, liberalism, and racial theory

Graham (1990) explains that racial theory was originated from advances in science, like biology, but mostly from bad takes of social scientists promoting notions of *"[social] evolution" as the "survival of the fittest [humans]."* Moreover, he claims:

> The idea of race as it was formulated in the nineteenth century seems to have served that function both within particular countries and in maintain or at least in justifying the economic and political power exercised by some nations over others [...] The idea of race also made possible, paradoxically, for mestizos and mulattoes –by identifying themselves with white elites as against Indian or black majorities– to accept theories that justified with domination over "colored" populations. (Graham 1990)

Thus, the complex caste system from the colonial period justified social, economic, and racial disparities after the fall of the Ancient Regime.

After their independence in the early XIXth century, there are two relevant processes for the new Latin American states regarding the racial question. The first one is the nation-state building process. Without the sovereign, people in the Americas started to think about nationalities: Mexicans, Argentinians, or Venezuelans. It is not a subtle point since it was unclear who had citizenship in the new nation-states. Loveman (2014) explains that *"[s]laves, former slaves, Indian peoples, mestizos, and other castes fought on both sides of the wars for independence, as both sides held out promises of emancipation and equality."* For instance, as in the Civil War in the United States, the question about military service by slaves in Brazil caused significant controversies concerning their right to acquire freedom and citizenship (Izecksohn 2014).

[11] See Dell (2010) for the long-term consequences of the *mita* system in Peru.

Parallelly, the breakage with the colonial Regime implied the dissolution of the caste system. The liberalism tradition of the early XIXth century, centered on individual freedom, was incompatible with the *casta* corporate system. In the words of Loveman (2014), *"the end of the empire did, however, bring with explicit repudiation of the ideological rationale and legal architecture upon which the hierarchical society of castes has been created."* It was not only a matter of ideology, but also translated into formal institutions: *"across the region, newly penned republican constitutions declared the practice of official ethnoracial classification to be historically obsolete"* (Loveman 2014). The unintended consequence of the *color blindness* of the XIXth century states is that ethnoracial classification in the Americas disappeared until the late XXth century.

Mestizaje: The XXth century racial alternative

Between the late XIXth century and the mid-XXth century, amidst the nation-building process and the heyday of the racial theory, the racial question in Latin American countries followed two paths. Firstly, countries like Argentina, Uruguay, and Chile, intensified their efforts to whiten their population through selective migration of Europeans (Helg 1990). Nevertheless, other countries with a higher racial mixture from the colonial and pre-colonial periods changed their narrative. Countries as Mexico and Brazil promoted the formation of national identities by reinforcing the 'melting pot' ethnic identity of *mestizos* or *mulatos*.

Figure 2: Vasconcelo's Cosmic Race

Restricted by the historical experience of high racial mixture, the latter states sized the idea of promoting a common ethnicity descendant of the miscegenation between Indigenous, Europeans, and Africans. In the words of Knight (1990) regarding the aftermath of the Mexican Revolution: *"the old Indian/European thesis/antithesis had now given rise to a higher synthesis, the mestizo, who was neither Indian or European, but quintessentially Mexican."* Note how *"the process of mestizaje, sometimes seen as basically racial, is in fact social"* (Knight 1990). Then, instead of

dealing with race, these states created a monolithic ethnic identity almost synonymous to their national identity.[12]

There was an active movement of Latin American intellectuals responding to the racial theory seeking the whitening of population and promoting the *mestizo* and *mulato* identity. Franz Boas in Brazil was among the first intellectuals to demystify and refute "scientific" racism (Skidmore 1990). Later on, his student, Gilberto Freyre, argued that *"Brazil's ethnic potpourri [...] was an immense asset"* (Skidmore 1990). In Mexico, the philosopher José Vasconcelos baptized the mestizo racial mixture in the Americas as the *'Cosmic Race'*. Published in 1925 with the title *La Raza Cósmica: Misión de la Raza Iberoamericana* (*The Cosmic Race: Mission of the Ibero-American race*), Figure 2, Vasconcelos argued in his essay that racial hybridism most valuable virtue was *"the ability to blend different races possessing different qualities"* (Knight 1990).

It might be understated, but Latin American mestizaje politics were an appealing alternative for racial theory in the early XXth century. Skidmore (1990) presents historical evidence. An anti-racist Brazilian Manifesto before World-Ward II declared:

> People of Indian, European, and African origins have mixed in an atmosphere of such liberality and such complete absence of legal restrictions on miscegenation that Brazil has become the ideal land for a true community of people representing very diverse origins... This Brazilian philosophy on the treatment of races is the best weapon we can offer against the monstrous Nazi philosophy, which is murdering and pillaging in the name of race.

The mestizaje identity served as the *third way* to the salient racial as segregation and anti-miscegenation in the US or racial hate from the Nazi ideology. Later on, most Latin American countries followed the mestizaje politics.

Race nowadays

In the early XXIth century, the *mestizo* or *mulato* identity is still in force. As the next section will show, the vast majority of the population in Latin American countries define themselves as *mestizos* or *mulatos*, even when they belong to groups with different racial phenotypes. Nevertheless, even when the racial question was not as extreme as in the US or World War II Europe, through mestizaje politics, Latin American countries could veil racial inequalities within them given that everyone became *mestizo* or *mulato*.

The patterns of the colonial and post-colonial persist: whiter people are better off in many socio-economic dimensions. Moreover, different forms of racism are still present in everyday life. For example, whiteness is still regarded as an ideal aesthetic of beauty and wealth (Krozer and Urrutia

[12]Parallelly to *mestizaje* politics, other forms of racial theories and politics by the Mexican Revolutionaries were a profound sinophobia and *indigenismo*, *"yet another non-Indian formulation of the 'Indian problem'"* (Knight 1990).

Gómez 2021). As anecdotal evidence, Figure 3 shows an internet cartoon depicting the skin tone of different labor occupations.[13]. The cartoon ironically depicts how white individuals have higher status or are more affluent, while labor occupations with lower status and lower-paid are usually for people with darker skin tones.

Figure 3: Cartoon: Contemporary Racism in Latin America

Besides the historical and anecdotal evidence, it was recently that social sciences focused on developing methodologies to measure ethnic and racial identities and compile evidence on their disparities.[14] As the bulk of work previously mentioned studying the effects of ethnicity and race on economic outcomes, and alongside class and income, race is back in the center of attention for social researches.

In conclusion, race has returned. Tenorio-Trillo (2017) ironically states:

> Nowadays, whether one lives in Chicago or San Pedro de Macorís, the Dominican Republic, one has to be careful. The doorbell may ring at any moment, and one could carelessly open it to find a social scientist at the door asking how one identifies: Black? White? Mestizo? Hispanic? Latina? The pollster could be carrying a palette in her hand to contrast one's answer with the actual color of one's face (an unfair thing to do: our buttocks, not our faces, are the keepers of our true color).

[13]Taken from Cinismo Ilustrado: https://cinismoilustrado.com/

[14]Contemporary sociologists were the first to study differences in socio-economic outcomes between ethnic and racial groups (Telles and Murguia 1990).

Besides the best measurement method for skin or face tone, the 'colorism' fever might have important benefits for social science research (Dixon and Telles 2017). As this work will show, the use of color palettes represents an improvement in studying racial disparities in Latin America given the extended *mestizo/mulato* identity, resulting from the historical experience previously described. More importantly, given that racial disparities and racism are global phenomena. Learning from the Latin American experience, both historically and with contemporary evidence, can shed light on tackling racial inequalities in other latitudes.

3 Data

Measuring racial inequalities is a challenging task due to data restrictions. Few surveys and censuses register individual racial characteristics besides ethnic self-recognition, namely, whether the respondent sees herself as part of a specific ethnic group (i.e., White, Afro, Latino, Asian, among others). In other cases, the interviewer infers the ethnicity of the respondent. In some extreme cases, there are no available measures of racial categories (The Economist 2020).

Such a shortage of data is not by chance. Loveman (2014) argues that the new nation-states stopped registering race and ethnicity from national censuses since the beginning of the XIXth century. The practice responded mainly to ideological concerns: the new regimes would be *color blind* to its citizens. Even it is highly desirable to universalize citizenship and rights, the unintended consequence is that information on race and ethnicity was absent during the next two centuries.

To address the racial inequalities at the individual and national levels, I use the AmericasBarometer from the Latin American Public Opinion Project (LAPOP). The AmericasBarometer is a survey conducted every two years in most countries in the Americas with stratified nationally representative samples of voting age adults, using a common questionnaire score and country-specific modules.[15] From 2010, LAPOP has used the Project on Ethnicity and Race in Latin America (PERLA) palette developed by Telles and Martínez Casas (2019) and coauthors.[16] Figure 4 shows the PERLA color scale. The scale ranges from 1 to 11, where one is the lightest skin tone and eleven is the darkest. In practice, interviewers are asked to discretely annotate the respondent's skin color taking as reference the PERLA palette without showing the guides to respondents (Dixon and Telles 2017).

Given that it is a public opinion survey, most of LAPOP's questions are regarding beliefs and preferences. However, the critical feature of LAPOP data is the information on race and ethnicity. Using LAPOP data, I compile all the AmericasBarometer surveys that include the PERLA palette in the core questionnaire. The constructed sample includes more than 100 thousand individual

[15] See https://www.vanderbilt.edu/lapop/.
[16] See https://perla.soc.ucsb.edu/.

Figure 4: Perla Palette

observations from 25 countries across four waves (2012, 2014, 2016/2017, 2018/2019).[17] Table 7 in the appendix shows the sample size by country and wave.[18]

Figure 5 shows the distribution of skin tones by country. Racial characteristics measured by skin tone vary substantially across and within countries. For instance, the darkest-skin tones are a majority in the Caribbean. Nevertheless, there is a black-skinned tone population in every country, which is usually omitted since they are a minority. Medium-dark tones are the majority in Central American countries and countries with a high miscegenation historical experience, such as Mexico, Brazil, Bolivia, Colombia, Ecuador, or Peru. Lastly, the whitest-skin tones are more usual in countries with little miscegenation that experienced high shares of European migration during the XIXth and XXth century, like Argentina, Chile, and Uruguay.

As argued earlier, since ethnicity refers to cultural characteristics, it might differ from the racial phenotype. LAPOP works with six broad ethnic categories: Afro, Indigenous, Mestiza, Mulata, White, and other ethnic groups (i.e., Asian, Jew, among others). Figure 6 shows the ethnic distribution for each country. The majority in Caribbean countries define themselves as Afro origin, even when there is a high diversity of racial phenotype measured by skin tone. People who define themselves as White are the majority in Argentina, Chile, Costa Rica, and Uruguay. The interesting patterns of ethnicity and racialization arise analyzing countries with a high percentage of both white and medium-dark skinned populations. For instance, in every other country besides the countries where there is an Afro or White majority, most of the population defines themselves as Mestiza or Mulata. Consistent with the historical and anecdotal evidence presented in Section 2, such countries also happen to have a high historical miscegenation experience and a strong presence of *mestizaje* ideology.

To have a better understanding of the relation between race and ethnicity, Figure 7 shows the distribution of skin tones by each of the ethnic categories for the whole sample. The patterns previously described persist: people who define themselves as Afro have darker skin tones, while those who define themselves as White have whiter skin tones. People who define themselves as Indigenous, Mestiza, Mulata, or from other ethnic groups have mostly medium-dark skin tones, but there is considerable variation in skin tone distribution. Thus, even when the distribution of

[17]Due to availability on individual information –country province or municipality, as well as other relevant covariates–, the 2010 wave is only used for aggregated measures of racial inequality.

[18]Note that Table 7 shows the sample size by country and wave that has non-missing values for all of the covariates of interest and was used for Section 4 on racial disparities. For Section 5 the data just uses income and skin tone variables, and thus there is more data availability.

