

Unraveling perceived discrimination in Latin America and the Caribbean: the intertwined roles of skin color, ethnicity and gender

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Abstract

Latin America and the Caribbean (LAC) is a region characterized by its structural and persistent inequalities. Mounting evidence shows that these inequalities are rooted in ethnoracial hierarchies that have systematically excluded indigenous and Afro-descendant populations. Nevertheless, there is a lack of understanding of how these ethnoracial hierarchies intersect with gender stereotypes and shape experiences of unfair treatment. The current study addresses this gap by investigating how ethnicity, skin color, and gender jointly influence perceived discrimination in LAC, and examining the relationship between perceived discrimination by skin color and by gender across the region. To do this, we employ data from the 2023 Americas Barometers survey and multivariate ordinal regressions, which allow us to simultaneously model multiple dependent variables and the different parts of their correlation. Moving towards darker tones in the skin color palette is associated with higher odds of reporting skin-color discrimination. However, this effect depends on the respondents' ethnic identity; the increase in odds per darker shade is significantly lower in homogeneous groups (self-identified as Black or White) relative to heterogeneous groups like *mestizos*. Regarding gender discrimination, women report higher baseline odds than men. Yet, in certain ethnic groups, moving toward darker skin tones increases the odds of reporting gender discrimination for men, narrowing the gender gap. Finally, our empirical exercises show a strong correlation between the discrimination variables, indicating substantial unobserved overlap and attributional ambiguity. While this dynamic occurs all across the region, we do observe cross-country heterogeneity responding to the historical processes of each country.

Keywords— race, ethnicity, gender, inequality, discrimination

1 Introduction

For more than fifty years, Latin America and the Caribbean (LAC) has been consistently described as one of the most unequal regions in the world (Alvaredo, Bourguignon, Ferreira, & Lustig, 2025; Attanasio, de La O, Ferreira, Ibáñez, & Messina, 2025). Recent literature has highlighted that this inequality is multifaceted, encompassing dimensions such as income (Alvaredo et al., 2025), educational attainment (Fernández, Pagés, Székely, & Acevedo, 2025), health (Bancalari et al., 2025), wealth (Carranza, De Rosa, & Flores, 2025), and land ownership (Gáfaró, Ibáñez, Sánchez-Ordóñez, & Ortiz, 2025). Moreover, these inequalities reinforce one another throughout the life course, creating persistent differences in opportunities and socioeconomic trajectories that might be passed down across generations (Brunori, Ferreira, & Neidhöfer, 2025).

Throughout most of the 20th century, these inequalities were predominantly explained through a class-based lens rather than as the result of ethnoracial discrimination (E. E. Dixon A. R. Telles, 2017; E. E. Telles, 2004). This interpretation was grounded in nation-building narratives of *Mestizaje* (i.e., miscegenation) in countries such as Mexico and Brazil, which portrayed racial mixing as evidence of social inclusion. As a result, the disadvantages experienced by Afro-descendant and Indigenous populations were largely attributed to the intergenerational legacy of poverty and inequality rooted in colonial labor systems, leaving little room for open debate about contemporary racism.

However, a growing body of research has called this into question, indicating that discrimination is a key driver of these ethnoracial gaps (E. Telles & Bailey, 2013; E. E. Telles, Bailey, Davoudpour, & Freeman, 2025). The incorporation of ethnoracial indicators, including self-identified ethnicity and interviewer-rated skin color (E. Telles & Flores, 2013), into national censuses and surveys has backed extensive research showing that a large part of LAC functions as a *pigmentocracy* (Lipschutz, 1944), where social hierarchies are determined by ethnicity and skin color (see e.g. Castillo and Salgado (2026); Gómez-Echeverry (2024); Krozer and Gómez (2023); Painter II, Noy, and Holmes (2020); Perreira and Telles (2014); Sanchez, Doherty, and Dobbs (2021); E. Telles, Flores, and Urrea-Giraldo (2015); Torres, Salgado, Mackerna, and Núñez (2019); Woo-Mora (2026)).

Importantly, there is also evidence that the disadvantages experienced by ethnoracial minorities can be notably different for men and women. In LAC, Ñopo (2012) finds that ethnic and gender disadvantages compound, as gender wage gaps are particularly pronounced in indigenous and Afro-descendant communities. Taş, Reimão, and Orlando (2014) found similar intersectional patterns in education across Bolivia, Mexico, Peru, Senegal, and Sierra Leone. This pattern is not unique to the LAC region; while studying gender and ethnic wage gaps in China, Ma (2025) documents a comparable double penalty particularly severe for high-earning groups. Similarly, there is evidence of the gendered nature of ethnoracial stratification when considering migration status, where Piazzalunga (2015), Sprengholz and Hamjediers (2024) and Nagayoshi

(2024) find that immigrant women’s integration experience is shaped by the joint effects of their gender and nationality, producing wage outcomes that cannot be explained by either of these characteristics alone.

However, effectively identifying discrimination and disentangling the experience and perceptions of its perpetrators and victims is remarkably challenging. Discriminatory behavior frequently arises from the interplay of several personal attributes such as ethnicity, race, gender, or class. For instance, the effect of skin tone on perceived discrimination has been shown to depend on individuals’ gender (Dias, 2020) and ethnic self-identification (Canache, Hayes, Mondak, & Seligson, 2014; Layton & Smith, 2017). This implies that people cannot always accurately discern the origin of the discriminatory treatment they face; discrimination rooted in skin color is frequently perceived as gender-based discrimination (Layton & Smith, 2017) or as discrimination based on social class (A. R. Dixon, 2019). Consequently, distinct forms of perceived discrimination may overlap and blur, making it hard to separate their forms and catalysts.

This paper aims to shed light on the complex mechanisms underlying discrimination in LAC countries. It has two main objectives. First, it analyzes how gender, skin color, and ethnicity are connected to perceived discrimination based on skin color and gender. Second, it explores the relationship between perceived skin-color discrimination and perceived gender discrimination. To do so, we employ a multivariate ordinal regression model (Hirk, Hornik, & Vana, 2020) to study these different forms of perceived discrimination. This framework enables us to estimate both outcomes simultaneously, incorporate their correlation, and investigate whether the strength of their association varies across countries.

The remainder of this paper is organized as follows. Section 2 surveys the literature on the links between gender, skin color, and ethnicity and perceived discrimination, and examines how these relationships differ across national and institutional settings. Section 3 introduces the data, reports descriptive statistics, and details the empirical strategy. Section 4 presents and interprets the findings from the multivariate ordinal regression exercises. Finally, Section 5 concludes and situates the main results within the existing literature.

2 Discrimination in LAC

Discrimination refers to the unequal, unfair, or prejudicial treatment of individuals or groups on the basis of personal characteristics such as color, ethnicity, and gender (A. R. Dixon, 2019). Research on how multiple characteristics jointly shape discrimination distinguishes between *additive*, *amplified*, and *muted* effects (Pedulla, 2018). Although originally developed to explain how race and unemployment status jointly affect labor market discrimination, this framework provides a useful descriptive lens for considering how other personal characteristics may combine.

Additive effects occur when characteristics operate independently, such that belonging to multiple disad-

vantaged groups increases discrimination without changing the effect of the other characteristic. This would, for example, imply that women and darker-skinned individuals experience more discrimination, while the association between skin color and discrimination remains similar for men and women. Amplified effects occur when characteristics reinforce one another, so that their combined effect is greater than expected from their separate effects. This idea is closely related to intersectionality scholarship, which emphasizes that systems of disadvantage can intersect in ways that create experiences that cannot be understood by considering each characteristic separately (Collins, 2004; Crenshaw, 1997). An amplified effect would, for example, imply that darker skin is associated with a particularly strong disadvantage among women.

Muted effects, by contrast, occur when characteristics convey overlapping social information, reducing the additional relevance of one characteristic once another is known (Pedulla, 2018). This mechanism may be particularly relevant to ethnicity and skin color. Ethnoracial background can be communicated through characteristics such as language, accent, dress, or religious practices, meaning that skin tone may provide relatively little additional information when group membership is already strongly signaled. For example, the use of an Indigenous language may function as a salient marker of Indigenous identity independent of skin tone.

2.1 Perceived discrimination in LAC

While additive, amplified, or muted effects are developed to explain differences in discriminatory treatment itself, we use them to explain *perceptions* as discrimination. In contrast to discriminatory treatment, perceived discrimination involves at least two distinct processes: individuals must first determine whether an experience constitutes discrimination and, if so, attribute the reason, or reasons, for this discrimination (A. R. Dixon, 2019). Both processes introduce ambiguity between discriminatory treatment and reported perceptions of discrimination.

The first concerns whether unequal treatment is recognized as discrimination at all. Members of disadvantaged groups may face *attributional ambiguity*: unfavorable treatment can be interpreted as resulting from an irrelevant personal characteristic, but also from characteristics of the individual or situation that are unrelated to discrimination. Sociocultural norms may further shape whether discriminatory experiences are recognized and reported as such. For example, narratives such as the “Strong Black Woman” or “Superwoman” schemas may encourage women of color to emphasize resilience and self-reliance, potentially affecting whether adverse experiences are interpreted or reported as discrimination (P. Q. Yang, 2021; P. Q. Yang & Henderson, 2024). Consequently, differences in perceived discrimination between social groups need not map directly onto differences in the amount of discriminatory treatment they experience.

A second source of ambiguity concerns the perceived cause of discrimination. Even when an encounter is recognized as discriminatory, individuals may have difficulty identifying which personal characteristic triggered the treatment (A. R. Dixon, 2019). This attributional problem may be particularly relevant in LAC, where narratives of racial democracy and *Mestizaje* have historically blurred the boundaries between race, class, and other dimensions of inequality. As Layton and Smith (2017, p. 55) argue, “skin tone makes individuals vulnerable to poor treatment not just in explicitly racial situations but in scenarios in which even participants see class or gender as the likely explanation for poor treatment”.

