Does Corruption (Re)produce Discrimination?

Observational Evidence on the Relationship Between Race and Bribery in Latin America

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ABSTRACT. Does bureaucratic corruption perpetuate discrimination in Latin America? In particular, how does skin colour, a key predictor of racial marginalisation, factor into bribery targeting? In this study, I empirically examine the relationship between citizens' phenotype and individual corruption experiences using innovative survey data from nine countries for the period 2012-2017. The results show that respondents with darker skin tones are more likely to be targeted to pay bribes compared with those with a lighter shade at the region level. Additionally, the interaction between wealth and phenotype may not necessarily serve as the most accurate predictor of exposure to corruption victimisation. Among other notable findings, this study provides robust evidence that darkest-skinned people from indigenous countries are targeted at higher rates for corruption practices in comparison with their counterparts in Afro descendant nations. Consequently, I argue that the heterogeneity of the findings reflects the interplay of distinctive corruption dynamics and inequality patterns that may or may not be shared by countries.

Table of Contents

1. Introduction

Bureaucratic corruption –the paying of bribes to access public services– is a systemic problem in Latin America, jeopardising socio-economic conditions, and preventing the solution of pressing problems. Its socio-economic consequences have thus many different faces. Existing evidence has shown that these illicit practices reduce economic growth (Chatterjee, 2014), increase poverty and inequality (Warf and Stewart, 2016), lowered land productivity and accelerated deforestation (Bulte et. al., 2012), and impact negatively on human rights (Anand, 2012). For many citizens, encounters with corrupt officers and bureaucrats are also everyday facts of life. The latest Global Corruption Barometer (2019), which captures citizens' perceptions and experiences of corruption, found that more than one in five people in the region paid bribes to access public services in the preceding year.

This phenomenon of corruption is thus seen as inherently exclusionary, direct and indirectly related to historical discrimination, disparities, and inequalities patterns. (McDonald et.al., 2021). Certain types of corruption practices fundamentally involve particularistic access to public services such as education and health, in many cases based on a person's social status and gender, among other characteristics (Fisman and Golden, 2017). Their effects have, therefore, devastating consequences on political rights, material benefits, and access to essential goods for minority groups and vulnerable populations, perpetuating stigmatisation and reinforcing inequalities.

These features are intensified in Latin America, one of the most unequal regions globally with larger ethnoracially stratified populations. Centuries of colonialism, slavery from Africa and White national-building created social and racial castes with culturally and phenotypically diverse citizens (Tenorio-Trillo, 2017). A robust system based on pigmentation –that is, stratification by skin colour– has emerged as a main predictor of racial and ethnic group membership (Telles, 2014), socio-economic status (Woo-Mora, 2022), and a determinant of discrimination (Sidanius et. al., 2004; Villarreal 2010). These cleavages are certainly stronger in countries with visible indigenous and African descendant people, which may produce the likely conditions where corruption experiences can differ among members of societal groups based on their colour.

This is an important question because it speaks to the ways in which race factors into corruption. However, there is a surprising dearth of empirical evidence on this relationship despite the regional importance of both development and equality. While in corruption studies none have specifically focused attention on these personal' ascriptive characteristics as a decisive racial factor, this new research frontier of colourism in the Americas has analysed the relationship between corruption and skin indirectly, relying mostly on the occurrence of bribery as proxies to test citizens' exposure crime and victimisation. Consequently, it remains unclear from the existing research under what conditions we would expect skin tone to either promote or reduce individual experiences of different types of corruption practices.

In this dissertation, I advance the understanding of the relationship between bureaucratic corruption and discrimination by focusing on the effects of skin tone on individual citizens' experiences with bribery. Through a detailed examination of the predictive power of phenotypes, I investigate the effects of these discriminatory corruption colour-based practices in Latin America. This study is not intended to correct the existing literature, nor does it aim to pit skin tone against the central explanatory variables in the corruption and marginalisation debate. The goal here is to shed light on the racial implications of individual corruption experiences that have been overlooked until now.

I test this argument using survey data from the Latin America Public Opinion Project (LAPOP), for the period 2012-2017, in nine countries with large Afro descendants and indigenous populations.[1] LAPOP surveys incorporate a unique measure of each respondent's skin tone based

[1] In Latin America, Afro-descendants and indigenous populations are mostly represented by darker skin colour while mixed race (*Mestizos* and *Mulattoes*) and white are presented by lighter skin tones (Talles, 2014).

on the survey enumerator's observation. Also inquired about experiences of corruption, specifically whether respondents had to pay a bribe to secure various types of public services in the preceding twelve months. I used this observational data to probe: a) the extent to which skin colour influences the occurrence of bribery; b) the interactive effect of colour and wealth on these experiences; c) how phenotype factors into bribery in indigenous and Afro countries separately. All models include a full set of covariates such as gender, setting, wealth, education, and age.

The results demonstrate that skin tone is a significant predictor of corruption experiences at the regional level. I found that individual experiences of bribery substantially increase when individuals with darker phenotypes are targeted for the payment of bribes when dealing with police officers, healthcare services, the military, local and national authorities, and the legal and justice system. This effect is more pronounced when dealing with the courts and weaker with state officials. I did not find consistent evidence of the interactive effect of colour and wealth on bribery experiences, although I observed a strong, positive association of darker-skinned respondents being targeted for military bribes, especially in countries of Afro populations. The findings also suggest that dark phenotypes from indigenous countries are more likely to have paid bribes compared to those Afro. I argue that this result may be attributed to the widespread marginalisation and discrimination suffered by these groups over time.

I also found that this linkage varies widely across Latin America. A positive and significant association are presented in Bolivia, Costa Rica, Ecuador, Mexico, and Peru. In Guatemala and Dominican Republic, coefficients are positive, not significant. Two countries fall out of this trend: Brazil and Colombia. In both, white individuals are targeted for bribery at higher rates than brown and black individuals, but only in the latter case meaningful. This suggests that country heterogeneity reflects distinct corruption dynamics and marginalization schemas that must be interpreted within their specific local contexts. Thus, this dissertation makes novel contributions to the literature on the social consequences of race in the Americas, and to the study of individual determinants of corruption in the developing world.

The rest of the dissertation is organised as follows. Section 2 presents a theoretical framework that reviews the existing literature and sets the expectations for the relationship between corruption and racial discrimination based on skin tone in Latin America. Section 3 introduces the data and empirical strategy to test the hypotheses of this study. Sections 4 and 5 present the findings from a multicountry observational analysis and discuss our results on the relationship between skin colour and bribery experiences, locally and regionally. Finally, Section 6 provides a summary and conclusion, discussing the implications of this argument.

2. Theoretical Framework

This section provides a holistic view through which the relationship between skin colour and bribery reveals how corruption practices can be race-based discriminatory in Latin America. First, I begin with a literature review of the corruption-discrimination nexus, highlighting the vicious circle in which these two phenomena fuel and exacerbate each other. Second, I delve into the contextual background where historical racial discrimination and patterns of inequality are tied to skin tone in Afro and indigenous countries. Finally, I introduce the theoretical framework and outline the four key hypotheses of this dissertation.

2.a. Understanding the Corruption-Discrimination Nexus.

Broadly understood in political science and economics, the concept of corruption means the abuse of public power for private gain (Rose-Ackerman, 1978; Kaufmann, 1997). One of the most famous typologies has also extended and unfolded this definition in political ("grand") or bureaucratic ("petty") corruption (Langseth, 2000). Political corruption generally refers to top-level negotiations, as in the case of multi-national firms that pay commissions to state officials to get favoured treatment on public contracts. Petty corruption however is mostly used in the context of bribes, for instance, citizens engaging with municipality bureaucrats regarding transactions involving licensing requirements, application for social benefits, or approval of specific public service (Ariane et.al., 2007). Since the aim of this research is to evaluate corruption experiences at individual level, the study emphasises these low-scale practices.

Bureaucratic corruption is thus a fact of life in many societies in the developing world. According to the latest Global Corruption Barometer report (2019), more than one in four people in Africa, and more than one in five people in Latin America, paid bribes to access public services in the preceding year. Weak state capabilities –amongst other institutional factors– promote a low-scale corruption that hinders the provision of public services and goods. In these terms, petty corruption can be coercive in nature for many people. Corrupt actors leverage power asymmetries through the use of implicit or explicit threats and their privileged position to extort goods, services, money, or sexual acts in return for access to entitlements such as healthcare or identification papers (McDonald, Jenkins, and Fitzgerald, 2021). This coercivity component indicates that marginalised groups can suffer from an above-average chance of being exposed to petty corruption, in which corrupt actors such as police officers and other street-level bureaucrats target them intentionally for exploitation (Bullock and Jenkins, 2020).

Therefore, the phenomenon of corruption is seen as inherently exclusionary, direct and indirectly related to historical inequalities and disparities. Certain bureaucratic corruption practices fundamentally involve particularistic access to public services, in many cases based on a person's social status and gender (Lagunes, 2012). As You and Khagram (2005) argue, "in high-inequality societies, the large numbers of poor are more likely to be deprived of basic public services such as education and health care than in low-inequality countries. Hence, they are more likely to rely on petty corruption or to be the targets of bureaucratic extortion in their efforts to secure basic services". In a country level analysis, they show that greater income inequality coefficients on the GINI index are associated with higher levels of low-scale corruption score on the World Bank Institute's Control of Corruption Index.

On this basis, corruption and discrimination are part of the same vicious circle.[2] The historical marginalisation of vulnerable communities in the developing world is both a cause and an effect of exposure to systemic or entrenched patterns of discrimination. Consequently, the complex corruption-discrimination nexus is, above all, an intersectional dynamic: discrimination serves as a driver of corruption, leading to, enabling, and exacerbating these illicit practices among lower segments of the social pyramid; but it is also clear that discrimination facilitates corruption

[2] In this study, discrimination will be understood as "the action that generate disadvantages or differentiates between individuals based on their observable characteristics" (Kohler-Hausmann, 2011). Instead of other conceptualisations founded on individual motivation or interest, I take this sociological definition in which classifies an action as discriminatory based on the broader social structure in that society. Therefore, discriminatory practices include differential treatment based on ethnoracial stereotypes and the disproportionate effects on the basis of person's ascriptive characteristics, such as skin tones.

by elite groups within society, as it provides them with incentives to exploit marginalised individuals. Furthermore, since corruption is inherently discriminatory based on connections, power, and resources, as mentioned before, its disproportionate impact fuels or exacerbates discrimination, perpetuating social, economic, and cultural disparities. Their results are profound inequalities facilitated by the interplay of two phenomena in terms of race, gender, sexual orientation, and so forth.

Existing studies vary in the data and methodological approaches to analyse this relationship. At macro level evidence, the burden of corruption disproportionately impacts the most social and economically marginal communities. Studies on inequality indicate that corruption often skews income distribution in favour of powerful groups and can thereby exacerbate existing underlying socio-economic trends between different social classes (Zúñiga, 2017; Hunt, 2007). Therefore, corruption and discrimination conspire to increment wealth disadvantages and consolidate the power of some groups relative to others. Similarly, some scholars also argue for the regular presence of intersectional discrimination as a causal or enabling factor in corruption, for instance, class often overlaps with ethnicity to position people in relation to the corrupt state (Orjuela, et. al., 2016).

At micro level perspective, a number of studies have shown that low-scale corruption over-targets minority groups and disadvantaged people. Studies show that gay men in Russia and Nigeria, for instance, are over-exposed to extorsive forms of corruption, and this can also include entrapment leading to harassment and demands for bribes by police officers (Mallory, et. al., 2015; Giwa et al., 2020). In another study, Ellis and Blackden (2006) find that businesswomen there are more frequently targeted with demands for bribes from corrupt subnational public officials than businessmen. These findings also resonate with Yamb and Bayemi (2017) work, they show that state agents in a monopoly public service, such as doctors working at public hospitals in Cameroon, can discriminate users according to their self-reported ethnicity in order to collect more bribes.

While compelling, none of these studies that examine this nexus have focused attention on personal' ascriptive characteristics as a decisive factor in corruption practices.

What emerges from previous evidence is that the relationship between low-scale corruption and discrimination varies widely by context, mainly depending on social inequality and historical cleavages. My focus on Latin America is thus motivated by the potentially explanatory power that its racial and ethnic diversity has in the likely relationship with individual corruption experiences. In a region with large ethnoracial stratification, racial attributes are reflected in the unequal distribution of material benefits, access to rights, and influence across members (Kohler-Hausmann, 2011). At individual level, the conjunction of visible traits related to diverse racial stereotypes also informs behaviours and interactions within and across social groups (Johnson, 2019). Following the theory and evidence, both elements may facilitate a disproportionate impact on certain groups on the basis of personal ascriptive characteristics by encoding regional ethnoracial significance into the rationale of corruption.

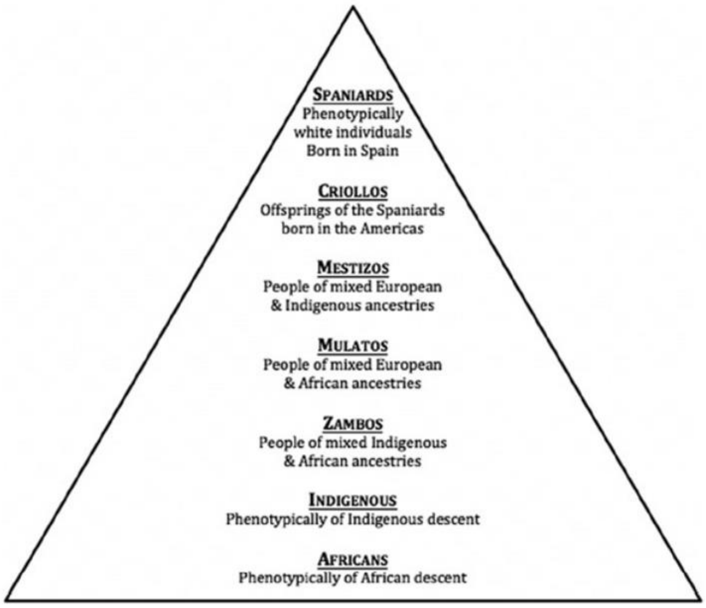
2.b. Historical Background: Racial Discrimination and Inequality Tied to Skin Tone in the Americas.

Race and ethnicity occupy a central place in the history of Latin America (Tenorio-Trillo, 2017). Centuries of colonialism, slave trade from Africa for forced labour, white national construction, and several waves of migration from Europe created territories with enormous racial and ethnic diversity. It results was a complex social caste system based on ethnoracial stratifications, and primarily formed on skin colour and phenotypical characteristics (Graham, 1990). Figure 1 illustrates the social stratification during the colonial period, where *peninsulares*[3] and their descendants (criollos), formed part of the upper class, while indigenous groups, African descent, and those mixed race (mulatos and mestizos) were relegated to the bottom of the social pyramid (Appelbaum, et. al., 2003). Even though this caste system has been more flexible than,

[3] The *peninsulares* were those who born in Spain and held the highest positions in colonial society (Gabbert, 2012).

for instance, the United States racial hierarchies, being white meant being closer to the European imaginary and, therefore, having a higher social status and class (Dixon and Telles, 2017). This racial inequality persisted well even after the Independence processes in the 19th century, leading scholars to label some countries of the region as "pigmentocracies", where skin tone determined social status and power (Telles and Martinez-Casas, 2019).[4]

Figure 1. Latin American Social Caste Pyramid.



Note: 18th century Latin American racial caste system paintings by Miguel Cabrera (Katzew, 1996).

In line with literature showing Latin America is a pigmentocracy, in which skin colour is often more predictive than race, one major consequence of this is that phenotype is strongly correlated with individual well-being (Sidanius, et. al., 2004) as well as socio-economic status (Bailey et. al, 2016). Evidence shows also that skin tone is an important predictor of wealth and education attainment for indigenous people (Telles, 2014; 2012), as it is for Afro-Latin descendants across much of the Americas (Monk, 2015; Telles and Paschel, 2014). Using LAPOP surveys, for instance, Johnson (2019) shows that 29 percent of people having very light skin tone are

[4] I will primarily use the term *colour* in this dissertation, but it should be understood to include the broader process of racialisation in Latin America and the Caribbean, in which skin tone plays a critical role. In the regional context, the reader should bear in mind that *colour* is more prevalent than *race*. Davis (1991) and Telles (2004), for instance, contend that colour does not just refer to one's skin and argue for the interchangeability of *race* and *colour* in the English language.

impoverished compared to 50 percent of respondents with medium and dark skin tone and to 46 percent of respondents with very dark skin colour. These findings also resonate with Woo-Mora (2022) study. The author finds that inequalities between skin tone groups correlate with lower economic development at the national and subnational level, in which skin tone drives the significant racial gap in Latin America.

In this manner, skin tone becomes the basis by which individuals cognitively judge others and match them to both colour and race-based stereotypes in ethnoracially stratified Latin American societies. And because skin tone encodes membership in social groups in the regional context, it plays a central role in perceptions of discrimination. Thus, a growing body of evidence analyse skin tone as a key predictor to estimate discriminatory outcomes in the region. Canache and co-authors (2014), for instance, show that darker-skinned people in Latin America perceive colour discrimination at greater rates than lighter-skinned people. In a recent study, Dixon (2019) also finds that among those who perceive class and colour-based discrimination, darker skin is associated with perceiving a greater frequency of class discrimination, even when wealth is held constant.

This legacy of colour-based racial hierarchies also implies that phenotype is a determinant of experiences of discrimination and victimisation. This is crucial because it speaks about the likely conditions under which corruption experiences can differ among members of societal groups. However, there is a lacuna of empirical evidence on the relationship between corruption interactions and citizens' phenotype, the latter understood as a predictor of racial discrimination. Only a few works, to my best knowledge, have found robust evidence in this area. Thus, Cawvey et al. (2018) find that alongside perceived discrimination, citizens with darker skin report experiencing crime (including bribery) more frequently than people with lighter skin tones within the region. Johnson (2019) also finds that people with darker skin colour report more frequent exposure to vote buying than people with lighter skin tones. Supplemented with experimental evidence, the author notes that vote buying based on skin tone is particularly detrimental for indigenous and black voters in Panama. Finally, in a field experiment in Mexico City, Lagunes et al. (2010) find that police officers are more likely to solicit bribes from drivers whose clothing, car, and skin tone indicate that they are lower class. Although it is unclear to what extent this finding is generalisable outside Mexico.

While compelling, existing studies examine the relationship between skin pigmentation and corruption experiences indirectly. Most of them use individuals' bribery experiences as a proxy for negative events, rather than as the main variable of interest. Such an empirical strategy draws generalizations about the occurrence of bribery and, as a result, overlooks heterogeneity across different types of bureaucratic corruption practices and possible variations within different countries. Another issue is that their measures of corruption encompass the concept broadly, including vote-buying, clientelism, patronage, crime, and bribery. This neglects to distinguish between different high-level and petty-level forms of corruption. Assumptions about citizens' skin pigmentation, corruption practices, and individual experiences remain therefore unexplored. Since the evidence to support their claims is indirect or at a different level of analysis, their conclusions likely face serious ecological fallacy problems. Yet, what is relevant is that this new research frontier on colourism demonstrates that cognitive expectations of stereotypes are associated with skin tone and thus operate in ways that may defy expectations based on a person's objective social status or position.

2.c. The Relationship Between Skin Colour and Bribery: When Corruption (Re)produce Discrimination.

While a growing number of scholars have explored the intricate relationship between corruption and various forms of discrimination, limited attention has been given to the extent of overlap between citizens' phenotype and racial disparities within corruption contexts. My study builds upon these earlier findings by developing a theory that elucidates the linkage between bureaucratic corruption and colour-based discrimination in Latin America. This region-specific theory is put to the test through the analysis of survey data gathered from a diverse range of democratic countries characterised by varying degrees of ethnoracial stratification and socio-economic development. Employing individual-level data, I investigate how individuals' encounters with bribery, both as offerors and recipients, exhibit different patterns based on their skin pigmentation. This endeavour aims to shift the scholarly focus from country-level case studies to regional-level observational analysis of corruption and discrimination, thereby enhancing our comprehension of the intricate mechanisms linking these two phenomena in this part of the developing world.

On this basis, if bribery is the most common type of low-level corruption that individuals experience to access public services such as health, security, and justice system. Citizens' phenotypic characteristics play a significant role as social differentiator, determining thus experiences of discrimination based on race within ethnoracially stratified societies. Therefore, skin pigmentation should be a key prediction of the occurrence of bribery, essential for understanding how bureaucratic corruption reproduces and perpetuates racial discrimination in Latin America. In an effort to test this theory, I posit the first and main hypothesis that can be examined: **H1**. *Experiences of corruption are expected to be at higher rates for darker-skinned citizens compared to lighter-skinned citizens*.

