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Ethnic, Linguistic, and Religious Heterogeneity and Preferences for Public Goods and Redistribution in Latin America

ABSTRACT One of the most prominent political-economic arguments is that heterogeneity undermines support for public goods and redistribution. Past research, however, has been mostly cross-sectional, used weak measures of heterogeneity, under-studied Latin America, and did not examine the multiple bases of heterogeneity. We assess negative (fractionalization and between-group inequality [BGI]) and positive (compensation) hypotheses with time-varying measures of ethnic, linguistic, and religious heterogeneity. We analyze four different preferences using up to six survey waves with over 200,000 Americas Barometer respondents across 24 Latin American and Caribbean countries. We estimate both fixed-effects models focusing on within-country variation and multilevel models focusing on between-country variation. Regardless of estimation technique, the prevailing pattern is statistical insignificance for both heterogeneity and BGI coefficients. The results largely contradict the fractionalization hypothesis, as only four of the 108 relevant heterogeneity coefficients are significantly negative. There is slightly more support for the BGI hypothesis, and especially ethnic BGI. Still, most BGI coefficients are insignificant and linguistic BGI is significantly positive in most models. The compensation hypothesis receives more support, as almost half of the heterogeneity coefficients are significantly positive. We conclude by cautioning against universal claims that heterogeneity undermines support for public goods and redistribution. **KEYWORDS** heterogeneity, redistribution preferences, public goods, comparative social policy, ethnicity, Latin America and the Caribbean

One of the most prominent claims in political economy is that ethnolinguistic heterogeneity undermines support for public goods and redistribution (Alesina, Baquir, and Easterly 1999; Banerjee, Iyer, and Somanathan 2005; Desmet, Weber, and Ortuño-Ortín 2009; Habyarimana et al. 2007; Luttmer 2001).¹ This claim reflects long-standing theoretical arguments that ethnolinguistic homogeneity facilitated the class solidarity needed to fuel welfare state development (Hechter 2004). Many attribute the weakness of the American welfare state to the fact that the United States was historically more heterogeneous than Europe (Alesina and Glaeser 2004; Lipset and Marks 2000) and/or that it currently has more immigration and racial/ethnic heterogeneity (Luttmer 2001). An interdisciplinary group of scholars argue that heterogeneity undermines public investment in infrastructure, schools, and social policies (e.g., Alesina, Baquir, and Easterly 1999) and undermines trust and cohesion (e.g., Dinesen, Schaeffer, and Sønderskov 2020; Robinson 2020). As a result, there seems to be a consensus that

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heterogeneous societies tend to have weaker welfare states, state capacity, and development (Alesina et al. 2003; Besley and Persson 2011; La Porta et al. 1999; Nunn 2008).

The literature has evolved, and alternative hypotheses have emerged. Rather than simply heterogeneity, Baldwin and Huber (2010) point to a related but distinct phenomenon, between-group inequality (BGI), as undermining support for public goods and redistribution. And in contrast to both the fractionalization and BGI hypotheses, a smaller emerging literature conjectures that rising heterogeneity can actually increase preferences for public goods and redistribution. According to this compensation hypothesis, citizens seek welfare state protection from perceived insecurities associated with social changes like increasing diversity and immigration. Even though macro-level outcomes are often analyzed, the literature agrees that heterogeneity should work through the micro-level mechanism of individual preferences (Alesina, Baquir, and Easterly 1999; Brady and Finnigan 2014; Burgoon, Koster, and van Egmond 2012; Habyarimana et al. 2007; Lieberman and McClendon 2013; Mau and Burkhardt 2009; Morgan and Kelly 2017; Steele 2016). Therefore, a large scholarly literature claims that heterogeneity significantly influences individual preferences for public goods and redistribution.

We advance beyond past research by addressing at least four issues. First, past research has been mostly cross-sectional. Second, prior measures of ethnolinguistic heterogeneity have weaknesses. Third, the literature tends to focus disproportionately on certain global regions and under-studies Latin America and the Caribbean. Fourth, the literature has mainly focused on ethnicity and not fully examined multiple bases of heterogeneity.

We analyze up to six survey waves of the AmericasBarometer by the LAPOP Lab (www.vanderbilt.edu/lapop) for 24 Latin American and Caribbean countries from 2008 to 2018. We estimate *both* fixed-effects models focusing on within-country variation and multilevel models focusing on between-country variation. We construct time-varying heterogeneity measures based on nationally representative survey data with both the Herfindahl and BGI indices (see Methods, below). We analyze four different individual-level preferences, regarding whether the government should reduce income inequality, create jobs, provide healthcare, or ensure welfare. The models adjust for relevant individual-level ethnic, linguistic, and religious identities and a variety of individual- and country-level factors. All together, we assess whether over-time or between-country variation in country-level ethnic, linguistic, and religious heterogeneity is associated with those four preferences.

THEORETICAL BACKGROUND

We now present the arguments, evidence, and testable implications for three influential hypotheses. Two of them, *fractionalization* and *between-group inequality*, expect that heterogeneity is negatively associated with the preferences just listed. The third, the *compensation hypothesis*, expects that heterogeneity is positively associated with those preferences. We then discuss the limitations of prior research.

The Fractionalization Hypothesis

One of the most prominent arguments in the literature is that ethnolinguistic “fractionalization” is negatively associated with public goods. Fractionalization refers to the number and size of different groups, and is usually measured with the Herfindahl index. Purportedly, members of a given ethnic, religious, or linguistic group lack solidarity, cohesion, and trust with members of other groups (Dinesen, Schaeffer, and Sønderkov 2020; Enos and Gidron 2018; Hechter 2004; Koopmans and Schaeffer 2016). This occurs partly because of widely recognized (albeit socially constructed) differences in salient social and physical characteristics, difficulties communicating between groups, fewer network ties and lower trust between groups, and high transaction costs for bridging these divides. On the one hand, individuals tend to presume they have the capacity to sanction fellow group members for noncooperation (Habyarimana et al. 2007). On the other hand, individuals tend to perceive other groups as less deserving of support (Enos and Gidron 2018; Fink and Brady 2020). As a result, it is more difficult to politically mobilize diverse societies toward collective goals for public welfare. Consequently, individuals become less supportive of public goods and redistribution.

Extensive evidence shows that societies with high fractionalization tend to have smaller governments, weaker public goods, and less redistribution (Alesina, Baquir, and Easterly 1999; Alesina et al. 2003; Banerjee, Iyer, and Somanathan 2005; Desmet, Weber, and Ortuño-Ortín 2009). For instance, Alesina and Glaeser (2004) attribute Europe’s having greater redistribution than the United States to Europe’s greater homogeneity. Closely related, many argue that the increase in immigration in Europe has reduced public support for social policy and redistribution (e.g., Mau and Burkhardt 2009). In the United States, a higher share of African Americans in one’s community has a negative relationship with support for welfare programs (Fullerton and Dixon 2009; Luttmer 2001).

The testable implications of the fractionalization hypothesis are clear, partly because these scholars claim this is a generic theory. The Herfindahl index should be negatively associated with individual-level preferences for public goods and redistribution. As we explain below, this negative association should hold not only for ethnic but also for linguistic and religious heterogeneity. Further, as this is a generic theory, and even though much of the evidence has been cross-sectional, these associations should also hold over time.