Evidence for such misattribution has been documented for class and color. A. R. Dixon (2019) shows that darker-skinned individuals report higher levels of perceived class discrimination even after wealth is taken into account, whereas lower socioeconomic status is not associated with greater perceived color discrimination once skin color is held constant. This asymmetry suggests that discriminatory experiences associated with skin color may sometimes be interpreted through a class-based lens, reflecting the influence of dominant narratives of *Mestizaje* that obscure the role of race. Furthermore, (A. R. Dixon, 2019, p. 45) argues that “future work should also examine other forms of discrimination and how these overlap.” In particular, she highlights gender-based discrimination as a promising avenue, noting that “the importance of gender in *Mestizaje* ideologies has not had the same salience in colloquial or scholarly conversations given the focus on class and color.”

Evidence from Brazil suggests that perceived gender discrimination cannot be understood in terms of gender alone. Layton and Smith (2017) finds that skin color is also strongly associated with perceived gender discrimination: the difference between individuals with the lightest and darkest skin tones exceeds the overall difference between men and women, while the combination of being female and having darker skin further increases perceived gender discrimination. These findings indicate that the characteristic to which discrimination is attributed does not necessarily correspond to the only characteristic shaping the discriminatory experience.

A similar complexity applies to perceived skin-color discrimination. Unsurprisingly, darker-skinned individuals generally report higher levels of perceived color discrimination (Hersch, 2011; Nichols, 2013; Perreira & Telles, 2014). Yet, the form that color-based disadvantage takes may differ between men and women. Research suggests that some forms of racial discrimination disproportionately affect men, whereas others are more salient for women (Harnois & Ifatunji, 2011). Women of color, for example, may be sexualized or evaluated against racialized beauty standards (Collins, 2004; Wade, 2010b). In LAC in particular, lighter skin is more strongly associated with attractiveness among women than among men (Figueroa, 2013; Figueroa & Moore, 2013), and women are more likely to engage in practices such as skin lightening or hair modification in response to appearance-based inequalities (Figueroa, 2013; Lewis et al., 2013). Men of color, by contrast,

are more often subjected to stereotypes portraying them as aggressive, criminal, or hypersexual (Collins, 2004). Gender may therefore shape both the forms of color-based discrimination individuals encounter and how those experiences are perceived.

In addition to gender and skin color, ethnicity may independently shape perceived discrimination. Although race and ethnicity are sometimes used interchangeably, they capture different dimensions of social position. In this paper, skin color is treated as an indicator of race (see E. E. Dixon A. R. Telles (2017) for a detailed discussion of the relationship between race and skin color), whereas ethnicity refers to individuals' self-identification. Ethnic identification is shaped by social and psychological processes and does not necessarily correspond to visible characteristics. Skin color, by contrast, is immediately observable and can strongly influence how individuals are categorized by others. Because discriminatory treatment frequently depends on external classification, visible characteristics may have consequences that differ from those associated with self-identification (Sanchez et al., 2021).

This distinction is particularly important in LAC, where racial categories are fluid and the boundaries between ethnicity and color are often blurred across regions and over time (Gómez-Echeverry, 2024). Broad ethnic categories can contain considerable phenotypic diversity, particularly among groups such as Mestizos and Indigenous populations (Woo-Mora, 2026). Empirical research accordingly shows that ethnicity and skin color independently contribute to perceived discrimination. Individuals identifying as White generally report lower levels of discrimination than those identifying as Indigenous, Black, or Mulato, while darker skin is associated with more perceived discrimination even among respondents sharing the same ethnoracial identity (Canache et al., 2014). Thus, relying on either self-identified ethnicity or skin color alone may obscure important dimensions of ethnoracial discrimination (Roth, 2010).

Taken together, these arguments highlight the complexity of studying perceived discrimination. Researchers examining perceived discrimination need to account for two distinct sources of ambiguity. First, individuals may differ in whether unequal treatment is recognized and reported as discrimination at all. This makes additive, amplified, and muted effects more difficult to interpret than in research on discriminatory treatment, because observed differences may reflect not only differences in treatment but also differences in the recognition or reporting of discrimination across groups. A muted effect, for example, may arise because a marginalized group is less likely to recognize or report discriminatory experiences rather than because the additional discriminatory effect of a particular characteristic is genuinely smaller. Second, even when unequal treatment is recognized as discrimination, individuals may be uncertain about the characteristic to which it should be attributed. Consequently, the personal characteristic associated with discriminatory treatment need not correspond to the form of discrimination that is reported: skin color may, for instance, contribute to experiences reported as gender discrimination. Examining multiple personal characteristics alongside mul-

multiple forms of perceived discrimination therefore allows us to assess both how characteristics jointly relate to reported discrimination and the extent to which different forms of perceived discrimination overlap in their underlying correlates.

2.2 LAC context

Mestizaje played a crucial role in the foundational narratives of several countries of LAC, with the most notorious examples being Vasconcelos’ *cosmic race* in México and Freyre’s *racial democracy* in Brazil. These miscegenation frameworks portrayed their nations as inclusive and harmonious societies in which racial prejudices were virtually nonexistent. However, it has been consistently shown that these narratives have not effectively materialized in social inclusion. Instead, *Mestizaje* schemes have obscured the root of ethnoracial disparities by framing them as the sole consequence of class stratification (A. R. Dixon, 2019; E. Telles & Flores, 2013; Wade, 2010a). Nonetheless, the ethnoracial narratives have been far from homogeneous across LAC. Countries like Argentina, Uruguay, and Costa Rica have adopted models similar to the United States, pursuing *blanqueamiento* (whitening) policies where European immigration was actively promoted while simultaneously invisibilizing Indigenous and Afro-descendant communities.

Importantly, regardless of whether centered around the mixture or separation of ethnoracial groups, the ideological projects in the region were profoundly gendered. Mestizaje narratives, for their part, often categorized indigenous and Afro-descendant women as vessels of miscegenation while European women embodied ideals of purity and beauty (Montecino, 1996; Wade, 2010b). Similarly, *blanqueamiento* ideologies placed whiteness as a feminine ideal, linking lighter skin with not only beauty but also with being cultured and moral (Figueroa, 2013).

3 Data and Methodology

3.1 Data

For the analyses, we used the 10th wave of the Americas Barometer from the Latin American Public Opinion Project (LAPOP). This survey data includes information from 26 countries of the Americas collected between January and August 2023. The survey’s sample design treated voting-age adults as the universe and ensured national and regional representativeness through a stratified multi-stage cluster sampling design (LAPOP, 2023). The samples in each country were stratified by municipality size, urban/rural area, and region. Within each selected household, the interviewers surveyed a unique respondent, provided they met the age requirements, thereby ensuring an equal distribution between genders at the national level.

In addition to measures of public preferences and behavior, the LAPOP 2023 wave included two variables related to perceived discrimination, self-reported ethnicity and gender, and an external skin color assessment. For the discrimination variables, respondents were asked “*Thinking about the last five years, have you ever felt discriminated against or have you been badly or unjustly treated?*” in relation to their skin color and their gender or sex. There were four possible answers to these two questions: “*Never*”, “*A few times*”, “*Sometimes*”, and “*Many times*”. The skin color was reported by interviewers after the survey’s implementation, using an 11-point color palette as originally introduced in the Project on Ethnicity and Race in Latin America (PERLA) (E. Telles et al., 2015). Ethnicity was captured as a categorical variable, and extra customized response categories were included in each country to encompass the ethnoracial diversity within each region. To maintain comparability across countries, we limit ourselves to the core ethnoracial categories including “*Blanca*”, “*Mestizo*”, “*Indígena*”, “*Negra*”, “*Mulato*”, and “*Otra*”. The extra response categories were recoded as “*Indígena*” or “*Otra*” when needed (e.g., *Maya Yucatec* was recoded as “*Indígena*” and *Hindú* as “*Otra*”). To see the full recoding process of this variable, refer to the [GitHub repository](#), where the code for all the analyses can be found. Finally, gender was recorded as a categorical variable with three possible responses, including “*Man/Male*”, “*Woman/Female*”, and “*Does not identify as either man or woman*”. Since respondents in the latter group accounted for only 0.8% of the sample, and to simplify the analyses, we recoded gender as a dichotomous variable with $Gender = 1$ when the respondent was female and $Gender = 0$ when the respondent was male. Our final sample comprised 32,557 observations, clustered in 21 countries in LAC. The final sample did not include Canada and the United States, as they are not part of the LAC region, nor Nicaragua, Costa Rica, or Haiti due to a lack of information on the key variables under study.