Different types of corruption experiences are likely to vary in how strongly they target people according to their phenotypes. For this, we should consider that individuals can avoid paying bribes by purchasing welfare goods such as health and education in the private market. However, this is more difficult to do when there are no private alternatives to state-provided goods and services. The interactions of non-substitutable goods and services (e.g., security, permits, licenses, or dispute resolutions through the justice system) are the most frequent spheres where people are exposed to corrupt practices and therefore where racial discrimination can flourish. I thus expect the effect of skin colour and bribery experience to be larger in those sectors monopolised by the state such as the courts, police officers or military. Indeed, there is evidence that government employees have larger incentives to ask for bribes when they provide services that are monopolized by the state (Rose and Peiffer, 2015). I thus posit the following hypothesis: **H2**. *The effect of skin colour on corruption experiences is expected to be stronger when that experience is related to non-substitutable public services.*

As discussed above, there are many factors often considered key mediators in the corruption-discrimination nexus. Evidence shows that wealth is an important predictor of the occurrence of corruption in the region and elsewhere (Hellman and Kaufman 2002; de Ferranti, et. al., 2004). Thus, empirical works at the individual level, using observational data, suggest that poorer people are less able to pay bribes to secure access to public services and that more wealthy individuals are more likely to offer to pay or be targeted for bribes (Guerrero and Rodriguez-Oreggia, 2005). These logics cannot escape to the effect of skin tone. Demands for bribes tend to affect most sectors of society in the Americas, however, a stronger effect is likely to be common amongst those affluent individuals. Therefore, I state the following hypothesis: **H3**: *Experiences of corruption are expected to be positive and significant among wealthy darker-skinned citizens.*

While darker skin tones are mostly concentrated in countries with indigenous and Afro-descendant populations, we may observe different results amongst them. In Latin America, indigenous communities are often one of the most stigmatised and discriminated-against segments of national populations. They are consistently poorer than the non-indigenous population (even than Afro-descendant people), with evidence pointing to significant disadvantages in health, education, and labour market outcomes as well as in access to essential public services and goods (Hall and Patrinos, 2012). Their phenotype can also mark a visible difference compared with other groups. For instance, in Mexico, a country with much larger presence of indigenous people, the opinion questionnaire of the 2010 National Survey on Discrimination found that 54.8 percent of respondents believed that people received abuse in the street based principally on their skin colour within the country. For all this, their living circumstances may make indigenous people over-targets for petty corruption, particularly because of the widespread exclusion from most economic and political processes enhances their vulnerability to bribery. Therefore, I posit this last hypothesis:

H4. *I expect a significant and stronger relationship between skin colour and bribery in countries with large and visible indigenous populations.*

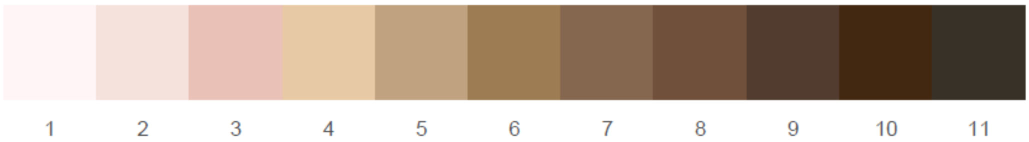
3. Data and Empirical Strategy

Under what conditions does bureaucratic corruption perpetuate discrimination? In particular, how does skin colour –as regional determinant of racial inequality– factor into bribery targeting in Latin America? This section explains the data and empirical strategy employed to answer this research question. The study presents nested logit regression models on the relationship between skin colour and different types of reports paying or having been asked for bribes for access to public services such as healthcare or in the interaction with local government, police officers, and the legal and justice system, among others. These models test the previous hypotheses by observing how the magnitude and significance of skin colour influence the occurrence of bribery by controlling for a full set of covariates, including age, gender, education, wealth, and area of residence.

I test the hypotheses using regional data from three waves (2012, 2014, and 2016/2017) of LAPOP survey. This project is conducted in 31 countries in Latin America and the Caribbean between 2004 and 2021. It is a face-to-face 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. I exploit this rich data set that disentangles questions on individual corruption experiences as well as citizens' phenotype dimensions. Since 2010, LAPOP in association with the Project on Ethnicity and Race in Latin America (PERLA) has included questions on racial attitudes and identification. As Figure 2 shows, LAPOP includes PERLA' skin-colour palette, which provides an observer measure of the respondents' phenotype as scored by the interviewer.[5] The LAPOP survey thus provides direct evidence to test our corruption discrimination hypotheses.

[5] The PERLA colour palette compliments the self-reported measures of race and ethnicity. The colour palette was specifically designed to evaluate skin colour specifically in Latin America (Talles and Paschel, 2014).

Figure 2: PERLA Colour Palette.



Note: Based on Telles and Martínez-Casas (2019).

Indigenous and African descendant people can be found in many countries in Latin America, but the magnitude and visibility of these groups vary across nations. For the purpose of this study, I limit the case selection to nine democracies with large, visible black and indigenous populations. These countries encompass the four principals with substantial Afro-descendant populations –Brazil, Colombia, Costa Rica, and the Dominican Republic– and the main five with large indigenous populations –Bolivia, Ecuador, Guatemala, Mexico, and Peru. Each of these nations has a population of approximately 10 percent or more self-identified black or indigenous according to their national census and LAPOP sample. This categorises the countries by which historically marginalised and disadvantaged group is most populous in each (Talles and PERLA, 2014). The LAPOP dataset compiled includes circa 45,000 individual observations from these nine cases. Missing values were excluded for the pooled sample. While in the majority of the countries the sample size has approximately 4,500 observations, in Bolivia roughly 7,700 and in Peru 5,500. Therefore, I use LAPOP sample weights to make the results representative at the regional level and comparable across countries and waves (Castorena, 2021).[6]

In 2014, the Economic Commission for Latin America (ECLA) estimated that Afro-descendant peoples numbered 750,000 (8%) in Costa Rica. Just under 4 percent of the pooled LAPOP sample for Costa Rica self-identified as Afro, but I retain it in the analysis for one important reason: it represents a theoretically significant case of blackness victimisation and

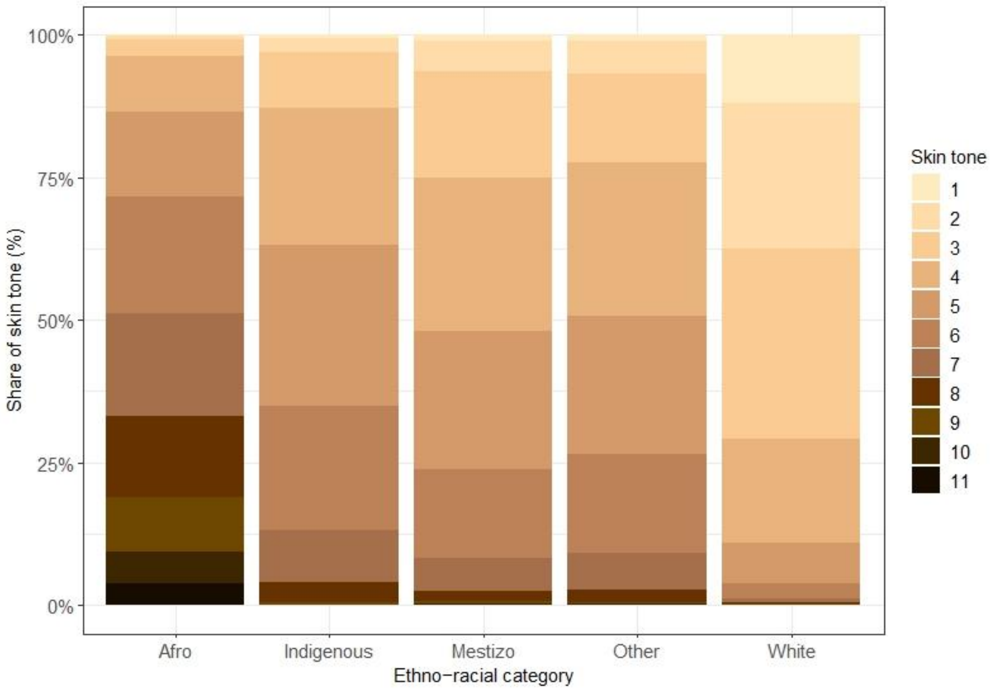
[6] In models in which I pool data from all nine countries, data are weighted using the "*weight1500*" (also called "*wt*") country weight, as recommended by LAPOP. So, each nation's sample contributes a value of N = 1,500.

colour-based racism within the social sciences literature. Moreover, more than 8 percent of the pooled LAPOP sample for Costa Rica self-identified as Indigenous or similar ethnicity, meeting the 10 percent minority threshold applied in the other eight countries. ECLA also estimated that indigenous peoples comprised 1.8 million (11%) in Chile. However, I exclude this country from the principal analysis due to the fact that less than 1,5 percent of the pooled LAPOP sample for Chile self-identified as indigenous. I also opted to exclude Venezuela from the analysis. While it stands as one of the central cases of indigenous movements in the Americas, the last decade of political instability and poor democratic governance may produce a rampant low-scale corruption that could potentially skew the sample selection.

These nine cases also enable me to assess the shared dimensions of marginalisation for indigenous and black populations and address a significant gap in corruption studies. Such studies often tend to concentrate on ethnic or racial groups separately, analysing these communities in isolation. There are valid reasons for disaggregating the study of race and ethnicity, for instance, as these groups have been integrated into national identity and citizenship in distinct manners. However, individuals of indigenous and African descent share a common reality of colour-based discrimination in the Latin American region. Given my emphasis on the relationship between corruption and discrimination based on observable racial characteristics, this analysis investigates Afro descendants and indigenous populations collectively. This approach seeks to explore the corruption-related discrimination that emerges from ascriptive factors, situated at the intersection of both worlds.

Figure 3 below plots the distribution of skin tones by each of the ethno-racial categories in the pooled 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, Mestizo, or Other ethnic groups have mostly medium-dark skin tones, but there is considerable variation in skin tone distribution. Even when skin colours are broadly correlated to the distribution of self-reported ethnicity, there is a large diversity of racial phenotypes within ethno-racial groups. Thus, using the information on skin tone has significant advantages over using self-reported ethnicity, among them, the measure is extraneous to respondents' perceptions.[7]

Figure 3: Self-Reported Ethnoracial Categories and Skin Tone.



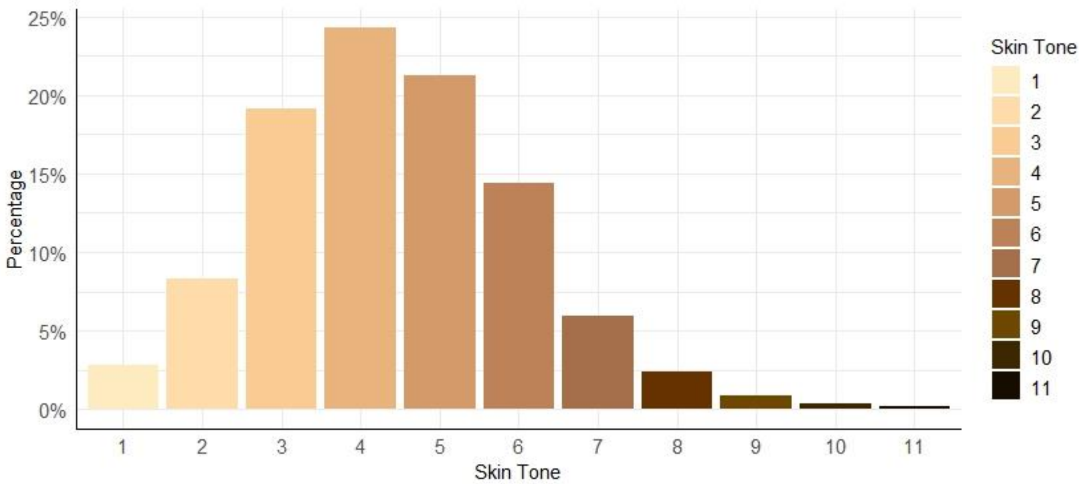
Note: Share of each skin tone for each broad ethnoracial category in the sample.

Therefore, I construct my primary independent variable of interest using the interviewer's classification of the respondents' skin tone. The original variable in the dataset of the PERLA colour palette ranges from one (the lightest category) to eleven (the darkest category). As we can see in Figure 4, the graph displays the distribution of skin tones across countries in the pooled sample, revealing that the majority of individuals have a medium-tone phenotype. But as Canache and co-authors (2014) mentioned, "the social significance of skin colour is inherently relative". A

[7] Skin tone is not the only key dimension for Latin America's racialisation and therefore racial discrimination. Other elements as hair type, accent, eye colour, even stature affect the conception of race. Nevertheless, skin colour is the most salient dimension (Telles and Paschel, 2014).

respondent, for instance, with a score of 5 on the PERLA palette would be relatively dark skinned in Costa Rica and Colombia, average in Ecuador, and relatively light skinned in the Dominican Republic and Guatemala. To capture this situational variation, I standardised the original variable at regional-level.[8] I rescale this variable to range from 0 to 1. Thus, the coefficient on this variable can be interpretated as the expected change in a 0-1 outcome associated with a change from the lightest to darkest skin tone.

Figure 4: Skin Tone Distribution in Percentage.



Note: Distribution of PERLA colour palette in the nine countries of the sample selection.

To test the hypotheses, I need to measure the payment of bribes for public services, serving as my primary dependent variables. In the LAPOP survey, respondents' answers were binary, indicating whether they were targeted to pay bribes (1) or not (0) to access the specified services within the preceding twelve months. The survey encompasses a set of questions posed to all respondents concerning the payment of bribes to police officers, courts, state officials, municipality bureaucrats, the military[9], and healthcare services.[10] Furthermore, in order to have a

[8] Standardised Colour$_{ir}$= $\frac{Colour_{ir} - Colour_r}{Stand.Dev.Colour_r}$ where *r* refers to region *r* in the respondent's country. *Colour* is the original eleven-point variable from LAPOP. This standardised colour variable has also been validated and utilised in previous works (e.g., Canache et. al., 2014; Johnson, 2019).

[9] The military bribe item was not included in the surveys of Costa Rica.

[10] While LAPOP survey also inquiries about the payment of bribes in schools and work, none of these contexts are explicitly indicated as being provided by public authorities. Given the research's focal point on bureaucratic corruption, I decided to exclude these two items from the analyses.

holistic comprehension of how Latin Americans are targeted by petty corruption practices, I create an additional a key dependent variable defined as *Corruption Experience Index* measuring whether people have paid bribes –or have been asked to paid– to get access at least one of the public services mentioned before. I rescale the index to restrict it between 0 and 1. The greater the index value, the more service corruption a respondent has experienced.

I also include a set of additional control variables in each of the models for socio-demographic factors that are likely to influence the propensity of being targeted for bribes. These variables measure for female, wealth, rural, age, education, and interviewer skin tone. *Female* is dichotomous and coded as 1 if the respondent is female. *Material Wealth Index* measure is constructed as a composite variable (PCA) ranging from 0 to 13, indicating how many of 13 household items the respondent possesses according to LAPOP survey.[11] I encoded the index to vary from 0 to 1, in which the greater index value, the more material wealthy is an individual. *Age* is a continuous variable from eighteen to ninety-nine years, and a square of age (*Age*^{2}) is used to captures non-linear effects. *Rural* is a dummy variable that takes a value of 1 if the respondent lives in a rural area. *Education* is a continuous variable ranging from 0 to 18 years of schooling. For the nested models, I encoded into "none" (0), "primary" (1 to 6), "secondary" (7 to 12), and "postsecondary" (12 to 18). *Interviewer skin tone* is based on a rating by the interviewer using the same chromatic scale detailed above. Table A.1 shows the sample descriptive statistics in the Supplementary Material.

Given that my dependent variables are binary, I employ binomial logit regression models to test the hypotheses. In order to account for any potential unobserved or unmeasured variations between countries, I also incorporate country fixed effects into the analyses. The calculation of

[11] I employ this measure of material wealth due to the absence of an individual-level income question in LAPOP. The household items are television, refrigerator, telephone, cellular, car, washing machine, microwave, motorcycle, indoor plumbing, indoor bathroom, computer, TV, and access to internet. This variable has also been previously validated and utilised in previous studies as an alternative to income-based measures in developing countries (e.g., Dixon, 2019).

odds ratio coefficients for each of the regression models constitutes the approach used for presenting the results in the following section.

It is important to point out that survey-based corruption measurements may be inaccurate. Scholars have argued that due to fear of reporting sensitive behaviours, respondents may feel uncomfortable admitting that they have been targeted by public officials or paid bribes to obtain public services (Treisman, 2007). Therefore, corruption experiences may be sometimes underreported due to social desirability pressures. One strategy to identify this issue is when a significant portion of individuals opt not to respond. But within the pooled sample, substantial proportions reported paying bribes and, according to our corruption experience index, just under 1 percent of individuals evaded all questions about their experiences. Perhaps future studies should validate the following findings using experimental methods that better capture this sensitive information; however, my results provide a robust indication of how skin pigmentation factors into bribe targeting in the region. Notably, using data from three waves of survey can improve the robustness of any findings to methodological or idiosyncratic biases of a unique round.

4. Findings

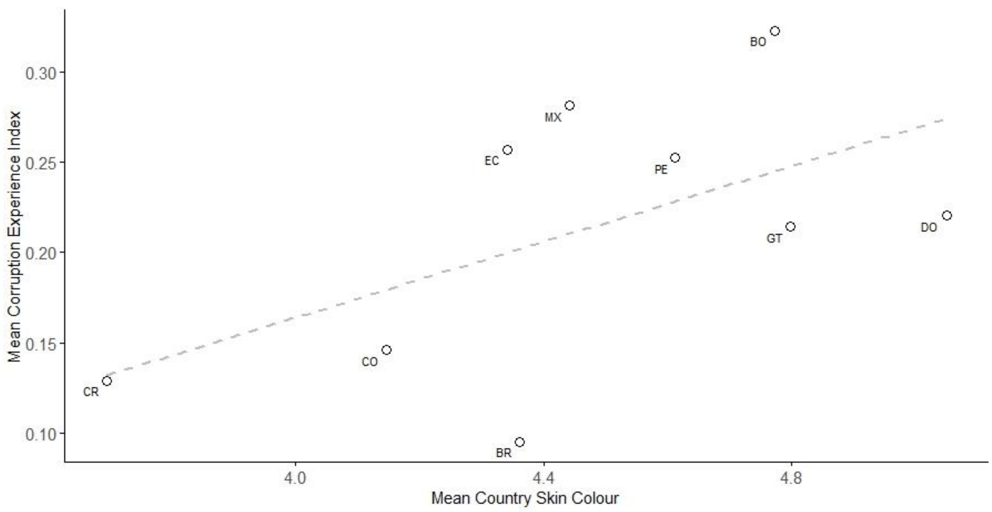
This section presents the main findings of this study. The first part reflects on the relationship between skin pigmentation and individual corruption experiences, presenting its results at the regional and national levels. The second part presents the results of the interactive effect of skin colour and material wealth on the occurrence of bribery. The third part analyses the results of this relationship grouping Afro and indigenous countries separately. I explain each of these findings in turn.

In our full sample, more than 22 percent of respondents reported paying at least one bribe to access public services. The most common corruption experience reported is paid or asked for a bribe to deal with police officers (14.5%) and government authorities (7%); and is less frequent when dealing with the military (3.3%) and courts (3.4%). Despite Latin America combining substantial levels of bureaucratic corruption, there are considerable variations within across the nine countries. Table A.1 in the Appendix shows the proportion of those reporting giving bribes in different countries surveyed by LAPOP in the sample selection. For instance, less than 10 percent of respondents in Brazil reported having experienced bribery, compared with 32 percent in Bolivia and 28 percent in Mexico.

On average, respondents exhibit a medium to lighter skin tone. The mean standardized skin tone at the regional level in the pooled sample is 3.6 points according to the PERLA colour palette, with variations ranging from 4.2 in Guatemala to 2.7 in Costa Rica. It is important to note that every country has at least one individual representing both the lightest and darkest skin tones possible. Additionally, a comparison between countries with significant black and indigenous populations reveals slight disparities in the overall distribution. Hence, in nations with prominent indigenous communities, the mean skin tone of the population approaches nearly 3.5 points, whereas in countries with Afro-Latin and black populations, this value averages around 3.6 points.

Initial evidence of a potential relationship between skin colour and bribery experiences can be observed in Figure 5 below. This graph illustrates the country's mean corruption experiences against the country population's mean skin tone. We can see that there is a positive correlation between phenotype and individual corruption experiences at the aggregate level. While variations exist among countries, where some outliers are presented in the pooled sample, the general pattern suggests that skin colour appears to drive the occurrence of bribery. These variations likely stem from various factors, whereby citizens with darker skin tones are situated; in countries with large indigenous populations, for instance, darker-skinned citizens might be more frequently targeted to pay bribes in order to access public healthcare services or secure their legal representation in the judiciary system. In what follows, I estimate a series of models to test my hypotheses that citizens' phenotype has a robust effect on individual bribery experiences.

Figure 5: Corruption Experiences and Skin Colour



Note: The graph compares each country's mean corruption experience index against their population's mean skin tone.

4.a. Skin Colour and Individual Corruption Experiences in Latin America.

In this section, I test my first and main hypothesis: corruption is expected to target darker-skinned citizens at higher rates compared to lighter-skinned citizens. As discussed earlier, I estimate pooled models for three waves of LAPOP (2012, 2014, and 2016/2017). The results of my estimations are displayed in Table 2 below. I report odds ratio coefficients for logit regression models estimating reported experiences with bribery based on skin colour, a set of control variables and dummy country fixed effects. The model includes the standardized measure of skin tone at regional level. Positive coefficients are expected for the independent variable, effects that would signify that, compared with people who have a light/white phenotype, all other respondents have higher likelihoods of targeting by bureaucratic corruption based on the basis of their darker skin-colour. The results of models using unmatched data for each country can be found in Appendix Tables A.3.

Table 2. Odds ratio from logit regression models predicting corruption experiences based on skin colour. Matched data.

	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.810***	2.381**	1.709***	1.746**	1.907***	1.992***	1.685***
	(0.102)	(0.293)	(0.137)	(0.185)	(0.178)	(0.205)	(0.086)
Female	0.998	1.263**	0.965	0.999	1.144*	1.092	0.993
	(0.030)	(0.086)	(0.040)	(0.054)	(0.053)	(0.061)	(0.025)
Rural	1.046	1.136	1.192***	1.177**	1.319***	1.146	1.094**
	(0.035)	(0.098)	(0.049)	(0.062)	(0.059)	(0.070)	(0.029)
Material Wealth Index	3.289***	1.610*	2.946***	1.384*	0.684**	2.223***	2.308***
	(0.079)	(0.219)	(0.106)	(0.142)	(0.145)	(0.155)	(0.067)
Age	1.039***	1.032*	1.056***	1.024*	0.987	1.003	1.027***
	(0.005)	(0.015)	(0.007)	(0.010)	(0.008)	(0.010)	(0.004)
Age^2	0.999***	1.000*	0.999***	1.000**	1.000	1.000*	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.044	0.478*	0.803	0.786	0.720*	0.947	0.999
	(0.110)	(0.309)	(0.147)	(0.198)	(0.147)	(0.226)	(0.084)
Secondary education	1.385**	0.484*	1.016	0.741	0.626**	1.064	1.208*
	(0.110)	(0.308)	(0.146)	(0.198)	(0.150)	(0.225)	(0.085)
Postsecondary education	1.705***	0.511*	1.585**	0.707	0.537***	1.170	1.515***
	(0.114)	(0.317)	(0.151)	(0.205)	(0.161)	(0.233)	(0.088)
Interviewer Skin Tone	0.992	0.918**	0.999	0.991	1.065***	0.990	1.003
	(0.011)	(0.030)	(0.014)	(0.019)	(0.018)	(0.021)	(0.009)
Constant	-4.688***	-3.810***	-5.593***	-3.035***	-2.893***	-4.410***	-3.549***
	(0.179)	(0.501)	(0.240)	(0.325)	(0.270)	(0.342)	(0.141)
N	44,415	6,620	44,415	11,371	24,951	39,941	44,695

Source: LAPOP 2012-2016/2017.
Note: Matched sample. Odd Ratios. Standard errors are in parentheses. All regressions models are weighted by population. The dependent variable is the payment of bribery, coded 1 if the respondent has paid and been asked for a bribe in a year, and 0 if not. Skin tone is standardised at regional-level, and the reference group for education is "None". Country dummies are included in analysis but omitted from the table for ease of presentation. Coefficients are statistically significant at *p<0.05, **p<0.01, ***p<0.001.