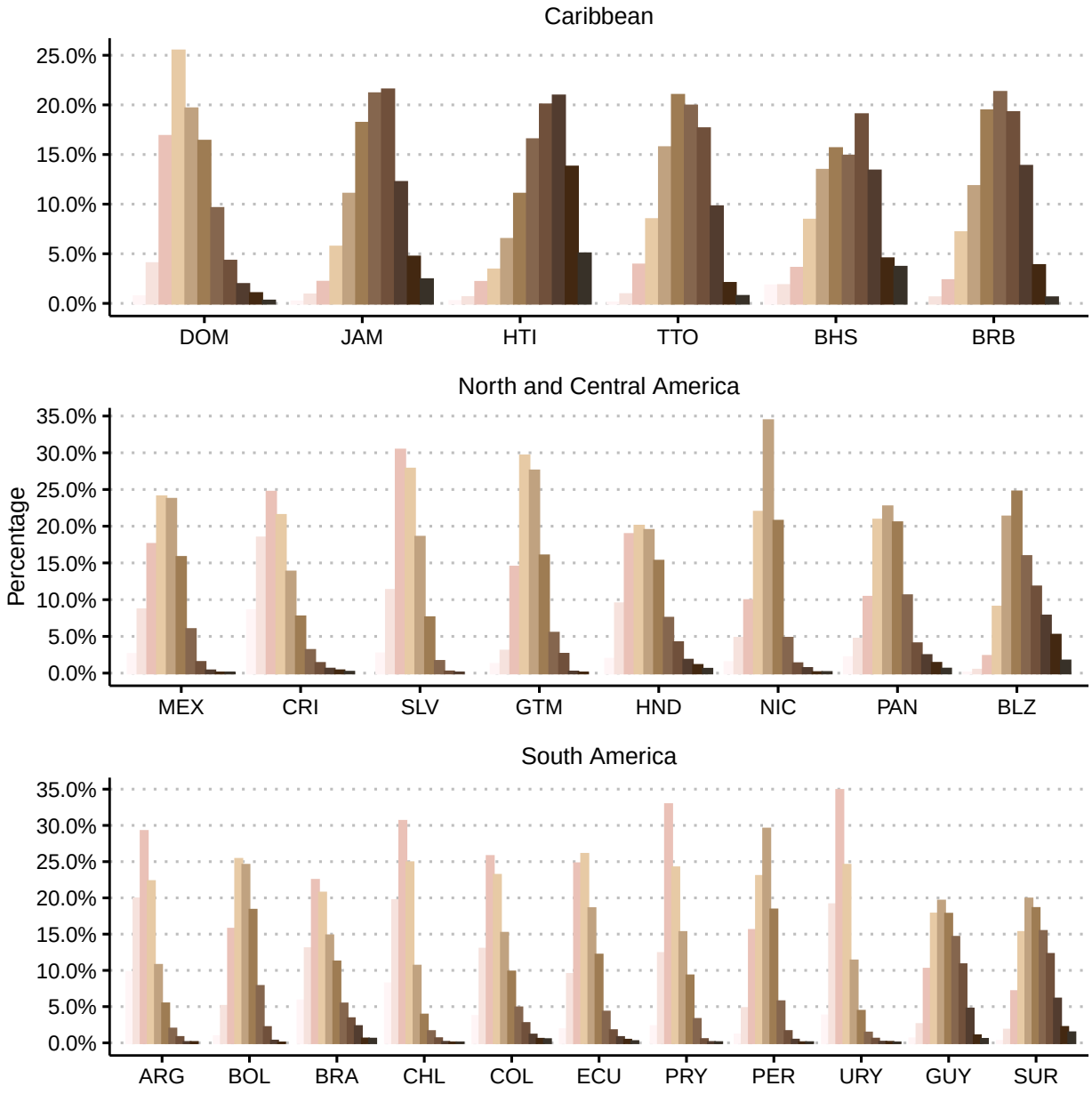

Figure 5: Skin tone distribution by country

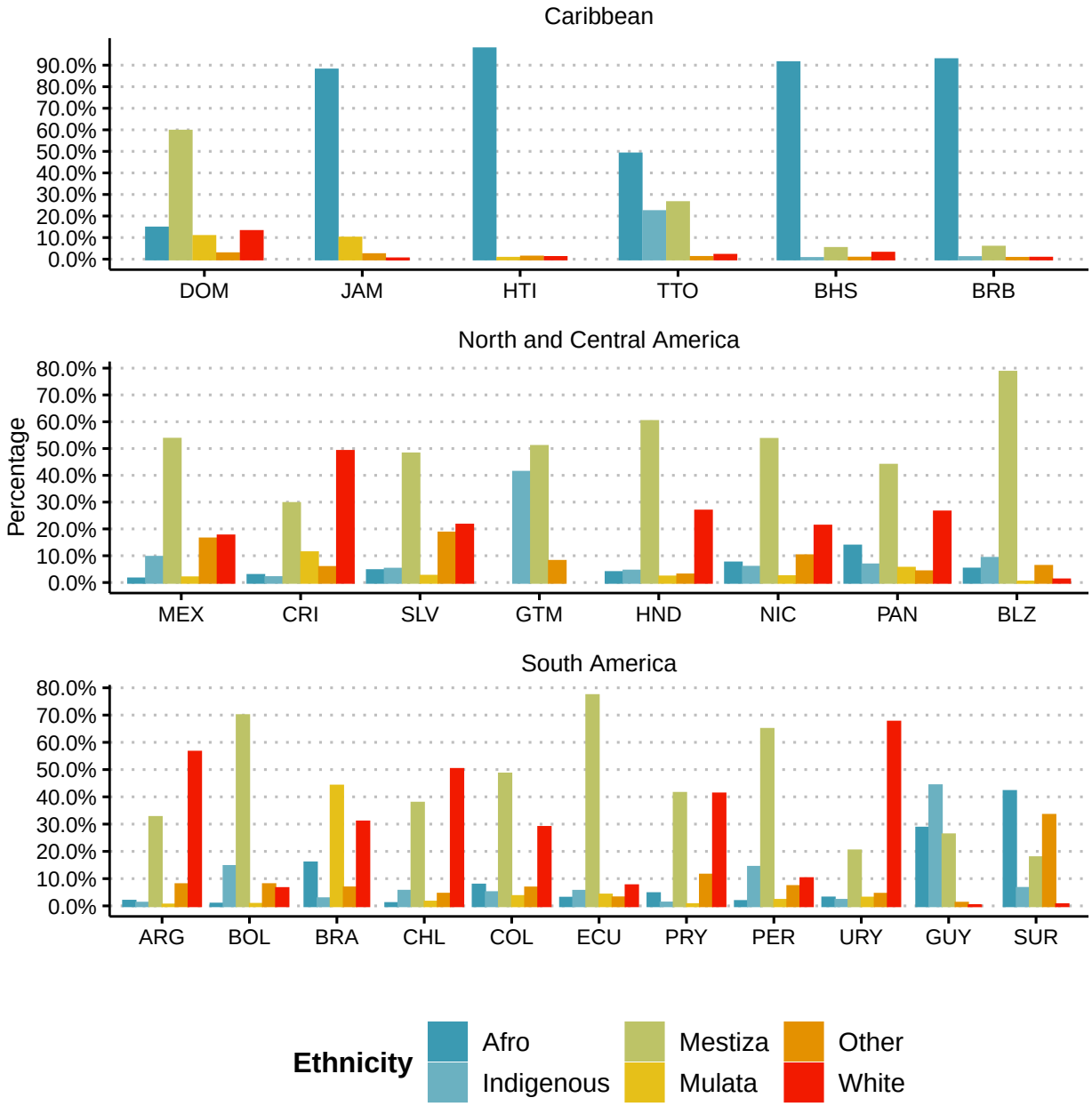

Figure 6: Ethnicity distribution by country

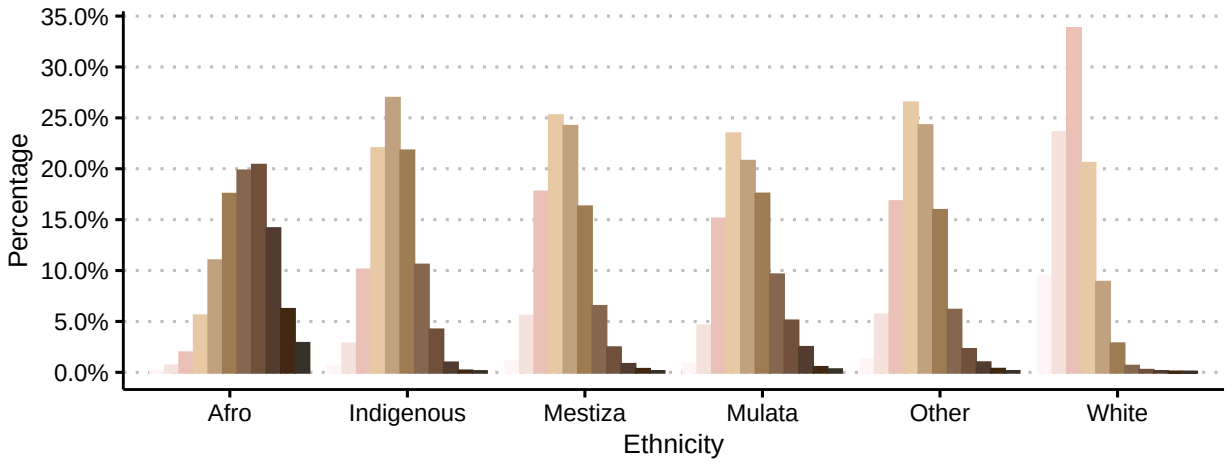

Figure 7: Ethniciy and Race

skin tones is broadly correlated to the distribution of self-reported ethnicity, there is large diversity of racial phenotypes within an ethnic group.

Using the information on skin tone has significant advantages over using self-reported ethnicity. Since the *mestizaje* ideology is strong in Latin American countries, ethnicity might hide racial disparities. Namely, analyzing economic disparities between ethnic groups might depict a general overview of the inequalities, but it might veil the disparities within broadly defined ethnic groups such as the Mestiza and Mulata populations. Therefore, the PERLA palette and the LAPOP data present an important advantage to deepen the study of racial inequalities in the region.

Besides ethnicity- and race-related questions, LAPOP also includes information on socio-demographics, such as age, gender, region, urban or rural household, years of schooling, occupational status, marital status, and household size. One shortcoming is that income is poorly measured. The survey asks about self-reported monthly household income by brackets, but for each country and wave the brackets' values change. Thus, to proxy for a continuous measure of income, I compute the bracket's median value for each monthly household income reported in the country's local currency. After, I divide the continuous measure of monthly household income between the household size to obtain a rough measure of income per capita. Lastly, to make a valid comparison for a country across time and between different countries, I use World Bank's Purchase Parity Power 2019 rates to convert local currencies. Figures 16 and 17 in the appendix shows the household income distribution by each country.[19]

As an alternative measure of household income and wealth, I construct a household asset index with information on whether the household has sewage, a bathroom in the house, television, number of vehicles, among others (Torche 2015).[20] I use Principal Component Analysis to reduce

[19]A critical problem of the constructed proxy of income is that there is a non-trivial amount of individuals who either do not report income or report zero income. I use sample correction procedures for my estimates.

[20]The complete asset list includes television, refrigerator, phone, cellphone, computer, number of vehicles, mo-

the dimensionality and use the first component to get a household asset index. Figure 18 in the appendix shows the unconditional correlation between monthly household income and the household asset index. Lastly, to have an alternative measure of income, I use Machine Learning techniques to predict monthly household income per capita with the set of variables used to construct the household asset index.[21] Descriptive statistics for the sample used for Section 4 are at Table 8 in the appendix. With information on racial phenotype, measured by skin color, and proxies of income per capita and household wealth, I can analyze racial inequalities for the region both at individual and aggregate levels.

4 Racial Disparities

In this section, I use the LAPOP data at the individual level to analyze skin tone effect on a set of socio-economic outcomes. I follow the disparities approach, which accounts for inequalities in outcomes solely due to group membership. For instance, social status or ethnic groups might have disparities in economic outcomes. Then, economic outcomes are a function of the membership to different groups –racial, ethnic, socio-economic–and other individual characteristics –income, education–and individual needs and preferences (Fleurbaey and Schokkaert 2011).

4.1 Identification strategy

To estimate the effect of skin tone on income, I use the following econometric specification:

$$y_i = \beta t_i + x_i \alpha + c_i \gamma + \theta_i + \eta_i + \varepsilon_i \tag{1}$$

Where y_i is the income per capita of individual i; t_i is the continuous PERLA measure of skin tone; x_i is a vector of observable characteristics, θ_i is a geographic dummy variable or fixed effect –country, province, or municipality– and η_i is a time fixed effect.[22] Lastly, c_i is a vector of unobserved characteristics.

Figure's 8 Panel A shows a scatter plot of the predicted income per capita (log) and the PERLA color scale for the whole sample. After accounting for country and year fixed effects, the linear regression depicts a negative gradient between income and darker PERLA skin tones. Figures 20 and 21 in the appendix show sizable variation in mean income levels by country, but in most countries, the negative gradient between skin tone and income persist.

torcycle, washing machine, microwave, sewage, and a bathroom in the house.

[21] I implement a linear prediction model with K-Fold Cross-Validation and sample splitting (Hastie, Tibshirani, and Friedman 2009) and use the SuperLearner package in R.

[22] Note that I do not observe the same unit i across multiple periods. Thus, I include the geographic and time fixed effects only indexed at the individual i.

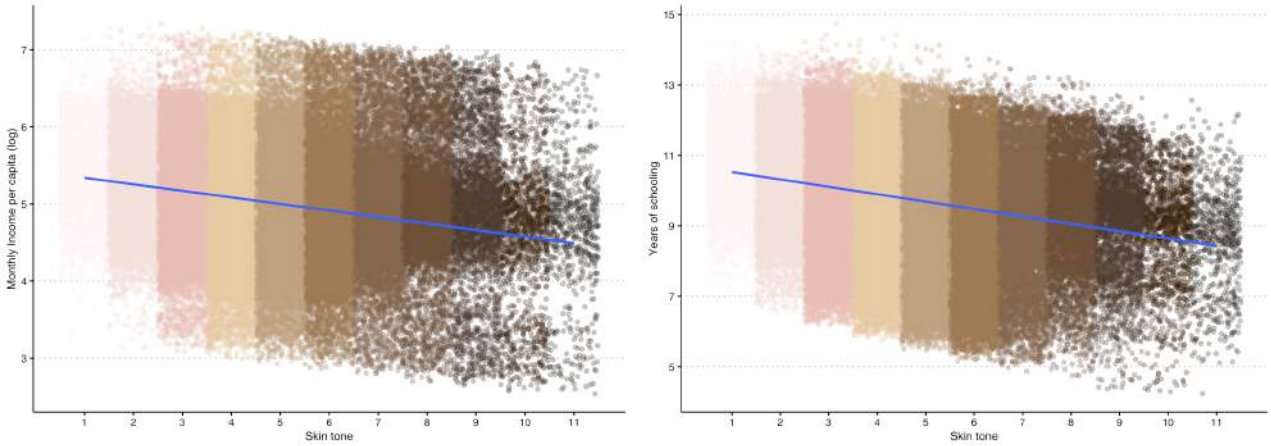

Figure 8: Skin tone gradient for mean monthly income per capita and years of schooling

Nevertheless, the previous gradients can be biased for multiple reasons. Panel B also shows a negative gradient for skin tone and years of schooling. Thus, Figure's 8 Panel A negative gradient does not account for relevant observed –education, gender, or experience– and unobserved characteristics –individual ability, parental background, early childhood, networks– that affect monthly household income per capita. Thus, the previous estimates suffer from omitted variable bias. Besides, there might be measurement error bias given the survey's methodology to register respondent skin tone. I use the Spatial First Difference research design to obtain an unbiased estimate of skin tone on income.

Spatial First Differences (SFD)

Researches face several restrictions for causal inference with cross-sectional data. When one wants to estimate a treatment's causal effect on an outcome of interest, and there is no panel-data structure, a discontinuity on a score, or available instruments, relevant endogeneity concerns arise from omitted variables bias. Druckenmiller and Hsiang (2018) propose a new research design to deal with unobserved heterogeneity using cross-sectional data to identify causal effects: Spatial First Differences (SFD). Druckenmiller and Hsiang (2018) argue that "unobserved heterogeneity in cross-sectional context is captured by non-stationary trends in outcomes across space." Alternatively, as Tobler's First Law of Geography points out: *"everything is related to everything else, but near things are more related than distant things"* (Kelly 2020). Thus, if units are *densely packed across physical space*, omitted variables bis can be purged using a differencing approach where the spatial position of observations can be located and organized, such as it is commonly used in time-series contexts.