The Between-Group-Inequality Hypothesis

Baldwin and Huber (2010) present an innovative revision of the fractionalization hypothesis (see also Alesina, Michalopoulos, and Papaioannou 2016). They critique the Herfindahl index for focusing exclusively on the number and size of ethnic groups, neglecting how these groups differ in substantively meaningful ways. They redirect attention to the economic differences between groups and in turn propose a BGI index: the Gini inequality coefficient between the wealth means for the groups. They argue that BGI assesses how antagonistic the economic interests of different groups are to each other, and that it probably also captures durable hierarchies between groups. These

antagonistic interests and durable hierarchies undermine collective solidarity for public goods and redistribution. Baldwin and Huber demonstrate that BGI departs considerably from ethnic and linguistic fractionalization. While neither ethnic nor linguistic fractionalization is significantly associated with public goods provision in a cross section of 46 societies, BGI is robustly, significantly negative.

Morgan and Kelly (2017) provide an exemplary cross-sectional multilevel analysis of preferences for redistribution using the 2008 and 2010 LAPOP data. Following Baldwin and Huber, Morgan and Kelly measure BGI as a country-level variable and preferences as individual-level support for state policies to reduce income inequality. They find BGI significantly undermines preferences for redistribution, while ethnic fractionalization is insignificant. Indeed, BGI has the largest effect of any variable on preferences for redistribution. Interestingly, they also find that BGI interacts significantly with indigenous identity to weaken the otherwise significant positive preference among that group.

The BGI hypothesis expects that preferences will be lower where BGI is higher. Although past studies (Baldwin and Huber 2010; Morgan and Kelly 2017) focus on the BGI for ethnic groups, it should extend to linguistic and religious groups as well. If BGI reflects substantial differences between groups, and it has a generally corrosive effect on public goods provision, BGI in linguistic and religious groups should also undermine preferences. After all, linguistic and religious identities and groups could be just as, if not more, salient than ethnic identities. In addition, these recent studies find that while BGI is significantly negative, ethnic and linguistic fractionalization are not significant when BGI is included in the models. According to Baldwin and Huber and Morgan and Kelly, BGI is also more important for preferences than income inequality, as it combines the theoretically relevant issue of income inequality with salient social cleavages between groups.

The Compensation Hypothesis

In contrast to the fractionalization and BGI hypotheses, an emerging literature supports a compensation hypothesis to account for a positive relationship between heterogeneity and public goods (e.g., Charnysh 2019). For instance, across Zambian districts, Gisselquist, Leiderer, and Nino-Zarazua (2016) find a “diversity dividend” such that more ethnically heterogeneous districts have greater public goods provision. Especially when heterogeneity combines with politicians advocating for and mobilizing ethnically distinct localities, diverse communities might even receive greater public goods (e.g., Cruz, Labonne, and Querubin 2020; Singh and vom Hau 2016).

Some evidence for the compensation hypothesis comes from studies of increases in immigration over time—often the main source of rising heterogeneity—and social policy preferences (e.g., Brady and Finnigan 2014). Rising immigration can induce two processes, each of which increases preferences for redistribution and public goods. First, rising immigration heightens perceptions of insecurity and competition, and in turn, respondents prefer stronger welfare programs to compensate and protect themselves (Kitschelt 1997). Perceptions of immigrants as an economic risk or threat are associated with preferences for redistribution (Ervasti and Hjerm 2012). For example, Finseraas

(2008) shows that beliefs that immigrants reduce wages or take away jobs are positively associated with support for redistribution. Burgoon and colleagues (2012) find that the percentage of people in one's occupation who are foreign born increases support for redistribution, partly because it increases the perception of one's risk of unemployment or poverty. Such perceptions of insecurity and threat appear to be strongest amid sudden and visible increases in immigration flows (Fink and Brady 2020; Hopkins 2010).

Second, rising immigration and heterogeneity enable greater contact between different ethnic, linguistic, and religious groups. Contact theory has long argued that exposure to out-groups encourages knowledge, tolerance, trust, respect, compassion, and empathy and reduces anxiety and uncertainty (e.g., Pettigrew 2008). By facilitating perspective-taking and out-group friendship, contact reduces natives' sense of immigrant threat (Adida, Lo, and Platas 2018). For example, a large Latino population in one's state both reduces negative stereotypes of Latinos and attenuates the otherwise negative relationship between negative stereotypes of Latinos and support for welfare spending (Fox 2004). Rather than universally and generically undermining trust, social capital, and public goods, heterogeneity can often be quite conducive to "prosocial" behaviors and beliefs in a context of social integration, economic interdependence, and politically inclusive institutions (Baldassarri and Abascal 2020).

Limitations of Prior Research

An extensive literature has investigated how welfare states and public goods function in rich democracies and established well-acknowledged general theories, with the fractionalization, BGI, and compensation hypotheses being only three of these. However, accumulating evidence suggests that theories that hold for advanced industrialized states do not always travel well to other world regions (Noy 2011). For instance, Kaufman and Segura-Ubiergo (2001) found empirical evidence for counter-cyclical social spending cycles in Latin America, with governments reducing spending in response to increased economic openness, contrary to spending patterns in mature welfare states (see also Wibbels 2006).² Welfare states in Latin America are also more strongly marked by family structure and the sexual division of labor (Franzoni 2008) and labor informality (Perry et al. 2007). Unsurprisingly, citizen preferences about public goods provision in developing countries in general (Dion and Birchfield 2010) and in Latin America in particular (e.g., Berens 2015; Holland 2018) challenge existing theories. Thus it is vital to examine to what extent theories which claim generality, or even universalism, hold up in different geographical and socioeconomic contexts.

Despite clear and valuable contributions, prior research on how heterogeneity relates to public goods provision tends to have at least four limitations. First and most important, past research—and especially the most highly cited studies—has been overwhelmingly cross-sectional (Alesina, Baquir, and Easterly 1999; Alesina et al. 2003; Desmet, Weber, and Ortuño-Ortín 2009; Easterly and Levine 1997; Luttmer 2001; Nunn 2008). For instance, Baldwin and Huber (2010) rely on a cross section of 46 countries using the World Values Survey. Although Morgan and Kelly (2017) include two waves of LAPOP data, their multilevel models treat the data as cross-sectional.

Indeed, most use time-invariant indices of ethnic fractionalization, and the indices were often measured several decades before the dependent variable is observed (Alesina et al. 2003; Easterly and Levine 1997). While cross-sectional analyses are valuable, even the best cannot rule out salient unobserved characteristics of countries. As there are certainly unobserved factors confounded with heterogeneity or preferences, there is a salient threat to internal validity (Kustov and Pardelli 2018; Lee 2018; Pardelli and Kustov 2022). Indeed, Wimmer (2016) persuasively argues that any relationship between ethnic heterogeneity and low public goods provision is likely spurious because both factors are confounded with unobserved historical weak state capacity (e.g., reflecting other scars of colonialism besides simply fractionalization). Over-time analyses can rule out such stable unobserved cross-national differences (Brady and Finnigan 2014; Dinesen, Schaeffer, and Sønderskov 2020; Fink and Brady 2020; Singh and vom Hau 2016).