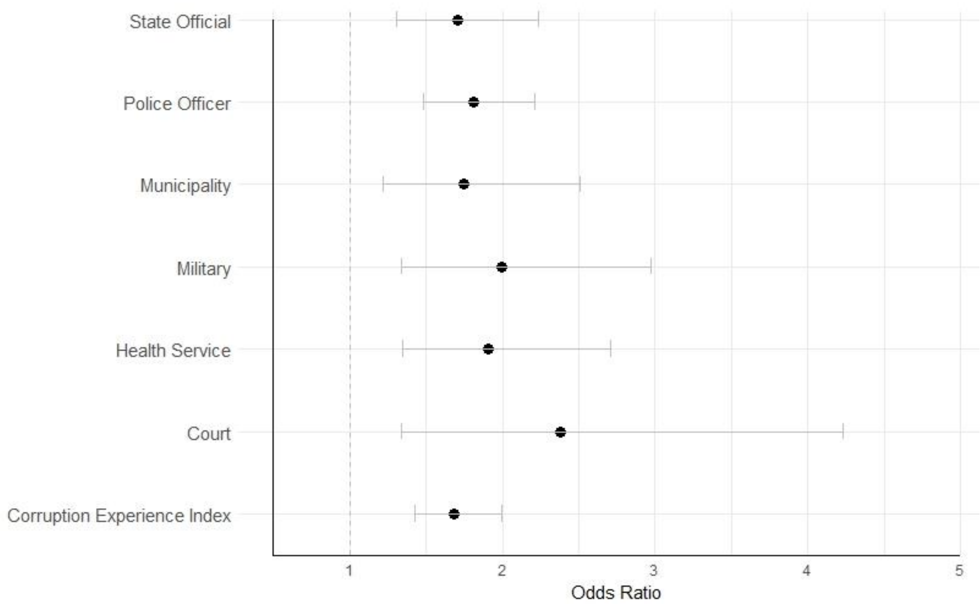
The findings provide confirmatory evidence for hypothesis **H1**. I find a positive and statistically significant relationship between skin colour and corruption experience across all varieties of bribery: for police officers, courts, government officials, municipalities, healthcare services, and the military. The strongest relationship is between skin tone and being targeted to pay bribes in the courts, although with greater variation. The weakest, but still statistically significant, is when dealing with state authorities. Irrespective of the sector, logit models suggest that skin pigmentation in Latin America is meaningfully and positively associated with all forms of bureaucratic corruption experience. In short, I can reject the null hypothesis in all types of bureaucratic corruption cases and therefore for the key dependent variable, corruption experience index, in the pooled sample. Although its effects vary across countries.

Of the nine countries that I analysed for the association between the standardised skin colour variable and our corruption experience index, respondents with darker skin tones are more likely to be targeted to bribery in seven of the nine countries. Yet, I find evidence of a statistically significant association only in Bolivia, Costa Rica, Ecuador, Mexico, and Peru. In Guatemala and the Dominican Republic, the coefficients are positive although I cannot reject the null hypothesis. The odds ratio varies across these countries, ranging between 1.2 and 2.4. The 3.6 odds ratio for Peru is markedly larger than the others, a result that is possibly due to the fact that, with a substantial population reported corruption experiences, but also an important portion of darker skin tone, and thus likely somewhat more salient than in the other nations.

There are two exceptions to this meaningful pattern: Brazil and Colombia. In these countries with large, visible Afro-Latin populations, the coefficient has a negative association –and marginally significant only in Colombia– between skin tone and corruption experience, holding all else variables constant. In principle, both cases do not constitute cases of corruption discrimination based on skin tone. These results, however, hold significant implications as they support prior evidence pointing to the discriminatory nature of corruption practices: despite an underlying shared tendency at the regional level, it is unique contextual factors that contribute to heterogeneity and lead to inconsistent findings across countries.

Contrary to my forecast, the evidence in support of hypothesis **H2** is less consistent. I do not identify a clear pattern regarding the relationship between skin colour and corruption experiences with different forms of state-run delivers. These findings are displayed graphically in Figure 6 below, which plots odd ratios from logit models for each type of experience of bureaucratic corruption. The models predict ambiguous results between substitutable and non-substitutable public services. Skin tone has the greater impact on being targeted by bribes in cases involving the courts, the military, and police officers (which offer less substitutable public services) than for more substitutable services such as local governments (which can offer a mix of substitutable services like energy supply or microcredits). However, there is also a strong effect related to experiencing corruption within the healthcare system (which can be replaced with private clinics and medicine). Furthermore, it is worth noting that this surpasses the predicted effect of experiencing corruption with national bureaucracy' members, which were expected to have a stronger influence.

Figure 6: Effects of Skin Colour on Likelihood of Different Types of Corruption Experiences.



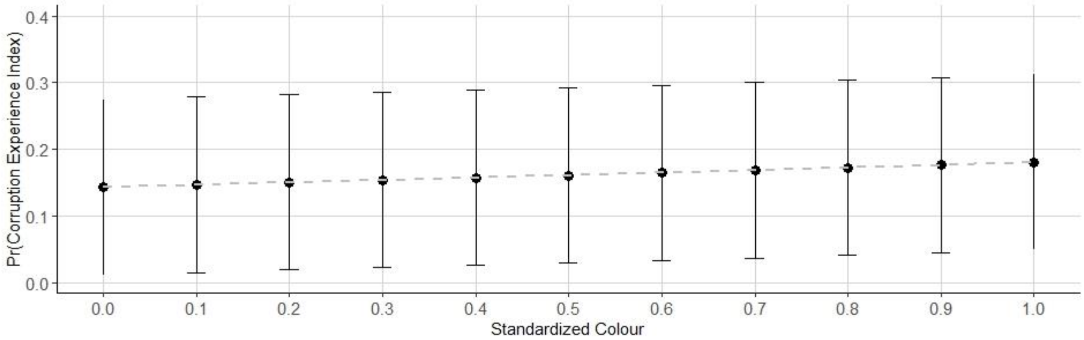
Note: The graph displays point estimates with their 95% confidence intervals. Seven separate regressions were estimated, one for each type of experience of bureaucratic corruption. Data are derived from odds ratio reported in Table 3.

At country level, the results exhibit variations across corruption types. Robust association between skin colour and police bribery are evident in Costa Rica, Ecuador, Peru, and Mexico, whereas Colombia displays a negative and statistically significant relationship. It is worth noting that in Costa Rica, the odds ratio is remarkably amplified, exceeding that in the matched data by a factor of at least 10. Additionally, citizens with darker skin tones in Mexico and Ecuador are notably more susceptible to bribery in courts-related matters compared to their counterparts within the sample. An exception to this pattern is Dominican Republic, where the association is negative and marginally significant. In Ecuador and Guatemala, a consolidate effect of phenotype on corruption involving the military is observed. In these cases, the odds of reporting bribes are approximately 6 and 5 times higher, respectively, than those reported in nested models. Furthermore, for Mexican citizens, the effect of skin tends to be greater for being targeted to paid bribes for access to health, which individuals with darker skin have 7 times the odds of experiencing corruption in this service.

Interesting findings also emerge when examining bribery experiences involving national and local forms of government. For instance, the relationship between skin tone and interactions with state officials is positive in seven out of the nine cases, and statistically significant in five of them –specifically Costa Rica, Ecuador, Guatemala, Peru, and Mexico. While likelihood ratio tests suggest that this association with municipality bribery is also positive in seven countries, the null hypothesis can be rejected in just two cases, Bolivia and Peru. Conversely, in Colombia, the results show a significant negative association between skin tone and corruption in any form of government: the darker the skin colour, the fewer reported bribery experiences with both municipality as well as state authorities. In Brazil, however, I do not find any significant results of the relationship between skin tone and the six types of corruption, whether positive or negative.

Nevertheless, the effects of skin colour on the occurrence of bribery are of considerable magnitude at aggregated data. To be sure, and as Figure 7 makes clear, variation in skin colour matters a great deal in predicting variation in the individual corruption experience index at regional level –the likelihood an individual will target to pay bribes to access public services increase substantially when will identify with a darker phenotype. With other variables held constant, we see the effects of skin tones on the predicted probabilities that a respondent reports having been targeted to paid –or having asked– bribes. The results from the nested models are depicted by the dashed line. The clear lesson is that each skin tone category corresponds to a consistent increase in the likelihood of experiencing corruption. Looking at the graph, the increment is clearly smooth but consequential. Where skin tone equals 0, a white respondent has, on average, only .12 likelihood of experience to have been target of corruption, versus marks almost .20 for respondent with a very dark phenotype.

Figure 7: Predicted probability by skin colour. Nested models.



Note: Predicted probability of experiencing corruption at every level of the standardized skin colour variable. All covariates are held at their observed values. Data are derived from coefficients reported in Table 3. Ninety-five percent confidence intervals reported.

What is the substantive significance of these results? To explore this, I made a series of predictions about the likelihood of reports paying bribes by a hypothetical 37-year-old woman from a rural area, a secondary education and the mean level of each variables, varying only in her phenotype. These predictions are shown in Table 4 below and data derived from nested models reported in Table 2. The differences in predicted probabilities between light and dark skin tones for our corruption experience index reflect that a woman in the lightest quartile skin colour (.25 in the standardized colour variable) has a 22.8 percent probability of being targeted or exposed to petty corruption in contrast to a 25.4 percent of darkest quartile skin tone (.75 in the standardized colour variable). Findings also consolidate that the highest gap in analysing different types of corruption is the payment of bribery when dealing with the courts, which rises to a difference of more than 4 percent. By contrast, darker phenotypes were associated with only a 3.6 percent greater likelihood of military corruption encounters whereas light tones were 4.8 percent in the sample.

Table 4. Experiences of Corruption: Predicted Probabilities. Pooled Data.			
	Predicted probability for:		
Paid bribe for/to:	**Lightest quartile**	**Darkest quartile**	**Difference (% points)**
Police Officer	14.6%	16.1%	+1.5
Court	11.5%	15.6%	+4.1
State Official	7.0%	8.0%	+1.0
Municipality	16.7%	19.9%	+3.2
Health Service	7.3%	9.8%	+2.5
Military	3.6%	4.8%	+1.2
Corruption Experience Index	22.8%	25.4%	+2.6

In all models, I controlled for the regional mean of wealth index and education level, so the effect is unlikely to be driven purely by a resource effect by which those with greater amounts of material resources or level of education are more likely to come exposed to the payment of bribery to access to public services or any other type of bureaucratic process within public institutions. Also, I controlled for the regional mean of the interviewer's skin tone to avoid any pre-discriminatory assumptions about who are taking the survey. Overall, the results give me strong evidence for **H1** –corruption experiences are more likely to happen among darker skin colour citizens–, but less consistent to support **H2** –such experiences are greater for non-substitutable (courts) as well for substitutable public services (health).

4.b. The interactive effect of Skin Tone and Wealth on Experiences of Bribery.

In this section, I turn to my third argument, focusing on whether the association between skin pigmentation and corruption experiences interacts with social and economic conditions of respondents. Are wealthy dark skin citizens more likely to experience bribery in opposition to their poorer counterparts in Latin America? I expect that wealthier respondents with darker skin tones might encounter a higher likelihood of being targeted for bribery than those with the same phenotype but lower socio-economic statuses. Table 5 presents nested models in which standardised skin colour and our material wealth index are interacted as an explanatory variable, controlling by the same set of independent variables used before. The full models for each country are presented in Appendix, Tables A.6.

Table 5. Odd ratios from logit regression models predicting corruption experiences and interacting standardized skin tone and material wealth. Matched data.

	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	2.315	1.064	1.495	0.228	2.354	25.955***	1.847
	(0.441)	(1.233)	(0.595)	(0.786)	(0.800)	(0.910)	(0.370)
Standardized Skin Tone	1.145	2.303	1.361	3.918**	1.244	0.315**	1.214
	(0.261)	(0.719)	(0.364)	(0.467)	(0.438)	(0.535)	(0.216)
Female	0.998	1.263**	0.965	1.000	1.143*	1.097	0.992
	(0.030)	(0.086)	(0.040)	(0.054)	(0.053)	(0.061)	(0.025)
Rural	1.044	1.136	1.191***	1.183**	1.315***	1.138*	1.092**
	(0.035)	(0.098)	(0.049)	(0.062)	(0.059)	(0.070)	(0.029)
Material Wealth Index	2.430***	1.574	2.549***	2.368**	0.497	0.675	1.849***
	(0.177)	(0.506)	(0.239)	(0.319)	(0.331)	(0.368)	(0.149)
Age	1.039***	1.032*	1.056***	1.024*	0.987	1.003	1.027***
	(0.005)	(0.015)	(0.007)	(0.009)	(0.008)	(0.011)	(0.004)
Age^2	0.999***	1.000*	0.999***	1.000**	1.000	1.000*	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.041	0.478*	0.802	0.785	0.719*	0.941	0.997
	(0.110)	(0.309)	(0.147)	(0.198)	(0.147)	(0.227)	(0.084)
Secondary education	1.377**	0.484*	1.013	0.742	0.624**	1.046	1.204*
	(0.110)	(0.308)	(0.146)	(0.198)	(0.150)	(0.225)	(0.085)
Postsecondary education	1.699***	0.511*	1.582**	0.706	0.536***	1.159	1.511***
	(0.114)	(0.317)	(0.151)	(0.205)	(0.161)	(0.233)	(0.088)
Interviewer Skin Tone	0.992	0.918**	1.000	0.990	1.065***	0.991	1.003
	(0.011)	(0.030)	(0.014)	(0.019)	(0.018)	(0.021)	(0.009)
Constant	-4.514***	-3.797***	-5.507***	-3.340***	-2.728***	-3.741***	-3.424***
	(0.200)	(0.565)	(0.272)	(0.367)	(0.311)	(0.389)	(0.159)
N	44,415	6,620	44,415	11,371	24,951	39,941	44,695

Source: LAPOP 2012-2016/2017.
Note: Matched sample. Odd Ratios. All regression models are weighted by population. Standard errors are in parentheses. The dependent variable is the payment of bribery, coded 1 if the respondent has paid and been asked for a bribe in a year, and 0 if not. Skin tone is standardized at regional level, and the reference group for education is "None". Country dummies are included in analysis but omitted from the table for ease of presentation. Coefficients are statistically significant at *p<0.05, **p<0.01, ***p<0.001.

The results indicate contradict evidence for supporting hypothesis **H3**. While I do find that interaction coefficients hold considerable significance and are positive only for bribery experiences involving military officers, I cannot reject the null hypothesis when it comes to dealings with the police, government employees, the sanitary public system, the courts, and therefore our corruption index. Skin colour is affected by the interaction with these variables having a positive but null effect on corruption experience index. The results are thus consistent in country models. I find no evidence of a relationship between the interactive effect of colour and wealth on our corruption experience index in any of the nine cases. This result goes against the grain of much research on the corruption-wealth nexus.

However, I observe interesting outcomes. Affluent darker-skinned respondents are more likely to pay bribes when dealing with public security forces in general, and this likelihood is meaningfully and extremely higher when those experiences are related to the military in particular. Draws attention how strong is the magnitude, comparing with the coefficients of the rest of bribery types. This association is positive and meaningfully just in two of the eight countries, being the effect significant amongst nations with substantial Afro-Latin populations (Colombia and the Dominican Republic). This may suggest an intersectional dynamic between race, wealth and corruption. In contexts of daily crime and a high degree of vulnerability of Afro descendants' communities as happen in both countries, black and brown individuals with more resources are not only more capable of paying a "bribery fee" to ensure their own security but are also more susceptible to targeting by military officers for extortion based on their ethnoracial difference.

The second significant finding is that, in the case of local governments, the interactive model is not statistically significant, but it presents a unique reversal: individuals with darker skin tones and more material wealth are less likely to encounter bribery experiences while accessing local services, certificates, or even welfare provisions from their municipalities. Only for Guatemala this relationship is meaningfully and positively associated. This evidence is intriguing and might be due to the nuanced interplay between the effect of different skin colours and varying levels of wealth on the occurrence of corruption. For instance, due to the often-close association between skin tone and poverty, previous studies have indicated that middle-class black individuals in Latin American countries may be perceived as economically disadvantaged (Silva and Reis, 2011). Thus, the convergence of wealth and phenotype, may not necessarily serve as the most accurate predictor of exposure to bribery experiences.

Comparing the results from models across countries, interactive coefficients are only positive and statistically significant in the cases of Bolivia –when corruption is related to health public services– as well as in the Dominican Republic –when dealing with state officers. While the analyses above is counter to expectations for **H3**, this suggests heterogeneity in the interactive models. More importantly, this leaves open the possibility that corrupt officers may be interpreting possible scenarios of extortion that may be due to the person's colour as resulting from their socio-economic status. This could be arisen because of the close association between darker skin and economic disadvantages of individuals, or perhaps due to the power of nation-building discourses of "money whitening", which downplaying the role of colour in favour of social class.[12]

4.c. Darker-Skinned Citizens and Corruption Experiences in Indigenous Countries.

Corruption literature indicates that both social groups and geographical bounders are relevant, especially when analysing it relationship with historical discriminatory patterns. In this section, I ask: Do darker-skinned citizens from indigenous countries have a higher likelihood of experiencing corruption compared to those from Afro nations? Because indigenous communities are especially exposed to corruption, a risk that is heightened by the structural exploitation their individuals face, I expect a significant and stronger relationship between skin colour and bribery in the set of indigenous nations. I show descriptive statistics in Appendix, Table A.1. I also present the models that estimate the frequency of our corruption experience index based on skin tone within these two groups of countries in Table 7, controlling by the same set of variables of first models in this study. The full regressions are presented in Appendix, Tables A.8.

[12] The idea of money whitening has deep historical roots in Latin America and the Caribbean. As Talles and Peschel (2014) note, it may be linked to the practice of "*gracias al sacar*" whereby people –typically mixed-race free persons who had accumulated enough material resources– in the colonial-era with its castas system would purchase certificates of whiteness from the crown.

The mean skin tone suggests that, on average, people from indigenous nations tend to be slightly darkest compared to individuals from Afro countries. Although the standard deviations suggest much overlap in the colour distribution, as mentioned before. Notably, 27% of respondents from countries with indigenous communities reported paying at least one bribe to access public services in the preceding year. The percentage decreased to 14% amongst respondents from those Afro. In every question asked about the payment of bribes, individual from indigenous nations reported at higher rates. Prima facie evidence reflects that the colour-based disparity in the occurrence of corruption might be more pronounced within indigenous-heritage countries.

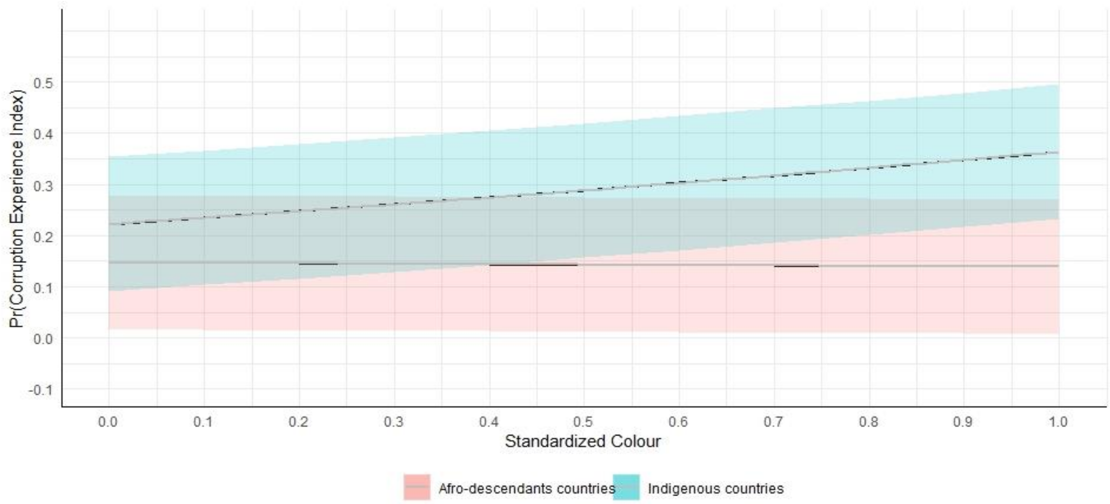
Table 8. Odds ratio from logit regression models predicting corruption experiences based on skin colour. Matched data from Indigenous (Bolivia, Ecuador, Guatemala, Mexico, Peru) and Afro (Brazil, Colombia Costa Rica, Dominican Republic) countries.

	Indigenous countries	**Afro countries**
	Corruption Experience Index	Corruption Experience Index
Standardized Skin Tone	2.026***	1.093
	(0.103)	(0.159)
Female	1.010	0.955
	(0.030)	(0.047)
Rural	1.051	1.229***
	(0.034)	(0.056)
Material Wealth Index	2.201***	2.708***
	(0.078)	(0.130)
Age	1.037***	1.004
	(0.005)	(0.008)
Age^2	0.999***	1.000*
	(0.000)	(0.000)
Primary education	0.936	1.302
	(0.093)	(0.196)
Secondary education	1.172	1.455
	(0.094)	(0.196)
Postsecondary education	1.451***	1.896**
	(0.099)	(0.202)
Interviewer Skin Tone	1.003	1.004
	(0.012)	(0.014)
Constant	-2.064***	-2.907***
	(0.153)	(0.270)
N	26,838	17,857

Source: LAPOP 2012-2016/2017.
Note: Matched data. Odd Ratios. All regressions models are weighted by population. Standard errors are in parentheses. The dependent variable is the payment of bribery, coded 1 if the respondent has paid and been asked for a bribe in a year, and 0 if not. Skin tone is standardized at regional-level, and the reference group for education is "None". Country dummies are included in analysis but omitted from the table for ease of presentation. Coefficients are statistically significant at *p<0.05, **p<0.01, ***p<0.001.