3.2 Descriptive Statistics

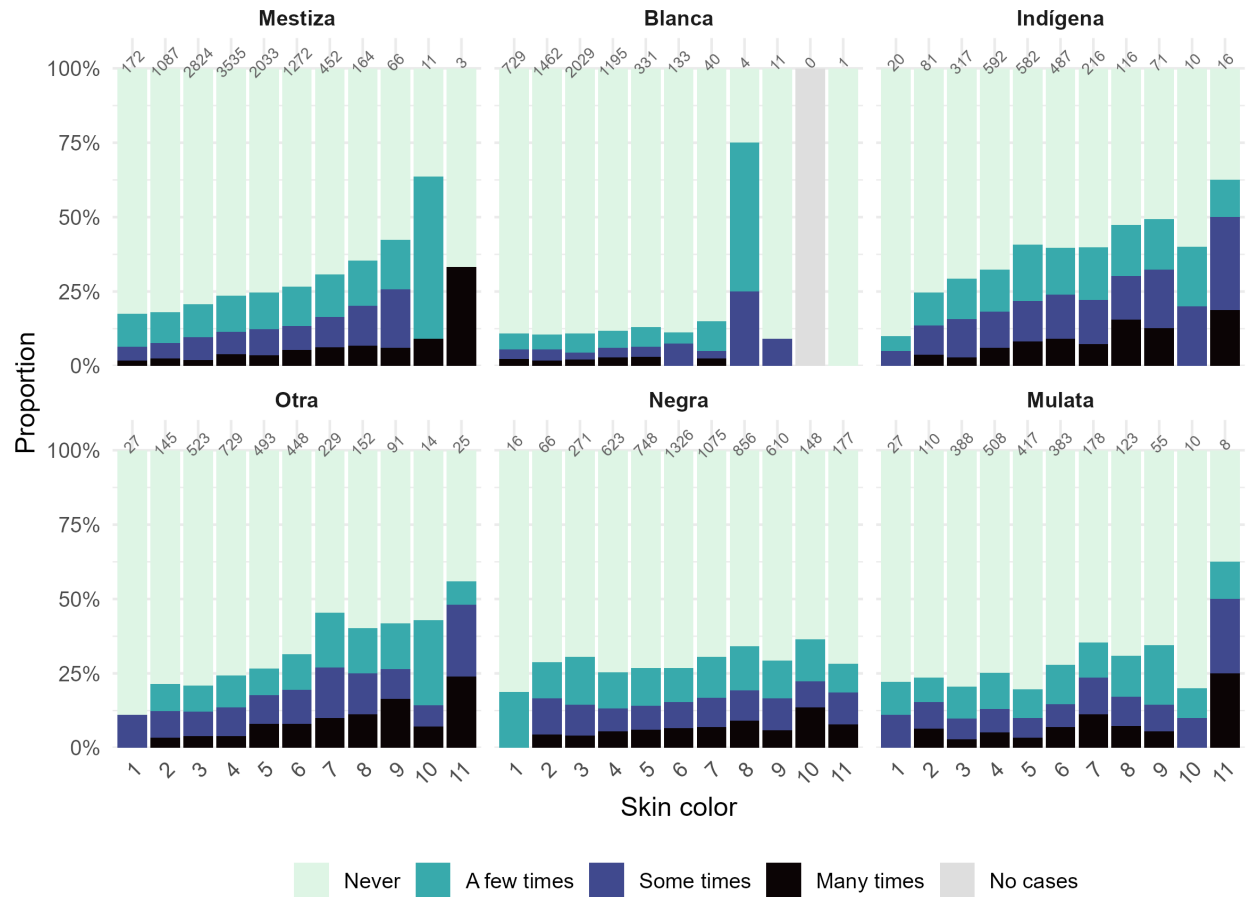
[Figure 1](#) decomposes the perceived discrimination due to skin color in panel (a) and gender in panel (b). Panel (a) shows how perceived discrimination based on skin color varies by ethnic self-identification and the PERLA color palette. Noticeably, with the exception of people identifying as *Negra* or *Blanca*, there is an upward trend where individuals with darker skin tones perceive higher discrimination than other people with lighter skin tones within the same ethnic group. In contrast, there is little to no variation across the PERLA color palette within the individuals self-categorized as *Negra* and *Blanca*, with the former group showing only a sudden peak at the 8th step of the color palette because of the few cases observed in this ethno-racial combination. In turn, panel (b) of [Figure 1](#) breaks down the perceived discrimination based on sex/gender by the respondent’s gender and ethnicity. This panel indicates that, regardless of their ethnic self-identification, women perceive more discrimination due to their sex/gender than men. For both women and men, the ethnic

group with the largest reports of gender-based perceived discrimination is the *Indígena*.

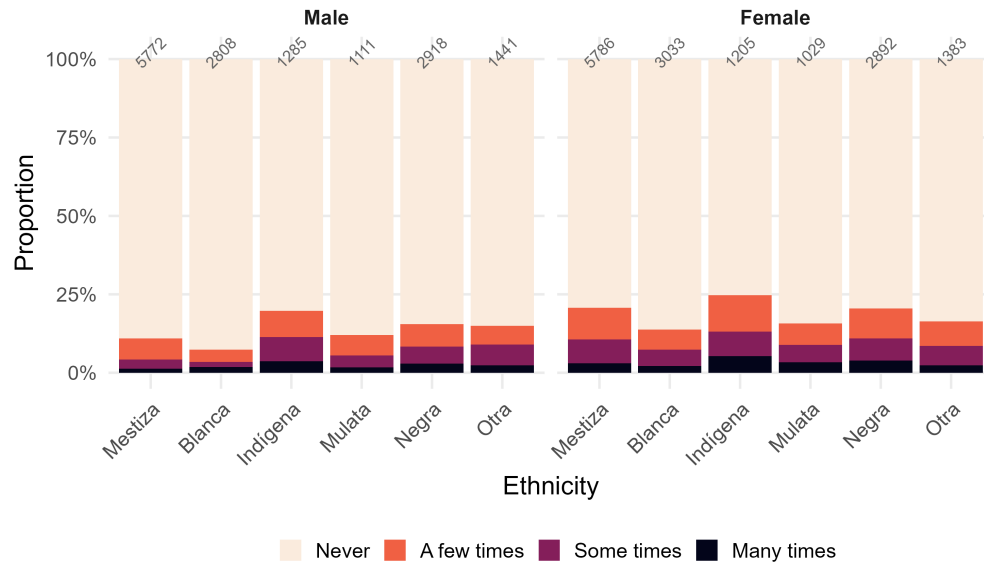
Figure 2 shows tile plots with contingency tables per country comparing the perceived discrimination by skin color, on the vertical axis, to the perceived discrimination by sex/gender on the horizontal axis. The percentages in every plot are calculated by row and represent the proportion of respondents in each category of sex/gender-based perceived discrimination conditional on the experienced discrimination by skin color. Across all the countries in Figure 2, the tile plots share a visual pattern defined by a dominant column on the left and a nearly empty lower-right triangle. The dark column on the left implies that, regardless of their experiences based on skin color, the vast majority of respondents report never perceiving discrimination based on their sex/gender. However, this column fades while moving from the bottom to the top, indicating that as the frequency of perceived skin color discrimination increases, respondents are substantially more likely to report concurrent sex/gender discrimination. In turn, the light lower-right triangle implies that individuals who have not perceived being discriminated against by skin color are unlikely to report being discriminated against by sex/gender, and that perceived discrimination by sex/gender is rarely more frequent than perceived discrimination by skin color.

Besides the general patterns aforementioned, Figure 2 also shows heterogeneity across countries, as evidenced by individuals who have perceived being discriminated against many times. Thus, in countries like Uruguay, respondents are distributed mainly between two groups: one that has never experienced gender discrimination, regardless of whether they have experienced color discrimination, and another one where the two types of discrimination coincide in frequency. In contrast, for countries like Peru, knowing whether a person has perceived skin color discrimination many times cannot be immediately translated into equally frequent perceived discrimination by sex/gender, as the probabilities that it happened only a few times or some times are not negligible.

Lastly, Table 1 presents the descriptive statistics of the LAPOP 2023 data, using the corresponding sampling weights. We see that the sample is, in its majority, rural (68%) residents, with secondary education (32%). The average respondent's skin color according to the PERLA palette is 4.53, virtually indistinguishable from that of the interviewers (4.45). Confirming the strong effect of the Mestizaje narrative present in the region, the majority of the respondents self-identify as either *Mestiza* (37%) or *Blanca* (19%). Regarding the employment status, Table 1 shows that around half of the sample is employed (52%), while 12% and 15% are actively looking for a job or dedicated to the household, respectively. The remaining part of the sample is either studying, retired, or not working and not actively looking for a job.