Second, the heterogeneity data underlying the fractionalization literature (e.g., Alesina et al. 2003; Easterly and Levine 1997; Fearon 2003) have significant weaknesses (Kustov and Pardelli 2018; Kymlicka and Banting 2006; Patsiurko, Campbell, and Hall 2012; Posner 2004). The estimates of ethnic group shares are usually based on Soviet geographers in the 1970s or earlier, encyclopedias, or CIA *World Factbooks*. These sources have uncertain, often unknown, and typically untraceable origins. They coded various ethnic and linguistic groups inconsistently (Kymlicka and Banting 2006; Patsiurko, Campbell, and Hall 2012).³ And they assign each country one time-invariant score regardless of the haphazard timing and long time lags of the underlying data (Posner 2004). For example, Alesina and colleagues' estimates of ethnic heterogeneity for our sample of countries are variously based on the early-to-mid-1980s (three countries), near 1990 (10 countries), the mid-1990s (10 countries), and 2001 (two countries).⁴

Third, prior research disproportionately focuses on Europe versus the U.S., or Sub-Saharan Africa, where heterogeneity–redistribution trade-offs are clearest. Kymlicka and Banting (2006:297) criticize the universal framing from “two contexts that are arguably atypical.” For instance, evidence from Sub-Saharan Africa might not generalize, given its unique, long-standing challenges and weak state capacity (Nunn 2008; Wimmer 2016). With a few exceptions (Berens and Deeg 2022; Meseguer and Kemmerling 2016; Morgan and Kelly 2017), Latin America and the Caribbean have been relatively under-studied. This region features substantial variation in ethnic, religious, and linguistic heterogeneity; both low- and middle-income countries; political contention over inequality, redistribution, and public goods (Huber and Stephens 2012); and substantial variation in preferences. Of its more than 600 million residents, roughly 8% are indigenous, and 30% are of African descent (Hooker 2005:287). In some countries (e.g., Argentina, Chile, and Costa Rica) there is an overlap between ethnic identities due to greater phenotypical similarities and Spanish as a shared language. In others there are large indigenous minorities (Madrid 2008) and/or a politically salient history of slavery and colorism (e.g., Brazil; Telles 2014). Therefore, Latin America is worthy of study just like the U.S., Europe, or Africa.

Fourth, the literature has not fully examined the multiple bases of heterogeneity. Ethnicity creates a social identity and the feeling of being part of an in- or out-group. The theoretical rationales of the fractionalization, between-group-inequality, and compensation hypotheses all build on the salience of a group identity. But politically salient social identities can be created through a variety of channels, with ethnicity being just one of them. While race and ethnicity fit the popular impression of heterogeneity, it is also worthwhile to examine other salient sociocultural differences such as language and religion.⁵ If heterogeneity is more strongly felt through differences in language or religion rather than ethnicity in some contexts, we may prematurely reject the fractionalization, between-group inequality, or compensation hypotheses. We therefore need to broaden the theoretical concept of heterogeneity.

While a few studies examine linguistic heterogeneity and/or measure the linguistic distance between languages (e.g., Desmet, Weber, and Ortuño-Ortín 2009), much less research exists on linguistic and especially religious heterogeneity. This limitation is most pronounced in the BGI literature, which has concentrated solely on ethnicity. In our data, respondents self-identify over 50 mother tongues. Yet in Latin America there is even greater religious heterogeneity than linguistic heterogeneity, and our data reveal about as much religious heterogeneity as ethnic heterogeneity. On balance, religion might be an equally or even more influential marker of ideational differences in the particular context of Latin America (Trejo 2009). As a result, and regardless of any skepticism about their relevance or salience in Latin America, whether linguistic or religious heterogeneity matters is an empirical question.

DATA AND METHODS

The individual-level data are from the Americas Barometer survey. This standardized and nationally representative survey has been fielded every two years since the early 2000s. We use all waves with available data: 2008, 2010, 2012, 2014, 2016, and 2018.⁶ The preferences and ethnic, linguistic, and religious identity items have been present since 2008, but inconsistently. And the country coverage has continuously expanded since 2008. Therefore, although we use data on 132 country-years, the number and sample of countries differs across the four dependent variables and three heterogeneity variables (see Table A1 in the appendix). We pledge to make data and code publicly available for replication.

Dependent Variables

We examine four different individual-level preferences, capturing a range of beliefs about redistribution and public goods. Again, to give the fractionalization, BGI, and compensation hypotheses more opportunity to be demonstrated in the statistical analyses, we measure public goods and redistributive preferences along multiple dimensions rather than just one. We study support for public welfare, preferences for redistribution, support for job creation by the state, and support for public healthcare provision. The responses are all on a Likert scale from 1, strongly disagree, to 7, strongly agree.

Public welfare is based on whether respondents agree that “the (Country) government, more than individuals, should be primarily responsible for ensuring the well-being of the people.” *Redistribution* is based on “the (Country) government should implement strong policies to reduce income inequality between the rich and the poor.” *Job creation* is based on “the (Country) government, more than the private sector, should be primarily responsible for creating jobs.” And *healthcare* is based on “the (Country) government, more than the private sector, should be primarily responsible for providing health care services.”

The redistribution and public welfare items have been the most frequently analyzed (Berens 2015; Carnes and Mares 2015; Morgan and Kelly 2017). They are similar to items commonly used in rich democracies (Beramendi and Rehm 2016; Brady and Finnigan 2014; Mau and Burkhardt 2009). Support for redistribution and public welfare capture general attitudes and beliefs about the role of the state in the provision of public goods. Healthcare, a key social policy, is less abstract for respondents because of frequent contact and need. Rather than redistribution, healthcare preferences measure the respondents’ concrete—and possibly immediate—demand for a specific public good. Finally, public job creation captures support for an active role of the state in the labor market. It goes beyond social consumption by looking at individuals’ demand for social investment policies (Bonoli 2013).

Considering all four items enables a comprehensive analysis of multiple dimensions of preferences and avoids prematurely rejecting the fractionalization, BGI, or compensation hypothesis by restricting the analysis to, for example, a redistributive preference measure. There is substantial variation in preferences between countries, and over time within countries (Figures A1–A4 in the appendix). The mean responses for all four are high, which is typical for items that do not remind respondents that greater public goods / redistribution could involve higher taxation/costs. The pooled mean for public welfare is 5.65 on a scale from 0 to 7 (standard deviation [SD] 1.59); for redistribution, 5.55 (SD 1.7); for healthcare, 6.08 (SD 1.36); and for job creation, 5.74 (SD 1.56). As a robustness test, we recoded the four items into binary variables measuring only very high support (categories 1–5 becoming 0, and 6–7 becoming 1) and found similar results.⁷ Another robustness test scales the four items into a single index using principal component analysis. This unfortunately reduces the number of observations, as all four items are available only in 2010 and 2012. Still, these robustness checks corroborate the results and conclusions (see Table S18 in the supplement in the online version of the journal).

Heterogeneity Measures

Rather than secondary sources, Fearon (2003:198–99) argues that survey-based estimates of ethnic, linguistic, and religious groups would be the “ideal.” Indeed, a few move beyond secondary-source-based estimates (Alesina et al. 2003; Fearon 2003) to construct survey-based estimates (Gerring et al. 2015; Robinson 2020). Likewise, we use the LAPOP surveys to estimate the heterogeneity indices because they are nationally representative, high quality, and standardized (Logan et al. 2020). We calculate the Herfindahl indices

for ethnicity, language, and religion, using weights provided by LAPOP. The Herfindahl index is the standard measure of heterogeneity:

$$H_k = 1 - \sum_{i=1}^N s_i^2$$

where i refers to the individual, s the ethnic group, and k the social characteristic (ethnicity, language, or religion). It ranges from 0 to 1, with higher values indicating greater heterogeneity. Note that the Herfindahl index effectively weights the number of groups by size. If a group is very small, it contributes little to the index. In turn, the index allows different countries to have different numbers of groups.⁸ Figure S1 (in the online supplement) plots the kernel densities of the three heterogeneity indices.