The regression analyses evidence thus supporting hypothesis **H4**. Darker-skinned citizens from indigenous countries are more likely to paid –or having asked for– bribes. By grouping the five countries with mostly indigenous population (Bolivia, Ecuador, Guatemala, Mexico, and Peru), I find a significant and positive correlation between skin colour and our corruption experience metric, as well as in the case of the six types of bribery in the models. As expected, a weaker association and surprisingly not significant in all any corruption forms is observed in the four aggregate nations with substantial black and Afro populations (Brazil, Colombia, Costa Rica, and the Dominican Republic). Similar to the first sets of regressions in this study, the strongest association is between skin tone and being targeted to paid bribes in the courts. Although in these results the weakness is when dealing with the public sanitary system.

Figure 8: Predicted probability by skin colour. Matched data.



Note: Predicted probability of experiencing corruption at every level of the standardized skin colour variable. All covariates are held at their observed values. Data are derived from coefficients reported in Table 9. Ninety-five percent confidence intervals reported in each colour-band.

While I cannot reject the null hypothesis for the models involving Afro countries, exploring the substantive effect of skin colour on individual experiences of corruption in both groups is an interesting exercise. I examine the predicted probabilities of colour-based disparities leading to bribery experiences in Figure 8 above. The graph illustrates that an individual's phenotype is a robust predictor when it comes to experiencing encounters with bribery to access public services in indigenous countries in contrast to African-descendant nations, holding all covariates at their observed values. For a respondent with the darkest skin pigmentation living in a predominantly Afro-nation, the probability of experiencing corruption in a year is approximately 15%, a clear reduce in frequency when looking at lightest skin in the scale. In contrast, this probability increases to roughly 35% for their counterpart within countries characterised by visible indigenous populations. Therefore, this difference is more than double when it comes to the effect of skin tone on being targeted or extortion by corrupt practices.

The historical displace by former colonial regimens, in which the indigenous peoples, the first natives, where forced to abandon their socio-political domains; a White state-building organisation in which public officials were (and are) the ultimate *patron* of access to public services; and the often-limited protection afforded to indigenous communities by state actors such as the legal system and justice tribunals; this analysis in favour of my last hypothesis **H4** contribute with new and robust evidence showing that darkest-skinned people from these indigenous countries are potentially targets for corruption practices. One possible explanation may be due to their widespread exclusion and discrimination suffer from many social, cultural, economic and political processes, as some scholars have noted (Castellino, 2020).

4.d. Robustness Checks.

To ensure that the results are no driven by data or modelling choices, I conducted a series of robustness checks using different empirical strategies and sub-samples. Results from these are available in Appendix, Tables A.10.

Firstly, to verify that the results are not driven by outliers, I excluded from the sample those countries with extremely high levels of dark skin tone and high levels of bribery victimisation. Excluded from the pooled sample observations from the Dominican Republic and Bolivia respectively. The effects of skin colour on bribery experiences remain positive, large and statistically significant after excluding for the nested models these two countries.

The models described above assume that corruption experiences and individual attributes are associated in the same way across all countries. However, bribery tends to be more pervasive in some societies than others. I therefore estimated a series of models leaving out one country each time and found there to be little change in the substantive or statistical significance. These analyses lend support to the results reported above when the pooled sample is used. The effect of colour on each corruption experience is still positive and significant after excluding each individual country.

As a final robustness check, the nested models were estimated using country specific standardised measures of skin tone. This standardisation recognises the relative aspect of the social meaning of skin colour by considering the skin colour distribution within each country. The patterns of results are similar to the standardised PERLA scale at regional level. Our analyses still confirm that skin tone is a positive and significant predictor of the likelihood of paying bribes; there is no substantive difference in the key results between these models and those reported above. I thus confident that my results are not driven by model or data choices.

5. Discussion

This section provides a discussion of the findings. I divide my analysis into three parts. First, I explore how the effects of skin colour on individual experiences of corruption can be interpreted within the context of Latin America, according to our specific-regional theory. Second, I analyse and attempt to provide some explanations for the key country differences presented in the previous section. Third, I present the most salient methodological limitations and discuss how further research can address and expand upon these barriers.

5.a. Corruption is not Colour Blind at Regional Level.

Our results indicate that having a dark skin tone makes respondents more likely to be targeted to pay bribes for accessing public services at aggregated level. For each increase of one unit on our standardised skin tone scale, I find that the odds of experiencing corruption changed by a factor of 1.6. The discriminatory impact of corruption becomes evident when its effects weight most heavily on those who are socially and economically vulnerable, as brown and black individuals from indigenous and Afro countries are. This result aligns with a vast body of evidence within the corruption literature, suggesting that these forms of low-scale corruption distort the distribution of public resources and services impartiality, thus generating disproportionate effects on the rights and needs of the most marginalised communities.

It is also important to emphasise that these results corroborate previous research conducted on similar countries within the region, which shows that darker skin pigmentation is highly associated generally with negative events and experiences of victimisation. The findings contribute to existing scholarship, confirming that the observed patterns reported in published papers are not merely the result of selecting countries where surveys show significant correlations. In a broader context, these patterns also align with the established body of research in the field of Latin American studies, indicating that skin tone often better captures diverse experiences of discrimination, including the intersection with various forms of low-scale corruption, as extended by the scope of this study.

According to some scholars, marginalised groups may directly lose out to corruption when individuals cannot afford for certain kind of private services such as health or education (Alesina et.al., 2016). As these communities are often excluded due to their social status or identity, it follows that these vulnerable individuals exposed to discrimination are more likely to pay bribes to access to non-substitutable services. While I find a positive and meaningful effect in all six types of bribery, including police officers, courts, state officials, municipality, health service, and the military, there is not a clear pattern to the results that skin colour have a weaker linkage with bribery with those state services which cannot be easily substituted by private alternatives. Darker-skinned tones have, for instance, one of the strongest effects related to experiencing corruption when dealing with the public healthcare system (which can be replaced with private hospitals).

Furthermore, our interactive models do not suggest that wealthy individuals with darker skin in Latin America are more likely to be targeted for bribes. The null results are surprising, given the vast literature on wealth and corruption. When examining the interactive effect on corruption experience index, I find a positive but not statistically significant relationship in the pooled sample. Interestingly, having resources and dark shade seem to play a big role by corrupt militaries to interpret unfair treatment, especially in nations with Afro communities. However, for other forms of corruption, such as those involving local governments, this linkage has the opposite effect, although it is not statistically significant. This leaves room for nuances in the wealth-corruption nexus literature, especially within the complex ethnoracial landscape of the Americas. Perhaps national narratives on whiteness and beliefs of "money whitening", which suggest that upward economic and social mobility could confer whiteness, can contribute with insights to variations in the prevalence of bribery among individuals to varying degrees.

Despite the inclusion of countries with unique histories and contemporary circumstances, there are, however, a few notable patterns distinguishing the Afro descendant and indigenous nations. The key finding is that individuals with dark phenotypes from indigenous-tradition countries are more likely to experience corruption. These individuals represent a vulnerable group that has historically faced exclusion and poor treatment within these geographics, highlighting the interplay between coercive corruption practices and deep-seated racism. Their exposure to specific forms of corruption is exacerbated by long-standing structural discrimination and often limited protection from public institutions (Doyle, 2014). This can be explained, for instance, by the stronger relationship between skin colour and bribery to access the justice system in our study.

However, there are some reservations about these results. Among indigenous countries, there is less variation in skin tone due to a concentration of the skin tone distribution away from the darkest phenotypes. Additionally, historically, cultural differences, including clothing and dialects, served as the primary distinctions among indigenous people. In opposition, Afro people were perceived as culturally assimilated, although phenotypically distinct from the presences of *white* and *mestizo* populations (Wade, 1997). As some scholars noted, decades of indigenous movements have led to a heightened awareness of prejudice, racism and discrimination among this group (Mijeski et al., 2011). The cultural, rather than racial framing, perhaps explains a negative stereotype in the mental maps of a large segment of population, and consequently, its translation to the rationale of corruption.

Examining these effects has important contributions to the existing literature on the linkage between corruption and discrimination. If corruption involves an inequal access to public services based on historical patterns of colourism and racial disparities, this suggests that both phenomena imply an intersectional, on-going mechanism that is mutually reinforce in Latin America. If corruption elevates the cost of transactions for access public goods and services among vulnerable groups through the addition of an additional fee not simply because the corrupt requires it, but to punish or reassert the gulf in social place, this may suggest that corruption can be seen as a simply another vehicle for colour-based discrimination. Finally, if corruption preys intentionally on browns and black individuals because they have been seen socially acceptable to exploitation, this may suggest that racial discrimination reduces the constraints on corrupt behaviour because the official corrupt are more likely to have less to fear if they targeted individuals from marginalised groups.

5.b. Analysing Country Differences.

While phenotype is a key predictor of the occurrence of bribery in the region, I argue that country heterogeneity reflects distinctive local corruption dynamics and racial patterns that may or may not be shared by countries. Our findings, for instance, indicate consistent trends between colour and corruption experiences across nations, with some variation in magnitude. Dark phenotypes drive bribery in Bolivia, Costa Rica, Ecuador, Mexico, and Peru. In the latter, skin colour operates in a more pronounced manner when it comes to being targeted for bribes in comparison to the pooled data. Peruvian with the darkest skin colour are roughly 24 percent more likely to be targeted as bribes victims than those with similar phenotypes in the pooled data.[13] Probably due to its large population identified as indigenous and more than 8 percent as Afro, Peru offers a unique case of validation of our theoretical expectations that is highlighted by a specific racial schema.

In Colombia, the outcome is unique and meaningful: white people experience more frequently being targeted to pay bribes than black individuals. For Brazil, Guatemala, and Dominican Republic I do not find a significant effect, whether positive or negative. A contextual explanation of Brazil may suggest that bribery are not the prevailing issues when talking about

[13] According to predicted probabilities, where skin tone equals 0, a white respondent has, on average, only .18 likelihood of experience to have been target of corruption (in our corruption experiences index), versus marks almost .44 for respondent with a very dark phenotype, with all covariates held at their observed values for Peru.

different forms of corruption in the country (France, 2019), supported by the lowest bribery reports in our sample selection. For the rest, I do not have any solid theoretical argument at my hand that can shared light over these results. However, this disparity is intriguing as it suggests that victims of corruption may not be uniformly affected based on their skin tone. This discrepancy could thus potentially warrant individual case studies or experimental methods for future research.

In Ecuador and Mexico, skin colour is a particularly powerful predictor of bribery in the courts relative to other experiences. Structural discrimination against vulnerable groups in both nations has resulted in unequal access to justice, with greater barriers to asserting their rights and entitlements, making them easier targets for corruption (Faundez, 2010). When we also consider the scarcity of public interest lawyers, cultural differences, and the opportunity to exploit those seen as "easy targets", it creates a combination that primarily affects individuals with dark phenotypes, who are mostly indigenous peoples here. This reinforces our theoretical stance that country differences are influenced by national features, including power imbalances and constant victimisation.

Our findings in Costa Rica are also quite interesting: dark skin tone is a reliable predictor of experiences with corrupt police officers. Even though the country ranks among the lowest in the regional LAPOP survey when comparing, on average, corruption victimization by the police, this relationship is the stronger within our sample. However, these differences open up interesting discussions and questions. The implications of having high rates of police abuse and brutality, coupled with greater crime victimisation against minorities, as some scholars have found significant in Costa Rica compared to other Central American nations (Cruz, 2015), may provide a clue as to why the effect of colour is more prominent in this context.

A last key finding is that the significant interaction with colour and armed forces bribes, using current socio-economic conditions, are only valid for Colombia, Dominican Republic, and Ecuador. Omitting these countries would lead to a null interaction effect in the pooled sample.

This would suggest that our results at regional level should be read as a potential skew resulting from the larger increase in the coefficients of these cases. Yet interaction model suggests that affluent respondents with dark phenotypes in these countries are more likely to being targeted for bribery to military officials, whether pay for private security or avoid troubles. One possible interpretations of this evidence, for instance, is that discretionary manoeuvres within the defence sector may be closely linked to wealthy individuals seeking protection from paramilitary groups in local Colombian communities (Stone, 2019). Future research will benefit from studying more in-depth this relationship.

5.c. Methodological Limitations and Future Areas of Research.

This study has a number of limitations, and its results should be corroborated using data from other countries and survey waves and alternative research designs. The main limitation is that it ultimately leaves open the question of omitted variable bias. Do corrupts bureaucrats actually target citizens based on skin colour –in effect, on the basis of racial characteristics? Given direct observational measures have their own limits in explaining the causal mechanism behind this relationship between skin tone and bribery experiences. Perhaps turning to experimental evidence could reduce social desirability biases and, at the same time, isolate the independent causal role of citizens' skin phenotype on corrupts decision of whose target to bribery.

Our findings and patterns can also motivate future areas of research into bribery as an arena of racial disparities in Latin America, which may not mirror inequalities in other sectors. For instance, wealth in and of itself may not provide much information about this linkage in the general panorama, but perhaps gender, location, or ethnoracial self-identification can shed light on this issue. Similarly, future research could also use panel data to supplement the cross-national analyses presented here, as well as longitudinal observations across time, are productive avenues for continuing inquiring in this area.

Finally, further studies will be necessary to thoroughly understand brown and black individuals' involvement in bribery. Peru, Colombia, and Costa Rica offer interesting cases to analyse why the effect of colour has substantial differences on directions and magnitudes. These complementary explanations will offer a greater understanding of how its characteristics affect the linkage. As new data becomes available, researchers could investigate the impact of racial ascriptions and the frequency of corruption experiences on how this relationship is affected by the contexts of marginalisation as well as perceptions of discrimination in the region.

6. Conclusions

While an increasing number of scholars have examined the linkage between corruption and discrimination from various angles in the developing world, some of them have delved into the extent to which race factor into corruption practices, and only a few have questioned if skin tone –a regional predictor of race– plays a role in the lived experiences of bribery among Latin Americans. The aim of this dissertation was explored this question in nine countries with large, visible African descendant and indigenous populations. I developed a theoretical framework that posited that bureaucratic corruption practices are inherent race-based discriminatory, where respondents' skin tone serves as a highly informative indicator of their racial identity and bribery the most common everyday form of corruption.

Through an multicountry observational analysis from LAPOP survey (2012-2017), I found that darker-skinned individuals are more likely to being targeted to pay bribes to secure different types of public services in Latin America. The effect of colour is stronger when the experience is related to the courts and weaker when dealing with municipalities. The results support the idea that this personal' ascription informed the behaviours of the agents of corruption, were brown and black individual becomes potential targets. Moreover, considering that skin tone is a key predictor of discrimination due to the historical background in the region, our results shown therefore how are interplayed with corruption practices and how both phenomena exacerbate each other according to historical marginalisation patterns.

Second, while corruption scholarship has shown that affluent people are more frequently target to corruption, our findings indicated a null effect in the interaction model between skin tone and wealth on corruption experience index. In some cases, the direction was positive, in other was negative. I found a positive, strong association when the experience is related to pay bribe to the military, potential skew by the larger coefficients in the cases of Colombia and the Dominican Republic. This evidence may suggest that the convergence of respondent factors, such as high wealth and a darker phenotype, may not necessarily serve as the most accurate predictor of exposure to diverse individual bribery experiences.

Third, I found that socio-geographical context matters in the study of this relationship. Skin tone is a key predictor of corruption experiences in the set of indigenous countries, comparing against the Afro descendant nations. A possible interpretation can be due that dark skin tones in these countries are represented mostly with indigenous communities, one of the most vulnerable and marginalised group in the Americas. Again, the interplay between political underrepresentation and social and cultural discrimination may facilitated the condition in which corruption practices operate, and vice versa. Under these conditions, disproportionate impact we can observe among skin colour in all six of the different types of individual bribery encounters analysed in this work.

Finally, the results call for considering this relationship within these latitudes. In Peru, I found that darker-skinned citizens experience more frequently corruption compared to the other counties. In Mexico and Ecuador, colour is a powerful predictor of bribery in the courts relative to other experiences. Conversely, in Costa Rica, dark skin tones are a reliable predictor of experiences with corrupt police officers, while in Colombia the relationship is significant but opposite: white people are more likely to pay bribes. In Brazil, no significant association between phenotype and corruption was found, whether positive or negative. Thus, while phenotype is a crucial predictor of bribery experiences in the region, I argued that country heterogeneity reflects distinctive dynamics of corruption victimisation and race at local level.

As emphasised throughout this dissertation, the findings underscore the profound socio-cultural conditions within which bureaucratic corruption practices operate in the Americas. Skin colour, legacy of colonial times, is the best racial identity predictor and a crucial determinant of victimisation and discrimination. Perhaps, what this study brings is that bribery, one of the most direct and corrosive forms of corruption, is not merely an institutional failure but an instrument that perpetuates and exacerbates longstanding racial hierarchies. As argued here, the causal relationship is not unidirectional; the corruption-discrimination nexus forms a self-reinforcing cycle, where both elements cannot be analysed separately. Future research in Latin American studies stands to benefit from investigating the socio-political consequences of corruption and race, while by examining racial schemas and its history can bring fresh air to the corruption scholarship in the developing world.

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Appendix A

Table A.1.

Means for variables of interest.												
	Countries:											
	Bolivia	Brazil	Colombia	Costa Rica	Dominican Republic	Ecuador	Guatemala	Mexico	Peru	Pooled Sample	Indigenous Countries	Afro Countries
Bribery to Police Officer	0.21	0.05	0.09	0.04	0.16	0.13	0.16	0.21	0.17	0.14	0.18	0.09
Bribery to Court	0.11	0.03	0.06	0.05	0.16	0.20	0.12	0.16	0.11	0.11	0.14	0.06
Bribery to State Official	0.10	0.02	0.05	0.03	0.07	0.08	0.05	0.10	0.08	0.07	0.08	0.04
Bribery to Municipality	0.21	0.07	0.10	0.12	0.15	0.20	0.15	0.17	0.18	0.17	0.19	0.10
Bribery to Health Service	0.13	0.04	0.03	0.08	0.05	0.11	0.05	0.06	0.06	0.07	0.09	0.05
Bribery to Military	0.04	0.02	0.03	--	0.09	0.03	0.02	0.03	0.02	0.03	0.03	0.05
Corruption Exp. Index	0.32	0.10	0.14	0.12	0.22	0.25	0.21	0.28	0.25	0.22	0.27	0.15
Skin Tone	4.77	4.36	4.14	3.69	5.05	4.34	4.79	4.44	4.61	4.49	4.61	4.31
Standardized Skin Tone	0.37	0.36	0.37	0.36	0.36	0.36	0.38	0.34	0.36	0.40	0.36	0.36
Female	0.64	0.66	0.70	0.48	0.73	0.62	0.43	0.53	0.74	0.62	0.60	0.64
Material Wealth Index	0.41	0.63	0.54	0.66	0.49	0.52	0.40	0.55	0.46	0.51	0.46	0.18
Rural	0.65	0.86	0.78	0.63	0.71	0.65	0.48	0.78	0.68	0.69	0.65	0.75
Age	38.65	38.68	38.14	42.37	39.88	39.01	38.76	40.49	39.23	39.41	39.17	39.78
Education	10.22	8.65	9.69	8.80	9.50	10.86	7.07	9.11	11.07	9.54	9.79	9.16
Interviewer Skin Tone	4.49	4.15	4.24	4.30	4.69	4.00	4.52	4.62	4.44	4.39	4.43	4.34
N	7,780	4,532	4,549	4,528	4,548	4,532	4,554	4,636	5,647	45,306	27,149	18,157

Tables A.3.