In terms of identification, the authors argue that the Conditional Independence Assumption:

$$E[y_i|t_j] = E[y_j|t_j] \quad \forall i \neq j \tag{2}$$

where the potential outcome of unit i under treatment t_j, is equal to potential outcome of unit j

under t_j, is a demanding assumption since it assumes all units are comparable between each other. However, if one assumes a Local Conditional Independence Assumption, where:

$$E[y_i|t_{i-1}] = E[y_{i-1}|t_{i-1}] \quad \forall\{i, i-1\} \tag{3}$$

one accepts that the potential outcome of two adjacent units, i and $i-1$ is equal under treatment t_{i-1}. Thus, neighboring units are better countrerfactuals of each other. Note that assumption in equation (3) is less demanding than the same in equation (2). More importantly, it is fairly similar as the Continuity Assumption used in RD designs. Or as Druckenmiller and Hsiang (2018) points out, Local Conditional Independence assumes a discontinuity for every pair of adjacent units. Druckenmiller and Hsiang (2018) use simulations, two empirical applications, and a specification experiment omitting all possible observable covariates, to show how SFD successfully deals with omitted variable bias.

To estimate SFD, Druckenmiller and Hsiang (2018) propose a simple estimator that compares each units to its immediately adjacent neighbor:

$$\begin{aligned} y_i - y_{i-1} &= (t_i - t_{i-1})\beta + (x_i - x_{i-1})\alpha + (c_i - c_{i-1})\gamma + (\varepsilon_i - \varepsilon_{i-1}) \\ \Delta y_i &= \Delta t_i \beta_{SFD} + \alpha_{SFD}\Delta x_i + \Delta c_i \gamma + \Delta\varepsilon_i \\ \Delta y_i &= \beta_{SFD}\Delta t_i + \alpha_{SFD}\Delta x_i + \Delta\varepsilon_i \end{aligned} \tag{4}$$

where $\Delta c_i \gamma = 0$ under Local Conditional Independence Assumption (equation (3)). Such estimator filters the influence of variables that vary little across space. SFD can be implemented in single- or two-dimensional space by organizing observations and pairing units to its adjacent unit.

In practice, I exploit the geographical and time variation of LAPOP data and do the following. For each country-municipality and date of survey, I arrange the observations in the survey by their identification number assigned. Afterward, I use first-differencing and estimate the same specification as in equation (1). Given the survey design, the adjacent identification number units' are adjacent in space. See Figure 22 in the appendix.[23] Thus, by using SFD, I can uncover the causal effect of skin tone on income.

The SFD specification is the following:

$$\Delta y_i = \beta\Delta t_i + \Delta x_i \alpha + \theta_i + \eta_i + \varepsilon_i \tag{5}$$

Where Δy_i is the spatial first difference on the outcome of interest, in this case, monthly household income; Δt_i is the spatial first difference on skin tone measured by the PERLA palette, and Δx_i is a vector of spatial first differences on sociodemographic covariates. Since the data is from samples for different countries and waves, all regressions include geographic fixed effects –country,

[23] Also see LAPOP's sample design: https://www.vanderbilt.edu/lapop/insights/IMN004en.pdf.

province/state, municipality—, θ_i, and year fixed effects, η_i. I use LAPOP sample weights to make the results comparable across countries and waves representative at the national level (Castorena 2021).[24]

4.2 Racial gap estimates

Table 1 shows the OLS estimates of the racial gap using the econometric specification in equation (1). Column 1 shows that once accounting for differences in income between years and countries, an increasing one tone in the PERLA scale correlates with a decrease of 6 percent on monthly income per capita. To test for non-linearities, Column 2 introduces the squared skin tone measure. Effectively, skin tone's effect on income is negative but decreasing as individuals have darker skin tones. Column 3 includes a vector of sociodemographic controls as sex, age, years of schooling, ethnicity, a measure of interpersonal trust, occupational status, marital status, urbanization rate, and religion. The coefficients on skin tone remain negative and statistically significant. Moreover, note that only Afro, Other, and Indigenous ethnic categories have a statistically negative correlation with income with respect to the Mestizo base category. The same happens with gender: females have lower incomes than males. Columns 4 and 5 use finer geographic fixed effects at the province- and municipal-level, respectively. PERLA scale coefficients decrease but remain negative and statistically significant. Lastly, Column 6 uses a subsample with information on occupations. Using municipal and year fixed-effects, and even accounting for differences between different occupations –agriculture, artisans and mechanics, laborers, technician, administrative staff, scientist, managers, military–, skin tone coefficient are negative and statistically significant. Thus, contrary to the belief that only 'class' or 'occupational status' shape income differences, results suggest race also shapes unequal economic outcomes in Latin America.

Are the results biased due to the omission of relevant unobserved characteristics? Table 2 shows the coefficients for the SFD specification in equation (5).[25] The SFD coefficients show that, if anything, OLS estimates are biased towards zero. Columns 1 to 4 in Table 2 replicate, respectively, Columns 3 to 6 in Table 1. The causal estimates of skin tone on income imply that an increasing one darker skin tone in the PERLA scale causes a decrease of 8 percent on monthly income per capita, where there are non-linearities that decrease the effect slightly with darker skin tones. Again, the coefficients are statistically significant, even accounting for municipal- and year fixed-effects and the sample with info occupations. To test the robustness of the results, I use two alternative measures of economic welfare: a household asset index and the predicted income using the household assets. While the skin tone coefficients change in magnitude due to the mean and variance of the latter

[24]For this subsection, I only use observations with strictly positive income. For later subsections, I use sample selection corrections, which do not change the results.

[25]Note that the number of observations falls drastically for the SFD estimates since the first-differencing operation of adjacent units by each municipality and date drops the first unit.

Table 1: Skin tone effect on income: OLS

	Dependent variable:					
	Monthly income per capita (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
PERLA scale	-0.063***	-0.167***	-0.087***	-0.079***	-0.077***	-0.084***
	(0.009)	(0.028)	(0.019)	(0.010)	(0.007)	(0.023)
PERLA scale (squared)		0.010***	0.005**	0.005***	0.004***	0.006**
		(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
1[Female]			-0.168***	-0.174***	-0.175***	-0.272***
			(0.014)	(0.008)	(0.007)	(0.018)
Age			0.006***	0.006***	0.006***	0.022***
			(0.002)	(0.001)	(0.001)	(0.004)
Age (squared)			0.000	0.000	0.000	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling			0.075***	0.074***	0.070***	0.076***
			(0.003)	(0.002)	(0.001)	(0.003)
1[Afro]			-0.036	-0.036*	-0.027	-0.101**
			(0.029)	(0.019)	(0.017)	(0.046)
1[Indigenous]			-0.166***	-0.128***	-0.114***	-0.170***
			(0.026)	(0.018)	(0.015)	(0.039)
1[Mulata]			-0.040	-0.021	-0.016	-0.074
			(0.045)	(0.020)	(0.017)	(0.045)
1[Other]			-0.128***	-0.120***	-0.117***	-0.130***
			(0.019)	(0.015)	(0.013)	(0.034)
1[White]			0.000	-0.015	-0.020**	-0.055**
			(0.020)	(0.011)	(0.009)	(0.025)
Interpersonal trust			0.040***	0.041***	0.040***	0.045***
			(0.005)	(0.004)	(0.004)	(0.010)
Num.Obs.	96,615	96,615	96,615	96,615	96,615	11,563
R2 Adj.	0.269	0.271	0.429	0.445	0.459	0.461
R2 Within	0.011	0.014	0.228	0.201	0.179	0.209
Socio-demographic controls			X	X	X	X
Occupational controls						X
FE: Country	X	X	X			
FE: Province				X		
FE: Municipality					X	X
FE: Year	X	X	X	X	X	X
SE Cluster level	by: Country	by: Country	by: Country	by: Province	by: Municipality	by: Municipality

Notes: Clustered standard errors in parenthesis. Besides the coefficients in table, sociodemographic controls include: marital status, occupation status –working, taking care of the home, actively looking for a job, not working and not looking for a job, not working but have a job, studying, retired–, locality size –metro area, big city, medium city, small city, or rural area–, and religion. Occupational controls include indicator variables of types of labor –agriculture, artisans and mechanics, laborers, technician, administrative staff, scientist, managers, military–. *p<0.1; **p<0.05; ***p<0.01

Table 2: Skin tone effect on income: SFD

	Dependent variable:					
	Monthly income per per capita (log)				Predicted Income pc (log)	Household asset (z-score)
	(1)	(2)	(3)	(4)	(5)	(6)
PERLA scale	-0.081***	-0.081***	-0.081***	-0.084***	-0.025***	-0.049***
	(0.014)	(0.010)	(0.009)	(0.030)	(0.004)	(0.006)
PERLA scale (squared)	0.005***	0.005***	0.005***	0.006*	0.001***	0.002***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)	(0.001)
1[Female]	-0.180***	-0.179***	-0.179***	-0.265***	-0.030***	-0.045***
	(0.014)	(0.009)	(0.008)	(0.025)	(0.003)	(0.005)
Age	0.005**	0.005***	0.005***	0.021***	-0.001**	-0.001
	(0.002)	(0.002)	(0.001)	(0.005)	(0.001)	(0.001)
Age (squared)	0.000	0.000	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling	0.065***	0.065***	0.065***	0.074***	0.028***	0.049***
	(0.002)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
1[Afro]	-0.034	-0.034*	-0.034*	-0.077	-0.001	-0.013
	(0.027)	(0.019)	(0.018)	(0.061)	(0.007)	(0.011)
1[Indigenous]	-0.093***	-0.093***	-0.092***	-0.163***	-0.061***	-0.108***
	(0.030)	(0.019)	(0.017)	(0.057)	(0.009)	(0.013)
1[Mulata]	-0.008	-0.008	-0.006	-0.028	-0.008	-0.029**
	(0.030)	(0.018)	(0.019)	(0.060)	(0.007)	(0.012)
1[Other]	-0.095***	-0.095***	-0.095***	-0.145***	-0.043***	-0.057***
	(0.021)	(0.020)	(0.017)	(0.045)	(0.007)	(0.010)
1[White]	-0.016	-0.016	-0.016	-0.022	-0.010**	-0.014*
	(0.012)	(0.011)	(0.011)	(0.034)	(0.004)	(0.007)
Interpersonal trust	0.031***	0.031***	0.030***	0.034***	0.012***	0.025***
	(0.005)	(0.004)	(0.004)	(0.013)	(0.002)	(0.003)
Num.Obs.	79,833	79,833	79,833	7,898	91,996	91,996
R2 Adj.	0.160	0.157	0.146	0.116	0.116	0.150
R2 Within	0.161	0.161	0.160	0.193	0.129	0.163
Socio-demographic controls	X	X	X	X	X	X
Occupational controls				X		
FE: Country	X					
FE: Province		X				
FE: Municipality			X	X	X	X
FE: Year	X	X	X	X	X	X
SE Cluster level	Country	Province	Municipality	Municipality	Municipality	Municipality

Notes: Clustered standard errors in parenthesis. Besides the coefficients in table, sociodemographic controls include: marital status, occupation status –working, taking care of the home, actively looking for a job, not working and not looking for a job, not working but have a job, studying, retired–, locality size –metro area, big city, medium city, small city, or rural area–, and religion. Occupational controls include indicator variables of types of labor –agriculture, artisans and mechanics, laborers, technician, administrative staff, scientist, managers, military–. *p<0.1; **p<0.05; ***p<0.01

variables, the causal effect is still negative and statistically significant. Thus, darker skin tones have a causal effect on lower economic outcomes.

4.3 Mechanism: Testing racial discrimination

The previous results show there is a big racial gap in income in Latin American countries. However, what drives the racial gap? There are multiple mechanisms as candidates: for instance, differential access to public goods or occupational segregation. Figure 9 shows the skin tone distribution by broad occupational status. High occupational status jobs as directors, managers, professionals, scientists, and intellectuals tend to have whiter skin tones. Almost 50% of the high occupational status workers have skin tones between the first and third colors of the PERLA palette. Mid-level professionals, salesmen, and workers in the third sector also have a high share of whiter individuals. Nonetheless, the mean color for the latter medium status jobs is the fourth PERLA color. Finally, the low-status occupations, such as jobs in the first sector as agriculture or mechanics, tend to have darker skin tones: more than half of these workers have skin tones between the fourth and sixth PERLA colors. These stylized facts suggest there is racial occupational segregation affecting the racial gap.

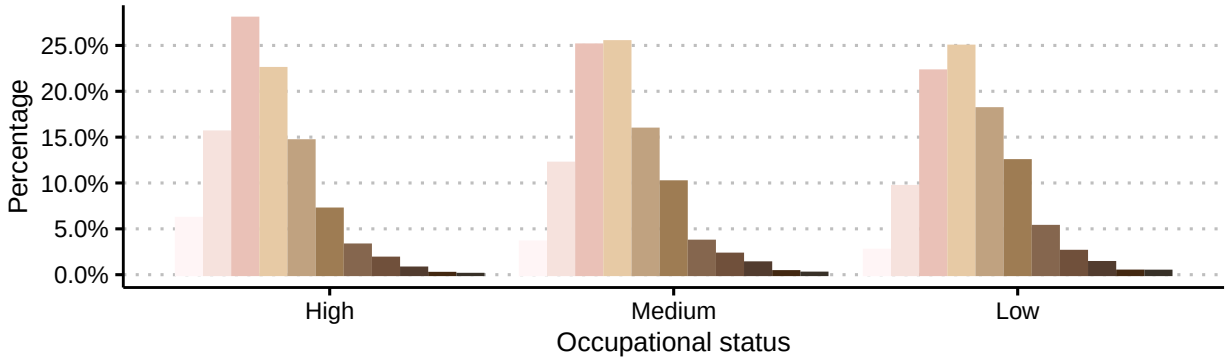

Figure 9: Racial Occupational Segregation

Nonetheless, besides occupational segregation, differences in access to public goods, or inequality of opportunity (Ferreira and Gignoux 2011), economic literature has argued that discrimination is the main mechanism driving ethnic-racial disparities in Latin America (Ñopo, Chong, and Moro 2009). Nevertheless, as argued earlier, causal inference of racial discrimination using cross-sectional data is not innocuous. To overcome such a problem, I combine an Oaxaca-Blinder (OB) decomposition for continuous variables proposed by Ñopo (2008b) with the SFD design to test whether racial discrimination explains the racial gap.