(a) Discrimination by skin color over ethnicity



(b) Discrimination by skin color over gender

Figure 1: Perceived discrimination based on (a) skin color and (b) gender

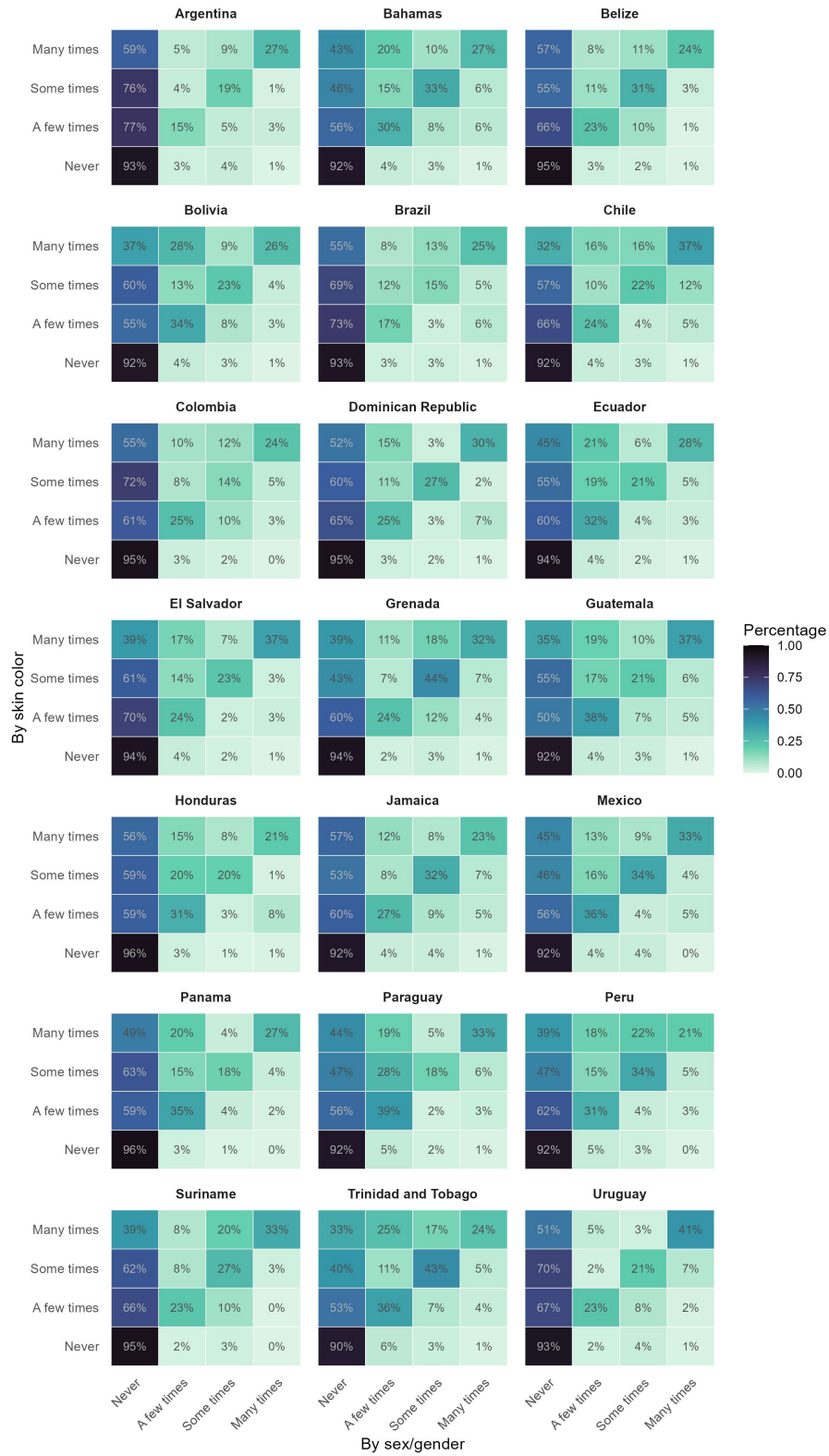


Figure 2: Perceived discrimination by sex/gender conditional on perceived discrimination by skin color

Variable	N	Mean	SD	Min	Max
Age	32,557	40.44	16.52	16	96
Number of household members	32,404	4.10	2.17	1	25
Numbers of children under 13 in the household	32,449	0.97	1.23	0	16
Respondent's skin color	32,500	4.53	1.97	1	11
Interviewer's skin color	32,460	4.45	1.73	1	11
Gender	32,055			1	2
<i>Male</i>	15,954	0.50			
<i>Female</i>	16,101	0.50			
Ethnicity	31,112			1	6
<i>Mestiza</i>	11,636	0.37			
<i>Blanca</i>	5,947	0.19			
<i>Indígena</i>	2,520	0.08			
<i>Mulata</i>	2,212	0.07			
<i>Negra</i>	5,919	0.19			
<i>Otra</i>	2,878	0.09			
Residence	32,557			1	2
<i>Rural</i>	22,097	0.68			
<i>Urban</i>	10,460	0.32			
Educational level	32,369			1	7
<i>Secondary complete</i>	10,225	0.32			
<i>None</i>	790	0.02			
<i>Primary incomplete</i>	3,142	0.10			
<i>Primary complete</i>	4,019	0.12			
<i>Secondary incomplete</i>	5,595	0.17			
<i>Tertiary incomplete</i>	3,454	0.11			
<i>Tertiary complete</i>	5,144	0.16			
Income ranges	28,386			1	15
<i>01</i>	3,215	0.11			
<i>02</i>	3,089	0.11			
<i>03</i>	3,019	0.11			
<i>04</i>	2,722	0.10			
<i>05</i>	2,372	0.08			
<i>06</i>	1,900	0.07			
<i>07</i>	1,878	0.07			
<i>08</i>	1,843	0.06			
<i>09</i>	1,527	0.05			
<i>10</i>	1,381	0.05			
<i>11</i>	1,010	0.04			
<i>12</i>	1,140	0.04			
<i>13</i>	1,040	0.04			
<i>14</i>	952	0.03			
<i>15</i>	1,298	0.05			
Employment status	32,365			1	7
<i>Employed, Working</i>	15,026	0.46			
<i>Employed, Not working</i>	1,891	0.06			
<i>Actively looking for a job</i>	4,001	0.12			
<i>Student</i>	2,156	0.07			
<i>Dedicated to Household</i>	4,969	0.15			
<i>Retired or unable to work</i>	2,872	0.09			
<i>Not working and not looking for a job</i>	1,450	0.04			

Table 1: Descriptive statistics

3.3 Methodology

Since our outcomes are two correlated ordinal variables, we employ the multivariate ordinal regression model introduced by [Hirk, Hornik, and Vana \(2019\)](#) to evaluate corporate credit ratings. Under this model, the observed ordinal responses Y_{ij} for subject i in the outcome j is assumed to arise from an underlying latent variable Y_{ij}^* according to the following mechanism:

$$Y_{ij} = r_{ij} \Leftrightarrow \tau_{j,r_{ij}-1} \leq Y_{ij}^* \leq \tau_{j,r_{ij}}, \quad (1)$$

where $j \in J = \{s, g\}$ indexes the set of perceived discrimination variables (i.e., Y_{is} for skin color discrimination and Y_{ig} for gender discrimination). The term $r_{ij} \in \{1, \dots, R_j\}$ denotes the observed response category of respondent i to item j , and $\boldsymbol{\tau}_j = (\tau_{j,r_0}, \dots, \tau_{j,R_j-1})^\top$ is a vector of suitable threshold parameters specific

to the outcome j , such that $-\infty \equiv \tau_{j,r_0} < \tau_{j,r_1} < \dots < \tau_{j,R_j-1} \equiv \infty$. Additionally, let $D_{is} = (\tau_{s,r_{is}-1}, \tau_{s,r_{is}}]$ and $D_{ig} = (\tau_{g,r_{ig}-1}, \tau_{g,r_{ig}}]$ be the threshold ranges corresponding to the perceived discrimination by skin color and gender, respectively.

The relationship between the unobserved variable, Y_{ij}^* , and the independent variables, $\mathbf{x}_{ij}$, is given by a linear function of the form:

$$Y_{ij}^* = \beta_{j0} + \mathbf{x}_{ij}^\top \boldsymbol{\beta}_j + \varepsilon_{ij}, \quad (2)$$

where β_{j0} is the outcome-specific intercept, $\mathbf{x}_{ij}$ is a vector of explanatory variables, $\boldsymbol{\beta}_j$ their corresponding regression coefficients, and ε_{ij} the idiosyncratic error term. For all the estimated models, we employ the default identification employed in the `mvord()` package in R by setting the intercept to zero ($\beta_{0j} = 0$) and fixing the error variances to 1 ($\sigma_{ij} = 1$), allowing all threshold parameters to be freely estimated.

Similar to univariate ordinal regression, there are multiple ways of specifying the joint distribution of the error vector, $\boldsymbol{\varepsilon}_i = (\varepsilon_{is}, \varepsilon_{ig})^\top$, when using multivariate ordinal models. Typical specifications rely on multivariate normal errors (multivariate probit) or multivariate logistic extensions. However, for these specifications, the joint distributions impose restrictions on the error correlation matrix, and variables are assumed to be correlated only at the mean, ignoring their relationship at the extremes of their distribution (i.e., no tail dependence). This matters to us because we want to be able to detect whether respondents reporting high discrimination on one dimension are disproportionately likely to do so on the other as well. Thus, we use the t -copula multivariate distribution with logistic marginals and $\nu = 8$, as proposed by [Hirk et al. \(2019\)](#).

Given that we employ the default identification method and the t -copula error distribution, the error variances are not estimated. Hence, defining the residual correlation matrix, $\boldsymbol{\Sigma}_i$, reduces to modeling the off-diagonal elements. Besides, since our model contains only two dependent variables ($q = 2$), the error correlation reduces to an individual-specific term ρ_i , which we model as a function of country indicators using a Fisher Z-transformation of the form:

$$\frac{1}{2} \log \left(\frac{1 + \rho_i}{1 - \rho_i} \right) = \alpha_0 + \mathbf{cntr}_i^\top \boldsymbol{\alpha}, \quad \rho_i = \frac{e^{2(\alpha_0 + \mathbf{cntr}_i^\top \boldsymbol{\alpha})} - 1}{e^{2(\alpha_0 + \mathbf{cntr}_i^\top \boldsymbol{\alpha})} + 1}, \quad (3)$$

where $\mathbf{cntr}_i$ is a vector of country fixed effects, with Mexico as the reference category, $\boldsymbol{\alpha}$ their associated parameters, and α_0 denotes the intercept. Given this modeling strategy, ρ_i is constant across all respondents within a given country $p \in \{1, \dots, 21\}$, and we can simplify the notation by specifying the correlation as a country-specific parameter ρ_p .

Crucially, the model-implied correlation, ρ_p captures the residual correlation and it will generally differ from the unconditional correlation between Y_{is}^* and Y_{ig}^* per country, which also considers the explanatory

power of the independent variables. More specifically, assuming that $\text{Cov}(\mathbf{x}_{ip}^\top \boldsymbol{\beta}_s, \varepsilon_{ig}) = \text{Cov}(\mathbf{x}_{ip}^\top \boldsymbol{\beta}_g, \varepsilon_{is}) = 0$ and given the definition in Equation (1) and the identification restrictions, we have that:

$$\text{Corr}(Y_{ips}^*, Y_{ipg}^*) = \frac{C_p + \rho_p}{\sqrt{(V_{ps} + 1)(V_{pg} + 1)}}, \quad (4)$$

where $C_p = \text{Cov}(\mathbf{x}_{ip}^\top \boldsymbol{\beta}_s, \mathbf{x}_{ip}^\top \boldsymbol{\beta}_g)$ denotes the cross-covariance between the perceived discrimination risk factors, and $V_{ps} = \text{Var}(\mathbf{x}_i^\top \boldsymbol{\beta}_s)$ and $V_{pg} = \text{Var}(\mathbf{x}_{ip}^\top \boldsymbol{\beta}_g)$ denote the part of the variances of the perceived discrimination by skin color and gender, respectively, that our model explains. Note that C_p , V_{ps} , and V_{pg} are computed per country by using the overall parameters $\boldsymbol{\beta}_s$ and $\boldsymbol{\beta}_g$ and the matrix of explanatory variables per country, $\mathbf{x}_{ip}$. Substantially, ρ_p captures the unexplained part of the relationship between the two types of perceived discrimination, which can be caused by localized stereotypes or respondent styles, among other additional factors.