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Bolivia.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.006	1.430	1.415	2.215*	1.458	0.775	1.422*
	(0.216)	(0.605)	(0.284)	(0.371)	(0.341)	(0.416)	(0.187)
Female	1.002	1.451*	1.045	0.948	1.234*	1.527***	1.002
	(0.061)	(0.173)	(0.081)	(0.102)	(0.095)	(0.126)	(0.053)
Rural	1.049	1.031	1.234*	1.212	1.138	1.147	1.075
	(0.067)	(0.190)	(0.092)	(0.115)	(0.102)	(0.131)	(0.058)
Material Wealth Index	4.171***	3.651**	2.711***	2.382**	1.031	2.354**	3.387***
	(0.174)	(0.460)	(0.228)	(0.292)	(0.285)	(0.332)	(0.154)
Age	1.063***	1.060*	1.081***	1.029	0.976	1.006	1.036***
	(0.011)	(0.028)	(0.015)	(0.017)	(0.015)	(0.021)	(0.009)
Age^2	0.999***	0.999*	0.999***	1.000	1.000	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.028***	1.015	1.043***	0.987	0.967	0.988	1.021**
	(0.008)	(0.019)	(0.010)	(0.012)	(0.011)	(0.015)	(0.006)
Interviewer Skin Tone	0.918**	0.898	0.976	0.901*	1.074	0.939	0.945
	(0.027)	(0.075)	(0.036)	(0.045)	(0.042)	(0.053)	(0.023)
Constant	-2.710***	-3.937**	-4.662***	-1.975***	-1.580**	-3.052***	-1.886***
	(0.376)	(0.729)	(0.371)	(0.453)	(0.408)	(0.519)	(0.232)
N	7,723	1,755	7,782	2,648	4,524	7,726	7,754

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Brazil.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.569	0.250	1.160	0.241	1.750	3.054	0.925
	(0521)	(1.622)	(0.724)	(1.099)	(0.692)	(0.727)	(0.390)
Female	0.782	1.963	1.076	1.814	1.958**	0.940	1.081
	(0.144)	(0.523)	(0.206)	(0.319)	(0.229)	(0.212)	(0.110)
Rural	0.941	3.339	1.024	1.193	2.818**	0.718	1.158
	(0.215)	(1.040)	(0.308)	(0.463)	(0.401)	(0.282)	(0.165)
Material Wealth Index	1.379	0.765	0.886	3.558	0.561	0.621	1.241
	(0.422)	(1.217)	(0.577)	(0.869)	(0.575)	(0.603)	(0.308)
Age	0.981	0.946	1.071	1.112	0.978	1.061	1.008
	(0.024)	(0.070)	(0.042)	(0.064)	(0.030)	(0.044)	(0.018)
Age^2	1.000	1.000	0.999	0.998	1.000	0.999	1.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Education	1.064**	0.925	1.114***	0.983	0.938*	1.081*	1.021
	(0.023)	(0.065)	(0.031)	(0.043)	(0.031)	(0.033)	(0.016)
Interviewer Skin Tone	1.050	0.967	1.014	1.019	1.045	1.098	1.032
	(0.035)	(0.115)	(0.049)	(0.075)	(0.048)	(0.049)	(0.026)
Constant	-3371***	-2.265***	-5.767***	-4.883***	-3.421***	-5.390***	-2.838***
	(0.603)	(1.975)	(0.931)	(1.430)	(0.864)	(0.955)	(0.455)
N	4,485	815	4,489	777	2,823	4,484	4,490

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Colombia.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	0.291**	1.123	0.212*	0.150*	3.786	0.173	0.318**
	(0.418)	(1.418)	(0.599)	(0.890)	(0.946)	(0.927)	(0.353)
Female	0.798*	1.759	0.754	1.052	1.375	1.124	0.889
	(0.112)	(0.446)	(0.156)	(0.236)	(0.301)	(0.254)	(0.097)
Rural	0.988	4.769	1.206	1.573	1.020	0.925	1.078
	(0.154)	(1.041)	(0.232)	(0.345)	(0.329)	(0.318)	(0.130)
Material Wealth Index	3.932***	1.638	1.558	0.607	1.953	2.007	2.310**
	(0.324)	(1.176)	(0.462)	(0.678)	(0.788)	(0.689)	(0.273)
Age	1.040	1.089	1.050	1.084	0.975	0.943	1.015
	(0.025)	(0.087)	(0.032)	(0.048)	(0.042)	(0.044)	(0.018)
Age^2	0.999**	0.999	0.999	0.999	1.000	1.000	1.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Education	1.063***	1.095	1.124***	1.043	1.039	1.030	1.068***
	(0.017)	(0.059)	(0.025)	(0.035)	(0.039)	(0.038)	(0.014)
Interviewer Skin Tone	0.961	1.050	1.009	1.013	1.100	0.989	0.963
	(0.032)	(0.104)	(0.045)	(0.070)	(0.074)	(0.069)	(0.028)
Constant	-3.134***	-7.572***	-4.841***	-3.616***	-5.029***	-2.530**	-2.446***
	(0.516)	(2.172)	(0.723)	(1.061)	(1.124)	(1.005)	(0.413)
N	4,429	506	4,427	915	2,124	4,427	4,436

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Costa Rica.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military (Item not included)	Corruption Experience Index
Standardized Skin Tone	13.015***	1.775	3.116*	1.411	3.189*	-	2.475**
	(0.442)	(1.119)	(0.517)	(0.637)	(0.429)	-	(0.286)
Female	1.826**	2.104*	1.527*	1.060	0.871	-	1.051
	(0.147)	(0.359)	(0.166)	(0.195)	(0.137)	-	(0.091)
Rural	1.062	2.020	1.060	0.947	2.577***	-	1.358**
	(0.154)	(0.471)	(0.181)	(0.223)	(0.169)	-	(0.101)
Material Wealth Index	1.832	0.874	3.622*	2.820	0.874	-	1.551
	(0.475)	(1.104)	(0.574)	(0.685)	(0.458)	-	(0.306)
Age	1.051	1.076	1.038	1.055	1.015	-	1.020
	(0.028)	(0.075)	(0.029)	(0.034)	(0.022)	-	(0.015)
Age^2	0.999**	0.999	0.999	1.000	1.000	-	1.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	-	(0.000)
Education	0.982	0.983	1.027	1.021	0998	-	1.016
	(0.020)	(0.046)	(0.022)	(0.024)	(0.018)	-	(0.027)
Interviewer Skin Tone	1.028	0.980	1.027	1.036	1.057	-	1.019
	(0.044)	(0.046)	(0.022)	(0.058)	(0.040)	-	(0.027)
Constant	-5.234***	-5.074**	-5.871***	-4.576***	-3.880***	--	-3.336***
	(0.688)	(1.730)	(0.759)	(0.974)	(0.612)	-	(0.404)
N	4,471	727	4,464	1,063	2,957	-	4,479

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Dominican.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.244	0.106	0.757	2.628	0.633	1.320	1.223
	(0.326)	(1.267)	(0.459)	(1.098)	(0.717)	(0.409)	(0.286)
Female	0.821*	0.722	0.829	0.562	0.916	0.869	0.871
	(0.096)	(0.317)	(0.132)	(0.331)	(0.206)	(0.121)	(0.086)
Rural	1.313**	2.134	1.359*	0.959	1.181	1.385*	1.179
	(0.105)	(0.425)	(0.154)	(0.354)	(0.209)	(0.134)	(0.090)
Material Wealth Index	6.663***	1.172	7.355***	8.316*	0.995	5.310***	4.724***
	(0.241)	(0.815)	(0.334)	(0.860)	(0.29)	(0.300)	(0.213)
Age	1.028	1.086	1.030	0.952	0.985	1.022	1.001
	(0.017)	(0.067)	(0.022)	(0.056)	(0.032)	(0.022)	(0.014)
Age^2	0.999***	0.999	0.999	1.001	1.000	0.999*	1.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Education	1.031*	0.923*	1.065***	1.001	0.958	1.014	1.036**
	(0.012)	(0.041)	(0.017)	(0.044)	(0.027)	(0.042)	(0.011)
Interviewer Skin Tone	0.994	1.102	1.032	1.070	1.005	0.963	1.004
	(0.033)	(0.119)	(0.046)	(0.118)	(0.072)	(0.042)	(0.029)
Constant	-3.047***	-2.248	-4.682***	-2.233	-1.559	-3.190***	-2.073***
	(0.407)	(1.518)	(0.557)	(1.408)	(0.835)	(0.513)	(0.348)
N	4,445	371	4,450	396	2,334	4,450	4,452

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Ecuador.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	4.537***	13.408***	3.024**	1.587	0.928	9.525***	2.490***
	(0.348)	(0.658)	(0.428)	(0.504)	(0.478)	(0.629)	(0.274)
Female	0.820*	1.417*	0.604***	0.712*	0.694**	0.634*	0.708***
	(0.093)	(0.176)	(0.113)	(0.135)	(0.128)	(0.177)	(0.072)
Rural	1.214	0.943	1.688***	1.224	2.075***	1.862*	1.280**
	(0.101)	(0.181)	(0.134)	(0.145)	(0.145)	(0.215)	(0.077)
Material Wealth Index	1.865*	1.867	1.647	0.604	0.354**	1.794	1.063
	(0.250)	(0.449)	(0.311)	(0.357)	(0.351)	(0.490)	(0.192)
Age	1.043*	1.035	1.055*	1.004	1.007	1.009	1.055***
	(0.017)	(0.036)	(0.021)	(0.026)	(0.022)	(0.035)	(0.013)
Age^2	0.999**	1.000	0.999*	1.000	1.000	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.061***	1.012	1.072***	0.958*	0.968	1.038	1.036***
	(0.014)	(0.024)	(0.017)	(0.019)	(0.018)	(0.027)	(0.010)
Interviewer Skin Tone	1.039	0.876*	1.088*	0.960	1.316***	0.880*	1.123***
	(0.032)	(0.059)	(0.038)	(0.047)	(0.041)	(0.066)	(0.024)
Constant	-4.390***	-2.981**	-5.323***	-0.397	-2.657***	-4.565***	-3.230***
	(0.420)	(0.874)	(0.525)	(0.641)	(0.560)	(0.806)	(0.320)
N	4,387	869	4,390	1,418	2,770	4,401	4,452

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Guatemala.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin To	1.277	5.919	2.619*	2.313	0.855	6.039*	1.359
	(0.304)	(1.392)	(0.483)	(0.605)	(0.736)	(0.843)	(0.272)
Female	1.193*	0.653	1.114	1.568**	1.860**	1.504	1.187*
	(0.084)	(0.405)	(0.134)	(0.163)	(0.204)	(0.233)	(0.075)
Rural	0.910	1.622	0.921	0.936	0.662	0.879	0.865
	(0.093)	(0.460)	(0.148)	(0.178)	(0.238)	(0.258)	(0.083)
Material Wealth Index	3.462***	0.943	3.196**	0.730	0.761	2.288	2.870***
	(0.231)	(1.121)	(0.364)	(0.465)	(0.621)	(0.645)	(0.208)
Age	1.045**	0.943	1.099***	1.047	0.969	1.008	1.046**
	(0.016)	(0.072)	(0.027)	(0.031)	(0.034)	(0.046)	(0.014)
Age²	0.999***	1.000	0.999***	0.999	1.000	1.000	0.999***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Education	1.033**	0.963	1.040*	1.005	0.961	0.986	1.032*
	(0.012)	(0.055)	(0.018)	(0.022)	(0.029)	(0.033)	(0.010)
Interviewer Skin Tone	1.067	0.550**	0.911	1.115	0.991	0.986	1.031
	(0.040)	(0.204)	(0.066)	(0.076)	(0.09)	(0.033)	(0.036)
Constant	-3.453***	2.016	-5.281***	-3.498***	-1.827*	-4.184***	-2.955***
	(0.398)	(1.838)	(0.665)	(0.793)	(0.933)	(1.105)	(0.352)
N	4,418	257	4,419	1,255	1,898	4,424	4,438

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Mexico.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	2.770***	17.358**	2.412**	2.539	9.668***	3.784*	2.661***
	(0.267)	(1.018)	(0.359)	(0.516)	(0.601)	(0.614)	(0.238)
Female	1.001	1.232	0.965	1.101	0.682*	1.257	0.941
	(0.077)	(0.288)	(0.104)	(0.151)	(0.177)	(0.181)	(0.068)
Rural	0.962	0.863	1.142	0.858	0.461***	1.092	0.930
	(0.099)	(0.365)	(0.142)	(0.196)	(0.189)	(0.227)	(0.087)
Material Wealth Index	2.768***	1.971	3.076***	2.660*	1.833	1.019	2.632***
	(0.209)	(0.762)	(0.284)	(0.406)	(0.481)	(0.486)	(0.187)
Age	1.003	0.957	1.055**	1.011	1.009	0.971	0.993
	(0.014)	(0.051)	(0.020)	(0.027)	(0.029)	(0.031)	(0.012)
Age²	1.000	1.000	0.999**	1.000	1.000	1.000	1.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.048***	1.011	1.043**	0.975	0.942*	0.982	1.022*
	(0.011)	(0.037)	(0.014)	(0.020)	(0.025)	(0.026)	(0.010)
Interviewer Skin Tone	0.935*	0.747**	0.940	0.984	0.800***	1.018	0.943*
	(0.027)	(0.104)	(0.036)	(0.051)	(0.060)	(0.063)	(0.023)
Constant	-2.027***	-0.699	-4.129***	-1.948**	-1.547*	-3.068***	-1.182***
	(0.339)	(1.333)	(0.479)	(0.634)	(0.764)	(0.781)	(0.297)
N	4,479	415	4,475	1,334	2,275	4,449	4,601

Odd ratios from binomial logit regression models predicting corruption experiences based on skin colour. Peru.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	3.762***	1.879	2.590**	3.756**	2.381	2.084	3.660***
	(0.267)	(0.746)	(0.359)	(0.482)	(0.533)	(0.679)	(0.234)
Female	1.175	0.860	1.109	1.163	2.362***	1.622*	1.286***
	(0.086)	(0.250)	(0.115)	(0.159)	(0.209)	(0.241)	(0.075)
Rural	1.035	0.866	1.086	1.805***	1.206	1.194	1.078
	(0.089)	(0.255)	(0.125)	(0.166)	(0.169)	(0.219)	(0.077)
Material Wealth Index	2.533***	0.819	2.746***	1.420	0.533	0.446	1.731**
	(0.195)	(0.586)	(0.263)	(0.357)	(0.404)	(0.489)	(0.170)
Age	1.039**	0.974	1.035	0.995	0.958*	0.943	1.033**
	(0.014)	(0.039)	(0.019)	(0.026)	(0.025)	(0.033)	(0.012)
Age²	0.999***	1.000	1.000*	1.000	1.000	1.000	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.074***	1.035	1.110***	1.011	0.973	1.113***	1.073***
	(0.012)	(0.031)	(0.016)	(0.021)	(0.021)	(0.030)	(0.010)
Interviewer Skin Tone	0.951	0.963	0.927	1.012	1.041	0.931	0.955
	(0.031)	(0.089)	(0.043)	(0.058)	(0.064)	(0.081)	(0.027)
Constant	-3.686***	-1.837	-4.858***	-2.480***	-2.225***	-3.698***	-3.146***
	(0.353)	(1.027)	(0.474)	(0.665)	(0.664)	(0.845)	(0.301)
N	5,578	905	5,573	1,565	3,246	5,582	5,593

Tables A.6.

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Brazil.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	27.773	0.001	5.978	0.048	0.004	31.657	0.632
	(2.648)	(8.667)	(3.660)	(5.494)	(3.614)	(3.625)	(1.960)
Standardized Skin Tone	0.178	17.431	0.360	1.857	40.719	0.078	1.237
	(1.827)	(5.082)	(2.512)	(3.828)	(2.174)	(2.461)	(1.301)
Female	0.773	1.998	1.069	1.844	1.992**	0.918	1.082
	(0.145)	(0.524)	(0.207)	(0.320)	(0.229)	(0.212)	(0.110)
Rural	0.944	3.341	1.026	1.177	2.796**	0.724	1.157
	(0.215)	(1.040)	(0.308)	(0.463)	(0.401)	(0.282)	(0.165)
Material Wealth Index	0.394	10.332	0.456	10.592	4.324	0.066	1.470
	(1.080)	(3.245)	(1.474)	(2.154)	(1.469)	(1.535)	(0.786)
Age	0.982	0.945	1.071	1.111	0.979	1.062	1.008
	(0.024)	(0.070)	(0.042)	(0.064)	(0.030)	(0.044)	(0.018)
Age²	1.000	1.000	0.999	0.998	1.000	0.999	1.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Education	1.064**	0.922	1.114***	0.983	0.937	1.082*	1.021
	(0.023)	(0.066)	(0.031)	(0.043)	(0.031)	(0.033)	(0.016)
Interviewer Skin Tone	1.048	0.970	1.015	1.023	1.049	1.093	1.032
	(0.035)	(0.116)	(0.049)	(0.075)	(0.048)	(0.049)	(0.026)
Constant	-2.530***	-3.764	-5.312***	-5.645**	-4.635***	-3.918**	-2.948***
	(0.898)	(1.891)	(1.301)	(1.996)	(1.182)	(1.326)	(0.656)
N	4,485	815	4,489	777	2,823	4,484	4,490

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Bolivia							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	2.233	1.159	3.495	0.628	39.710*	78.409*	2.580
	(0.965)	(2.525)	(1.260)	(1.597)	(1.659)	(1.920)	(0.848)
Standardized Skin Tone	0.693	1.334	0.780	2.762	0.315	0.101*	0.934
	(0.498)	(1.340)	(0.664)	(0.845)	(0.768)	(0.983)	(0.421)
Female	1.001	1.450	1.044	0.949	1.217*	1.522***	1.001
	(0.061)	(0.173)	(0.081)	(0.102)	(0.095)	(0.126)	(0.053)
Rural	1.045	1.030	1.226	1.217	1.114	1.126	1.070
	(0.067)	(0.191)	(0.092)	(0.116)	(0.102)	(0.131)	(0.058)
Material Wealth Index	3.177**	3.474	1.766	2.739	0.271	0.540	2.446**
	(0.370)	(0.191)	(0.489)	(0.631)	(0.670)	(0.728)	(0.329)
Age	1.063***	1.060*	1.081***	1.030	0.976	1.006	1.036***
	(0.011)	(0.028)	(0.015)	(0.017)	(0.015)	(0.021)	(0.009)
Age²	0.999***	0.999	0.999***	1.000	1.000	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.028***	1.015	1.043***	0.987	0.967**	0.987	1.021**
	(0.008)	(0.019)	(0.010)	(0.045)	(0.011)	(0.015)	(0.006)
Interviewer Skin Tone	0.919**	0.878	0.978	0.901*	1.075	0.945	0.956*
	(0.027)	(0.075)	(0.036)	(0.045)	(0.042)	(0.053)	(0.023)
Constant	-2.574***	-3.910***	-4.443***	-2.061***	-0.972*	-2.326***	-1.732***
	(0.321)	(0.865)	(0.460)	(0.542)	(0.490)	(0.604)	(0.270)
N	7,723	1,755	7,782	2,648	4,524	7,726	7,754

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Colombia.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	0.101	0.000	1.513	0.285	0.091	90.478*	0.305
	(1.841)	(6.640)	(2.684)	(3.819)	(4.482)	(4.052)	(1.554)
Standardized Skin Tone	1.161	160.898	0.165	0.307	12.269	0.001**	0.638
	(1.177)	(3.986)	(1.746)	(2.350)	(2.374)	(2.678)	(0.971)
Female	0.796*	1.791	0.755	1.047	1.377	1.143	0.888
	(0.112)	(0.448)	(0.156)	(0.237)	(0.301)	(0.255)	(0.097)
Rural	0.988	4.627	1.206	1.575	1.017	0.936	1.078
	(0.154)	(1.042)	(0.232)	(0.345)	(0.329)	(0.319)	(0.130)
Material Wealth Index	9.045**	46.888	1.345	0.948	5.168	0.085	3.570*
	(0.745)	(2.842)	(1.059)	(1.517)	(1.976)	(1.554)	(0.632)
Age	1.040	1.093	1.050	1.085	0.974	0.943	1.015
	(0.025)	(0.088)	(0.032)	(0.048)	(0.042)	(0.044)	(0.018)
Age²	0.999**	0.999	0.999	0.999	1.000	1.000	1.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Education	1.061***	1.085	1.124***	1.042	1.038	1.034	1.067***
	(0.017)	(0.059)	(0.025)	(0.026)	(0.039)	(0.038)	(0.014)
Interviewer Skin Tone	0.961	1.044	1.009	1.012	1.101	0.990	0.964
	(0.033)	(0.104)	(0.045)	(0.070)	(0.074)	(0.069)	(0.028)
Constant	-3.637***	-9.502***	-4.752***	-3.868**	-5.511***	-0.672	-2.699***
	(0.657)	(2.659)	(0.924)	(1.313)	(1.442)	(1.281)	(0.531)
N	4,429	506	4,427	915	2,124	4,427	4,436

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Costa Rica.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military (Item not included)	Corruption Experience Index
Skin Tone x Wealth	2.436	0.200	0.242	0.321	0.710	-	0.519
	(2.564)	(6.744)	(3.087)	(3.864)	(2.471)	-	(1.652)
Standardized Skin Tone	7.073	5.221	8.501	3.163	4.017	-	3.879
	(1.811)	(4.672)	(2.245)	(2.816)	(1.723)	-	(1.166)
Female	1.828***	2.107*	1.530*	1.062	0.872	-	1.052
	(0.147)	(0.360)	(0.166)	(0.195)	(0.137)	-	(0.091)
Rural	1.058	2.031	1.065	0.948	2.581***	-	1.361**
	(0.155)	(0.472)	(0.181)	(0.223)	(0.170)	-	(0.101)
Material Wealth Index	1.226	1.644	6.536	4.313	1.001	-	2.021
	(1.247)	(2.888)	(1.414)	(1.604)	(1.081)	-	(0.735)
Age	1.051	1.076	1.037	1.055	1.015	-	1.019
	(0.028)	(0.075)	(0.029)	(0.034)	(0.022)	-	(0.015)
Age²	0.999**	0.999	0.999	1.000	1.000	-	1.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	-	(0.000)
Education	0.986	0.981	1.026	1.021	0.998	-	1.015
	(0.020)	(0.046)	(0.022)	(0.024)	(0.018)	-	(0.012)
Interviewer Skin Tone	1.029	1.064	1.026	1.036	1.056	--	1.019
	(0.044)	(0.105)	(0.049)	(0.058)	(0.040)	-	(0.027)
Constant	-4.963***	-5.480*	-6.282***	-4.872***	-3.970***	-	-3.514***
	(1.037)	(2.441)	(1.185)	(1.404)	(0.894)	-	(0.030)
N	4,471	727	4,464	1,063	2,957	-	4,479

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Dominican.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	6.896	0.406	10.718*	0.012	11.277	246.932**	5.733
	(1.546)	(5.615)	(2.232)	(4.958)	(3.794)	(2.019)	(1.353)
Standardized Skin Tone	0.438	0.171	0.050*	35.951	0.214	0.064*	0.493
	(0.900)	(3.215)	(1.384)	(3.092)	(1.851)	(1.193)	(0.762)
Female	0.818	0.722	0.822	0.562	0.911	0.858	0.868
	(0.096)	(0.317)	(0.132)	(0.332)	(0.229)	(0.121)	(0.086)
Rural	1.310	2.145	1.355*	0.964	1.173	1.377*	1.176
	(0.105)	(0.426)	(0.154)	(0.355)	(0.209)	(0.134)	(0.090)
Material Wealth Index	3.313*	1.600	1.420	44.054	0.408	0.722	2.507
	(0.607)	(0.067)	(0.846)	(2.063)	(1.497)	(0.787)	(0.534)
Age	1.028	1.086	1.030	0.952	0.985	1.022	1.001
	(0.017)	(0.067)	(0.022)	(0.056)	(0.032)	(0.022)	(0.014)
Age²	0.999**	0.999	0.999	1.001	1.000	0.999*	1.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Education	1.032*	0.923*	1.067***	0.999	0.959	1.016	1.036**
	(0.012)	(0.041)	(0.017)	(0.045)	(0.027)	(0.016)	(0.011)
Interviewer Skin Tone	0.995	1.099	1.035	1.067	1.008	0.966	1.005
	(0.034)	(0.119)	(0.047)	(0.118)	(0.072)	(0.043)	(0.029)
Constant	-2.668***	-2.409	-3.736***	-3.200	-1.159	-2.097**	-1.741***
	(0.506)	(1.818)	(0.712)	(1.776)	(1.044)	(0.647)	(0.175)
N	4,445	371	4,450	396	2,334	4,450	4,452