To calculate the Herfindahl index for ethnic heterogeneity, we calculate the number of groups and weighted group size in each country-year. All LAPOP respondents can identify ethnically as White, Mestizo, Indigenous, Black, Mulatto, or Other.⁹ The data also allow respondents to claim a variety of other specific ethnicities (e.g., Quechua, Maya Ketchi, or Moreno). This enables us to incorporate more than 28 ethnic categories (see Table S1 in the online supplement). Because we use the LAPOP survey's responses, this gives respondents the choice to self-identify their ethnicity (Robinson 2020). This presumes self-identified ethnic identity is salient to respondents and society. As Gerring and colleagues (2015:167) argue, survey-based measures empower respondents to classify themselves, and this "presumably reflects the subjective nature of ethnic identity as it exists in a particular time and place. We expect that the most salient aspects of ethnicity will color respondents' answers."

We repeat these steps for linguistic heterogeneity. The language question is, "What is your mother tongue, that is, the language you spoke first at home when you were a child?" Along with response categories Spanish, Other (Indigenous), and Other Foreign, LAPOP also lists the "most common indigenous languages" (see Table S1). The language item was omitted in 2016 and 2018 and only asked in seven countries in 2008.

We use the same approach for religious heterogeneity. For religious denomination, LAPOP has used ten response categories since 2010 (see Table A2 in the appendix): Catholic; Protestant, mainline Protestant/Protestant non-Evangelical; non-Christian Eastern Religions; none; Evangelical/Pentecostal; Mormon; traditional/native religions; Jewish; agnostic/atheist; and Jehovah's Witness. In 2008, only seven were used.¹⁰ Therefore, to maximize the study period, we recode the more extensive categories into the seven 2008 categories.¹¹

The mean for ethnic heterogeneity is 0.533 (SD 0.168); for linguistic heterogeneity, 0.199 (SD 0.237); and for religious heterogeneity, 0.540 (SD 0.145; see Table A3). While there is more between-country than within-country variation in these measures, there is also substantial and sufficient within-country over-time variation. In several countries, heterogeneity increased, such as ethnic heterogeneity in Argentina, Mexico, and Nicaragua. Others, such as Honduras, exhibit a decline. Overall, ethnic and religious heterogeneity are greater than linguistic heterogeneity (Figure S1).

Baldwin and Huber (2010:648) advocate benchmarking survey-based estimates. Our first year (2008) ethnic heterogeneity estimates correlate moderately and positively with Alesina and colleagues' (2003) ($r = 0.33$) and Fearon's (2003) estimates ($r = 0.45$). Recall, prior ethnic fractionalization scores have uncertain, often unknown, and typically untraceable sources; inconsistent coding of ethnicity; and old and haphazard timing of underlying data (see notes 3 and 4). Also recall, Fearon (2003) argues that surveys are preferable to secondary sources. Thus it makes sense that our survey-based ethnic fractionalization scores are not perfectly correlated with prior estimates. By contrast, the correlations are very strong between our and Alesina and colleagues' scores for linguistic fractionalization ($r = 0.88$) and religious fractionalization ($r = 0.81$), and Fearon's scores for religious fractionalization ($r = 0.77$). As another external check, percent foreign-born (World Bank 2022) correlates moderately and positively with our linguistic heterogeneity estimates—slightly more strongly than the correlation between percent foreign-born and Alesina and colleagues' linguistic heterogeneity.

BGI Measures

We estimate BGI for each of ethnicity, language, and religion as defined above. We use LAPOP's asset indicators to calculate the population-weighted mean wealth of each group. As LAPOP's income data are not comparable across country-years and suffer from high non-response, we calculate a wealth index from several indicators of assets (Filmer and Pritchett 2001): refrigerator, telephone, cellphone, TV, car, multiple cars, washing machine, microwave, motorcycle, indoor plumbing, indoor bath, computer, internet, flat-panel TV, and sewage system. We use multiple correspondence analysis to reduce these binary response categories into a scale (higher value = higher wealth). We then calculate the population-weighted Gini coefficient of wealth across ethnic, linguistic, and religious groups. As with heterogeneity, there is more between- than within-country variation, but there is more than sufficient over-time within-country variation in the BGI estimates.

Baldwin and Huber's BGI estimates are mostly based on World Values Survey (WVS) income measures. Unfortunately, the WVS provides insufficient documentation, lacks usable population weights, and has widely varying and often unreported response rates. The WVS income measures underlying these BGI estimates also have high missingness (Donnelly and Pop-Eleches 2018) and are dramatically below prevailing international standards for income measurement (Brady et al. 2018). Unlike the WVS, LAPOP provides meticulous documentation of response rates and missingness, and has usable population weights. Like us, Morgan and Kelly (2017) use the LAPOP wealth data to calculate BGI.¹² However, they do not use the population weights; they combine the unweighted wealth measures with Fearon's (2003) ethnicity data to calculate time-invariant BGI estimates. Because we use LAPOP ethnicity data rather than Fearon's time-invariant data, we have time-varying measures of BGI. Finally, going beyond Morgan and Kelly, we also calculate BGI for linguistic and religious groups.

Individual- and Country-Level Controls

At the individual level, we adjust for ethnicity, language, or religion with the indicators described above. Because the indicators are not available in all survey waves, the main models include the particular identity related to the given measure of heterogeneity (i.e., ethnic identities with ethnic heterogeneity). In results available on request, we find similar results (albeit with a much smaller N) when including all three identities simultaneously.

We adjust for a standard set of individual-level variables from the welfare and redistribution attitudes literature (Beramendi and Rehm 2016; Berens 2015; Burgoon, Koster, and van Egmond 2012; Brady and Finnigan 2014; Carnes and Mares 2015; Holland 2018; Mau and Burkhardt 2009; Morgan and Kelly 2017). Specifically, we include binary variables for being *female* and *urban* residence, *age* (in years) and *age-squared*, and *years of education*. With private employment as the reference, we include binary measures for *public employee*, *retired*, *unemployed*, and *non-employed* (e.g., homemakers and students). We adjust for the aforementioned *wealth* index. We also include *religiosity*, measured as frequency of church attendance.¹³ By incorporating education, wealth, and public and private employment, the individual-level controls broadly capture social class (Brady et al. 2018). Especially during the period studied here, social class surely competes with ethnic, religious, and linguistic identities as a critical driver of preferences.

At the country level, we adjust for *GDP per capita* and the rate of *inflation* (World Bank 2022). Because low state capacity may reduce demand for state-led welfare provision and redistribution (Holland 2018), we control for *government effectiveness* from the Worldwide Governance Indicators (World Bank 2022). The variable ranges from -2.5 to 2.5 , with higher values indicating higher effectiveness. We also include the *Gini coefficient* of inequality in post-tax and transfer income (Solt 2009, version 8-9). Recent research suggests income inequality is not terribly consequential for redistribution preferences (Beramendi and Rehm 2016; Dion and Birchfield 2010), especially in Latin America (Berens 2015; Carnes and Mares 2015; but see Morgan and Kelly 2017). Still, we adjust for income inequality given classic political economy models. Alleviating concerns with post-treatment bias, we get similar results if we omit the country-level controls (Tables S11–S13). As testing multiple hypotheses may increase the likelihood of false positives, we apply a Bonferroni correction of p -values as an additional robustness test (Table S17). The results provide even less support for the impact of heterogeneity and buttress our conclusions.