Since we employ a logit link function, the regression coefficients from our analyses should be interpreted in terms of marginal log-odds (McCullagh, 1980). To provide more accessible interpretation, we exponentiate the linear predictor in Equation (2) to obtain cumulative odds ratios (ORs). Let $\tilde{\mathbf{x}}_{ij}$ be the same vector as $\mathbf{x}_{ij}$ except a discrete increase in a single variable x_v in $\mathbf{x}_{ij}$ from x_{ijv} to $\tilde{x}_{ijv} = x_{ijv} + \Delta_{ijv}$. The resulting odds ratio is:

$$\frac{\Pr(Y_{ij} \leq k \mid \tilde{\mathbf{x}}_{ij}) / \Pr(Y_{ij} > k \mid \tilde{\mathbf{x}}_{ij})}{\Pr(Y_{ij} \leq k \mid \mathbf{x}_{ij}) / \Pr(Y_{ij} > k \mid \mathbf{x}_{ij})} = \exp(\beta_{jv}), \quad (5)$$

where β_{jv} is the coefficient corresponding to the v -th variable in the explanatory vector. Thus, $\exp(\beta_{jv})$ provides the multiplicative change in the odds of reporting greater perceived discrimination associated with a one-unit increase in x_v , *ceteris paribus*. For categorical and binary variables, the interpretation is analogous considering a unit increase as the difference between the base and the indicated category, holding everything else constant (Long & Freese, 2014).

Let $\mathbf{Y}_i = (Y_{is}, Y_{ig})^\top$ be a vector with our dependent variables and $\boldsymbol{\delta}$ a vector with all the thresholds, regression, and correlation parameters we intend to estimate. Then, the likelihood of the multivariate ordinal regression model is given by:

$$\mathcal{L}(\boldsymbol{\delta}) = \prod_{i=1}^n \Pr(\mathbf{Y}_i; \boldsymbol{\delta})^{w_i} = \prod_{i=1}^n \left[\int_{D_i} f_{i,q_i}(\mathbf{Y}_i^*; \boldsymbol{\delta}) d\mathbf{Y}_i^* \right]^{w_i}, \quad (6)$$

where $w_i \geq 0$ are the survey sampling weights, f_{i,q_i} is the bivariate joint error density function, and D_i is a Cartesian product of D_s and D_g defining the latent space over which the bivariate error distribution is integrated.

To approximate the full likelihood presented in Equation (6), the procedures in the `mvord()` package use a pairwise likelihood constructed from bivariate marginal distributions. In general, in multivariate cases $q \geq 2$, estimation is achieved by maximizing this pairwise log-likelihood, that can be expressed as:

$$p\ell(\boldsymbol{\delta}) = \sum_{i=1}^n w_i \left[\mathbb{1}_{\{|J| \geq 2\}} \sum_{k < l \in J} \log(\Pr(Y_{ik} = r_{ik}, Y_{il} = r_{il})) + \mathbb{1}_{\{|J|=1\}} \sum_{k \in J} \log \Pr(Y_{ik} = r_{ik}) \right]. \quad (7)$$

In our particular case, where we consider a balanced panel and deal only with two dependent variables, Equation (7) simplifies to

$$p\ell(\boldsymbol{\delta}) = \sum_{i=1}^n w_i \log \left(\int_{\tau_{s,r_{is}-1}}^{\tau_{s,r_{is}}} \int_{\tau_{g,r_{ig}-1}}^{\tau_{g,r_{ig}}} f_{i,2}(Y_{is}^*, Y_{ig}^*) dY_{is}^* dY_{ig}^* \right). \quad (8)$$

Under standard maximum likelihood, the Hessian of the estimated log-likelihood alone is enough to obtain valid standard errors, since it converges to Fisher's information matrix. Nonetheless, this equivalence does not hold directly under our composite likelihood because Equation (8) is a pairwise approximation rather than the true joint likelihood. Instead, once we obtain $\hat{\boldsymbol{\delta}}$, we compute both the Hessian, $H(\hat{\boldsymbol{\delta}})$, and the variability matrix, $V(\hat{\boldsymbol{\delta}})$ (i.e., the matrix capturing the covariance of the score contributions), and combine them into the Godambe (sandwich) information matrix to obtain consistent standard errors. For model comparisons, we use the composite-likelihood(CL) analogues of the AIC and BIC proposed by [Varin and Vidoni \(2005\)](#), which replace the usual penalty for the number of parameters with a term based on $H^{-1}V$ to remain valid under the pairwise-likelihood approach. For further details on multivariate ordinal regression models and their implementation in R, refer to [Hirk et al. \(2020\)](#).

We estimate three progressively complex models to evaluate how the inclusion of key covariates alters our estimations. Our baseline specification (Model 1) includes only the core characteristics under study: skin color, ethnicity, and sex. We expand on this by considering non-linear relationships between these variables; thus, in our second specification (Model 2), we include all two-way interactions among them. Finally, our full model (Model 3) incorporates a comprehensive set of control variables, including: number of people in the household, number of children under the age of 13, age, age squared, urban/rural residence, educational level, income in ranges, current occupation, and the interviewers' skin color.

4 Results

4.1 Main results

Table 2 shows the cumulative ORs and their corresponding Confidence Intervals (CIs) for the two dependent variables across all the different model specifications. According to the CL-AIC, Model 3, which includes the entire set of control variables, provides the best fit. This contrasts with the results from the CL-BIC, which indicates that Model 2 should be preferred. Methodological research indicates that, when the main goal is prediction and when the true model is not included in the candidate set, the AIC outperforms the BIC in model selection (Burnham & Anderson, 2004; Y. Yang, 2005). Additionally, simulation research shows that, even with the true model in the candidate set, when the sample size, n , is much larger than the square of the estimated parameters, k^2 , the AIC is still preferred over the BIC (Vrieze, 2012). Given these insights, and considering that we have a notably large sample size (i.e., $n = 26,598$), we guide our model selection using the CL-AIC and interpret the model with the full set of control variables.

To facilitate the interpretation of the interaction effects and have a more detailed view of the way that ethnoracial and gender characteristics intertwine, we complement the results from Table 2 with plots of the models' estimated probabilities in Figure 2. Panel (a) of Figure 2 shows the predicted probabilities of the perceived discrimination based on skin color against the external skin color measure across ethnic groups and faceted by response category. For Panel (b) of Figure 2, we construct the difference between women and men in their probability of reporting being discriminated against due to their sex/gender many times, and its corresponding standard error (i.e., by taking the square root of the sum of the male and female variances), and plot it against the respondent's skin color, faceted by ethnicity.

The results from the left panel of Table 2 indicate that, as expected, skin color has a statistically significant effect on the probability of perceiving discrimination based on skin color. Specifically, each unit increase on the PERLA scale raises the odds of reporting higher levels of color-based discrimination by 15.2% (OR = 1.152[1.110, 1.196]). Ethnicity also plays a role in determining the perceived skin color discrimination. In relation to the *Mestiza* group, respondents self-categorizing as *Indígena* (OR = 1.792 [1.269, 2.531]) and *Negra* (OR = 1.744 [1.300, 2.340]) have substantially higher odds of reporting skin-color discrimination, while individuals identified as *Blanca* report significantly lower odds (OR = 0.692 [0.517, 0.927]). In contrast, there were no significant baseline differences between mestizos and those in the *Mulata* (OR = 1.220 [0.843, 1.767]) and *Otra* (OR = 0.885 [0.646, 1.214]) groups. Regarding gender, neither the main effect of being female, nor its interaction with skin color or the ethnic categorizations are statistically significant, indicating that the skin-color discrimination operates equally across genders.

In addition, the effect of the respondents' skin color on their perceived discrimination based on this trait

is not homogeneous across ethnic groups. On the one hand, relative to the *Mestiza* group, the interaction terms reveal that the incremental effect of skin color is significantly weaker for both *Blanca* and *Negra* respondents ethnic groups. For *Blanca* respondents, the effect of each unit of skin darkening is reduced by a multiplicative factor of 0.924 (OR = 0.924 [0.856, 0.996]), while for *Negra* respondents, it is reduced by a factor of 0.939 (OR = 0.939 [0.896, 0.984]). On the other hand, the effect of the respondent’s skin color on perceived discrimination based on this trait is stronger for individuals in the *Otra* group than for their counterparts in the *Mestizo* group (OR = 1.081 [1.023, 1.143]). This is further illustrated in panel (a) of Figure 5, where the probabilities of being discriminated against based on skin color for the *Blanca* and *Negra* show virtually parallel trends across respondents’ skin color, while the remaining ethnic groups present larger slope magnitudes.

The results from the right panel of Table 2 show how sex and skin color determine the probability of gender-based perceived discrimination. Unsurprisingly, women have odds of reporting higher levels of gender-based discrimination 3.254 (OR = 3.254 [2.636, 4.017]) times higher than men. Besides sex, we found that darker skin tones associate with increments in the probability of reporting discrimination based on gender (OR = 1.094 [1.046, 1.144]), and that people in the *Negra* ethnic group have substantially higher odds of being discriminated against than their counterparts identified as *Mestiza* (OR = 1.589 [1.132, 2.232]).