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Ecuador.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	0.153	1.185	0.423	7.866	1.114	299.993	1.279
	(1.628)	(2.771)	(2.009)	(2.399)	(2.388)	(3.128)	(1.297)
Standardized Skin Tone	12.258**	12.265	4.814	0.569	0.883	0.388	2.198
	(0.926)	(1.596)	(1.164)	(1.300)	(1.195)	(1.878)	(0.713)
Female	0.821	1.418	0.604***	0.713	0.694**	0.632**	0.707***
	(0.093)	(0.176)	(0.113)	(0.135)	(0.128)	(0.178)	(0.072)
Rural	1.217	0.944	1.688***	1.224	2.075***	1.844**	1.279**
	(0.102)	(0.181)	(0.134)	(0.145)	(0.145)	(0.215)	(0.077)
Material Wealth Index	3.762*	1.743	2.273	0.282	0.340	0.198	0.971
	(0.658)	(1.207)	(0.814)	(0.954)	(0.959)	(1.302)	(0.513)
Age	1.043*	1.036	1.055*	1.004	1.007	1.009	1.055***
	(0.017)	(0.036)	(0.021)	(0.026)	(0.022)	(0.035)	(0.013)
Age²	0.999**	1.000	0.999*	1.000	1.000	1.000	0.999***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.061***	1.012	1.072***	0.958	0.968	1.037	1.036***
	(0.014)	(0.024)	(0.017)	(0.019)	(0.018)	(0.027)	(0.010)
Interviewer Skin Tone	1.040	0.876*	1.089*	0.958	1.316***	0.878*	1.123***
	(0.032)	(0.059)	(0.038)	(0.047)	(0.041)	(0.066)	(0.024)
Constant	-4.705***	-2.942**	-5.509***	0.002	-2.638***	-3.267**	-3.181***
	(0.544)	(1.075)	(0.682)	(0.792)	(0.698)	(1.069)	(0.409)
N	4,387	869	4,390	1,418	2,770	4,401	4,452

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Guatemala.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	4.820	246.399	0.463	0.006*	0.049	5.323	2.254
	(1.231)	(6.446)	(1.881)	(2.564)	(3.191)	(3.399)	(1.103)
Standardized Skin Tone	0.604	0.610	3.829	23.387*	2.539	2.849	0.936
	(0.660)	(3.024)	(1.047)	(1.327)	(1.369)	(1.745)	(0.574)
Female	1.200*	0.677	1.111	1.533**	1.836**	1.512	1.191*
	(0.084)	(0.406)	(0.134)	(0.164)	(0.205)	(0.233)	(0.075)
Rural	0.911	1.582	0.920	.927	0.658	0.882	0.865
	(0.093)	(0.458)	(0.149)	(0.179)	(0.239)	(0.257)	(0.083)
Material Wealth Index	1.965	0.084	4.245	4.840	2.236	1.197	2.140
	(0.500)	(2.721)	(0.783)	(1.060)	(1.286)	(1.473)	(0.449)
Age	1.046**	0.942	1.098***	1.045	0.969	1.008	1.046**
	(0.016)	(0.073)	(0.027)	(0.031)	(0.034)	(0.046)	(0.014)
Age²	0.999***	1.001	0.999***	0.999	1.000	1.000	0.999***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Education	1.032**	0.938	1.041*	1.005	0.960	0.986	1.032**
	(0.012)	(0.055)	(0.066)	(0.022)	(0.029)	(0.033)	(0.010)
Interviewer Skin Tone	1.066	0.554**	0.911	1.114	0.997	0.870	1.031
	(0.040)	(0.203)	(0.066)	(0.076)	(0.097)	(0.117)	(0.036)
Constant	-3.173***	-2.880	-5.420***	-4.340***	-2.2838***	-3.886**	-2.815***
	(0.452)	(2.105)	(0.756)	(0.908)	(1.035)	(1.255)	(0.399)
N	4,418	257	4,419	1,255	1,898	4,424	4,438

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Mexico.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	1.646	0.002	1.749	0.248	4.482	1.015	2.393
	(1.215)	(4.086)	(1.655)	(2.231)	(2.686)	(2.741)	(1.069)
Standardized Skin Tone	2.065	704.657*	1.716	5.825	4.431	3.752	1.612
	(0.765)	(2.641)	(1.071)	(1.427)	(1.519)	(1.644)	(0.659)
Female	1.001	1.224	0.965	1.101	0.681*	1.257	0.941
	(0.077)	(0.289)	(0.104)	(0.151)	(0.177)	(0.181)	(0.068)
Rural	0.960	0.885	1.139	0.868	0.459***	1.092	0.926
	(0.099)	(0.369)	(0.142)	(0.197)	(0.189)	(0.227)	(0.087)
Material Wealth Index	2.326	21.345	2.529	4.362	1.019	1.014	1.937
	(0.473)	(1.747)	(0.645)	(0.893)	(1.158)	(1.122)	(0.419)
Age	1.003	0.957	1.055**	1.012	1.009	0.971	0.933
	(0.014)	(0.051)	(0.020)	(0.027)	(0.029)	(0.031)	(0.012)
Age²	1.000	1.000	0.999***	1.000	1.000	1.000	1.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.048***	1.008	1.043**	0.976	0.942*	0.982	1.023*
	(0.011)	(0.038)	(0.014)	(0.020)	(0.025)	(0.026)	(0.010)
Interviewer Skin Tone	0.936*	0.742**	0.940	0.982	0.801***	1.018	0.944
	(0.027)	(0.103)	(0.036)	(0.051)	(0.059)	(0.063)	(0.024)
Constant	-1.919***	-2.115	-4.003***	-2.271**	-1.21	-3.065**	-0.995**
	(0.429)	(1.646)	(0.606)	(0.862)	(0.960)	(0.981)	(0.375)
N	4,479	415	4,475	1,334	2,275	4,449	4,601

Odd ratios from logit regression models predicting corruption experiences based on skin colour and wealth. Peru.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Skin Tone x Wealth	1.790	321.221	0.209	0.492	0.065	0.012	2.515
	(1.115)	(3.234)	(1.496)	(1.998)	(2.280)	(2.768)	(0.976)
Standardized Skin Tone	2.788	0.126	6.127*	5.416	7.686	17.055	2.310
	(0.639)	(1.682)	(0.897)	(1.139)	(1.113)	(1.486)	(0.540)
Female	1.173	0.848	1.115	1.164	2.384***	1.650	1.283***
	(0.086)	(0.250)	(0.115)	(0.159)	(0.209)	(0.242)	(0.075)
Rural	1.034	0.866	1.087	1.804***	1.208	1.198	1.077
	(0.089)	(0.255)	(0.125)	(0.166)	(0.169)	(0.220)	(0.077)
Material Wealth Index	2.047	0.100	4.856**	1.850	1.426	2.138	1.239
	(0.452)	(1.327)	(0.606)	(0.825)	(0.909)	(1.095)	(0.393)
Age	1.039**	0.975	1.035	0.995	0.952*	0.942	1.033**
	(0.014)	(0.039)	(0.019)	(0.026)	(0.025)	(0.033)	(0.012)
Age²	0.999***	1.000	1.000*	1.000	1.000	1.000	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	1.074***	1.034	1.110***	1.011	0.974	1.115***	1.073***
	(0.012)	(0.030)	(0.016)	(0.021)	(0.021)	(0.030)	(0.010)
Interviewer Skin Tone	0.952	0.956	0.925	1.011	1.043	0.927	0.956
	(0.032)	(0.090)	(0.043)	(0.059)	(0.064)	(0.081)	(0.027)
Constant	-3.576***	-0.767	-5.170***	-2.613***	-2.685***	-4.472***	-2.980***
	(0.410)	(1.178)	(0.561)	(0.765)	(0.769)	(0.985)	(0.348)
N	5,578	905	5,573	1,565	3,246	5,582	5,593

Tables A.9.

Odd ratios from logit regression models predicting corruption experiences based on skin colour. Matched data. Indigenous Countries (Bolivia, Ecuador, Guatemala, Mexico, and Peru).

	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.848***	3.520***	2.028***	2.086***	1.651**	2.214***	1.910***
	(0.108)	(0.305)	(0.145)	(0.189)	(0.191)	(0.234)	(0.093)
Female	1.036	1.267*	0.966	1.014	1.160*	1.249**	1.012
	(0.034)	(0.099)	(0.047)	(0.060)	(0.061)	(0.077)	(0.030)
Rural	1.030	1.012	1.209***	1.215**	1.141*	1.194*	1.056
	(0.039)	(0.106)	(0.054)	(0.067)	(0.066)	(0.085)	(0.033)
Material Wealth Index	3.078***	1.835*	2.683***	1.490*	0.674*	1.539*	2.264***
	(0.089)	(0.247)	(0.120)	(0.156)	(0.168)	(0.197)	(0.077)
Age	1.044***	1.023	1.067***	1.019	0.983	0.993	1.035***
	(0.006)	(0.017)	(0.009)	(0.011)	(0.010)	(0.013)	(0.005)
Age^2	0.999***	1.000	0.999***	1.000*	1.000	1.000	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	0.988	0.444*	0.740	0.709	0.674*	0.679	0.950
	(0.121)	(0.365)	(0.160)	(0.214)	(0.170)	(0.246)	(0.095)
Secondary education	1.347*	0.497	0.913	0.650*	0.574**	0.735	1.164
	(0.121)	(0.364)	(0.159)	(0.214)	(0.175)	(0.247)	(0.096)
Postsecondary education	1.688***	0.568	1.425*	0.600*	0.473***	0.798	1.433***
	(0.125)	(0.374)	(0.165)	(0.222)	(0.186)	(0.258)	(0.100)
Interviewer Skin Tone	0.965*	0.862***	0.972	0.976	1.090***	0.929*	0.991
	(0.014)	(0.037)	(0.018)	(0.024)	(0.024)	(0.030)	(0.012)
Constant	-2.749***	-2.054***	-3.976***	-1.577***	-1.476***	-2.719***	-1.980***
	(0.187)	(0.540)	(0.253)	(0.329)	(0.299)	(0.390)	(0.153)
N	26,585	4,201	26,585	8,220	14,713	26,582	26,838

Odd ratios from logit regression models predicting corruption experiences based on skin colour. Matched data. Afro Countries (Brazil, Colombia, Costa Rica, and the Dominican Republic).

	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.321	0.473	0.950	0.647	1.681*	1.179	1.068
	(0.1454)	(0.510)	(0.145)	(0.340)	(0.244)	(0.246)	(0.123)
Female	0.919	1.355	0.971	1.060	1.102*	0.916	0.960
	(0.054)	(0.192)	(0.080)	(0.123)	(0.094)	(0.096)	(0.047)
Rural	1.145	2.43**	1.213	1.081	1.882***	1.198	1.220***
	(0.071)	(0.283)	(0.099)	(0.154)	(0.116)	(0.114)	(0.056)
Material Wealth Index	4.561***	1.137	4.178***	2.168*	0.795	3.259***	2.695***
	(0.164)	(0.508)	(0.225)	(0.368)	(0.276)	(0.247)	(0.131)
Age	1.026*	1.048	1.041**	1.036	0.990	1.019	1.004
	(0.011)	(0.037)	(0.014)	(0.021)	(0.014)	(0.018)	(0.008)
Age^2	0.999***	0.999	0.999***	1.000	1.000	0.999*	1.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.329	0.550	1.172	1.273	0.991	2.488	1.275
	(0.295)	(0.656)	(0.397)	(0.618)	(0.302)	(0.597)	(0.193)
Secondary education	1.617	0.486	1.635	1.206	0.893	2.964	1.417
	(0.239)	(0.652)	(0.393)	(0.620)	(0.307)	(0.592)	(0.193)
Postsecondary education	1.847*	0.359	2.403*	1.478	0.910	3.313*	1.848**
	(0.299)	(0.680)	(0.400)	(0.631)	(0.327)	(0.155)	(0.199)
Interviewer Skin Tone	1.000	1.040	1.025	1.026	1.043	1.011	1.002
	(0.017)	(0.054)	(0.023)	(0.036)	(0.026)	(0.029)	(0.014)
Constant	-4.588***	-3.688***	-5.472***	-3.581***	-2.658***	-5.663***	-2.861***
	(0.379)	(1.033)	(0.500)	(0.792)	(0.467)	(0.706)	(0.263)
N	17,830	2,419	17,830	3,151	10,238	13,359	17,857

Tables A.10.

Odd ratios from logit regression models predicting corruption experiences based on skin colour. Matched data excluding outliers (Bolivia and Dominican Republic).							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	2.327***	4.087***	1.997***	1.598*	2.279***	2.837***	1.844**
	(0.126)	(0.365)	(0.170)	(0.222)	(0.215)	(0.289)	(0.104)
Female	1.026	1.281*	0.947	1.035	1.116	1.048	1.000
	(0.036)	(0.109)	(0.049)	(0.064)	(0.064)	(0.085)	(0.030)
Rural	1.037	1.072	1.198**	1.208*	1.381***	1.127	1.104**
	(0.044)	(0.123)	(0.062)	(0.076)	(0.073)	(0.103)	(0.036)
Material Wealth Index	2.666***	1.352	2.433***	1.251	0.537***	1.147	1.832***
	(0.096)	(0.273)	(0.130)	(0.169)	(0.175)	(0.219)	(0.080)
Age	1.033***	1.000	1.056***	1.022	0.994	0.993	1.028***
	(0.096)	(0.019)	(0.009)	(0.012)	(0.010)	(0.015)	(0.005)
Age^2	0.999***	1.000	0.999***	1.000	1.000	1.000	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.077	0.592	0.817	0.886	0.714*	0.733	0.974
	(0.127)	(0.394)	(0.174)	(0.234)	(0.170)	(0.275)	(0.095)
Secondary education	1.465**	0.659	1.096	0.885	0.656*	0.956	1.202
	(0.128)	(0.394)	(0.174)	(0.234)	(0.175)	(0.276)	(0.096)
Postsecondary education	1.866***	0.677	1.732**	0.829	0.599**	1.192	1.548***
	(0.133)	(0.407)	(0.180)	(0.243)	(0.190)	(0.290)	(0.102)
Interviewer Skin Tone	0.991	0.905**	0.985	1.004	1.071	0.989	1.006
	(0.013)	(0.036)	(0.017)	(0.022)	(0.020)	(0.028)	(0.010)
Constant	-4.612***	-3.435***	-5.510***	-3.102***	-1.580**	-3.806***	-3.500***
	(0.209)	(0.629)	(0.286)	(0.320)	(0.408)	(0.443)	(0.163)
N	32,247	4,494	32,237	18,093	4,524	27,767	32,489

Odd ratios from binomial logistic regression models predicting corruption experiences based on standardized skin colour at country level. Matched data.							
	Paid bribes for/to:						
	Police Officer	Court	State Official	Municipality	Health Service	Military	Corruption Experience Index
Standardized Skin Tone	1.673***	1.963**	1.589***	1.523**	1.697***	1.812***	1.551***
	(0.088)	(0.251)	(0.118)	(0.161)	(0.152)	(0.168)	(0.073)
Female	0.998	1.263**	0.965	0.999	1.144*	1.092	0.995
	(0.030)	(0.086)	(0.040)	(0.054)	(0.053)	(0.061)	(0.025)
Rural	1.046	1.136	1.192***	1.177**	1.318***	1.146	1.093**
	(0.035)	(0.098)	(0.049)	(0.062)	(0.059)	(0.070)	(0.029)
Material Wealth Index	3.292***	1.593*	2.947***	1.373*	0.682**	2.232***	2.306***
	(0.079)	(0.219)	(0.106)	(0.142)	(0.145)	(0.155)	(0.067)
Age	1.039***	1.032*	1.056***	1.025*	0.987	1.003	1.027***
	(0.005)	(0.000)	(0.007)	(0.010)	(0.008)	(0.011)	(0.004)
Age^2	0.999***	1.000*	0.999***	1.000***	1.000	1.000**	1.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary education	1.044	0.481*	0.804	0.787	0.720	0.947	0.999
	(0.110)	(0.309)	(0.147)	(0.198)	(0.147)	(0.226)	(0.084)
Secondary education	1.384**	0.485*	1.016	0.741	0.627**	1.064	1.208*
	(0.110)	(0.309)	(0.146)	(0.198)	(0.150)	(0.225)	(0.085)
Postsecondary education	1.706***	0.512*	1.586**	0.705	0.537***	1.171	1.514***
	(0.114)	(0.318)	(0.151)	(0.205)	(0.162)	(0.233)	(0.088)
Interviewer Skin Tone	0.992	0.919**	0.999	0.992	1.065***	0.989	1.003
	(0.011)	(0.030)	(0.014)	(0.019)	(0.018)	(0.021)	(0.009)
Constant	-4.644***	-3.729***	-5.553***	-2.976***	-2.839***	-4.358***	-3.506***
	(0.177)	(0.498)	(0.239)	(0.323)	(0.268)	(0.339)	(0.139)
N	44,415	6,620	44,415	11,371	24,951	39,941	44,695