Oaxaca-Blinder (OB) decomposition for continuous variables

The OB decomposition is a widely used method in labor economics to study differences in earnings between two groups into two elements: the first one captures differences in observable character-

istics between the two analyzed groups, and the second one captures the differences in returns to those characteristics (Fortin, Lemieux, and Firpo 2011; Jann 2008; Ñopo 2008b).

Following Ñopo (2008b), the OB decomposition for a continuum of groups can be extended from a regression framework for two groups. First, let t_i denote a dummy variable indicating whether individual i belongs to a given group. Thus, one have the following 'simplified' equation:

$$y_i = \alpha_0 + \alpha_1 t_i + \varepsilon_i \tag{6}$$

Where y_i is the outcome of individual i, and α_1 represents the gap between the two groups: $\alpha_1 = E[y|t = 1] - E[y|t = 0]$.

To decompose the gap between the observed characteristics and their respective returns is necessary to estimate the following 'extended' equation:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 t_i + \beta_3 t_i \cdot x_i + \varepsilon_i \tag{7}$$

Where y_i and t_i represent the same variables as in Equation (6), and x_i is an n-dimensional vector of observable characteristics. Thus, β_1 represents the rewards to the observable characteristics for group 0, and $\beta_1 + \beta_3$ are the rewards to the observable characteristics for group 1. Coefficient α_1 from Equation (6) can be expressed as:

$$\begin{aligned}
\alpha_1 &= E[(\beta_0 + \beta_2) + (\beta_1 + \beta_3)x|t = 1] - E[\beta_0 + \beta_1 x|t = 0] \\
\alpha_1 &= (\beta_0 + \beta_2) + (\beta_1 + \beta_3)E[x|t = 1] - \beta_0 - \beta_1 E[x|t = 0] \\
\alpha_1 &= \beta_1(E[x|t = 1] - E[x|t = 0]) + \beta_2 + \beta_3 E[x|t = 1] \\
\alpha_1 &= \Delta^x_{OBD} + \Delta^0_{OBD}
\end{aligned}$$

Where $\Delta^x_{OBD} \equiv \beta_1(E[x|t = 1] - E[x|t = 0])$, represents the differences in the outcome due to average observable characteristics of the individuals, or composition effect; while $\Delta^0_{OBD} \equiv \beta_2 + \beta_3 E[x|t = 1]$ represents the differences in the outcome that cannot be explained by observable characteristics. Ñopo (2008b) formally shows that obtaining the two OB components is straightforward when t_i is a continuous measure.

Given the economic theory of discrimination, the component Δ^0_{OBD} is usually interpreted as a measure of discrimination. Nevertheless, when the researcher does not account for all observed and unobserved relevant factors affecting the outcome of interest, the component Δ^0_{OBD} will also capture differences due to unobserved heterogeneity between groups (Jann 2008). However, if SFD design purges the unobserved heterogeneity, when estimating OB decomposition using SFD instead of usual specifications in levels, the OB components capture differences solely due to discrimination. Thus, one can provide a causal estimate of racial discrimination.

I use both SFD and OB decomposition to obtain estimates of racial discrimination. In practice, I

use the following procedure:[26]

1. Estimate the SFD 'simplified' equation:

$$\Delta y_i = \alpha_0 + \alpha_1 \Delta t_i + \theta_i + \eta_i \varepsilon_i$$

   The coefficient of interest is α_1.

2. Estimate the SFD 'extended' equation:

$$\Delta y_i = \beta_0 + \beta_1 \Delta x_i + \beta_2 \Delta t_i + \beta_3 \Delta t_i \cdot \Delta x_i + \theta_i + \eta_i + \varepsilon_i$$

   The coefficients of interest are β_2 and β_3.

3. Estimate the average characteristics of the sample used to estimate equations in steps 1 and 2, namely $E[x]$.[27]

4. Obtain the component of the wage gap that cannot be explained by differences in average characteristics:

$$\Delta^0_{OBD} = \beta_2 + \beta_3 E[x]$$

5. Obtain the component of the wage gap that is explained by differences in average characteristics:

$$\Delta^x_{OBD} = \alpha_1 - \Delta^0_{OBD}$$

Given that my sample has a non-trivial amount of missing or zero reported income, I also use the Heckman correction and only use observations with strictly positive income (Heckman 1979; Rios-Avila 2019). I used province (or state) fixed effects, θ_i, and year fixed effects, η_i, to account for geographic and time between-differences in income. For inference, I use stratified bootstrapping to obtain the empirical distributions of the aggregated and detailed decomposition components.

4.4 Racial discrimination estimates

Table 3 shows the results for the Oaxaca-Blinder decomposition for continuous variables with SFD. Column 1 shows the results for my proxy of monthly income per capita. Combining the linear and quadratic terms of skin tone, an increase in one darker skin tone in the PERLA scale decreases income by nearly 11 percent. The OB discrimination component implies that once

[26] Note Δ^x_{OBD} and Δ^0_{OBD} stand for the OB components, while Δx_i stands for the first spatial difference of unit i and $i-1$ in the variable or vector of variables x_i.

[27] The set includes: sex; age; age squared; years of schooling; marital status; occupational status; ethnicity; urbanization or locality size; religion; interpersonal trust.

purging unobserved heterogeneity through SFD and interacting skin tone terms with all remaining observable characteristics, an increase in one darker skin tone decreases monthly income per capita by 7.5 percent due to discriminatory traits. Both coefficients are statistically significant at one percent. The latter results imply that the individual with the whitest skin tone has an average income nearly doubling the same of the darkest individual, where differences in observed average characteristics cannot explain 68% of the gap ($\Delta^0_{OBD}/\alpha_1 = \frac{-0.075}{-0.109} = 68.8\%$). Therefore, racial discrimination explains nearly two-thirds of the racial gap.

Table 3: Racial discrimination: OB Decomposition with SFD

	Dependent variable:		
	Income per capita (log)		Predicted Income per capita (log)
	(1)	(2)	(3)
Racial gap estimate	-0.109***	-0.134***	-0.041***
	(0.007)	(0.024)	(0.003)
OB discrimination effect	-0.075***	-0.079***	-0.024***
	(0.007)	(0.023)	(0.003)
OB composition effect	-0.034***	-0.055***	-0.016***
	(0.003)	(0.015)	(0.001)
Number of Observations	79,833	7,898	91,996
Socio-demographic controls	X	X	X
Occupational controls		X	
FE: Province	X	X	X
FE: Year	X	X	X

Notes: Bootstrapped estimates and standard errors based on 500 bootstrap replications. Sociodemographic controls include: sex, age, age squared, years of schooling, ethnicity, interpersonal trust, marital status, occupation status –working, taking care of the home, actively looking for a job, not working and not looking for a job, not working but have a job, studying, retired–, locality size –metro area, big city, medium city, small city, or rural area–, and religion. Occupational controls include indicator variables of types of labor –agriculture, artisans and mechanics, laborers, technician, administrative staff, scientist, managers, military–. *p<0.1; **p<0.05; ***p<0.01

As a robustness check, Table's 3 Column 2 shows the results only for subsample containing information on labor occupation. The racial gap semi-elasticity is minus 13 percent, where discrimination can explain almost 60% of the latter ($\Delta^0_{OBD}/\alpha_1 = \frac{-0.079}{-0.134} = 58.95\%$). Column 3 uses income predicted with household assets and confirms the above results: at least 58% of the racial gap is driven by racial discrimination ($\Delta^0_{OBD}/\alpha_1 = \frac{-0.024}{-0.041} = 58.53\%$).

To provide another set of evidence that confirms the racial discrimination hypothesis, I use LAPOP

questions self-reported experiences of discrimination. Using an SFD linear probability model, Table 4 shows that darker skin tones have a higher probability of reporting experiences of discrimination on the school or work, in public places, and by governmental institutions.

Table 4: Racial discrimination: Self-reported measures

	Dependent variable:		
	Self-reported discriminatory experience		
	on work or school	on public places	by governmental institutions
	(1)	(2)	(3)
PERLA scale	0.004**	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
Number of Observations	16,941	16,941	16,941
R2 Adj.	0.000	0.001	0.001

Notes: Heteroskedasticity-robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01

To summarize, there is a significant racial gap in Latin America. Considering a lower bound estimate, each skin tone of the PERLA palette correlates with a decrease of 8 percent on monthly income per capita, where more than half of the effect cannot be explained by differences in returns to average years of schooling, geographic region, or occupational status. Therefore, the paper provides convincing evidence that racial discrimination is driving the racial income gap.

4.5 Heterogeneous effects

If racial inequalities and discrimination are global phenomena, their expressions are local. Figure 10 shows the results for the SFD-OB decomposition using as dependent variable the proxy for monthly (log) income per capita country by country.[28] Skin tone gradient in income is negative and statistically significant for most Latin American countries, with a substantial between-country variation.

Interestingly, skin tone's semi-elasticities on income are high in countries with a high racial mixture and a sizable share of indigenous population. The skin tone income gradient is the steepest in Paraguay and Guatemala: an increase in the PERLA color palette correlates with a decrease in 25 percent in monthly income per capita, where between 70% and 100% of the effect is due to racial discrimination. Brazil comes next: skin tone semi-elasticity with income is minus 0.165, where 47% of the effect is driven by racial discrimination. Mexico and Bolivia share a semi-elasticity of minus 0.145, where racial discrimination explains between 80%-100% of the latter. Argentina, Ecuador, the Dominican Republic, Uruguay, Panama, and Chile follow the rank with

[28]Confidence intervals at 95 and 90 percent significance level using 500 bootstrap replications.

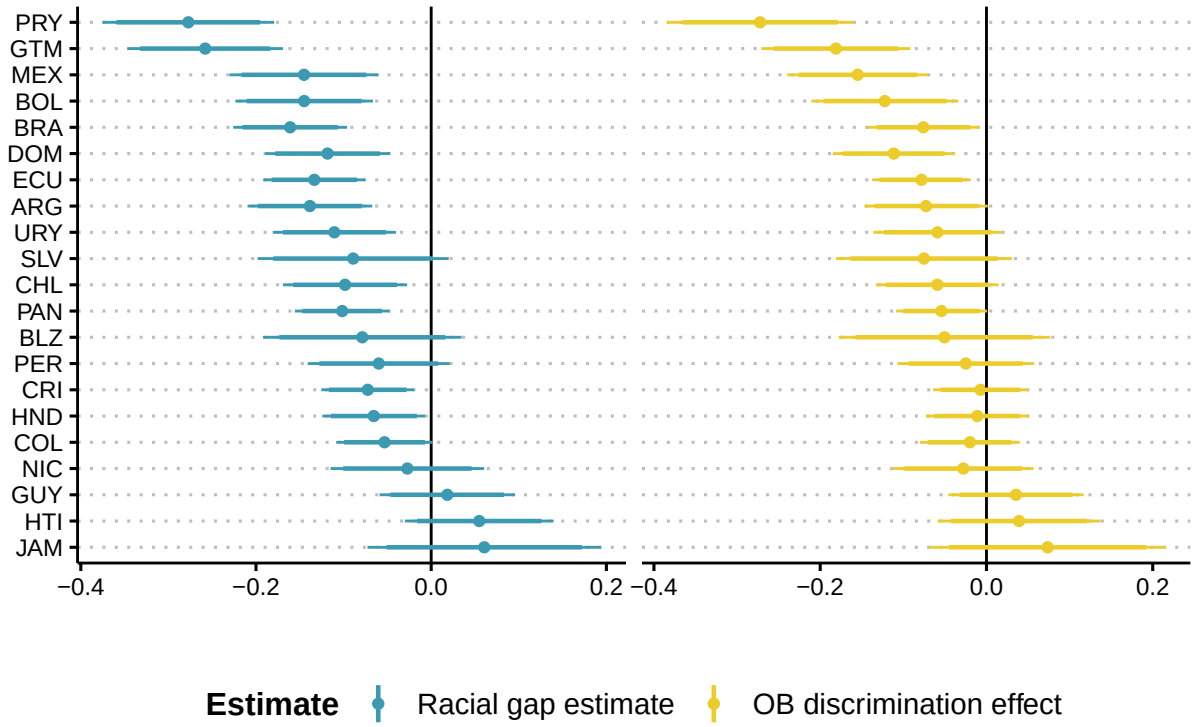

Figure 10: Skin tone effect on predicted income: OB decomposition by country

semi-elasticities ranging from minus 0.138 to minus 0.10, where at least more than half of the racial gap is explained by racial discrimination.[29]

In contrast, the estimates for Jamaica, Haiti, Guyana, and Nicaragua suggest no racial gaps or racial discrimination. The latter can be explained due to the skewed racial distribution towards blacked-skinned population, where race does not affect differences in income. Moreover, the sample size of these countries is considerably smaller. A third cluster of countries has racial gaps, but the SFD-OB estimate of racial discrimination is not statistically significant. Such is the case for Colombia, Honduras, Costa Rica, Peru, and Belize.

To test for other heterogeneous effects, I analyze the skin tone gradient on income gradient on subsamples by gender and ethnic self-affiliation. Using the SFD-OB procedure, there are no heterogeneous effects by gender, while only those who define themselves as 'Afro' or 'Mulato' have a more negligible effect of skin tone on income, though the estimates are noisy. Figure 23 in the appendix shows the results.[30] Nonetheless, estimates in Table 2 show that, independently of skin tone, females, as well as the population defining themselves as 'Afro,' 'Other,' and, especially, 'Indigenous' have less income.

[29] El Salvador follows a similar pattern, but due to sample size, its estimates are imprecise.

[30] Confidence intervals at 95 and 90 percent significance level using 250 bootstrap replications.

5 Racial Inequality and Economic Development

In this section, I use LAPOP data to compute aggregated measures of racial income inequality. The overreaching goal of this section is to test whether racial inequalities correlate with lower economic development, as shown for ethnic inequality by Alesina, Michalopoulos, and Papaioannou (2016).