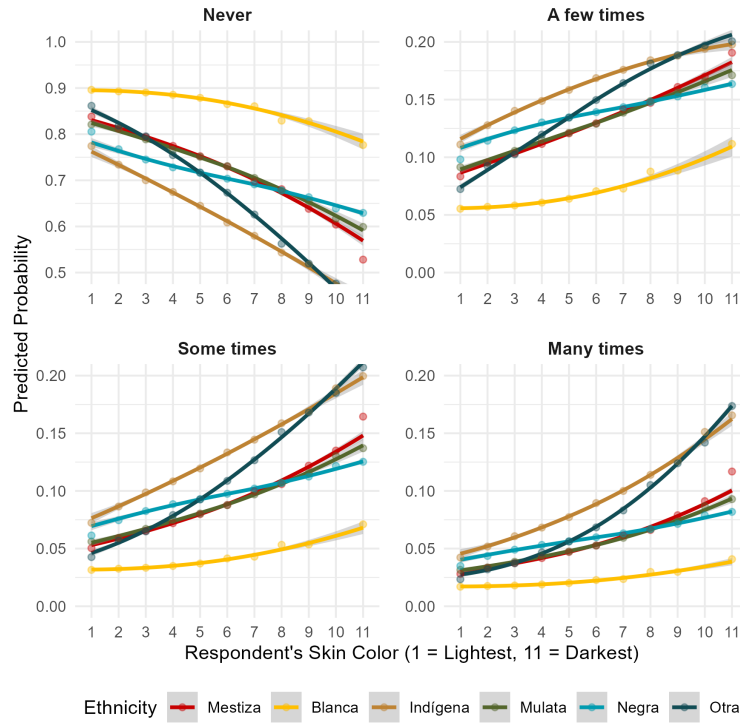
Moreover, there is a statistically significant interaction between female and skin color (OR = 0.933[0.895, 0.972]), indicating that the gap in perceived gender discrimination between women and men is narrower for individuals with darker skin tones than for those with lighter skin tones. This is also evidenced in panel (b) of Figure 3, where in multiple facets the probability of reporting being discriminated against by gender increases considerably for men as we move towards darker skin colors in the palette. For example, respondents who self-identify as *Negra* and have lighter skin tones, the gap between men and women is statistically different from zero, whereas this difference is indistinguishable from zero for the 10 and 11 points in the color palette.

There are also multiple statistically significant differences between the *Mestiza* group and the remaining ethnic groups in their gender gaps in perceived gender-based discrimination, as evidenced in the interaction terms in Table 2. The female-by-ethnicity interactions are all statistically different from 1 for the *Indígena* (OR = 0.619[0.487, 0.787]), *Mulata* (OR = 0.702[0.527, 0.936]), *Negra* (OR = 0.714[0.578, 0.881]), and the *Otra* (OR = 0.541[0.420, 0.696]) groups. This indicates that the gender gap in perceived discrimination is substantially smaller within these groups than compared to the reference category. This pattern can also be seen in panel (b) of Figure 3. In this panel, the *Mestiza* group shows the largest gender gaps at the lightest skin tones, while for most other ethnic groups this difference is less pronounced across all color shades.

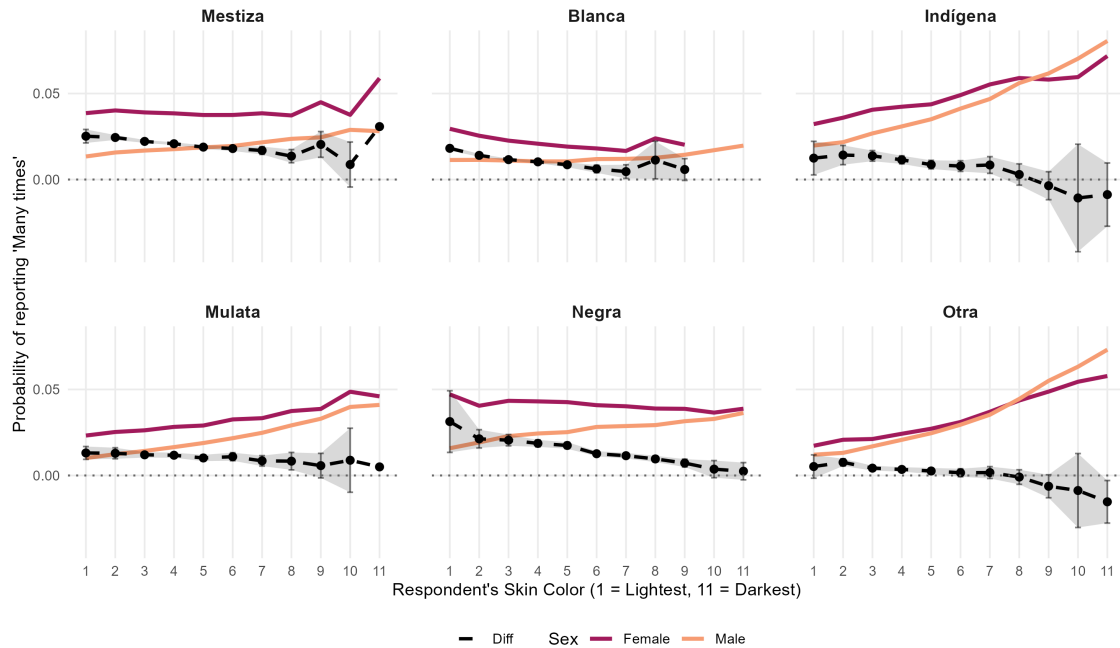
Furthermore, the socio-economic control variables included in Model 3 of Table 2 reveal distinct patterns regarding class across both outcomes. First, we see that people with tertiary education have higher odds

Variable	Discrimination based on Skin color			Discrimination based on Sex/Gender		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Skin color respondent	1.119***[1.099, 1.138]	1.139***[1.099, 1.181]	1.152***[1.110, 1.196]	1.051***[1.030, 1.072]	1.066**[1.020, 1.113]	1.094***[1.046, 1.144]
Female	0.891***[0.840, 0.945]	1.003 [0.840, 1.198]	1.029 [0.859, 1.234]	1.734***[1.618, 1.858]	2.940***[2.391, 3.614]	3.254***[2.636, 4.017]
Ethnicity = Blanca	0.478***[0.432, 0.530]	0.625**[0.469, 0.834]	0.692* [0.517, 0.927]	0.646***[0.580, 0.720]	0.853 [0.618, 1.177]	0.970 [0.700, 1.346]
Ethnicity = Indígena	1.691***[1.526, 1.875]	1.765**[1.255, 2.482]	1.792***[1.269, 2.531]	1.456***[1.294, 1.639]	1.236 [0.842, 1.815]	1.367 [0.926, 2.019]
Ethnicity = Mulata	1.006 [0.897, 1.129]	1.096 [0.761, 1.581]	1.220 [0.843, 1.767]	0.848* [0.738, 0.973]	0.680 [0.425, 1.090]	0.793 [0.492, 1.279]
Ethnicity = Negra	1.109* [1.015, 1.211]	1.638***[1.228, 2.184]	1.744***[1.300, 2.340]	1.119* [1.010, 1.239]	1.446* [1.035, 2.021]	1.589**[1.132, 2.232]
Ethnicity = Otra	1.212***[1.094, 1.342]	0.797 [0.584, 1.089]	0.885 [0.646, 1.214]	0.931 [0.823, 1.052]	0.665* [0.455, 0.972]	0.773 [0.526, 1.135]
Skin Color respondent:Female	—	0.984 [0.950, 1.019]	0.983 [0.949, 1.019]	—	0.930***[0.893, 0.969]	0.933***[0.895, 0.972]
Skin Color respondent:Ethnicity = Blanca	—	0.926* [0.859, 0.998]	0.924* [0.856, 0.996]	—	0.916* [0.845, 0.994]	0.922 [0.849, 1.002]
Skin Color respondent:Ethnicity = Indígena	—	1.014 [0.954, 1.078]	1.017 [0.955, 1.082]	—	1.091* [1.020, 1.168]	1.081* [1.009, 1.158]
Skin Color respondent:Ethnicity = Mulata	—	0.985 [0.922, 1.053]	0.976 [0.913, 1.043]	—	1.081 [0.995, 1.174]	1.060 [0.975, 1.152]
Skin Color respondent:Ethnicity = Negra	—	0.943* [0.901, 0.987]	0.939**[0.896, 0.984]	—	0.991 [0.940, 1.045]	0.970 [0.919, 1.024]
Skin Color respondent:Ethnicity = Otra	—	1.090**[1.032, 1.152]	1.081**[1.023, 1.143]	—	1.148***[1.076, 1.224]	1.130***[1.059, 1.207]
Female:Ethnicity =Blanca	—	0.948 [0.773, 1.164]	0.936 [0.760, 1.151]	—	0.895 [0.711, 1.125]	0.856 [0.679, 1.079]
Female:Ethnicity = Indígena	—	0.783* [0.637, 0.964]	0.782* [0.634, 0.964]	—	0.625***[0.493, 0.794]	0.619***[0.487, 0.787]
Female:Ethnicity = Mulata	—	0.979 [0.777, 1.233]	0.928 [0.735, 1.172]	—	0.779 [0.587, 1.033]	0.702* [0.527, 0.936]
Female:Ethnicity = Negra	—	0.958 [0.802, 1.145]	0.912 [0.761, 1.093]	—	0.799* [0.650, 0.983]	0.714**[0.578, 0.881]
Female:Ethnicity =Otra	—	0.959 [0.782, 1.177]	0.961 [0.781, 1.182]	—	0.549***[0.428, 0.705]	0.541***[0.420, 0.696]
Number of household members	—	—	1.023* [1.005, 1.042]	—	1.025* [1.004, 1.047]	—
Number of children under 13	—	—	1.008 [0.977, 1.041]	—	—	0.951**[0.917, 0.986]
Age	—	—	0.991 [0.980, 1.002]	—	—	0.992 [0.979, 1.005]
Age squared	—	—	1.000 [1.000, 1.000]	—	—	1.000 [1.000, 1.000]
Urban	—	—	0.936* [0.877, 0.999]	—	—	0.954 [0.883, 1.030]
Education = None	—	—	0.873 [0.698, 1.093]	—	—	1.213 [0.936, 1.571]
Education = Primary incomplete	—	—	1.020 [0.904, 1.150]	—	—	1.131 [0.981, 1.304]
Education = Primary complete	—	—	0.878* [0.788, 0.979]	—	—	0.855* [0.749, 0.977]
Education = Secondary incomplete	—	—	0.950 [0.869, 1.039]	—	—	0.836**[0.751, 0.931]
Education = Tertiary incomplete	—	—	1.216***[1.097, 1.349]	—	—	1.385***[1.235, 1.553]
Education =Tertiary complete	—	—	1.187***[1.082, 1.302]	—	—	1.440***[1.309, 1.605]
Income range = 2	—	—	0.974 [0.859, 1.105]	—	—	1.088 [0.939, 1.261]
Income range = 3	—	—	1.045 [0.921, 1.186]	—	—	1.019 [0.876, 1.185]
Income range = 4	—	—	0.952 [0.834, 1.085]	—	—	1.019 [0.875, 1.188]
Income range = 5	—	—	1.014 [0.886, 1.161]	—	—	1.045 [0.891, 1.225]
Income range = 6	—	—	0.972 [0.841, 1.123]	—	—	1.068 [0.903, 1.263]
Income range = 7	—	—	0.915 [0.789, 1.062]	—	—	1.034 [0.872, 1.226]
Income range = 8	—	—	0.756***[0.649, 0.881]	—	—	0.862 [0.721, 1.031]
Income range = 9	—	—	0.887 [0.758, 1.037]	—	—	0.988 [0.823, 1.187]
Income range = 10	—	—	0.872 [0.740, 1.027]	—	—	1.070 [0.887, 1.291]
Income range = 11	—	—	0.815* [0.678, 0.978]	—	—	0.927 [0.748, 1.148]
Income range = 12	—	—	0.865 [0.726, 1.030]	—	—	1.069 [0.877, 1.304]
Income range = 13	—	—	0.745**[0.616, 0.901]	—	—	1.062 [0.863, 1.307]
Income range = 14	—	—	0.810* [0.667, 0.983]	—	—	1.025 [0.827, 1.270]
Income range = 15	—	—	0.809* [0.681, 0.962]	—	—	1.170 [0.967, 1.415]
Occupation = Employed, Not working	—	—	1.044 [0.921, 1.184]	—	—	1.007 [0.870, 1.166]
Occupation = Actively looking for a job	—	—	1.229***[1.124, 1.345]	—	—	1.162**[1.049, 1.288]
Occupation = Student	—	—	1.064 [0.931, 1.217]	—	—	1.132 [0.979, 1.309]
Occupation = Dedicated to Household	—	—	0.824***[0.742, 0.914]	—	—	0.691***[0.615, 0.777]
Occupation = Retired or unable to work	—	—	0.815**[0.701, 0.947]	—	—	1.000 [0.839, 1.191]
Occupation = Not working and not looking for a job	—	—	0.854 [0.729, 1.000]	—	—	0.867 [0.719, 1.046]
Skin color interviewer	—	—	0.987 [0.969, 1.005]	—	—	1.008 [0.987, 1.029]
CL-AIC	65,189.8	65,100.5	64,549.1	65,189.8	65,100.5	64,549.1
CL-BIC	65,526.1	65,617.6	65,594.0	65,526.1	65,617.6	65,594.0
N	26,598	26,598	26,598	26,598	26,598	26,598