Estimation Technique

Recall, we emphasize the importance of over-time variation and netting out stable unobserved between-country differences. Therefore, one set of analyses employs two-way fixed-effects (FE) models with FEs for country and year of observation. The FE models also cluster standard errors by country. Preferences are represented by Y_{ijt} for individual i in country j in year t . The models include

a constant (β_o), individual-level characteristics (X_{ijt}), country-level variables (Z_{jt}), and country (S_j) and year (W_t) FEs:

$$Y_{ijt} = \beta_o + \beta_x X_{ijt} + \beta_z Z_{jt} + \beta_s S_j + \beta_w W_t + \varepsilon_{ijt}$$

The country FEs difference out stable characteristics (e.g., colonial legacies) that if not controlled for would lead to an omitted-variable bias. These models thus concentrate on the within-country temporal variation. The year FEs control for generic changes over time shared across countries.

Despite their well-known advantages, FE models have recently received criticism (e.g., Imai and Kim 2021; Plümper and Troeger 2019). While FE models are usually consistent, they are less efficient. Heterogeneity and BGI vary more between countries than within countries, and FE models may therefore provide an overly conservative test. Moreover, because the heterogeneity and BGI measures are survey based, one may be concerned that they lack reliability over time. If so, they could be analyzing random error more than actual substantive temporal changes. While we question the nearly exclusive prior focus on between-country variation, it would be worthwhile to replicate that approach for comparison (e.g., Morgan and Kelly 2017).

Therefore, another set of analyses employ random-intercept multilevel (ML) models. Each dependent variable Y_{ij} for the i th individual in the j th country is a function of country intercepts (β_{0j}), a set of fixed individual-level variables (X_{ij}), and an error term (ε_{ij}):

$$Y_{ij} = \beta_{0j} + \beta X_{ij} + \varepsilon_{ij}$$

Each country intercept (β_{0j}) is estimated as a function of a general intercept (γ_{00}) and a set of country-level variables (C_j) and an error term (u_{0j}):

$$\beta_{0j} = \gamma_{00} + \gamma_0 C_j + u_{0j}$$

Because the ML models pool multiple years for each country, we include year/wave FEs within the individual-level controls (X_{ij}). Thus, unlike cross-classified models (which are notoriously difficult to converge and consume considerable degrees of freedom), the ML models treat time as a nuisance that we net out in order to focus on *between*-country variation.

With 24 countries and six survey waves, and a maximum of six country-level variables, we should have sufficient statistical power to detect a significant coefficient for heterogeneity or BGI in both the FE and ML models (Elff et al. 2021). Indeed, another advantage of FE models is that they exploit the greater number of country-years than countries, whereas ML models only have as many level-2 units as there are countries. For comparison, because their ethnicity data are time-invariant and they treat the LAPOP data as cross-sectional, Morgan and Kelly (2017) have only 18 countries for five to six country-level variables. Similarly, Baldwin and Huber (2010) have only 46 countries for four to nine country-level variables. Still, FE and ML yield similar results if we omit the country-level controls to conserve degrees of freedom (Tables S11–S13).

Finally, there has been considerable recent critique of two-way FE models as a difference-in-difference strategy (Callaway, Goodman-Bacon, and Sant’Anna 2021). The key problem is treatment effect heterogeneity from staggered rollouts of binary treatments that lead to negative weights. With continuous treatments and no never-treated groups, as in this study, the novel estimators are not as feasible. Fortunately, Jakiela’s (2021) diagnostic tests confirm that our results are not sensitive to these issues.¹⁴

Ultimately, we are mostly interested in evidence that is robust regardless of precise estimation technique. Therefore, we pursue general patterns in results across two very different approaches—both FE and ML models—along with a wide variety of robustness checks and sensitivity tests. As becomes clear, our conclusions do not depend on the estimation technique.

RESULTS

Descriptive Patterns

Before the regression results, we display the macro-level bivariate patterns for the four dependent variables and the three types of heterogeneity. To make the figures comparable to our preferred two-way FE models, Figure 1 shows how over-time changes in heterogeneity (x -axes) correlate with over-time changes in preferences (y -axes). Specifically, we display the change from the earliest to the last year available in the surveys. This gives us the longest time span for redistribution and ethnic heterogeneity (2008 to 2018), but for the other outcomes and heterogeneities we can only observe a shorter range.¹⁵ The rows feature ethnic, linguistic, and religious heterogeneity, and each column features one of the four preferences. For presentation purposes, we dichotomize the dependent variables, classifying all those who strongly agree as 1 and all others as 0, following Morgan and Kelly (2017:200), before we aggregate them to the country mean. Descriptive statistics are reported in Table A3.

Ten of the 12 panels show positive correlations between changes over time in heterogeneity and aggregated preferences. For public welfare, healthcare, and job creation, an increase in (especially ethnic) heterogeneity correlates with increased support for public goods. These positive correlations contradict the fractionalization hypothesis and support the compensation hypothesis. That said, the correlations in many panels are weak. The only panels showing the negative correlation expected per the fractionalization hypothesis are those for redistribution preferences and ethnic heterogeneity (*top row, second from left*) and for redistribution preferences and religious heterogeneity (*bottom row, second from left*). And here, too, the slope is only marginally decreasing.

Ethnicity Models

Table 1 shows the models of preferences on ethnic heterogeneity and ethnic BGI. Again, we show both the FE models concentrating on within-country variation and the ML models concentrating on between-country variation. Reassuringly, the signs of the heterogeneity and BGI coefficients are consistent within outcomes in both FE and ML models. In fact, the magnitudes of coefficients are mostly similar across FE and ML

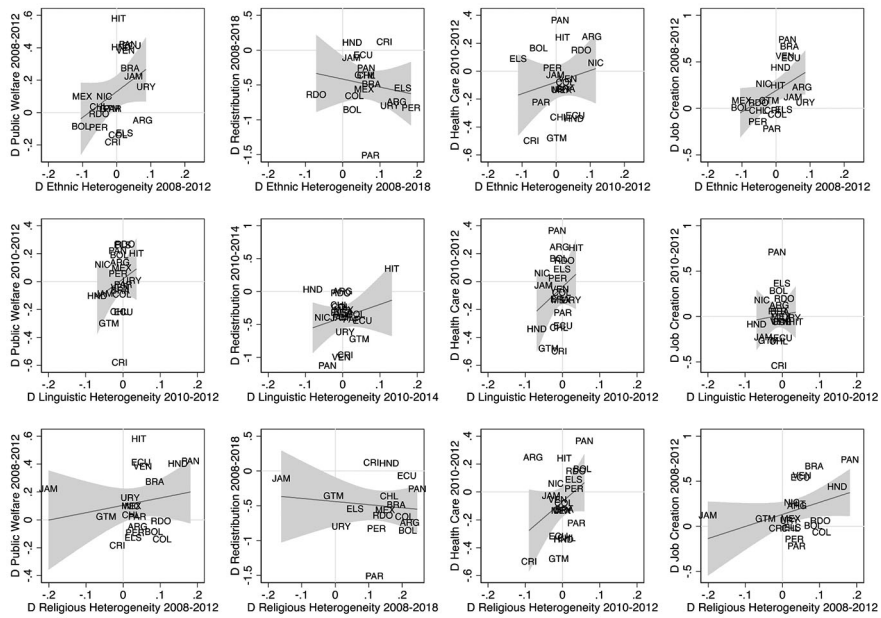


FIGURE 1. Bivariate correlations of over-time differences (D) in preferences and heterogeneity.

models. The coefficients are less statistically significant in the FE models, which makes sense given that the FE models are less efficient. However, the stability of coefficients across the two modeling strategies should build confidence that our results do not depend on the estimation technique.