Firstly, I compute inequality measures without any interpersonal comparison besides income. Using the computed monthly income per capita, I construct a bootstrapped Gini index for each country and year in the LAPOP sample.[31] Figure 24 in the appendix shows the correlation between my constructed Gini indexes of income inequality and the available Gini indexes of income inequality published by the World Bank. Though noisy, my aggregated measures of income inequality are positively correlated with both sets of measures. Thus, even when LAPOP data is not intended to measure income inequality, my measures of income inequality can partially describe the patterns of income inequality in Latin American countries.

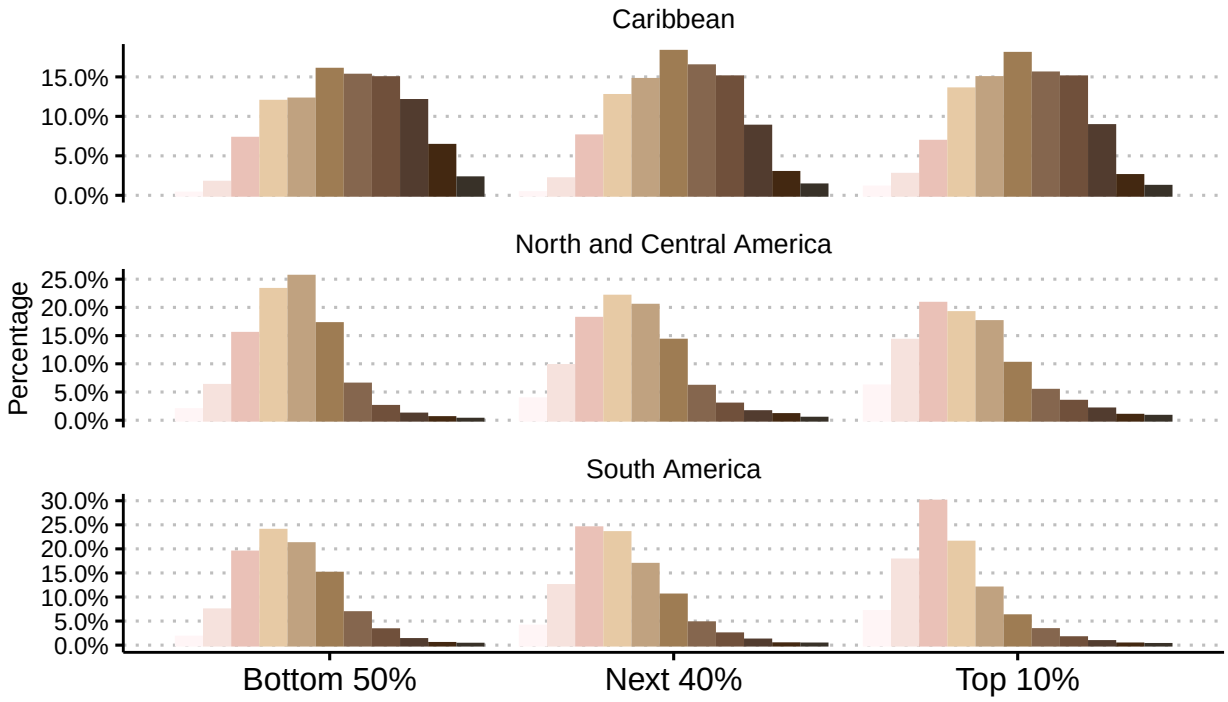

Figure 11: Skin tone distribution within quintiles of income

The attractive feature of LAPOP data is not its income information; but instead, it allows to construct the racial composition of each of the deciles of the income distribution. Figure 11 shows the distribution of skin tones for each decile of the income distribution by region in the continent. Except for the Caribbean countries, the bottom deciles have a majority of the population with skin tones within the range 4 and 6 of the PERLA scale, as upper deciles have most people with whiter skin tones. Consistent with literature in economics, sociology, and history, Latin Americans

[31] I use 50 bootstrap replications to compute the index each by country and year.

with darker skin tones have less income than their lighter skin tone peers. With the latter results in mind, I compute racial inequality measures at the national level.

5.1 Computing Racial-Inequality

Since I am interested in decomposing income inequality between racial categories, I use the mean log deviation (MLD) index to obtain the between and within components of income inequality given the PERLA scale color categories.[32] Equation (8) represents the MLD and its decomposition of the between and within components (Cowell 2000; Haughton and Khandker 2009):

$$MLD = \frac{1}{N}\sum_{i=1}^{N} ln\frac{\bar{y}}{y_i} = \sum_j \frac{N_j}{N} MLD_j + \sum_j \frac{N_j}{N} ln\frac{\bar{y}}{\bar{y}_j} \tag{8}$$

For each country and year of LAPOP's data, I decompose income inequality for its between and within components for racial groups.[33] Besides the racial inequality measures, I also use the broad ethnic categories used by LAPOP data to compute alternative ethnic inequality measures. Figure's 12 left panel shows the mean MLD between-group component across the study period for each country in the analysis. Bolivia, Colombia, Jamaica, Guatemala, the Dominican Republic, Brazil, and El Salvador have the highest mean MLD between-group component across the last decade. In contrast, Chile, Suriname, Guyana, Venezuela, Nicaragua, and Belize, have the lowest median MLD between-group components. The mean MLD between-group component for the region is 1.70.

The absolute MLD between-group component is not informative about the relative weight of racial inequality. To have a more intuitive measure of racial inequality, I compute the ratio of racial over total income inequality. Namely, the ratio of the MLD between-group component over the total MLD of income. The mean ratio of racial over total income inequality is 3.87 percent. Thus, in Latin American countries, 3.87 percent of the total income inequality is related to inequalities between racial groups measured by skin tone. Figure's 12 right panel shows the mean racial over total inequality ratio. With the relative measure, Bolivia, Guatemala, Colombia, Brazil, Uruguay, and Argentina have the highest mean ratios of racial over total income inequality. For the latter set of countries, nearly 5 percent of total inequality is due to differences in racial groups. Meanwhile, Chile, Nicaragua, Guyana, Belize, and Suriname, have the lowest mean ratios: around 2.5 percent.

Overall, the patterns by country are consistent with the aggregated measures of racial inequality presented in Section 4. Figure 13 shows that both the SFD racial gap estimates and the SFD-OB

[32]The MLD or the Generalized Entropy index GE(0) fulfills the properties of the axiomatic approach –transfer principle, population principle, decomposability principle, and scale-invariant– (Shorrocks 1984), as well as the path independent decomposability (Foster and Shneyerov 2000).

[33]I use 50 bootstrap replications to compute the index for each country and year.

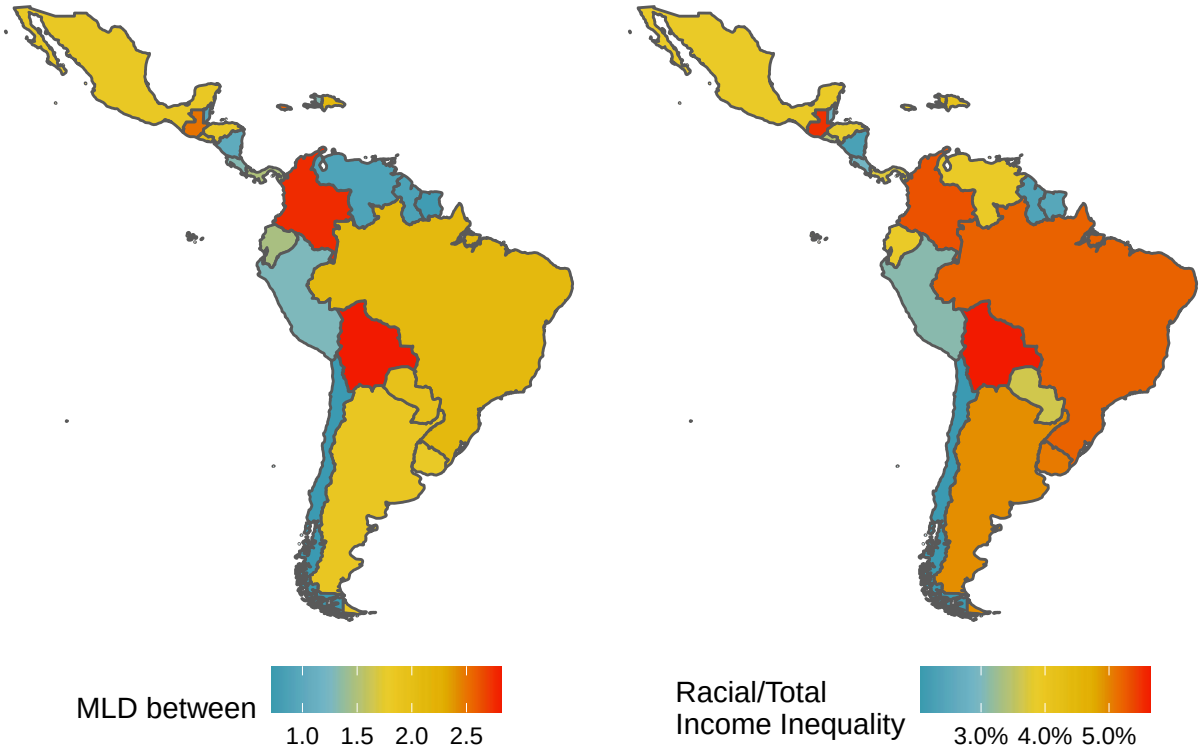

Figure 12: Racial-inequality in Latin America

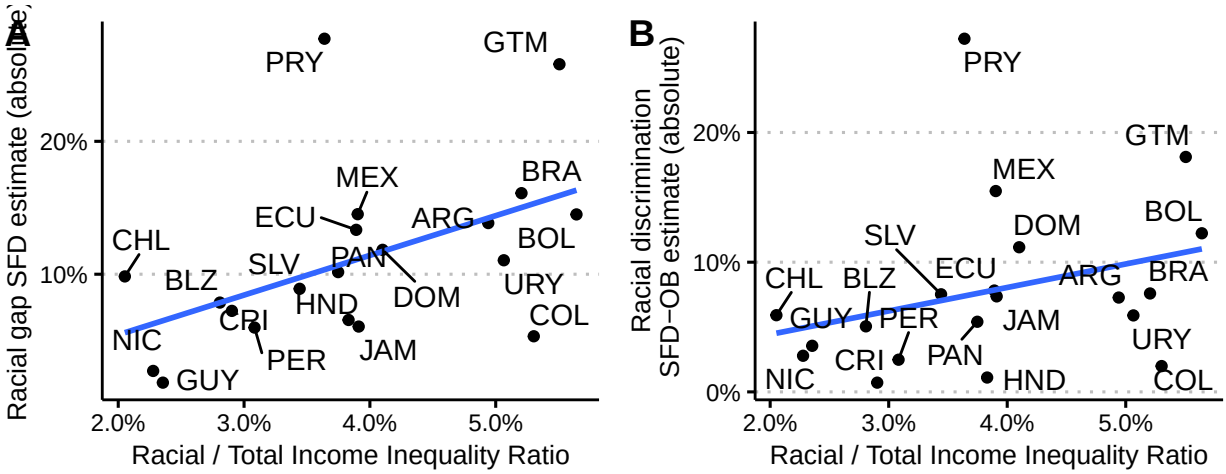

Figure 13: Micro and Macro Coefficients

racial discrimination component by country are closely correlated with the mean ratio of racial over total income inequality (MLD between groups over total MLD).

5.2 Racial-Inequality and the *Comsic Race*

To test whether *mestizaje* politics do veil racial inequalities, I regress the ratio of racial over total inequality with respect to the share of the population that defines themselves as *mestizo* or *mulato*. Controlling for country and year fixed effects, Column 1 in Table 5 shows that a one percent increase in the share of *mestizo* or *mulato* population correlates with an increase of 45 percent in the ratio of racial over total inequality, but only statistically significant at ten percent. Column 2 shows that the correlation becomes statistically significant after the inclusion of the ethnic inequality measures using the broad ethnic categories (i.e. Mestizo, Mulato, White, Afro, Indigenous, or Other). Column 3 shows the positive correlation persist after including controls as racial and ethnic indexes of fractionalization and segregation, as well as measures of spatial and administrative inequality (Alesina, Michalopoulos, and Papaioannou 2016). A one percent increase in the share of *mestizo* or *mulato* population increases the ratio of racial over total inequality by nearly 60 percent. Therefore, countries with a higher *mestizo* or *mulato* identity have higher racial inequality. Or, in plain words, the *Cosmic Race* idea veils racial inequalities.