Appendix B

```
## R coding (codes are written in the same order in which they appear in this dissertation)##

setwd("CXXXXXXXXX")

list.files()

library(visreg)

library(haven)

library(dplyr)

library(texreg)

library(jtools)

library(tidyr)

library(stargazer)

library(broom)

library(mice)

library(psych)

library(labelled)

library(tidyverse)

library(skimr)

library(ggplot2)

library(labelled)

library(scales)

library(ggthemes)

library(extrafont)

library(kableExtra)

library(survey)

#import data Bolivia

bolivia2012 <- read_dta("Bolivia_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)

bolivia2012 <- rename(bolivia2012,

                Country = pais,

                Police_Officer = exc2,

                Gov_Employee = exc6,

                Local_Gov = exc11,

                Work = exc13,

                Courts = exc14,

                Health = exc15,

                School = exc16,
```

```
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2,
                wt = weight1500)
bolivia2012 <- mutate(bolivia2012,
                Country = ifelse(Country == 10, "Bolivia", Country))
bolivia2014 <- read_dta("Bolivia_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16,
etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
bolivia2014 <- rename(bolivia2014,
                Country = pais,
                Police_Officer = exc2,
                Gov_Employee = exc6,
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2)
bolivia2014 <- mutate(bolivia2014,
                Country = ifelse(Country == 10, "Bolivia", Country))
bolivia2016 <- read_dta("Bolivia_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16,
etid, colorr, colori, dis7a, dis8a, dis9a, dis10a, dis11a, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15,
r18, r16, q2, wt)
```

```
bolivia2016 <- rename(bolivia2016,
            Country = pais,
            Police_Officer = exc2,
            Gov_Employee = exc6,
            Local_Gov = exc11,
            Work = exc13,
            Courts = exc14,
            Health = exc15,
            School = exc16,
            Military = exc20,
            Ethnic = etid,
            Skin_Tone = colorr,
            Interviewer_Skin_Tone = colori,
            Gender = sexi,
            Education = ed,
            Urban = ur,
            Income = q10new,
            Age = q2)
bolivia2016 <- mutate(bolivia2016,
            Country = ifelse(Country == 10, "Bolivia", Country))
bolivia_combined <- bind_rows(bolivia2012, bolivia2014, bolivia2016)
#import data Brazil
brazil2012 <- read_dta("Brazil_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)
brazil2012 <- rename(brazil2012,
            Country = pais,
            Police_Officer = exc2,
            Gov_Employee = exc6,
            Local_Gov = exc11,
            Work = exc13,
            Courts = exc14,
            Health = exc15,
            School = exc16,
            Military = exc20,
            Ethnic = etid,
            Skin_Tone = colorr,
            Interviewer_Skin_Tone = colori,
```

```
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2,
                    wt = weight1500)
brazil2012 <- mutate(brazil2012,
                    Country = ifelse(Country == 15, "Brazil", Country))
brazil2014 <- read_dta("Brazil_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid,
colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
brazil2014 <- rename(brazil2014,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2)
brazil2014 <- mutate(brazil2014,
                    Country = ifelse(Country == 15, "Brazil", Country))
brazil2016 <- read_dta("Brazil_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid,
colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
brazil2016 <- rename(brazil2016,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
```

```
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2)
brazil2016 <- mutate(brazil2016,
                    Country = ifelse(Country == 15, "Brazil", Country))
brazil_combined <- bind_rows(brazil2012, brazil2014, brazil2016)
#import data Colombia
colombia2012 <- read_dta("Colombia_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15,
exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2,
weight1500)
colombia2012 <- rename(colombia2012,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
```

```
Age = q2,
wt = weight1500)
colombia2012 <- mutate(colombia2012,
Country = ifelse(Country == 8, "Colombia", Country))
colombia2014 <- read_dta("Colombia_2014.dta") %>% select(pais, exc2, exc6, exc11, exc13, exc14, exc15, exc16, exc20, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
colombia2014 <- rename(colombia2014,
Country = pais,
Police_Officer = exc2,
Gov_Employee = exc6,
Local_Gov = exc11,
Work = exc13,
Courts = exc14,
Health = exc15,
School = exc16,
Military = exc20,
Ethnic = etid,
Skin_Tone = colorr,
Interviewer_Skin_Tone = colori,
Gender = sexi,
Education = ed,
Urban = ur,
Income = q10new,
Age = q2)
colombia2014 <- mutate(colombia2014,
Country = ifelse(Country == 8, "Colombia", Country))
colombia2016 <- read_dta("Colombia_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
colombia2016 <- rename(colombia2016,
Country = pais,
Police_Officer = exc2,
Gov_Employee = exc6,
Local_Gov = exc11,
Work = exc13,
Courts = exc14,
Health = exc15,
School = exc16,
```

```
Military = exc20,
Ethnic = etid,
Skin_Tone = colorr,
Interviewer_Skin_Tone = colori,
Gender = sexi,
Education = ed,
Urban = ur,
Income = q10new,
Age = q2)
colombia2016 <- mutate(colombia2016,
Country = ifelse(Country == 8, "Colombia", Country))
colombia_combined <- bind_rows(colombia2012, colombia2014, colombia2016)
#import data Costa Rica
costarica2012 <- read_dta("Costa Rica_2012.dta") %>% select(pais, exc2, exc6, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)
costarica2012 <- rename(costarica2012,
Country = pais,
Police_Officer = exc2,
Gov_Employee = exc6,
Local_Gov = exc11,
Work = exc13,
Courts = exc14,
Health = exc15,
School = exc16,
Ethnic = etid,
Skin_Tone = colorr,
Interviewer_Skin_Tone = colori,
Gender = sexi,
Education = ed,
Urban = ur,
Income = q10new,
Age = q2,
wt = weight1500)
costarica2012 <- mutate(costarica2012,
Country = ifelse(Country == 6, "Costa Rica", Country))
```

```
costarica2014 <- read_dta("Costa Rica_2014.dta") %>% select(pais, exc2, exc6, exc11, exc13, exc14, exc15, exc16,
etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)

costarica2014 <- rename(costarica2014,

        Country = pais,

        Police_Officer = exc2,

        Gov_Employee = exc6,

        Local_Gov = exc11,

        Work = exc13,

        Courts = exc14,

        Health = exc15,

        School = exc16,

        Ethnic = etid,

        Skin_Tone = colorr,

        Interviewer_Skin_Tone = colori,

        Gender = sexi,

        Education = ed,

        Urban = ur,

        Income = q10new,

        Age = q2)

costarica2014 <- mutate(costarica2014,

        Country = ifelse(Country == 6, "Costa Rica", Country))

costarica2016 <- read_dta("Costa Rica_2016.dta") %>% select(pais, exc2, exc6, exc11, exc13, exc14, exc15, exc16,
etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)

costarica2016 <- rename(costarica2016,

        Country = pais,

        Police_Officer = exc2,

        Gov_Employee = exc6,

        Local_Gov = exc11,

        Work = exc13,

        Courts = exc14,

        Health = exc15,

        School = exc16,

        Ethnic = etid,

        Skin_Tone = colorr,

        Interviewer_Skin_Tone = colori,

        Gender = sexi,

        Education = ed,
```

```
                    Urban = ur,
                    Income = q10new,
                    Age = q2)
costarica2016 <- mutate(costarica2016,
                    Country = ifelse(Country == 6, "Costa Rica", Country))
costarica_combined <- bind_rows(costarica2012, costarica2014, costarica2016)
#import data Dominican Republic
dominican2012 <- read_dta("Domenica Republic_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)
dominican2012 <- rename(dominican2012,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2,
                    wt = weight1500)
dominican2012 <- mutate(dominican2012,
                    Country = ifelse(Country == 21, "Dominican Republic", Country))
dominican2014 <- read_dta("Dominican Republic_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
dominican2014 <- rename(dominican2014,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
```

```
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2)
dominican2014 <- mutate(dominican2014,
                Country = ifelse(Country == 21, "Dominican Republic", Country))
dominican2016 <- read_dta("Dominican Republic_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
dominican2016 <- rename(dominican2016,
                Country = pais,
                Police_Officer = exc2,
                Gov_Employee = exc6,
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2)
dominican2016 <- mutate(dominican2016,
```

```
                      Country = ifelse(Country == 21, "Dominican Republic", Country))

dominican_combined <- bind_rows(dominican2012, dominican2014, dominican2016)

#import data Ecuador

ecuador2012 <- read_dta("Ecuador_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)

ecuador2012 <- rename(ecuador2012,
                      Country = pais,
                      Police_Officer = exc2,
                      Gov_Employee = exc6,
                      Local_Gov = exc11,
                      Work = exc13,
                      Courts = exc14,
                      Health = exc15,
                      School = exc16,
                      Military = exc20,
                      Ethnic = etid,
                      Skin_Tone = colorr,
                      Interviewer_Skin_Tone = colori,
                      Gender = sexi,
                      Education = ed,
                      Urban = ur,
                      Income = q10new,
                      Age = q2,
                      wt = weight1500)

ecuador2012 <- mutate(ecuador2012,
                      Country = ifelse(Country == 9, "Ecuador", Country))

ecuador2014 <- read_dta("Ecuador_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)

ecuador2014 <- rename(ecuador2014,
                      Country = pais,
                      Police_Officer = exc2,
                      Gov_Employee = exc6,
                      Local_Gov = exc11,
                      Work = exc13,
                      Courts = exc14,
                      Health = exc15,
                      School = exc16,
```

```
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2)
ecuador2014 <- mutate(ecuador2014,
                    Country = ifelse(Country == 9, "Ecuador", Country))
ecuador2016 <- read_dta("Ecuador_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
ecuador2016 <- rename(ecuador2016,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2)
ecuador2016 <- mutate(ecuador2016,
                    Country = ifelse(Country == 9, "Ecuador", Country))
ecuador_combined <- bind_rows(ecuador2012, ecuador2014, ecuador2016)
#import data Guatemala
guatemala2012 <- read_dta("Guatemala_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)
```

```
guatemala2012 <- rename(guatemala2012,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
                    Education = ed,
                    Urban = ur,
                    Income = q10new,
                    Age = q2,
                    wt = weight1500)
guatemala2012 <- mutate(guatemala2012,
                    Country = ifelse(Country == 2, "Guatemala", Country))
guatemala2014 <- read_dta("Guatemala_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15,
exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
guatemala2014 <- rename(guatemala2014,
                    Country = pais,
                    Police_Officer = exc2,
                    Gov_Employee = exc6,
                    Local_Gov = exc11,
                    Work = exc13,
                    Courts = exc14,
                    Health = exc15,
                    School = exc16,
                    Military = exc20,
                    Ethnic = etid,
                    Skin_Tone = colorr,
                    Interviewer_Skin_Tone = colori,
                    Gender = sexi,
```

```
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2)
guatemala2014 <- mutate(guatemala2014,
                Country = ifelse(Country == 2, "Guatemala", Country))
guatemala2016 <- read_dta("Guatemala_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis7a, dis8a, dis9a, dis10a, dis11a, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
guatemala2016 <- rename(guatemala2016,
                Country = pais,
                Police_Officer = exc2,
                Gov_Employee = exc6,
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2)
guatemala2016 <- mutate(guatemala2016,
                Country = ifelse(Country == 2, "Guatemala", Country))
guatemala_combined <- bind_rows(guatemala2012, guatemala2014, guatemala2016)


#import data Mexico
mexico2012 <- read_dta("Mexico_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis2, dis3, dis5, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, weight1500)
mexico2012 <- rename(mexico2012,
               Country = pais,
               Police_Officer = exc2,
```

```
                Gov_Employee = exc6,
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
                Age = q2,
                wt = weight1500)
mexico2012 <- mutate(mexico2012,
                Country = ifelse(Country == 1, "Mexico", Country))
mexico2014 <- read_dta("Mexico_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16,
etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
mexico2014 <- rename(mexico2014,
                Country = pais,
                Police_Officer = exc2,
                Gov_Employee = exc6,
                Local_Gov = exc11,
                Work = exc13,
                Courts = exc14,
                Health = exc15,
                School = exc16,
                Military = exc20,
                Ethnic = etid,
                Skin_Tone = colorr,
                Interviewer_Skin_Tone = colori,
                Gender = sexi,
                Education = ed,
                Urban = ur,
                Income = q10new,
```

```
Age = q2)

mexico2014 <- mutate(mexico2014,

Country = ifelse(Country == 1, "Mexico", Country))

mexico2016 <- read_dta("Mexico_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)

mexico2016 <- rename(mexico2016,

Country = pais,

Police_Officer = exc2,

Gov_Employee = exc6,

Local_Gov = exc11,

Work = exc13,

Courts = exc14,

Health = exc15,

School = exc16,

Military = exc20,

Ethnic = etid,

Skin_Tone = colorr,

Interviewer_Skin_Tone = colori,

Gender = sexi,

Education = ed,

Urban = ur,

Income = q10new,

Age = q2)

mexico2016 <- mutate(mexico2016,

Country = ifelse(Country == 1, "Mexico", Country))

mexico_combined <- bind_rows(mexico2012, mexico2014, mexico2016)

#import data Peru

peru2012 <- read_dta("Peru_2012.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)

peru2012 <- rename(peru2012,

Country = pais,

Police_Officer = exc2,

Gov_Employee = exc6,

Local_Gov = exc11,

Work = exc13,

Courts = exc14,

Health = exc15,
```

```
            School = exc16,
            Military = exc20,
            Ethnic = etid,
            Skin_Tone = colorr,
            Interviewer_Skin_Tone = colori,
            Gender = sexi,
            Education = ed,
            Urban = ur,
            Income = q10new,
            Age = q2)
peru2012 <- mutate(peru2012,
            Country = ifelse(Country == 11, "Peru", Country))
peru2014 <- read_dta("Peru_2014.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
peru2014 <- rename(peru2014,
            Country = pais,
            Police_Officer = exc2,
            Gov_Employee = exc6,
            Local_Gov = exc11,
            Work = exc13,
            Courts = exc14,
            Health = exc15,
            School = exc16,
            Military = exc20,
            Ethnic = etid,
            Skin_Tone = colorr,
            Interviewer_Skin_Tone = colori,
            Gender = sexi,
            Education = ed,
            Urban = ur,
            Income = q10new,
            Age = q2)
peru2014 <- mutate(peru2014,
            Country = ifelse(Country == 11, "Peru", Country))
peru2016 <- read_dta("Peru_2016.dta") %>% select(pais, exc2, exc6, exc20, exc11, exc13, exc14, exc15, exc16, etid, colorr, colori, dis7a, dis8a, dis9a, dis10a, dis11a, sexi, ed, ur, q10new, r1, r3, r4, r4a, r5, r6, r7, r8, r12, r14, r15, r18, r16, q2, wt)
```

```
peru2016 <- rename(peru2016,
        Country = pais,
        Police_Officer = exc2,
        Gov_Employee = exc6,
        Local_Gov = exc11,
        Work = exc13,
        Courts = exc14,
        Health = exc15,
        School = exc16,
        Military = exc20,
        Ethnic = etid,
        Skin_Tone = colorr,
        Interviewer_Skin_Tone = colori,
        Gender = sexi,
        Education = ed,
        Urban = ur,
        Income = q10new,
        Age = q2)
peru2016 <- mutate(peru2016,
        Country = ifelse(Country == 11, "Peru", Country))
peru_combined <- bind_rows(peru2012, peru2014, peru2016)
##creating datasets##
allwave_standarized <- bind_rows(peru_combined, mexico_combined, ecuador_combined, dominican_combined, costarica_combined, colombia_combined, brazil_combined, bolivia_combined, guatemala_combined)
allindi_standarized <- allwave_standarized %>%
  filter(Country %in% c("Peru", "Mexico", "Ecuador", "Bolivia", "Guatemala"))
allafro_standarized <- allwave_standarized %>%
  filter(Country %in% c("Dominican Republic", "Costa Rica", "Brazil", "Colombia"))
##Graphs on skin tone distribution and ethnoracial categories##
skin_tone_distribution <- table(allwave_standarized$Skin_Tone)
df_skin_tone <- data.frame(Skin_Tone = as.factor(1:11),
            Count = as.vector(skin_tone_distribution))
brown_palette <- c("#160D00", "#3D2700", "#6E4700", "#663300", "#A66F4C", "#BD8257", "#D59A69", "#E8B37D", "#FACB92", "#FFDCA9", "#FFEBC0")
reversed_brown_palette <- rev(brown_palette)
df_skin_tone$Percentage <- df_skin_tone$Count / sum(df_skin_tone$Count) * 100
ggplot(df_skin_tone, aes(x = Skin_Tone, y = Percentage, fill = Skin_Tone)) +
```

```
  geom_bar(stat = "identity") +
  scale_fill_manual(values = reversed_brown_palette) +
  labs(x = "Skin Tone", y = "Percentage", fill = "Skin Tone") +
  theme_minimal() +
  scale_y_continuous(labels = function(x) paste0(x, "%")) +
  theme(
    axis.line = element_line(color = "black", size = 0.5),
    panel.border = element_blank(),
    axis.text = element_text(family = "Times New Roman", size = 11),
    legend.text = element_text(family = "Times New Roman", size = 11),
    legend.title = element_text(family = "Times New Roman", size = 11)
  )
ggplot(allwave_standarized, aes(x = Ethnicity, fill = factor(Skin_Tone))) +
  geom_bar(position = "fill") +
  labs(x = "Ethno−racial category", y = "Share of skin tone (%)", fill = "Skin tone") +
  scale_fill_manual(values = reversed_brown_palette, labels = c("1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "11"),
na.translate = FALSE) +
  theme_bw() +
  scale_y_continuous(labels = scales::percent_format()) +
  theme(
    axis.text = element_text(family = "Times New Roman", size = 11),
    legend.text = element_text(family = "Times New Roman", size = 11),
    legend.title = element_text(family = "Times New Roman", size = 11)
  )
##setting the DV, IV, and covariates##
#standardized skin tone variable at regional level
region_stats <- allwave_standarized %>%
  group_by(Country) %>%
  summarize(
    Mean_Skin_Color = mean(Skin_Tone, na.rm = TRUE),
    SD_Skin_Color = sd(Skin_Tone, na.rm = TRUE)
  ) %>%
  ungroup()
allwave_standarized <- allwave_standarized %>%
  left_join(region_stats, by = "Country")


allwave_standarized <- allwave_standarized %>%
```

```
  mutate(
    Skin_Color_Standardized = (Skin_Tone - Mean_Skin_Color) / SD_Skin_Color
  )
min_skin_color <- min(allwave_standarized$Skin_Color_Standardized, na.rm = TRUE)
max_skin_color <- max(allwave_standarized$Skin_Color_Standardized, na.rm = TRUE)

allwave_standarized <- allwave_standarized %>%
  mutate(
    Rescaled_Skin_Color = round((Skin_Color_Standardized - min_skin_color) / (max_skin_color - min_skin_color), 1)
  )
#setting DV and control variables
Pay_Bribe <- allwave_standarized [, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")]
alpha(Pay_Bribe)
allwave_standarized$corruption_experience <- rowSums(allwave_standarized[, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")], na.rm = TRUE)
allwave_standarized$corruption_experience_dummy <- ifelse(allwave_standarized$corruption_experience > 0, 1, 0)
wealth_data_all <- allwave_standarized[, c("r1", "r3", "r4", "r4a", "r5", "r6", "r7", "r8", "r12", "r14", "r15", "r18", "r16")]
wealth_data_all[is.na(wealth_data_all)] <- 0
wealth_data_all <- scale(wealth_data_all)
wealth_pca_all <- prcomp(wealth_data_all, center = TRUE, scale. = FALSE, retx = TRUE, rank. = 1)
material_wealth_index_all <- wealth_data_all %*% wealth_pca_all$rotation
allwave_standarized$material_wealth_index_all <- material_wealth_index_all
allwave_standarized$material_wealth_index_all <- scale(allwave_standarized$material_wealth_index_all,
                                    center = min(allwave_standarized$material_wealth_index_all),
                                    scale = max(allwave_standarized$material_wealth_index_all) - min(allwave_standarized$material_wealth_index_all))
allwave_standarized <- rename(allwave_standarized,
                    Material_Wealth = material_wealth_index_all)
allwave_standarized$Wealth2 <- max(allwave_standarized$Wealth2) - allwave_standarized$Wealth2
allwave_standarized <- allwave_standarized %>% select(-Wealth)

allwave_standarized$Age_Log <- allwave_standarized$Age^2
allwave_standarized$Rural <- ifelse(allwave_standarized$Urban == 1, 1, 0)
allwave_standarized$Female <- ifelse(allwave_standarized$Gender == 2, 1, 0)
education_labels <- c("none", "primary", "secondary", "postsecondary")
```

```
allwave_standarized$Education_category <- cut(allwave_standarized$Education,
                                              breaks = c(-1, 0, 6, 12, 18),
                                              labels = education_labels)
allwave_standarized$Skin_Tone_Wealth <- allwave_standarized$Rescaled_Skin_Color *
allwave_standarized$Material_Wealth
##Plot mean skin tone vs mean corruption experience index##
proportion_data <- allwave_standarized %>%
  group_by(Country) %>%
  summarize(Proportion_Skin_Tone = mean(Skin_Tone, na.rm = TRUE),
            Proportion_Corruption_Experience = mean(corruption_experience_dummy, na.rm = TRUE))
proportion_data$CountryAbbrev[proportion_data$Country == "Peru"] <- "PE"
proportion_data$CountryAbbrev[proportion_data$Country == "Mexico"] <- "MX"
proportion_data$CountryAbbrev[proportion_data$Country == "Ecuador"] <- "EC"
proportion_data$CountryAbbrev[proportion_data$Country == "Dominican Republic"] <- "DO"
proportion_data$CountryAbbrev[proportion_data$Country == "Costa Rica"] <- "CR"
proportion_data$CountryAbbrev[proportion_data$Country == "Colombia"] <- "CO"
proportion_data$CountryAbbrev[proportion_data$Country == "Brazil"] <- "BR"
proportion_data$CountryAbbrev[proportion_data$Country == "Bolivia"] <- "BO"
proportion_data$CountryAbbrev[proportion_data$Country == "Guatemala"] <- "GT"
ggplot(proportion_data, aes(x = Proportion_Skin_Tone, y = Proportion_Corruption_Experience)) +
  geom_point(size = 3, shape = 21, fill = "white", color = "black") +
  geom_smooth(method = "lm", se = FALSE, color = "grey", linetype = "dashed") +
  labs(x = "Mean Country Skin Colour",
     y = "Mean Corruption Experience Index") +
  theme_minimal() +
  theme(
    axis.text = element_text(size = 11, family = "Times New Roman"),
    legend.title = element_blank(),
    legend.position = "none",
    panel.border = element_blank(),
    panel.grid.major = element_blank(),
    panel.grid.minor = element_blank(),
    plot.margin = margin(20, 30, 20, 20),
    axis.line = element_line(color = "black", size = 0.5),
    axis.ticks = element_line(color = "black", size = 0.5)
  ) +
  geom_text(aes(label = CountryAbbrev), hjust = 1.5, vjust = 1.5, size = 3)
```

```
##Regression models for H1 and H2. Nested models##

Policeall_s <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Courtsall_s <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

GovEmployeeall_s <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Municipalityall_s <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Healthall_s <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Militaryall_s <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Corruption_Experience_s <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

##odds ratio coefficients and tables##

calculate_odd_ratios <- function(model) {

 tidy_model <- tidy(model)

 coef_table <- coef(summary(model))

 odds_table <- data.frame(

   Variable = tidy_model$term,

   OddsRatio = exp(coef_table[, "Estimate"]),

   StandardError = coef_table[, "Std. Error"],

   P_Value = tidy_model$p.value,

   Constant = coef_table[1, "Estimate"],

   N = nrow(model$model)

 )

 odds_table$OddsRatio <- round(odds_table$OddsRatio, digits = 3)

 odds_table$StandardError <- round(odds_table$StandardError, digits = 3)

 odds_table$P_Value <- format.pval(odds_table$P_Value, digits = 3, eps = 0.001, style = "compact")

 odds_table$Variable <- ifelse(odds_table$P_Value < 0.001, paste0(odds_table$Variable, "***"),

                         ifelse(odds_table$P_Value < 0.01, paste0(odds_table$Variable, "**"),

                             ifelse(odds_table$P_Value < 0.05, paste0(odds_table$Variable, "*"),

                                 odds_table$Variable)))
```

```
  formatted_table <- kable(
    odds_table,
    align = c("l", "c", "c", "c", "c", "c"),
    col.names = c("Variable", "Odds Ratio", "Std. Error", "P-Value", "Constant", "N"),
    caption = "Odds Ratios Table"
  ) %>%
    kable_styling(
      full_width = FALSE,
      bootstrap_options = c("striped", "hover", "condensed", "responsive")
    )
  return(formatted_table)
}
odds_table_police <- calculate_odd_ratios(Policeall_s)
odds_table_police
odds_table_courts <- calculate_odd_ratios(Courtsall_s)
odds_table_courts
odds_table_state <- calculate_odd_ratios(GovEmployeeall_s)
odds_table_state
odds_table_municipality <- calculate_odd_ratios(Municipalityall_s)
odds_table_municipality
odds_table_health <- calculate_odd_ratios(Healthall_s)
odds_table_health
odds_table_military <- calculate_odd_ratios(Militaryall_s)
odds_table_military
odds_table_corruptionindex <- calculate_odd_ratios(Corruption_Experience_s)
odds_table_corruptionindex
##Plot odds ratio for each type of bribery experience##
coef_summary <- summary(Corruption_Experience_s)$coefficients
coef_estimates <- coef_summary[, "Estimate"]
coef_se <- coef_summary[, "Std. Error"]
odds_ratio <- exp(coef_estimates)
lower_bound <- exp(coef_estimates - 1.96 * coef_se)
upper_bound <- exp(coef_estimates + 1.96 * coef_se)
odds_data <- data.frame(
  Model = c("Police Officer", "Court", "State Official", "Municipality", "Health Service", "Military", "Corruption Experience Index"),
  OddsRatio = c(1.810, 2.381, 1.709, 1.746, 1.907, 1.992, 1.685),
```

```
  CI_Lower = c(1.481, 1.340, 1.305, 1.215, 1.344, 1.334, 1.423),
  CI_Upper = c(2.211, 4.228, 2.237, 2.509, 2.704, 2.974, 1.994),
  stringsAsFactors = FALSE
)
font <- "Times New Roman"
loadfonts(device = "win")
garamond_theme <- function() {
  theme_minimal() +
    theme(
      text = element_text(family = font, size = 11),
      axis.text.y = element_text(size = 11),
      axis.title.y = element_blank()
    )
}
odds_plot <- ggplot(data = odds_data, aes(x = OddsRatio, y = Model)) +
  geom_point(size = 3, color = "black") +
  geom_errorbarh(
    aes(xmin = CI_Lower, xmax = CI_Upper),
    height = 0.2,
    color = "grey",
    linewidth = 0.5
  ) +
  garamond_theme() +
  coord_cartesian(xlim = c(0.5, 5)) +
  labs(x = "Odds Ratio") +
  theme(plot.title = element_text(hjust = 0.3)) +
  geom_vline(xintercept = 1, linetype = "dashed", color = "gray", linewidth = 0.7) +
  scale_y_discrete(expand = c(0, 0)) +
  geom_segment(aes(x = 0.5, xend = 0.5, y = 0.5, yend = 7), color = "black", linewidth = 0.5) +
  geom_segment(aes(x = 0.5, xend = 5, y = 0.5, yend = 0.5), color = "black", linewidth = 0.5)
odds_plot
##Plot predicted probabilities for corruption experience index. Nested models##
newdata <- data.frame(Rescaled_Skin_Color = c(.0, .1, .2, .3, .4, .5, .6, .7, .8, .9, 1),
                      Female = 1,
                      Rural = 1,
                      Material_Wealth = 0.5143,
```

```
                    Age = 39.41,
                    Age_Log = 1801,
                    Education = 3.361,
                    Interviewer_Skin_Tone = 4.397)
pred_probs <- predict(Model_CorruptionIndex, newdata = newdata, type = "response")
pred_data <- cbind(newdata, pred_probs)
lower <- pred_probs - 1.96 * se
upper <- pred_probs + 1.96 * se
pred_data$lower <- lower
pred_data$upper <- upper
pred_data <- pred_data[, !duplicated(names(pred_data))]
ggplot(pred_data, aes(x = Rescaled_Skin_Color, y = pred_probs)) +
  geom_point(size = 3, color = "black") +
  geom_errorbar(aes(ymin = lower, ymax = upper), width = 0.02, color = "black") +
  geom_segment(aes(x = Rescaled_Skin_Color, xend = Rescaled_Skin_Color,
                   y = lower, yend = upper), color = "black", size = 0.3) +
  labs(x = "Standardized Colour", y = "Pr(Corruption Experience Index)") +
  theme_bw() +
  theme(
    axis.title = element_text(size = 11, family = "Garamond"),
    axis.text = element_text(size = 11, family = "Garamond"),
    legend.title = element_blank(),
    legend.position = "bottom",
    panel.border = element_blank(),
    panel.grid.major = element_line(color = "lightgray"),
    panel.grid.minor = element_blank(),
    axis.line = element_line(),
    plot.margin = margin(20, 30, 20, 20)
  ) +
  scale_x_continuous(
    limits = c(0, 1),
    breaks = seq(0, 1, 0.1),
    expand = expansion(mult = c(0.05, 0.05))
  ) +
  scale_y_continuous(
    limits = c(0.0, 0.4),
```

```
    breaks = seq(0.0, 0.4, 0.1),
    expand = expansion(mult = c(0.04, 0.04))
  ) +
  guides(color = guide_legend(override.aes = list(size = 2))) +
  geom_smooth(
    method = "loess",
    se = FALSE,
    color = "gray",
    linetype = "dashed"
  )
```

```
##Series of predictions on the likelihood of experiencing corruption by a 37-year-old woman##

Model_Police <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_Courts <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_GovEmployee <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_Municipality <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_Health <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_Military <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

Model_CorruptionIndex <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone , data = allwave_standarized, family = quasibinomial(), weights = wt)

allwave_standarized <- allwave_standarized[is.finite(allwave_standarized$Rescaled_Skin_Color), ]

dark_skin_data <- data.frame(Rescaled_Skin_Color = 0.75,
                             Female = 1,
                             Rural = 1,
                             Material_Wealth = 0.5143,
                             Age = 37,
                             Age_Log = 1801,
                             Education = 12,
                             Interviewer_Skin_Tone = 4.398)

light_skin_data <- data.frame(Rescaled_Skin_Color = 0.25,
```

```
                    Female = 1,
                    Rural = 1,
                    Material_Wealth = 0.5143,
                    Age = 37,
                    Age_Log = 1801,
                    Education = 12,
                    Interviewer_Skin_Tone = 4.398)
dark_skin_data$Predicted_Prob <- predict(Model_CorruptionIndex, newdata = dark_skin_data, type = "response")
light_skin_data$Predicted_Prob <- predict(Model_CorruptionIndex, newdata = light_skin_data, type = "response")
combined_data <- rbind(dark_skin_data, light_skin_data)
combined_data$Phenotype <- c("Dark Skin", "Light Skin")
dark_skin_pred_police <- predict(Model_Police, newdata = dark_skin_data, type = "response")
light_skin_pred_police <- predict(Model_Police, newdata = light_skin_data, type = "response")
dark_skin_pred_police
light_skin_pred_police
dark_skin_pred_courts <- predict(Model_Courts, newdata = dark_skin_data, type = "response")
light_skin_pred_courts <- predict(Model_Courts, newdata = light_skin_data, type = "response")
dark_skin_pred_courts
light_skin_pred_courts
dark_skin_pred_gov <- predict(Model_GovEmployee, newdata = dark_skin_data, type = "response")
light_skin_pred_gov <- predict(Model_GovEmployee, newdata = light_skin_data, type = "response")
dark_skin_pred_gov
light_skin_pred_gov
dark_skin_pred_muni <- predict(Model_Municipality, newdata = dark_skin_data, type = "response")
light_skin_pred_muni <- predict(Model_Municipality, newdata = light_skin_data, type = "response")
dark_skin_pred_muni
light_skin_pred_muni
dark_skin_pred_health <- predict(Model_Health, newdata = dark_skin_data, type = "response")
light_skin_pred_health <- predict(Model_Health, newdata = light_skin_data, type = "response")
dark_skin_pred_health
light_skin_pred_health
dark_skin_pred_mili <- predict(Model_Military, newdata = dark_skin_data, type = "response")
light_skin_pred_mili <- predict(Model_Military, newdata = light_skin_data, type = "response")
dark_skin_pred_mili
light_skin_pred_mili
dark_skin_pred <- predict(Model_CorruptionIndex, newdata = dark_skin_data, type = "response")
```