None of the eight models support the fractionalization hypothesis. Ethnic heterogeneity is never statistically significant and negatively signed. It is negatively signed in the two models for redistribution preferences, but is not near statistical significance. In the other six models for welfare, healthcare, and jobs preferences, heterogeneity is positively signed. Indeed, ethnic heterogeneity is statistically significant and positive in the ML model for welfare, healthcare, and jobs. An increase of ethnic heterogeneity from one SD below to one SD above the mean raises welfare demand by 0.39 units. Healthcare preferences rise by 0.24, and preferences for job creation by 0.49. Consistent with the compensation hypothesis, the ML models provide evidence that greater ethnic heterogeneity is associated with greater support for redistribution and public goods (for three of the four preferences).

The ethnic BGI coefficients in the FE models for all four preferences and in the ML model for healthcare do not reach statistical significance at the $p < .05$ level. However, the ethnic BGI coefficients in the ML models are statistically significant and negative for welfare, redistribution, and jobs. Also, the ethnic BGI coefficients are negatively signed in all eight models. These results broadly support the BGI hypothesis, although the results are not robust to FE estimations. Still, greater ethnic BGI is associated with weaker preferences and less support for redistribution and public goods.

TABLE 1. Fixed effects (FE) and multilevel (ML) models of preferences on ethnic heterogeneity variables in 24 countries in LAPOP data, 2008–2018

	(1) <i>Welfare</i> FE	(2) <i>Welfare</i> ML	(3) <i>Redist.</i> FE	(4) <i>Redist.</i> ML	(5) <i>Healthcare</i> FE	(6) <i>Healthcare</i> ML	(7) <i>Jobs</i> FE	(8) <i>Jobs</i> ML
Ethnic heterogeneity	1.241 (0.778)	1.155*** (0.158)	–0.106 (0.907)	–0.073 (0.136)	0.832 (0.688)	0.715*** (0.184)	1.532 (0.848)	1.440*** (0.155)
Ethnic BGI	–5.432 (6.027)	–5.167*** (1.461)	–8.122 (6.406)	–7.899*** (1.035)	–1.303 (6.047)	–2.764 (1.947)	–11.734 (6.812)	–11.319*** (1.426)
White	–0.036 (0.034)	–0.032* (0.014)	–0.111*** (0.023)	–0.109*** (0.012)	–0.041 (0.039)	–0.035* (0.015)	–0.051 (0.033)	–0.052*** (0.014)
Indigenous	0.023 (0.060)	0.031 (0.023)	0.069 (0.067)	0.060** (0.020)	0.046 (0.048)	0.023 (0.024)	–0.039 (0.054)	–0.047* (0.022)
Black	0.007 (0.035)	0.008 (0.023)	–0.044 (0.034)	–0.042* (0.020)	0.010 (0.029)	0.002 (0.023)	–0.001 (0.042)	–0.007 (0.023)
Mulatto	0.019 (0.042)	0.026 (0.028)	–0.052 (0.037)	–0.050* (0.023)	0.032 (0.044)	0.023 (0.028)	0.043 (0.051)	0.039 (0.028)
Moreno	–0.029 (0.025)	–0.027 (0.050)	–0.018 (0.024)	–0.018 (0.053)	–0.008 (0.025)	–0.010 (0.051)	0.085** (0.023)	0.082 (0.049)
N	103,523	103,523	154,033	154,033	73,753	73,753	103,963	103,963
Countries	24	24	24	24	24	24	24	24
Years	2008– 2012	2008– 2012	2008– 2018	2008– 2018	2010– 2012	2010– 2012	2008– 2012	2008– 2012
BIC	384,204.3	384,532.0	587,007.5	587,579.6	250,246.9	250,684.0	380,853.7	381,400.3

*** $p < .001$, ** $p < .01$, * $p < .05$.

Notes: The numbers in parentheses are standard errors. The reference categories are Mestizo and private employment. The coefficients for the controls are shown in Table A4 in the appendix.

We show the fuller set of variables for these models in Table A4, in the appendix. Briefly, being a White person has a fairly robust negative coefficient, there is evidence of an inverted-U-shaped relationship with age, and public employment is mostly positive. Confirming the salience of social class as a predictive identity, the most robust individual-level variable is the negative coefficient for wealth, which is statistically significant in all eight models, as expected. Most country-level controls are not robust, although inflation is significantly positive in all four ML models.

As mentioned, we conduct a wide variety of robustness checks. The results are broadly consistent with Table 1 when including heterogeneity (Table S2) or BGI (Table S14) separately; with logistic regression (Table S5); when interacting heterogeneity and

dominant-group membership to allow the heterogeneity coefficient to have stronger effects for the dominant group (Table S8)¹⁶; and when omitting country-level controls (Table S11). Contrary to both the fractionalization and compensation hypotheses, the heterogeneity coefficient is not statistically significant in 21 of the 36 coefficients we report (and many others not shown). Consistent with the compensation hypothesis, however, the heterogeneity coefficient is statistically significant and positive in 14 of 36 models. The one exception, consistent with the fractionalization hypothesis, is that heterogeneity becomes statistically significant and is negative for redistribution when BGI is omitted. But this is the only significantly negative ethnic heterogeneity coefficient across 36 models.

For ethnic BGI, the robustness checks are similar to Table 1. Consistent with the BGI hypothesis, ethnic BGI is significantly negative in the ML models for welfare, redistribution, and jobs. All together, ethnic BGI is significantly negative in 11 of 36 models. The notable exception is that ethnic BGI is not significant for welfare when omitting heterogeneity (Table S14). More importantly, the ethnic BGI coefficient is not statistically significant in 25 of 36 reported models (and many more) and is never significant with FE estimation.

Linguistic Models

Table 2 focuses on linguistic heterogeneity (see Table A5 for full models). Like Table 1, the coefficient signs are consistent across FE and ML models. With a few exceptions, the coefficient magnitudes are also similar across FE and ML models. Briefly, the controls are quite consistent with Table 1. Again, the most robust predictor is the individual-level variable for wealth.

Relevant to the fractionalization hypothesis, only one coefficient is statistically significant and negative. In the ML model (but not the FE model), linguistic heterogeneity is significantly negative for the healthcare preference, reducing preferences by 0.563 units when linguistic heterogeneity increases from one SD below to one SD above the mean. The other seven coefficients are insignificant, which undermines the fractionalization hypothesis. The results also do not support the compensation hypothesis, because the linguistic heterogeneity coefficients are never significantly positive, and positively signed only for redistribution preferences.