Table 5: Racial Inequality and *Mestizaje* Identity

	Dependent variable:		
	Racial over Total Inequality Ratio (log)		
	(1)	(2)	(3)
Share of Mestizo/Mulato (log)	0.446*	0.452**	0.601**
	(0.254)	(0.225)	(0.255)
Ethnic Inequality Ratio (log)		0.338***	0.356***
		(0.090)	(0.092)
Observations	109	109	109
R^2 within	0.039	0.213	0.296
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Robust standard errors in parenthesis. Controls include LAPOP based racial and ethnic indexes of fractionalization and segregation, as well as spatial and administrative inequality measures by Alesina, Michalopoulos, and Papaioannou (2016). *p<0.1; **p<0.05; ***p<0.01

5.3 Racial-Inequality and Economic Development

Following Alesina, Michalopoulos, and Papaioannou (2016), In this subsection I test whether racial inequalities correlate with lower economic development. I use measures of GDP per capita to measure economic development at the national level. Given that I have multiple cross-sections of LAPOP data, I can construct an unbalanced panel with information on racial inequalities, ethnic inequalities, and economic development for 24 Latin American countries across the last decade.[34]

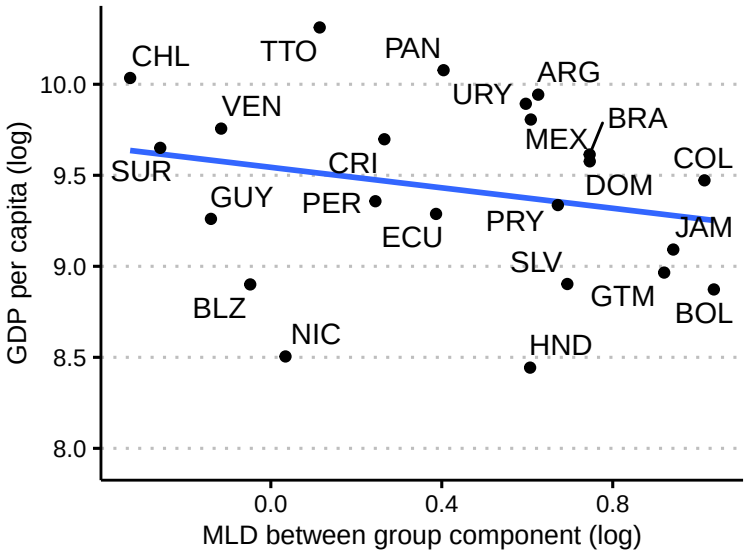

Figure 14: Racial-inequality and Economic Development

Figure 14 shows the unconditional correlation of the mean MLD between racial group component and mean (log) GDP per capita. At first glance, there is a mild negative correlation between racial inequality and lower economic development. To test more robustly the relation between racial inequality and economic development I use the following econometric specification:

$$y_{c,t} = \beta \textit{Racial Inequality}_{c,t} + \gamma X_{c,t} + \theta_c + \eta_t + \varepsilon_{c,t} \tag{9}$$

Where $y_{c,t}$ represents (log) GDP per capita of country c at time t; $\textit{Racial Inequality}_{c,t}$ is the (log) ratio of racial over total income inequality; $X_{c,t}$ represents a set of time-varying controls. One improvement of this analysis with respect to Alesina, Michalopoulos, and Papaioannou (2016) is the availability of multiple observations for each country. Thus, I can include country fixed effects θ_c to control for time-invariant characteristics that affect economic development and also are correlated with racial inequality at the national level. Lastly, I include year fixed effects η_t to account for common shocks to all countries in the period of study. I use bootstrapped cluster standard errors at the country level (Cameron, Gelbach, and Miller 2008; Roodman et al. 2019).

[34] I exclude the countries with only one available cross-section. Results are robust to the inclusion of the latter.

Table 6: Racial Inequality and Economic Development (1)

	Dependent variable:			
	GDP per capita (log)			
	(1)	(2)	(3)	(4)
Ratio Racial/Total Income Inequality (log)	-0.048^{***}	-0.039^{***}	-0.040^{***}	-0.041^{**}
	[0.016]	[0.015]	[0.015]	[0.017]
	(0.017)	(0.017)	(0.017)	(0.018)
Ratio Ethnic/Total Income Inequality (log)		−0.018	−0.018	−0.021
		[0.018]	[0.018]	[0.022]
		(0.017)	(0.017)	(0.018)
Spatial Inequality (log) × Time			0.001	0.0004
			[0.005]	[0.006]
			(0.002)	(0.002)
Administrative Inequality (log) × Time			0.003	0.004
			[0.010]	[0.010]
			(0.006)	(0.006)
Racial fractionalization (log)				0.042
				[0.272]
				(0.221)
Racial Segregation (log)				−0.249
				[1.263]
				(0.862)
Ethnic fractionalization (log)				0.048
				[0.106]
				(0.052)
Ethnic Segregation (log)				0.376
				[1.345]
				(0.928)
Num.Obs.	109	109	109	109
R2 Adj.	0.985	0.985	0.985	0.984
R2 Within	0.090	0.104	0.116	0.125
FE: Country	X	X	X	X
FE: Year	X	X	X	X

Notes: Bootstrapped standard errors clustering by country in brackets based on 500 bootstrap replications. Robust standard errors in parenthesis. Spatial and administrative inequality measures from Alesina, Michalopoulos, and Papaioannou (2016). *p<0.1; **p<0.05; ***p<0.01

Table 6 shows the results of the specifications in Equation (9). Column 1 shows that once accounting for country and year fixed effects, a one percent increase in the ratio of racial over total income inequality correlates with a decrease in 4.8 percent of GDP per capita, statistically significant at one percent. Column 2 includes my measures of ethnic inequality as a control to test whether racial-based inequalities are robust to accounting for broad ethnic-based inequalities. The elasticity decreases to 3.9 and remains statistically significant. Column 3 includes Alesina, Michalopoulos, and Papaioannou's (2016) measures of spatial and administrative inequality at the national level. More specifically, given there is one single measure of spatial and administrative inequality and I include country and year fixed effects, I interact the latter measures with the continuous year variable. The elasticity of interest barely changes. Column 4 includes constructed measures of racial and ethnic fractionalization at the country level and racial and ethnic segregation measures using LAPOP data. Overall, the coefficient of racial over total inequality remains statistically significant and increases marginally. The most robust specification implies that a one percent increase in the ratio of racial over total inequality correlates with a decrease of 4.1 percent in GDP per capita.

To test the robustness of the results, Table 9 in the appendix shows the coefficients by using only the (log) MLD between racial group component and controlling for total inequality using MLD total index. The results show that the racial group component drives the negative correlation of the ratio of racial over total inequality and economic development. Table 10 in the appendix includes Alesina, Michalopoulos, and Papaioannou's (2016) measures of ethnic inequality. My measure of racial inequality is robust to accounting for other measures of ethnic inequalities. Thus, rather than ethnic-based inequalities, racial-based inequalities hinder economic development in Latin America.

5.4 Historical Origins of Contemporary Racial Disparities

Lastly, the patterns are also broadly consistent with the historical evidence presented in Section 2. I use the SFD-OB estimates by country and historical data to make an exploratory analysis of the origins of contemporary racial disparities. Figure 15 shows the correlation between the SFD-OB racial gap point estimates from Section 4 and available contemporary and historical data. Panel A shows the share of the population defining themselves as 'Mestiza' or 'Mulata' correlates with a higher racial income gap. Thus, the results suggest that the unexplained component of the racial gap is higher in those countries with high *mestizaje* politics.

Using data on historical population patterns by McEvedy and Jones (1978),[35] Panel B shows countries with higher population density in 1400, namely places where there were pre-colonial societies, also have a higher racial income gap. Panel C shows there is a mild correlation between the share of European descent population (Putterman and Weil 2010) and the contemporary racial gap. Lastly, using Nunns's (2008) data on the share of slave population by 1750, the results suggest that the racial income gap is lower in countries where there was a high share of African slaves by

[35]Taken from Nunn and Puga (2012).

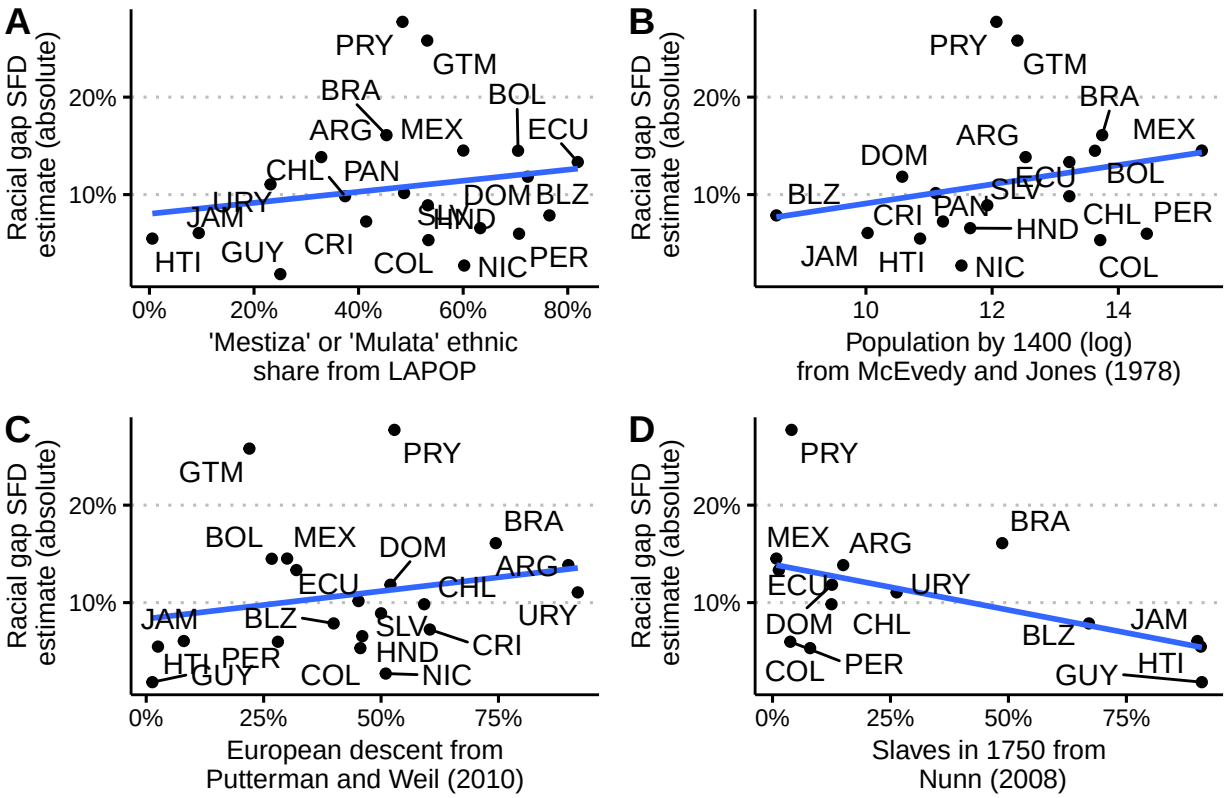

Figure 15: Historical Origins of Racial Disparities

the end of the XVIII century. The latter result is striking, since it suggests that slavery experience actually has fewer effects on contemporary racial disparities in Latin America. When comparing with the correlation with pre-colonial population, it is plausible that contemporary racial disparities were mainly driven by the xploitation of local pre-colonial labor, consistent with Arias and Dirod (2014) hypothesis and results. While the latter correlations are simply descriptive, future work must disentangle convincingly the historical patterns and mechanisms that explain contemporary racial inequality.

6 Conclusion

Racial disparities and discrimination are pending issues to solve globally. In this paper, I study racial inequalities at the individual and national levels in Latin America. Using the PERLA color palette instead of broad ethno-racial categories, I compile a data set of skin tone and income for more than 100,000 individuals in 25 Latin American countries during the last decade. I provide evidence of the welfare consequences of racial disparities at individual and aggregate levels in the region.

In the first part of the paper, I show causal evidence of a sizable income gap by skin tone throughout

the region. Out of the 11 tones in the PERLA color palette, the lower bound estimates show that each increase in a darker skin tone correlates with a decrease of 8 percent in monthly income per capita. Using a research design that purges unobserved heterogeneity and decomposition methods, I prove that nearly two-thirds of the racial gap is due to racial discrimination.

In the second part of the paper, I show that racial inequality, or income inequality between racial groups, hinders economic development at the national level. I compute measures of racial inequality using skin tone rather than broad ethno-racial categories. Firstly, I show that countries with a higher share of *mestizo* or *mulato* population have higher racial inequality. Thus, the *Cosmic Race* has veiled racial inequalities in Latin American countries. Furthermore, controlling for time-invariant characteristics and common-shock across countries, an increase in one percent of the ratio of racial over total income inequality decreases GDP per capita by 4 percent. Inequalities between racial groups have adverse effects on aggregate welfare.

Consistent with the historical and anecdotal evidence, racial discrimination drives the significant income racial gap in Latin America. A relevant shortcoming of the paper is that, given the nature of the data, I cannot disentangle what kind of discrimination drives the racial gap at the individual level: whether it is due to taste-based or statistical discrimination mechanisms Given there is significant heterogeneity country by country, further research needs to disentangle the exact mechanisms operating and explain the racial income gap at the local level.

There is valuable room for public policies. On a purely theoretical perspective, the results suggest that, since skin tone is fixed and there is little room for behavioral responses, taxing alternatives as 'tagging' (Akerlof 1978; Alesina, Ichino, and Karabarbounis 2011; Piketty and Saez 2013) could play an essential role in overcoming racial disparities at early year stages. However, consistent with recent literature (Derenoncourt and Montialoux 2020), the results suggest that progressive income and wealth taxation is also progressive in racial disparities. Moreover, the results highlight the relevance of attenuating racial inequalities to improve aggregate welfare. Alongside its critical role in economic development, there is a historical debt in reducing racial disparities for justice and reparation.

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Appendix

Table 7: LAPOP AmericasBarometer: Sample size by country and wave.