Table 2: Multivariate Ordinal Regression Results. Odds Ratio with 95% Confidence Intervals in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$



(a) Predicted probability of perceived skin-color discrimination, by skin color and ethnicity



(b) Predicted probability of perceived gender discrimination ('Many times'), and female-male gap, by skin color and ethnicity

Figure 3: Predicted discrimination probabilities by skin color, ethnicity and gender

than those with secondary education, for both skin color (complete tertiary: OR = 1.187 [1.082, 1.302]) and gender discrimination (complete tertiary: OR = 1.449 [1.309, 1.605]). Second, income shows diverging patterns for the two dependent variables. While higher income is associated with lower odds of perceiving skin color discrimination (e.g., Range 8: OR = 0.756 [0.649, 0.881]; Range 13: OR = 0.745 [0.616, 0.901]), income differences do not determine perceived gender discrimination. Finally, we see that people actively looking for a job have significantly higher odds than their employed counterparts of perceiving both skin color (OR = 1.229 [1.124, 1.345]) and gender discrimination (OR = 1.162 [1.049, 1.288]). On the contrary, individuals dedicated to household work report significantly lower odds than employed people across both outcomes (OR = 0.824 [0.742, 0.914] for skin color; OR = 0.691 [0.615, 0.777] for gender). Overall, these results show that gender discrimination is an issue across every income bracket, and that both racial and gender discrimination are strongly associated with having tertiary education and participating in the labor market.

4.2 Cross-country heterogeneity

Figure 4 shows the empirical decomposition of the correlation between the underlying continuous variables capturing the two types of perceived discrimination by country. Panel (a) of this figure plots the point estimates and confidence intervals of the country-specific residual correlations. Panel (b) of Figure 4 complements this information by mapping the structural components of the correlation presented in Equation (4). Concretely, this sub-figure plots the explained cross-covariance, C_p , of each country on the vertical axis against the explained variance of the perceived discrimination by skin color, V_1 , on the horizontal axis. To provide a comprehensive view on the correlation between Y_{ips}^* and Y_{ipg}^* , the size of the country markers correspond to the explained variance of the perceived discrimination based on gender, and the color filling those markers denotes the model-implied unconditional correlation.

Panel (a) on the left-hand side of Figure 4 shows that, except for Brazil, for most countries, the residual correlation is statistically indistinguishable from the LAC average, sitting at around 0.68. This indicates that, across most of Latin America, the correlation between the two types of discrimination is largely determined by factors not included in our model. Although, by their nature, we cannot observe the core drivers of these residual correlations, attributional ambiguity and individual differences in vigilance and reporting thresholds likely play a substantial role in these relationships. Previous literature has shown how social categorization in LAC is fluid, and ethnoracial hierarchies are confounded with class hierarchies, leading to misattribution of the roots of discrimination (A. R. Dixon, 2019).

While Panel (a) shows how most of the LAC have a shared experience related to skin color and gender

discrimination, Panel (b) of Figure 4 illustrates the region’s heterogeneity in terms of how sociodemographic characteristics shape perceived discrimination. Importantly, while the explained variance of the perceived gender discrimination, V_{pg} , lies within a narrow band of 0.36 to 0.48, the explained variance of the perceived skin color discrimination, V_{ps} , exhibits relatively large contrasts between countries, spanning 0.08 in Belize to 0.33 in Brazil. Therefore, the differences across the region in joint discrimination are mainly driven by variation in V_{ps} and the explained cross-covariance C_p .

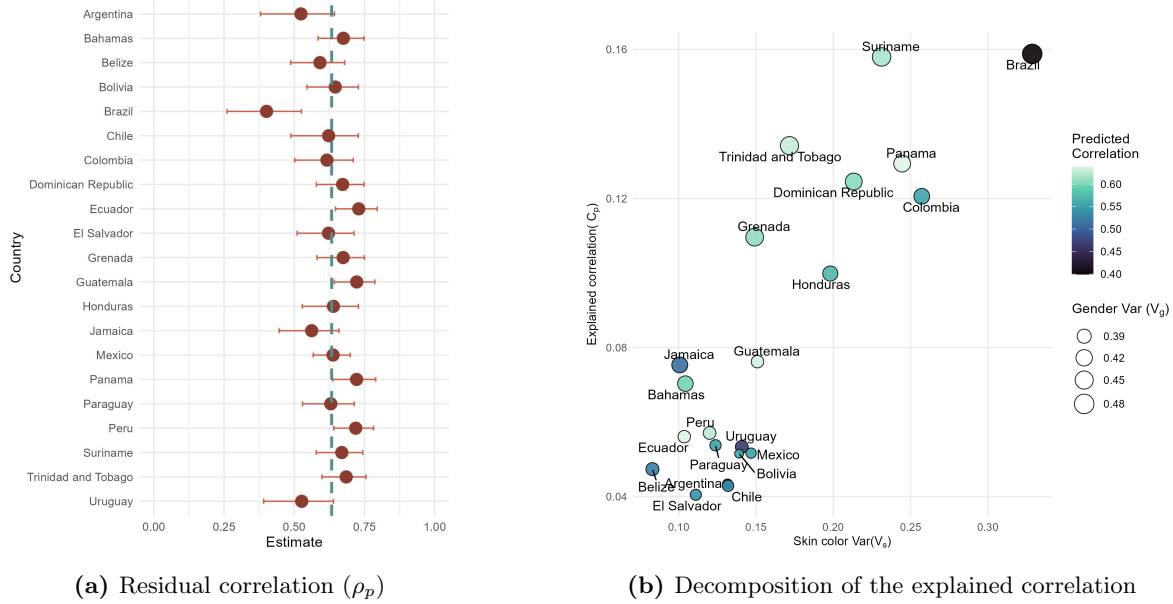


Figure 4: Correlation between discrimination variables by country

The results from Panel (b) of Figure 4 present the LAC as comprised of three clusters of countries. The first group, in the lower-left quadrant of the plot, is characterized by low V_{ps} and includes countries such as Argentina, Bolivia, and Mexico. The second group, positioned in the upper-middle and upper-right of the plot, has both moderate-to-high explained perceived skin color discrimination ($V_{ps} \approx 0.15 - 0.25$) and high cross-covariance ($C_p \geq 0.1$). The countries in this cluster are Grenada, Honduras, Trinidad and Tobago, Dominican Republic, Colombia, Panama, and Suriname. Finally, the third group consists solely of Brazil, an outlier in the region because of its notably large variance of the discrimination attributed to skin color that is explained by the model ($V_{ps} = 0.33$).