Contrary to the BGI hypothesis, linguistic BGI is never even negatively signed across the eight models. The linguistic BGI coefficient is actually significantly positive in six of the eight models. For instance, support for welfare increases by 0.53 (FE M9) or 0.51 (ML M10) units, and support for healthcare by 0.75 (FE M13) or 0.81 (ML M14) units, when linguistic BGI changes from one SD below to one SD above the mean. This directly contradicts the BGI hypothesis.

As with ethnic heterogeneity, the robustness checks buttress the main results. The linguistic heterogeneity coefficient is not statistically significant in 26 of 36 models. It remains significantly negative for health preferences in some models (e.g., Tables S9 and S12). Contrary to the fractionalization hypothesis and supportive of the compensation hypothesis, the notable exceptions are that linguistic heterogeneity is significantly positive

TABLE 2. Fixed effects (FE) and multilevel (ME) models of preferences on linguistic heterogeneity variables in 24 countries in LAPOP data, 2008–2018

	(9) <i>Welfare</i> FE	(10) <i>Welfare</i> ML	(11) <i>Redist.</i> FE	(12) <i>Redist.</i> ML	(13) <i>Healthcare</i> FE	(14) <i>Healthcare</i> ML	(15) <i>Jobs</i> FE	(16) <i>Jobs</i> ML
Linguistic hetero.	−0.478 (0.491)	−0.396 (0.213)	0.382 (0.552)	0.365 (0.209)	−0.818 (1.572)	−1.190*** (0.349)	−0.062 (0.525)	−0.099 (0.206)
Linguistic BGI	18.948* (8.367)	18.080*** (2.964)	0.094 (8.627)	0.306 (2.922)	26.870* (12.102)	28.830*** (3.622)	10.489 (9.340)	11.303*** (2.858)
Language indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	85,434	85,434	86,421	86,421	75,058	75,058	85,828	85,828
Countries	24	24	24	24	24	24	24	24
Years	2008– 2012	2008– 2012	2008– 2014	2008– 2014	2010– 2012	2010– 2012	2008– 2012	2008– 2012
BIC	315,652.6	316,282.7	319,985.2	320,732.2	254,273.1	255,068.6	311,464.4	312,371.7

*** $p < .001$, ** $p < .01$, * $p < .05$.

Notes: The numbers in parentheses are standard errors. The reference categories are Spanish and private employment. Mother tongue was missing in 2016 and 2018. The coefficients for the controls are shown in Table A5 in the appendix.

for six of the eight models when BGI is omitted (Table S3, and one model in Table S9). Thus, linguistic heterogeneity is mostly insignificant but more supportive of the compensation hypothesis than the fractionalization hypothesis.

The robustness checks buttress Table 2 for linguistic BGI as well. Across 36 different models, linguistic BGI is never significantly negative or even negatively signed. Linguistic BGI is insignificant in 15 of 36 models. In fact, linguistic BGI is significantly positive in 29 of 36 models, which contradicts the BGI hypothesis.

Religion Models

Table 3 shows the religious heterogeneity results. As in the other tables, the signs are consistent (but the magnitudes less so) between FE and ML models. The individual- and country-level controls show similar results, with wealth remaining the most robustly significant coefficient (Table A6). The one addition for religion is that the coefficient for Evangelical is significantly positive in seven of eight main models.

Contrary to the fractionalization hypothesis, we find no significant negative coefficients for religious heterogeneity. In fact, none of the religious heterogeneity coefficients are even negatively signed. Consistent with the compensation hypothesis, however, we find positive and significant coefficients for religious heterogeneity in all four ML models and in the FE model for jobs. Also, all eight coefficients are positively signed.

TABLE 3. Fixed effects (FE) and multilevel (ML) models of preferences on religious heterogeneity (7 categories) variables in 24 countries in LAPOP data, 2008–2018

	(17) <i>Welfare</i> FE	(18) <i>Welfare</i> ML	(19) <i>Redist.</i> FE	(20) <i>Redist.</i> ML	(21) <i>Healthcare</i> FE	(22) <i>Healthcare</i> ML	(23) <i>Jobs</i> FE	(24) <i>Jobs</i> ML
Religious hetero.	1.230 (0.634)	1.180*** (0.150)	1.047 (0.533)	1.091*** (0.115)	2.507 (1.844)	2.482*** (0.277)	1.904* (0.783)	1.853*** (0.148)
Religion BGI	1.877 (9.518)	0.383 (2.607)	−0.797 (12.569)	−1.560 (1.922)	−3.926 (12.928)	−7.135* (3.091)	−3.281 (10.020)	−4.904 (2.541)
Protestant	−0.002 (0.036)	−0.001 (0.019)	−0.016 (0.031)	−0.016 (0.016)	0.004 (0.023)	−0.001 (0.019)	−0.006 (0.027)	−0.004 (0.018)
Other non-Christian	−0.012 (0.048)	−0.029 (0.037)	−0.030 (0.040)	−0.034 (0.034)	0.004 (0.032)	−0.013 (0.033)	0.045 (0.062)	0.028 (0.036)
None	0.023 (0.027)	0.019 (0.020)	0.068** (0.023)	0.068*** (0.016)	0.010 (0.029)	0.007 (0.019)	−0.004 (0.027)	−0.007 (0.019)
Evangelical	0.075** (0.025)	0.077*** (0.015)	0.068* (0.027)	0.066*** (0.012)	0.057 (0.028)	0.052*** (0.015)	0.057** (0.017)	0.060*** (0.014)
Jehova	−0.050 (0.047)	−0.039 (0.039)	0.011 (0.037)	0.000 (0.035)	0.006 (0.039)	−0.012 (0.042)	−0.062 (0.054)	−0.044 (0.038)
Traditional religion	−0.012 (0.103)	−0.014 (0.052)	0.276*** (0.045)	0.265*** (0.045)	0.287* (0.117)	0.252*** (0.060)	0.090 (0.071)	0.073 (0.051)
Observations	104,341	104,341	154,599	154,599	73,918	73,918	104,816	104,816
Countries	24	24	24	24	24	24	24	24
Years	2008– 2012	2008– 2012	2008– 2018	2008– 2018	2010– 2012	2010– 2012	2008– 2012	2008– 2012
BIC	387,084.5	387,273.4	588,900.6	589,213.6	250,503.6	250,769.1	383,726.6	384,105.8

*** $p < .001$, ** $p < .01$, * $p < .05$.

Notes: The numbers in parentheses are standard errors. The reference categories are Catholic and employed. The coefficients for the controls are shown in Table A6 in the appendix.

Regarding the BGI hypothesis, religious BGI is only significantly negative for health-care preferences, and only in the ML model. Contrary to the BGI hypothesis, religious heterogeneity is statistically insignificant in seven of eight models and is positively signed for welfare preferences.

The robustness checks confirm the pattern of results in Table 3. Religious heterogeneity is significantly positive in 21 of 36 models, which supports the compensation hypothesis and contradicts the fractionalization hypothesis. And religious heterogeneity is never significantly negative across 36 models and is insignificant in 15 models, which

also contradicts the fractionalization hypothesis. Religious BGI is significantly negative in only four of 36 models and is not statistically significant in 32 of 36 models. These patterns do not really support the BGI hypothesis.