Country	ISO Code	2012	2014	2016/17	2018/19	Total
Mexico	MEX	807	1,434	1,435	1,434	5,110
Argentina	ARG	1,425	1,284	1,421	1,428	5,558
Bolivia	BOL	2,818	2,962	1,552	1,567	8,899
Brazil	BRA		1,455	1,433	1,425	4,313
Chile	CHL	1,416	784	1,540	1,575	5,315
Colombia	COL	1,301	1,400	1,318	1,578	5,597
Costa Rica	CRI	1,338	1,454	1,425	1,396	5,613
Dominican Republic	DOM	1,390	1,457	1,301	1,400	5,548
Ecuador	ECU	1,400	1,351	1,409	1,461	5,621
El Salvador	SLV	48	1,493	1,511	1,318	4,370
Guatemala	GTM	1,304	1,446	1,370	1,434	5,554
Honduras	HND	1,511	1,494	1,445	1,397	5,847
Jamaica	JAM	1,230	1,319	1,262	1,198	5,009
Nicaragua	NIC	1,543	1,519	1,461	1,478	6,001
Panama	PAN	1,532	1,439	1,412	1,422	5,805
Paraguay	PRY		1,429	1,324	1,408	4,161
Peru	PER	1,443	1,417	2,461	1,420	6,741
Uruguay	URY	1,253	1,241	1,432	1,484	5,410
Haiti	HTI	1,126	833			1,959
Belize	BLZ	816	958			1,774
Guyana	GUY	1,079	1,055			2,134
Suriname	SUR	780	1,690			2,470
Trinidad and Tobago	TTO	661	1,478			2,139
Bahamas	BHS		1,618			1,618
Barbados	BRB		1,544			1,544
	Total by wave	26,221	35,554	26,512	25,823	114,110

Table 8: LAPOP AmericasBarometer: Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Age	39.75	15.86	16	27	50	89
Skin tone (PERLA scale)	4.59	1.90	1	3	6	11
Years of schooling	9.83	4.23	0	6	12	18
Monthly Income per capita (PPP 2019)	251.97	297.74	1.22	75.59	314.40	2,955.34
Predicted Income per capita (PPP 2019)	219.15	139.94	0.09	119.02	289.85	808.12
Household size	4.39	2.14	1	3	5	17
Interpersonal trust	2.77	0.91	1	2	3	4
Gender						
Female	0.50	0.50	0	0	1	1
Male	0.0.50	0.50	0	0	1	1
Ethnicity						
Afro	0.12	0.33	0	0	0	1
Indigenous	0.08	0.27	0	0	0	1
Mestiza	0.45	0.50	0	0	1	1
Mulata	0.05	0.22	0	0	0	1
Other	0.07	0.25	0	0	0	1
White	0.23	0.42	0	0	0	1
Occupation						
Actively looking for a job	0.09	0.28	0	0	0	1
Not working and not looking for a job	0.03	0.17	0	0	0	1
Not Working but have job	0.04	0.20	0	0	0	1
Retired	0.08	0.28	0	0	0	1
Studying	0.07	0.26	0	0	0	1
Taking care of the home	0.18	0.39	0	0	0	1
Working	0.50	0.50	0	0	1	1
Marital Status						
Divorced or Separated	0.06	0.24	0	0	0	1
Living together	0.25	0.43	0	0	0	1
Married	0.33	0.47	0	0	1	1
Single	0.32	0.47	0	0	1	1
Widowed	0.04	0.20	0	0	0	1
Urbanization						
Big City	0.17	0.38	0	0	0	1
Medium City	0.16	0.36	0	0	0	1
Small City	0.15	0.36	0	0	0	1
Metropolitan area	0.22	0.41	0	0	0	1
Rural area	0.30	0.46	0	0	1	1
Religion						
Agnostic Atheist	0.02	0.13	0	0	0	1
Catholic	0.56	0.50	0	0	1	1
Evangelical	0.19	0.39	0	0	0	1
Hindu	0.003	0.06	0	0	0	1
Jehovahs Witness	0.01	0.09	0	0	0	1
Jewish	0.001	0.02	0	0	0	1
Mormon	0.004	0.06	0	0	0	1
Muslim	0.002	0.04	0	0	0	1
Non-Christian Eastern Religion	0.02	0.14	0	0	0	1
None	0.10	0.29	0	0	0	1
Other	0.01	0.12	0	0	0	1
Protestant	0.08	0.27	0	0	0	1
Traditional or Native Religion	0.01	0.08	0	0	0	1

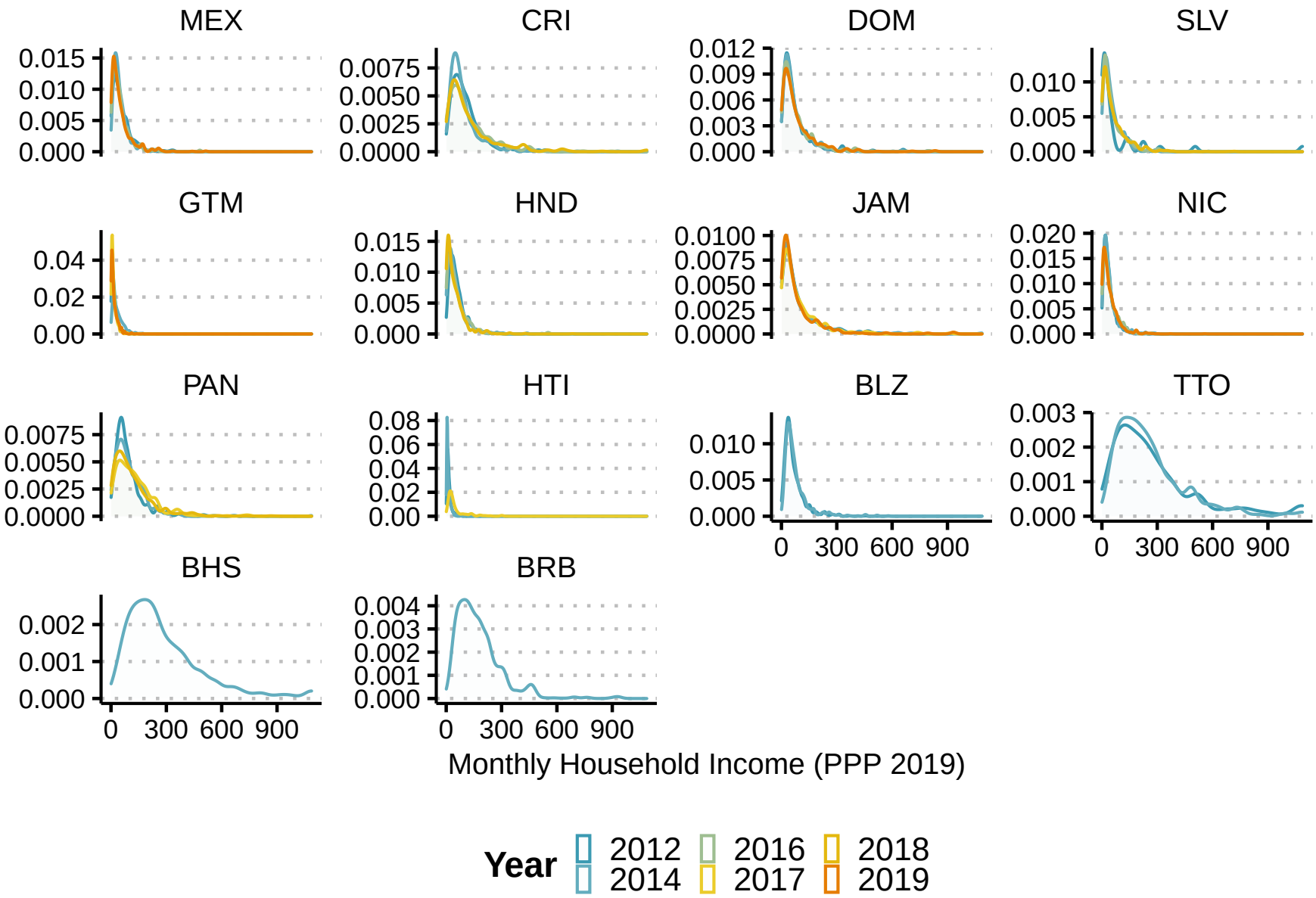

Figure 16: Monthly Household Income distributions by country (1)

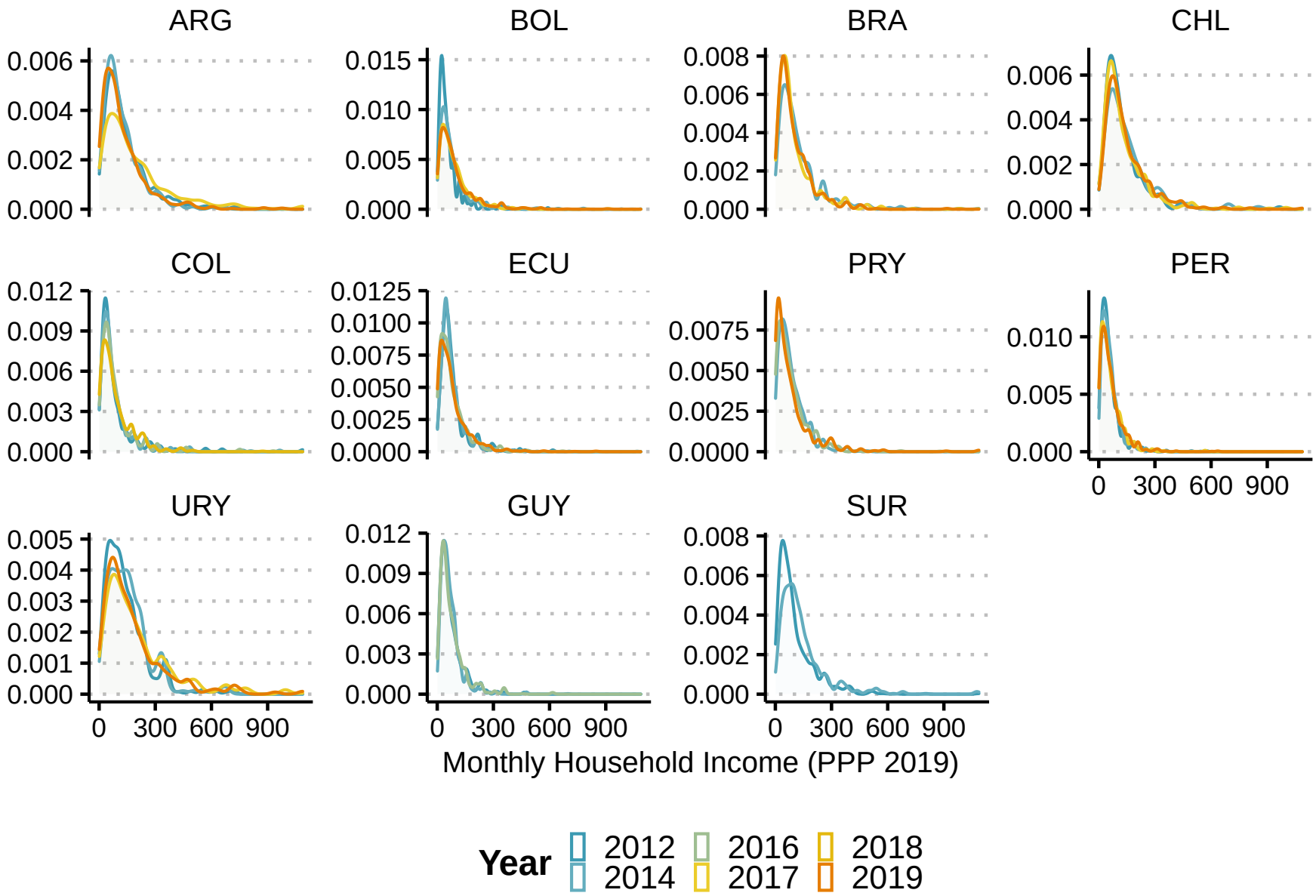

Figure 17: Monthly Household Income distributions by country (2)