light_skin_pred <- predict(Model_CorruptionIndex, newdata = light_skin_data, type = "response")

dark_skin_pred

light_skin_pred

##Interaction effect on Skin Colour and Wealth for H3. Nested models##

Police_effect_wealth_s <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Courts_effect_wealth_s <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

GovEmployee_effect_wealth_s <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Municipality_effect_wealth_s <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Health_effect_wealth_s <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Military_effect_wealth_s <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Corruption_Experience_effect_wealth_s <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

odds_table_police <- calculate_odd_ratios(Police_effect_wealth_s)

odds_table_police

odds_table_courts <- calculate_odd_ratios(Courts_effect_wealth_s)

odds_table_courts

odds_table_state <- calculate_odd_ratios(GovEmployee_effect_wealth_s)

odds_table_state

odds_table_municipality <- calculate_odd_ratios(Municipality_effect_wealth_s)

odds_table_municipality

odds_table_health <- calculate_odd_ratios(Health_effect_wealth_s)

odds_table_health

odds_table_military <- calculate_odd_ratios(Military_effect_wealth_s)

odds_table_military

odds_table_corruptionindex <- calculate_odd_ratios(Corruption_Experience_effect_wealth_s)

odds_table_corruptionindex

##Regression models for H4 (indigenous and Afro countries)##

##Analysis on indigenous nations

```
Pay_Bribe <- allindi_standarized [, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")]

allindi_standarized$corruption_experience <- rowSums(allindi_standarized[, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")], na.rm = TRUE)

allindi_standarized$corruption_experience_dummy <- ifelse(allindi_standarized$corruption_experience > 0, 1, 0)

wealth_data_all <- allindi_standarized[, c("r1", "r3", "r4", "r4a", "r5", "r6", "r7", "r8", "r12", "r14", "r15", "r18", "r16")]

wealth_data_all[is.na(wealth_data_all)] <- 0

wealth_data_all <- scale(wealth_data_all)

wealth_pca_all <- prcomp(wealth_data_all, center = TRUE, scale. = FALSE, retx = TRUE, rank. = 1)

wealth_index_all <- wealth_data_all %*% wealth_pca_all$rotation

allindi_standarized$wealth_index_all <- wealth_index_all

allindi_standarized$wealth_index_all <- scale(allindi_standarized$wealth_index_all,

                              center = min(allindi_standarized$wealth_index_all),

                              scale = max(allindi_standarized$wealth_index_all) - min(allindi_standarized$wealth_index_all))

allindi_standarized <- rename(allindi_standarized,

                 Material_Wealth = wealth_index_all)

allindi_standarized$Age_Log <- allindi_standarized$Age^2

allindi_standarized$Rural <- ifelse(allindi_standarized$Urban == 1, 1, 0)

allindi_standarized$Female <- ifelse(allindi_standarized$Gender == 2, 1, 0)

education_labels <- c("none", "primary", "secondary", "postsecondary")

allindi_standarized$Education_category <- cut(allindi_standarized$Education,

                              breaks = c(-1, 0, 6, 12, 18),

                              labels = education_labels)

allindi_standarized$Skin_Tone_Female <- allindi_standarized$Skin_Tone_Standardized_01 * allindi_standarized$Female

allindi_standarized$Skin_Tone_Wealth <- allindi_standarized$Skin_Tone_Standardized_01 * allindi_standarized$Wealth

#Regression models for H4 (indigenous)

Policeall_indi <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

Courtsall_indi <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

GovEmployeeall_indi <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

Municipalityall_indi <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)
```

```
Healthall_indi <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

Militaryall_indi <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

Corruption_Experience_indi <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Bolivia") + Interviewer_Skin_Tone, data = allindi_standarized, family = quasibinomial(), weights = wt)

##Analysis on Afro nations

Pay_Bribe <- allafro_standarized [, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")]

allafro_standarized$corruption_experience <- rowSums(allafro_standarized[, c("Police_Officer", "Gov_Employee", "Local_Gov", "Courts", "Health", "Military")], na.rm = TRUE)

allafro_standarized$corruption_experience_dummy <- ifelse(allafro_standarized$corruption_experience > 0, 1, 0)

wealth_data_all <- allafro_standarized[, c("r1", "r3", "r4", "r4a", "r5", "r6", "r7", "r8", "r12", "r14", "r15", "r18", "r16")]

wealth_data_all[is.na(wealth_data_all)] <- 0

wealth_data_all <- scale(wealth_data_all)

wealth_pca_all <- prcomp(wealth_data_all, center = TRUE, scale. = FALSE, retx = TRUE, rank. = 1)

wealth_index_all <- wealth_data_all %*% wealth_pca_all$rotation

allafro_standarized$wealth_index_all <- wealth_index_all

allafro_standarized$wealth_index_all <- scale(allafro_standarized$wealth_index_all,

                    center = min(allafro_standarized$wealth_index_all),

                    scale = max(allafro_standarized$wealth_index_all) - min(allafro_standarized$wealth_index_all))

allafro_standarized <- rename(allafro_standarized,

              Material_Wealth = wealth_index_all)


allafro_standarized$Age_Log <- allafro_standarized$Age^2

allafro_standarized$Rural <- ifelse(allafro_standarized$Urban == 1, 1, 0)

allafro_standarized$Female <- ifelse(allafro_standarized$Gender == 2, 1, 0)

education_labels <- c("none", "primary", "secondary", "postsecondary")

allafro_standarized$Education_category <- cut(allafro_standarized$Education,

                    breaks = c(-1, 0, 6, 12, 18),

                    labels = education_labels)

allafro_standarized$Skin_Tone_Female <- allafro_standarized$Skin_Tone_Standardized_01 * allafro_standarized$Female

allafro_standarized$Skin_Tone_Wealth <- allafro_standarized$Skin_Tone_Standardized_01 * allafro_standarized$Wealth

#Regression models for H4 (Afro)
```

```
Policeall_afro <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

Courtsall_afro <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

GovEmployeeall_afro <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

Municipalityall_afro <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

Healthall_afro <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

Militaryall_afro <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

Corruption_Experience_afro <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Costa Rica") + Interviewer_Skin_Tone, data = allafro_standarized, family = quasibinomial(), weights = wt)

##Plot predicted probabilities for H4. Indigenous and Afro countries##

ggplot(pred_data_combined, aes(x = Rescaled_Skin_Color, y = pred_probs, fill = Dataset)) +
 geom_line(size = 1, aes(group = Dataset)) +
 geom_ribbon(aes(ymin = lower, ymax = upper), alpha = 0.2) +
 labs(x = "Standardized Skin Colour", y = "Pr(Corruption Experience Index)") +
 theme_minimal() +
 theme(
  text = element_text(family = "Garamond", size = 11),
  legend.position = "bottom",
  axis.line = element_line(),
  plot.margin = margin(20, 30, 20, 20)
 ) +
 scale_x_continuous(
  limits = c(0, 1),  # Adjust the x-axis limits
  breaks = seq(0, 1, 0.1),
  expand = expansion(mult = c(0.05, 0.05))
 ) +
 scale_y_continuous(
  limits = c(-0.1, 0.6),
  breaks = seq(-0.1, 0.5, 0.1),
  expand = expansion(mult = c(0.05, 0.06))
```

```
  ) +
  guides(fill = guide_legend(override.aes = list(size = 2))) +
  geom_smooth(
    method = "loess",
    se = TRUE,  # Show 95% confidence interval
    color = "gray"
  ) +
  theme(legend.title = element_blank())
##Regression models H1, H2 and H3 for each country##
##Brazil
data_brazil <- allwave_standarized[allwave_standarized$Country == "Brazil", ]
data_brazil$Skin_Tone_Wealth <- data_brazil$Rescaled_Skin_Color * data_brazil$Material_Wealth
Policeall_b <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Courtsall_b <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
GovEmployeeall_b <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Municipalityall_b <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Healthall_b <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Militaryall_b <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Corruption_Experience_b <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Police_effect_wealth_br <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Courts_effect_wealth_br <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
GovEmployee_effect_wealth_br <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Municipality_effect_wealth_br <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Health_effect_wealth_br <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Military_effect_wealth_br <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
Corruption_Experience_effect_wealth_br <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_brazil, family = binomial())
##Bolivia
```

data_bolivia <- allwave_standarized[allwave_standarized$Country == "Bolivia",]

data_bolivia$Skin_Tone_Wealth <- data_bolivia$Rescaled_Skin_Color * data_bolivia$Material_Wealth

Policeall_bo <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Courtsall_bo <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

GovEmployeeall_bo <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Municipalityall_bo <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Healthall_bo <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Militaryall_bo <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log +Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Corruption_Experience_bo <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Police_effect_wealth_bo <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Courts_effect_wealth_bo <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

GovEmployee_effect_wealth_bo <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Municipality_effect_wealth_bo <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Health_effect_wealth_bo <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Military_effect_wealth_bo <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

Corruption_Experience_effect_wealth_bo <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_bolivia, family = binomial())

##Colombia

data_colombia <- allwave_standarized[allwave_standarized$Country == "Colombia",]

data_colombia$Skin_Tone_Wealth <- data_colombia$Rescaled_Skin_Color * data_colombia$Material_Wealth

Policeall_co <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Courtsall_co <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

GovEmployeeall_co <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Municipalityall_co <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

```
Healthall_co <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Militaryall_co <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Corruption_Experience_co <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Police_effect_wealth_co <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Courts_effect_wealth_co <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

GovEmployee_effect_wealth_co <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Municipality_effect_wealth_co <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Health_effect_wealth_co <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Military_effect_wealth_co <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

Corruption_Experience_effect_wealth_co <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_colombia, family = binomial())

##Costa Rica

data_costarica <- allwave_standarized[allwave_standarized$Country == "Costa Rica", ]

data_costarica$Skin_Tone_Wealth <- data_costarica$Rescaled_Skin_Color * data_costarica$Material_Wealth

Policeall_cr <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Courtsall_cr <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

GovEmployeeall_cr <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Municipalityall_cr <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Healthall_cr <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Corruption_Experience_cr <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Police_effect_wealth_cr <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())
```

Courts_effect_wealth_cr <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

GovEmployee_effect_wealth_cr <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Municipality_effect_wealth_cr <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Health_effect_wealth_cr <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

Corruption_Experience_effect_wealth_cr <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_costarica, family = binomial())

##Dominican Republic

data_dominican <- allwave_standarized[allwave_standarized$Country == "Dominican Republic",]

data_dominican$Skin_Tone_Wealth <- data_dominican$Rescaled_Skin_Color * data_dominican$Material_Wealth

Policeall_do <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Courtsall_do <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

GovEmployeeall_do <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Municipalityall_do <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Healthall_do <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Militaryall_do <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Corruption_Experience_do <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Police_effect_wealth_do <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Courts_effect_wealth_do <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

GovEmployee_effect_wealth_do <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Municipality_effect_wealth_do <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Health_effect_wealth_do <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Military_effect_wealth_do <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

Corruption_Experience_effect_wealth_do <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_dominican, family = binomial())

##Ecuador

data_ecuador <- allwave_standarized[allwave_standarized$Country == "Ecuador",]

data_ecuador$Skin_Tone_Wealth <- data_ecuador$Rescaled_Skin_Color * data_ecuador$Material_Wealth

Policeall_ec <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Courtsall_ec <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

GovEmployeeall_ec <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Municipalityall_ec <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Healthall_ec <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Militaryall_ec <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Corruption_Experience_ec <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Police_effect_wealth_ec <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Courts_effect_wealth_ec <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

GovEmployee_effect_wealth_ec <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Municipality_effect_wealth_ec <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Health_effect_wealth_ec <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Military_effect_wealth_ec <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

Corruption_Experience_effect_wealth_ec <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_ecuador, family = binomial())

##Guatemala

data_guatemala <- allwave_standarized[allwave_standarized$Country == "Guatemala",]

```
data_guatemala$Skin_Tone_Wealth <- data_guatemala$Rescaled_Skin_Color * data_guatemala$Material_Wealth

Policeall_gt <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Courtsall_gt <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

GovEmployeeall_gt <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Municipalityall_gt <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Healthall_gt <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Militaryall_gt <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Corruption_Experience_gt <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Police_effect_wealth_gt <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Courts_effect_wealth_gt <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

GovEmployee_effect_wealth_gt <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Municipality_effect_wealth_gt <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Health_effect_wealth_gt <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Military_effect_wealth_gt <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

Corruption_Experience_effect_wealth_gt <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_guatemala, family = binomial())

##Mexico

data_mexico <- allwave_standarized[allwave_standarized$Country == "Mexico", ]

data_mexico$Skin_Tone_Wealth <- data_mexico$Rescaled_Skin_Color * data_mexico$Material_Wealth

Policeall_mx <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Courtsall_mx <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

GovEmployeeall_mx <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())
```

Municipalityall_mx <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Healthall_mx <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Militaryall_mx <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Corruption_Experience_mx <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Police_effect_wealth_mx <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Courts_effect_wealth_mx <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

GovEmployee_effect_wealth_mx <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Municipality_effect_wealth_mx <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Health_effect_wealth_mx <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Military_effect_wealth_mx <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

Corruption_Experience_effect_wealth_mx <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_mexico, family = binomial())

##Peru

data_peru <- allwave_standarized[allwave_standarized$Country == "Peru",]

data_peru$Skin_Tone_Wealth <- data_peru$Rescaled_Skin_Color * data_peru$Material_Wealth

Policeall_pe <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Courtsall_pe <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

GovEmployeeall_pe <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Municipalityall_pe <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Healthall_pe <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Militaryall_pe <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + as.vector(Material_Wealth) + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Corruption_Experience_pe <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Police_effect_wealth_pe <- glm(Police_Officer ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Courts_effect_wealth_pe <- glm(Courts ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

GovEmployee_effect_wealth_pe <- glm(Gov_Employee ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Municipality_effect_wealth_pe <- glm(Local_Gov ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Health_effect_wealth_pe <- glm(Health ~ Skin_Tone_Wealth + Rescaled_Skin_Color +Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Military_effect_wealth_pe <- glm(Military ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

Corruption_Experience_effect_wealth_pe <- glm(corruption_experience_dummy ~ Skin_Tone_Wealth + Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + Education + Interviewer_Skin_Tone, data = data_peru, family = binomial())

##Robustness checks##

##Analysis excluding outliers

data_without_outliers <- subset(allwave_standarized, Country != "Bolivia" & Country != "Dominican Republic")

Policeall_outliers <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

Courtsall_outliers <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

GovEmployeeall_outliers <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

Municipalityall_outliers <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

Healthall_outliers <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

Militaryall_outliers <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

Corruption_Experience_outliers <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_outliers, family = quasibinomial(), weights = wt)

##Analysis excluding each individual country

data_without_bolivia <- subset(allwave_standarized, Country != "Bolivia")

data_without_brazil <- subset(allwave_standarized, Country != "Brazil")

data_without_colombia <- subset(allwave_standarized, Country != "Colombia")

data_without_costarica <- subset(allwave_standarized, Country != "Costa Rica")

data_without_dominican <- subset(allwave_standarized, Country != "Dominican Republic")

data_without_guatemala <- subset(allwave_standarized, Country != "Guatemala")

data_without_ecuador <- subset(allwave_standarized, Country != "Ecuador")

data_without_mexico <- subset(allwave_standarized, Country != "Mexico") data_without_peru <- subset(allwave_standarized, Country != "Peru")

Policeall_individual <- glm(Police_Officer ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

Courtsall_individual <- glm(Courts ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

GovEmployeeall_individual <- glm(Gov_Employee ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

Municipalityall_individual <- glm(Local_Gov ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

Healthall_individual <- glm(Health ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

Militaryall_individual <- glm(Military ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

Corruption_Experience_individual <- glm(corruption_experience_dummy ~ Rescaled_Skin_Color + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = data_without_peru, family = quasibinomial(), weights = wt)

##Analysis with standardized skin tone at country level

Policeall_skin_countrylevel <- glm(Police_Officer ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Courtsall_skin_countrylevel <- glm(Courts ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

GovEmployeeall_skin_countrylevel <- glm(Gov_Employee ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Municipalityall_skin_countrylevel <- glm(Local_Gov ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Healthall_skin_countrylevel <- glm(Health ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Militaryall_skin_countrylevel <- glm(Military ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)

Corruption_Experience_skin_countrylevel <- glm(corruption_experience_dummy ~ Skin_Tone_Standardized_01 + Female + Rural + Material_Wealth + Age + Age_Log + as.factor(Education_category) + relevel(factor(Country), ref = "Brazil") + Interviewer_Skin_Tone, data = allwave_standarized, family = quasibinomial(), weights = wt)