Looking at the two panels of Figure 4 in tandem, we can disentangle all the components of the correlation presented in Equation (4). This full picture indicates that although Brazil is ostensibly similar to Argentina and Uruguay, in reality these countries have stark differences in how two types of perceived discrimination interact. All three countries show a relatively low residual correlation, despite reaching these numbers in opposite ways. In Brazil, the observable sociodemographic characteristics account for a large part of

the variation in perceived skin color discrimination ($V_{ps} = 0.33$), lowering ρ_p considerably. Conversely, in Argentina and Uruguay, the low residual correlation is driven by the very low explained variance in skin color discrimination ($V_{ps} \approx 0.08 - 0.11$) and near-zero cross-covariance ($C_p \approx 0.04$). A plausible reason behind this low cross-covariance is the policies centered around *blanqueamiento*, which systematically marginalized the non-white population, leading to their current absence in these countries. Thus, the low correlation between skin color and gender present in Brazil, Argentina, and Uruguay shows two vastly different realities: one where racial discrimination is heavily determined by respondents’ characteristics (Brazil), and another where individual traits predict almost none of the variation of skin color discrimination (Argentina and Uruguay).

5 Discussion

This paper examined how personal characteristics shape perceived discrimination in Latin America and the Caribbean (LAC). Using a multivariate ordinal regression model (Hirk et al., 2020), we addressed two research questions. First, we examined how gender, skin color, and ethnicity are associated with perceived skin color and perceived gender discrimination. Second, we assessed the extent to which these two forms of perceived discrimination are related across countries in the region.

Our findings confirm previous research showing that both skin color and ethnicity independently shape perceptions of skin color discrimination in LAC. Consistent with Canache et al. (2014), respondents with darker skin tones report substantially higher levels of perceived skin color discrimination, even after accounting for ethnic self-identification. In addition, respondents self-identifying as *Blanca* report the lowest levels of perceived skin color discrimination, whereas Indigenous and *Negra* respondents report the highest levels. These findings reinforce the argument that interviewer-rated skin color and self-identified ethnicity capture complementary rather than interchangeable dimensions of ethnoracial inequality (Gómez-Echeverry, 2024; Roth, 2010).

Beyond these main effects, the relationship between skin color and perceived discrimination varies across ethnic groups. Although darker skin is associated with higher levels of perceived discrimination in all groups, the “penalty per shade” is smaller among individuals identifying as *Blanca* or *Negra* and largest within the more heterogeneous *Otra* category, which includes diverse self-identifications such as “Indian” and “Chinese”. Descriptively, these differences resemble muted and amplified discrimination patterns. One possible explanation is that, within relatively homogeneous groups, ethnic identification already conveys substantial information about how individuals are perceived by others, leaving skin tone with comparatively little additional relevance. Conversely, in more heterogeneous groups, skin color may provide a more salient basis for social classification. However, because we study perceived rather than observed discriminatory treatment,

these patterns should be interpreted cautiously. A weaker or stronger skin color gradient may reflect differences in discriminatory treatment, but also differences across ethnic groups in whether unequal treatment is recognized as discrimination or attributed specifically to skin color.

Contrary to our expectations, we find no evidence that women report higher levels of perceived skin color discrimination than men, nor that the relationship between skin color and perceived skin color discrimination differs by gender. One possible reason for this finding is that gendered racial stereotypes produce different forms of discriminatory treatment but similar overall levels of reported skin color discrimination. Women of color, for example, are more often sexualized and evaluated against dominant beauty standards, whereas men of color are more frequently stereotyped as hypersexual, aggressive, or criminal (Collins, 2004; Harnois & Ifatunji, 2011). Yet the absence of a gender difference in perceived discrimination does not necessarily imply the absence of gender differences in discriminatory treatment. Gendered sociocultural norms, such as the “Strong Black Woman” or “Superwoman” schemas, may make some women less likely to recognize or report adverse treatment as discrimination (P. Q. Yang, 2021; P. Q. Yang & Henderson, 2024). Alternatively, women with darker skin tones may recognize an encounter as discriminatory but be more likely to attribute it to gender rather than skin color.

This latter possibility becomes particularly relevant when considering perceived gender discrimination. As expected, women report substantially higher levels of perceived gender discrimination than men: they have 3.3 times higher odds of reporting greater levels of gender discrimination. Skin color also plays an important role in this type of discrimination. Comparing individuals at the lightest and darkest ends of the PERLA scale, those with the darkest skin tones have approximately 2.5 times higher odds of reporting greater levels of gender discrimination. In contrast to Layton and Smith (2017), however, this cumulative skin color difference does not exceed the overall gender difference. Nevertheless, the substantial association between skin color and an outcome explicitly framed in terms of gender illustrates the attributional ambiguity emphasized in our theoretical framework: the characteristic associated with discriminatory treatment does not necessarily correspond to the characteristic to which the experience is attributed.

The interaction between gender and skin color further shows that the skin color gradient in perceived gender discrimination is weaker among women than among men. Consequently, the gender gap narrows as skin color becomes darker, although women continue to report higher levels of perceived gender discrimination across the skin color scale. At the darkest point on the PERLA scale, the gender gap is approximately half the size of the gap observed at the lightest point. Descriptively, this resembles a muted effect, but it should not necessarily be interpreted as evidence that darker skin produces a smaller additional discriminatory disadvantage among women. The pattern may also arise from differences in how discriminatory experiences are recognized or attributed. Again, “Strong Black Woman” or “Superwoman” narratives portray Black women

as resilient, self-reliant, and able to endure adversity without acknowledging vulnerability or victimization, potentially shaping whether adverse experiences are recognized and reported as discrimination (P. Q. Yang, 2021; P. Q. Yang & Henderson, 2024).

Finally, we examined the relationship between perceived skin color discrimination and perceived gender discrimination. Consistent with Dixon’s (2019) argument that different forms of perceived discrimination may overlap, we find a relatively strong positive association between the two outcomes. Respondents reporting higher levels of skin color discrimination are also substantially more likely to report higher levels of gender discrimination. Moreover, descriptive analyses show that individuals who never report skin color discrimination are unlikely to report gender discrimination, whereas reports of gender discrimination rarely exceed reports of skin color discrimination.

These findings highlight the second source of ambiguity involved in perceived discrimination: even when unequal treatment is recognized as discriminatory, identifying its underlying cause may not be straightforward (A. R. Dixon, 2019; Layton & Smith, 2017). Interestingly, this ambiguity appears to be asymmetric. While perceived skin color discrimination is primarily associated with ethnoracial characteristics showing little variation by gender, the perceived gender discrimination is shaped not only by gender but also by skin color and ethnicity. This pattern is consistent with arguments about *Mestizaje*, according to which the racial dimension of unequal treatment may be obscured or interpreted through other social categories, such as socio-economic class. In other words, experiences partly structured by skin color or ethnicity may be perceived as gender discrimination without necessarily being identified as skin color discrimination.

Upon first glance, we find small cross-national variation in the residual correlation between the two forms of perceived discrimination. However, further decompositions of the correlation explained by our model show considerable heterogeneity in the LAC region. Our analyses indicate that, although countries like Brazil, Argentina, and Uruguay have similar residual correlations, they respond to notably different country dynamics. For Brazil, our model explains a large part of the correlation between the two discrimination variables due to the strong dependence between them, and the independent variables explain a large part of the perceived skin color discrimination. Our model also explains a large part of the correlation between skin color and gender discrimination in Argentina and Uruguay, but for opposite reasons as Brazil: the perceived discrimination measures are more independent, and there is little variance in the perceived discrimination by skin color we can explain. This highlights the contrasting historical backgrounds of these countries, with Brazil being strongly influenced by *mestizaje* ideologies and Argentina and Uruguay shaped by *blanqueamiento* policies.

This study has several limitations that should be considered when interpreting the findings. First, our measures of perceived skin color discrimination and perceived gender discrimination are each based on a single

survey question. Single-item measures may capture fewer discriminatory experiences and be more vulnerable to recall error than multi-item scales. Indeed, [Krieger, Smith, Naishadham, Hartman, and Barbeau \(2005\)](#) find that single-item measures are less reliable and correlate only weakly with validated multi-item measures of racial discrimination. Future research should therefore use validated multi-item scales to capture the frequency and diversity of discriminatory experiences more comprehensively.

Second, our analyses concern perceived rather than objectively observed discrimination. While perceptions remain important because they shape individuals' well-being, behavior, and responses to unequal treatment, they do not necessarily correspond directly to discriminatory treatment. As emphasized throughout this paper, observed differences in perceived discrimination may reflect differences in treatment as well as differences in whether such treatment is recognized as discrimination and how its cause is attributed ([P. Q. Yang, 2021](#); [P. Q. Yang & Henderson, 2024](#)). Consequently, the additive, amplified, and muted patterns identified in our analyses should be understood as patterns in *perceived* discrimination rather than direct evidence of equivalent patterns in discriminatory treatment.

Third, the cross-sectional nature of the data prevents causal inference. We cannot determine whether characteristics such as skin color and ethnicity causally affect perceptions of discrimination. Likewise, although we find a close association between perceived skin color discrimination and perceived gender discrimination, we cannot establish whether experiencing one form of discrimination increases the likelihood of perceiving the other. Longitudinal data would allow future research to examine how these forms of perceived discrimination develop over time and whether they influence one another.

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