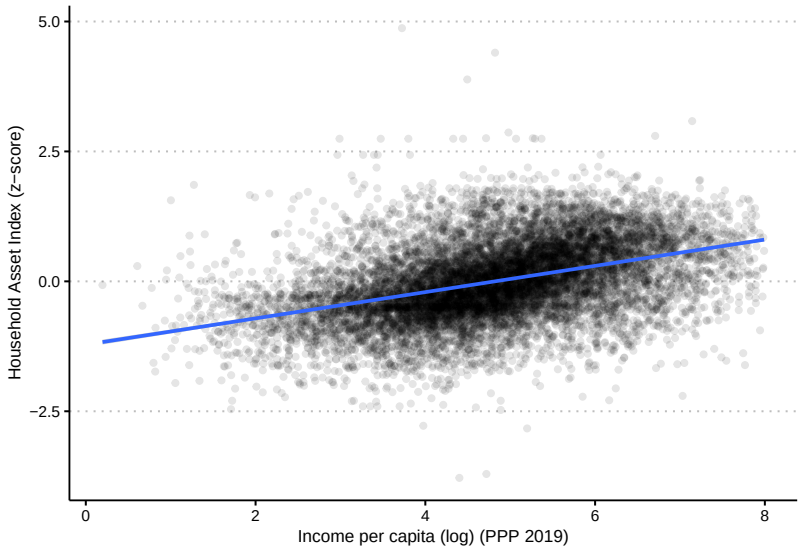

Figure 18: Income and Household Asset Index

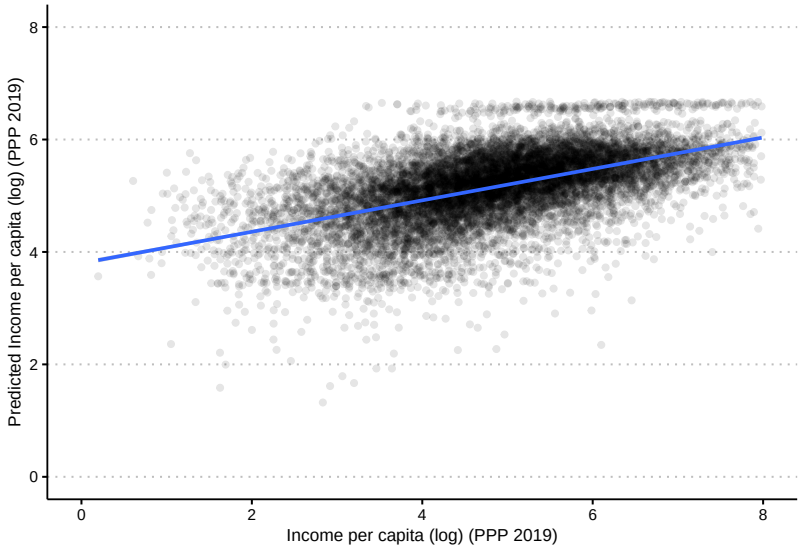

Figure 19: Income and predicted Income

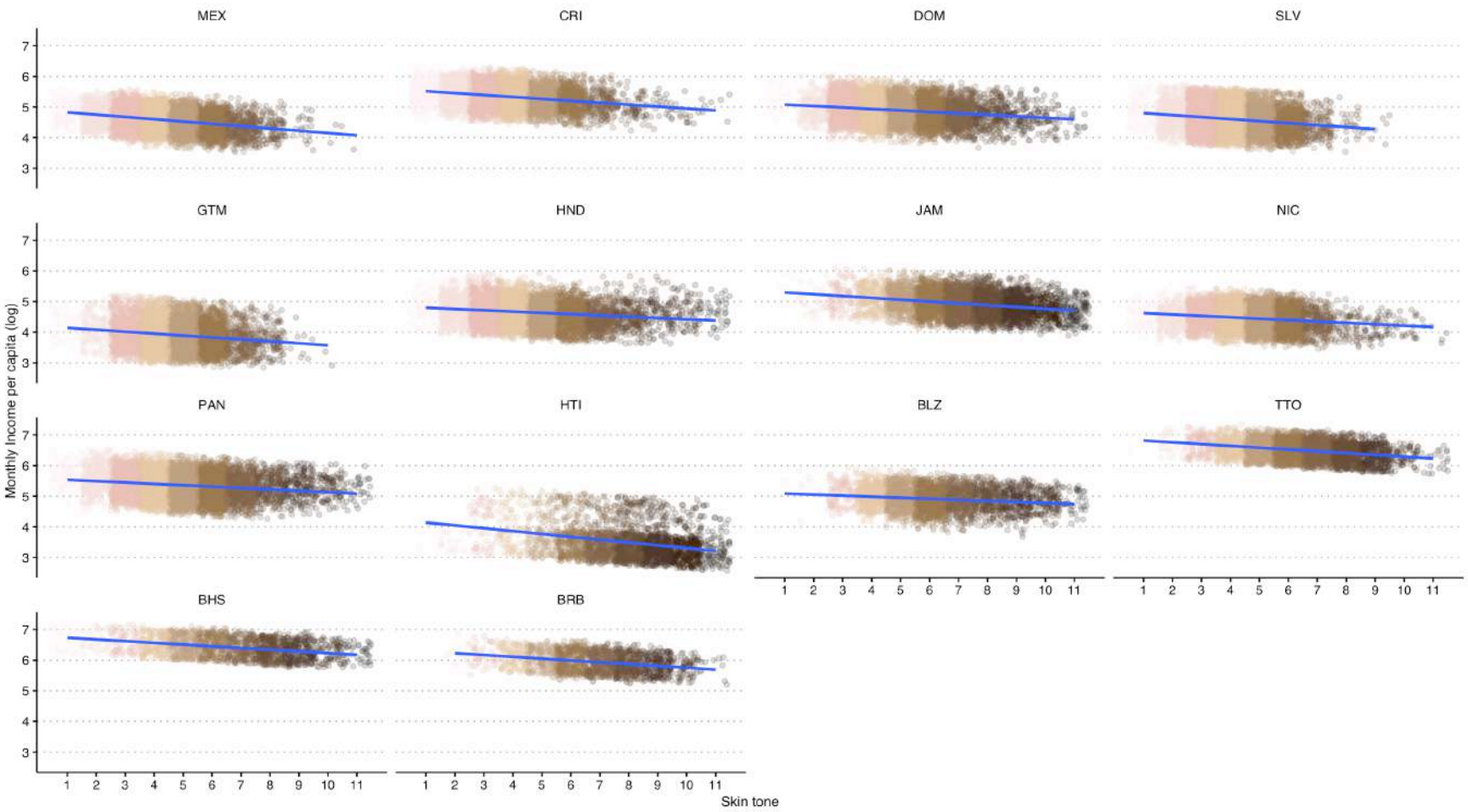

Figure 20: Skin tone gradient for mean monthly income per capita by country (1)

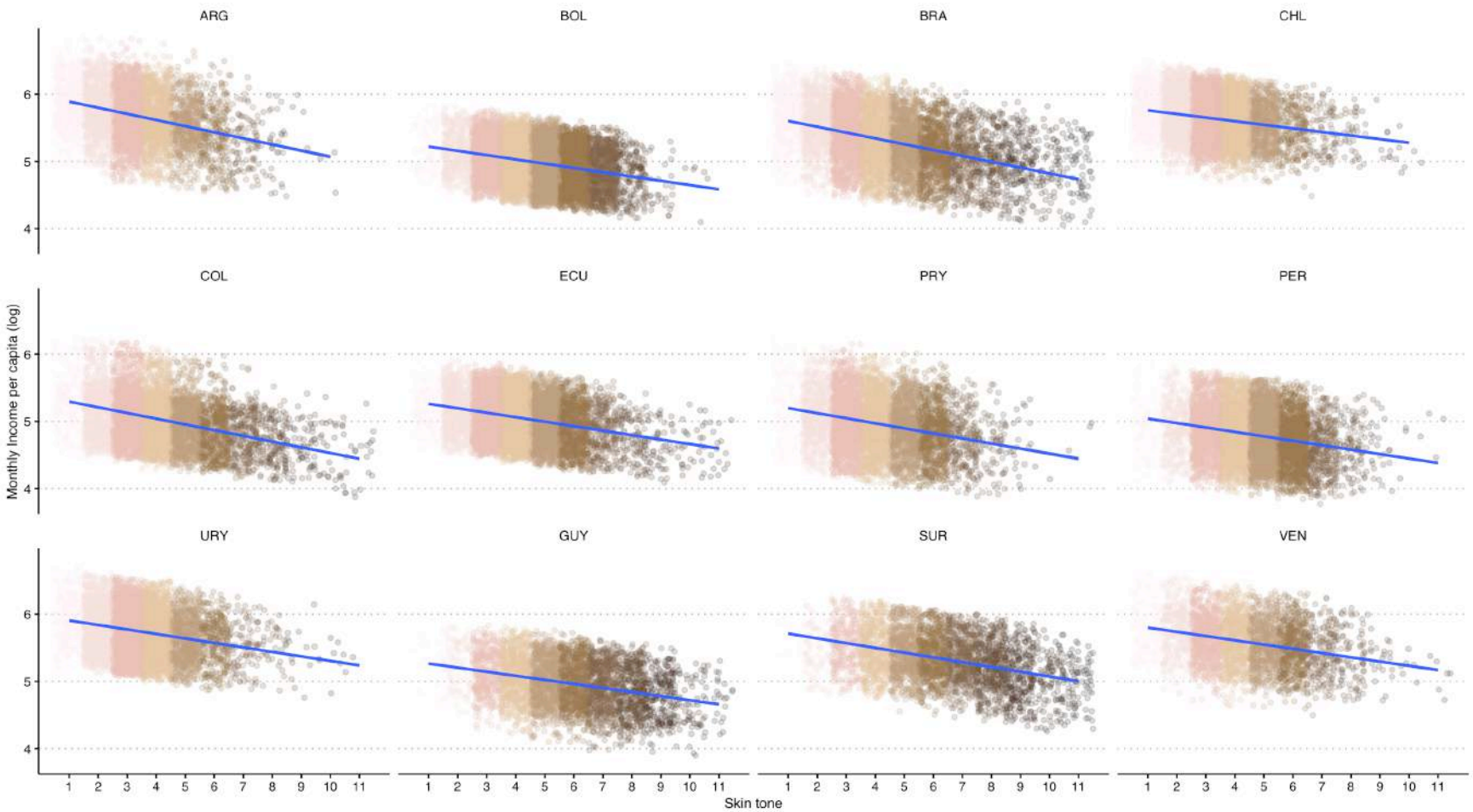

Figure 21: Skin tone gradient for mean monthly income per capita by country (2)

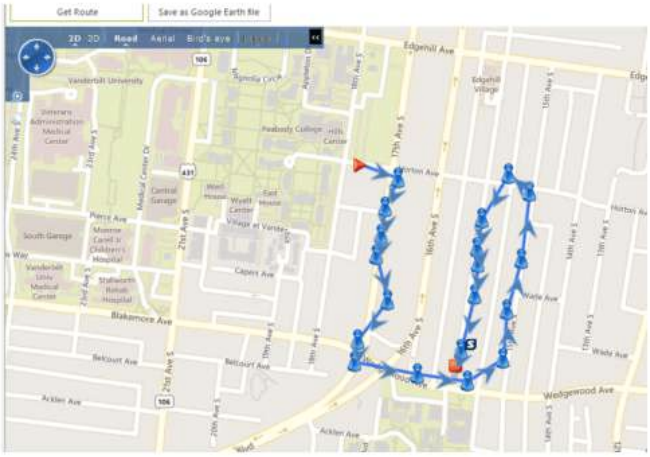

Figure 22: Spatial proximity of LAPOP interviewed units

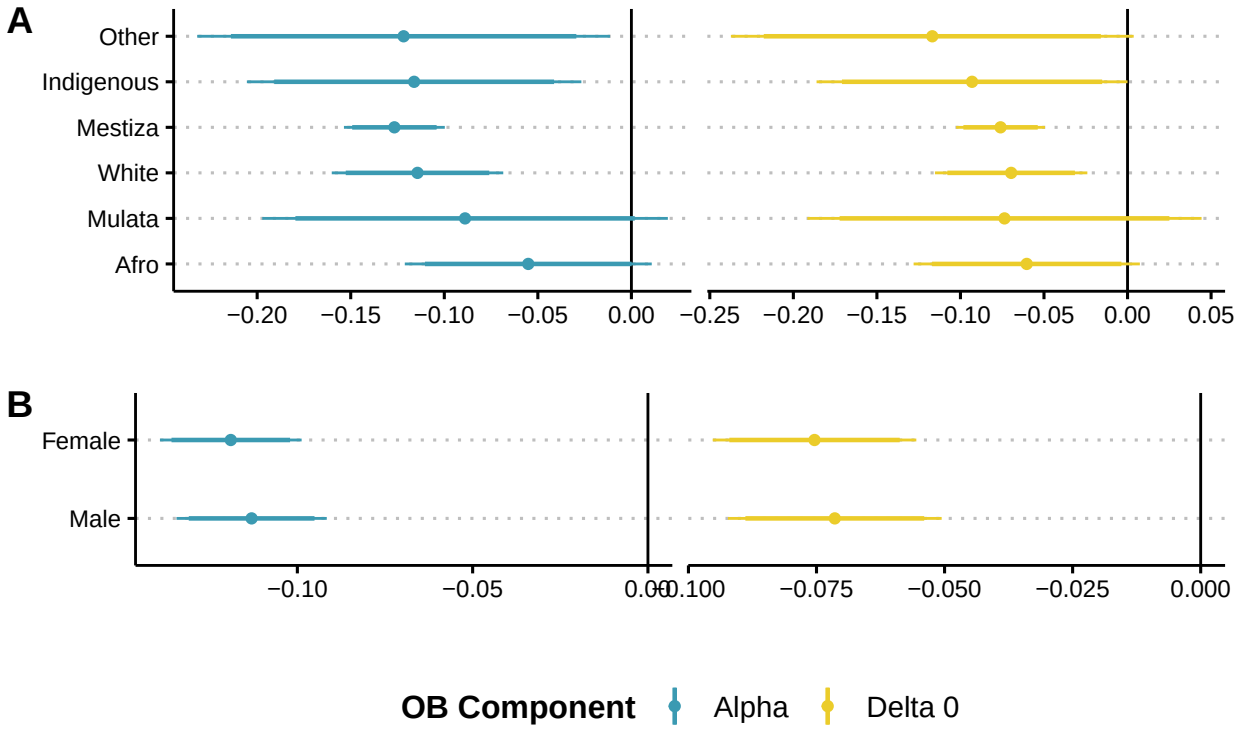

Figure 23: Skin tone effect on predicted income: OB decomposition by gender and ethnicity

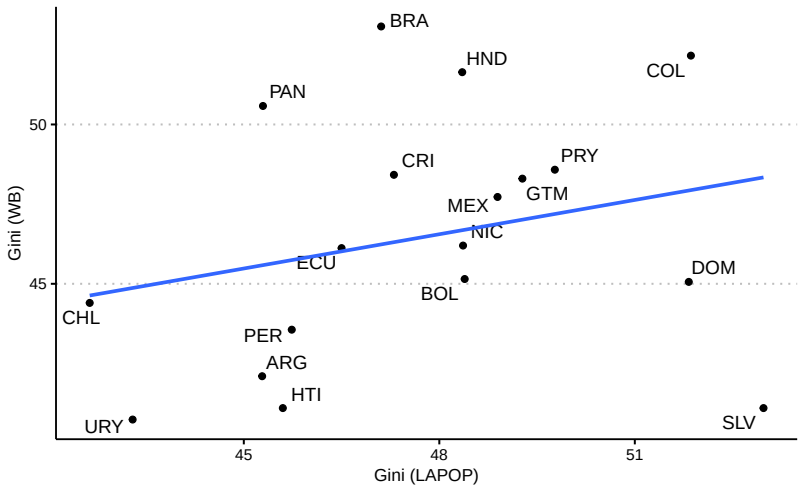

Figure 24: Inequality measures

Table 9: Racial Inequality and Economic Development (2)

	Dependent variable:		
	GDP per capita (log)		
	(1)	(2)	(3)
MLD Total (log)	0.040	0.049	0.052
	[0.069]	[0.076]	[0.086]
	(0.057)	(0.061)	(0.069)
MLD Between Racial groups (log)	-0.048^{***}	-0.040^{***}	-0.041^{**}
	[0.017]	[0.014]	[0.018]
	(0.018)	(0.017)	(0.018)
MLD Between Ethnic groups (log)		−0.018	−0.021
		[0.018]	[0.023]
		(0.014)	(0.016)
Observations	109	109	109
R^2 within	0.089	0.104	0.125
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Bootstrapped standard errors clustering by country in brackets based on 500 bootstrap replications. Robust standard errors in parenthesis. Controls include spatial and administrative inequality measures taken from Alesina, Michalopoulos, and Papaioannou (2016), and LAPOP based indexes of racial and ethnic fractionalization and polarization. *p<0.1; **p<0.05; ***p<0.01

Table 10: Racial Inequality and Economic Development (3)

	Dependent variable:	
	GDP per capita (log)	
	(1)	(2)
Racial/Total Inequality Ratio (log)	-0.049^{**}	-0.051^{**}
	[0.021]	[0.021]
	(0.020)	(0.021)
GREG Ethnic Inequality (log) × Time	0.007	
	[0.016]	
	(0.006)	
Ethnologue Ethnic Inequality (log) × Time		−0.0003
		[0.006]
		(0.002)
Observations	109	109
R^2 within	0.128	0.107
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes

Notes: Bootstrapped standard errors clustering by country in brackets based on 500 bootstrap replications. Robust standard errors in parenthesis. Controls include spatial and administrative inequality, and LAPOP based indexes of racial and ethnic fractionalization and polarization, and spatial and administrative inequality measures taken from Alesina, Michalopoulos, and Papaioannou (2016).
*p<0.1; **p<0.05; ***p<0.01
*p<0.1; **p<0.05; ***p<0.01