CONCLUSION

One of the most prominent political-economic arguments is that heterogeneity undermines support for public goods and redistribution. This study engages that argument while using arguably better measures of heterogeneity, concentrating on the understudied region of Latin America, and examining multiple bases of heterogeneity. We test three hypotheses, analyze four individual-level preferences, and measure both fractionalization and BGI. With over 200,000 respondents and up to six survey waves across 24 Latin American and Caribbean countries, the analyses incorporate considerable variation. We display both FE models focusing on within-country temporal variation and ML models focusing on between-country variation. We also conduct a wide variety of robustness checks.

The results largely contradict the fractionalization hypothesis. Only four of the relevant 108 heterogeneity coefficients are significantly negative. Indeed, only one of 36 reported ethnic heterogeneity coefficients is statistically significant and negative. Although linguistic heterogeneity is significantly negative for health preferences in some models, its coefficient is not statistically significant in 26 of 36 models. Contrary to the fractionalization hypothesis, linguistic heterogeneity is often significantly positive. In addition, we find no significant negative coefficients for religious heterogeneity. None of the 36 reported religious heterogeneity coefficients are even negatively signed.

There is slightly more support for the BGI hypothesis. Ethnic BGI is significantly negative in the ML models for welfare, redistribution, and jobs. Overall, ethnic BGI is significantly negative in 11 of 36 models. That said, the ethnic BGI coefficient is not statistically significant in 25 of 36 reported models and is never significant with FE estimation. Moreover, the clear majority of BGI coefficients are statistically insignificant. Also, surprisingly, linguistic BGI is significantly positive in 29 of 36 models, which contradicts the BGI hypothesis. Further, religious BGI is significantly negative in only four of 36 models and is not statistically significant in 32 of 36 models.

The compensation hypotheses actually receives the most support. All together, 42 of 108 reported heterogeneity coefficients are significantly positive. The ethnic heterogeneity coefficient is statistically significant and positive in 14 of 36 models. Linguistic heterogeneity is also significantly positive for six of eight models when BGI is omitted. Moreover, religious heterogeneity is significantly positive in 21 of 36 models. Also, one could plausibly view it as supportive of the compensation hypothesis that linguistic BGI is significantly positive in 29 of 36 models. That said, heterogeneity is not significantly positive in 66 of 108 reported models. Also, it is rarer for heterogeneity to be significantly positive with FE estimation. Thus, despite some evidence for it, the majority of our results do not clearly support the compensation hypothesis.

All together, the strongest pattern across our analyses is statistical insignificance for both heterogeneity and BGI. This prevailing pattern holds for ethnic, linguistic, and religious heterogeneity. It also holds across the four different individual-level preferences. The pattern of insignificance is most pronounced under FE estimation, but also holds with ML models.

Taking stock, the major conclusions of our study fall into two main themes. First, of the three hypotheses, compensation receives the most support. This pattern of results can be read optimistically. This suggests it is possible for countries to experience high or rising ethnic, linguistic, and religious heterogeneity while maintaining public support for redistribution and public goods. This conclusion is consistent with recent research on immigration and public support for social policy (Brady and Finnigan 2014; Burgoon, Koster, and van Egmond 2012). While rising immigration is certainly linked with extreme-right party voting and anti-foreigner sentiment, people can maintain pro-public goods and redistribution preferences and anti-immigrant sentiments at the same time. In developing countries, immigration may also have positive externalities by prompting greater local development to address humanitarian needs (Zhou and Shaver 2021). Contrary to the presumption that heterogeneity has uniform effects, countries appear to vary in how ethnic, linguistic, and religious animus is or is not coupled with preferences for redistribution and public goods. Indeed, our data point to countries where public support increased while they experienced rising heterogeneity (Figure 1, *upper right*). These could be valuable case studies for interrogating how states maintain both heterogeneity and strong states, and both diversity and egalitarianism (Gisselquist, Leiderer, and Nino-Zarazua 2016). Indeed, the variation in Figure 1 suggests a promising research agenda on why countries vary in these relationships (Kymlicka and Banting 2006).

Second, our study contributes to an emerging view that the field should be far more cautious in claiming there are generic, universalizing theories that apply to all world regions (see, e.g., Kaufman and Segura-Ubiergo 2001; Dion and Birchfield 2010; Noy 2011). In particular, we caution against universalizing the negative effects of heterogeneity and diversity (Brady and Finnigan 2014; Fox 2004; Gisselquist 2014; Kymlicka and Banting 2006; Singh 2011; Singh and vom Hau 2016; Wimmer 2016). Going forward, it would be productive for the field to moderate and qualify its conclusions. This is salient as the prior literature has been marked by consensus, which has influenced public policy and political debates on economic development, state capacity, multiculturalism, social policy, and egalitarianism. Relatedly, we hope to illustrate the often-underappreciated need to publish studies that fail to reject the null hypothesis. As others have shown, there is a problematic tendency to disproportionately publish statistically significant effects (Franco, Maholtra, and Simonovits 2014; Gerber and Malhotra 2008). Indeed, this tendency has probably enabled this particular literature's confidence and certainty to grow and even solidify. We conclude it is not true that heterogeneity and diversity are necessarily and universally incompatible with public goods and egalitarianism. More generally, we underscore that science—and especially this literature—needs disconfirming evidence as much as validating evidence.

Our results provide little evidence that heterogeneity is a major influence on preferences in Latin America. While a reader could selectively highlight a given result across the many models we show, we underline the prevailing pattern of insignificance. Further, while one might speculate that a lack of statistical power or measurement error can explain the null results, these cannot explain why the strongest pattern of significant results is positive and supports the compensation hypothesis. Rather than heterogeneity, our study provides support for other classic sources of preferences for public goods and redistribution. Individual-level ethnicity, sex, age, education, public employment status, and religion all certainly seem to play some role in driving individual-level preferences. If there is a pattern in terms of identity, the most robust pattern is that social class (embodied by wealth, education, and public and private employment status) remains a critical influence on preferences. In particular, our robust evidence for the central role of individual-level wealth deserves underlining, and this is relevant given recent works finding that poverty fails to be a simple predictor of public goods demand due to the truncated nature of welfare states in Latin America (Holland 2018). Further, the effects of unemployment and inflation point toward context-specific patterns of social policy preferences which may be driven by the particular pattern of labor market segmentation into formal and informal sectors (Altamirano, Berens, and Deeg 2022; Baker 2023). Unlike heterogeneity, these factors continue to present a promising direction for research on public support for redistribution and public goods. ■

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NOTES

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1. Strictly speaking, public goods entail nonrival consumption, non-excludability, and insufficient market supply. We simply use the term for commonly publicly provided services like healthcare.

2. With the exception of perhaps the European Union for southern Europe after the 2008 financial crisis, international actors such as international finance institutions are much more likely to intervene in developing countries' public policies compared to rich democracies. This alone may partly explain why developing countries diverge from general welfare state theories and rich democracies' spending priorities (Noy 2011, 2017, 2018).

3. For example, Kymlicka and Banting (2006:287) point out that Alesina and Glaeser's (2004) data classify ethnic groups in the U.K. based on race (White 93.7%, Indian 1.8%, Black 1.4%) but those in Canada based on a strange combination of linguistic and national origins (French 22.8%, Other Canadian 43.5%, British 20.8%, German 3.4%).

4. Fearon's (2003) data update countries to the early 1990s but also relies on CIA *World Factbooks* and encyclopedias as the main sources. In the 20 countries with data from both Alesina et al. and Fearon in our sample, their ethnic heterogeneity scores correlate at 0.88, and religious heterogeneity scores at 0.79.

5. Income and class differences between social groups may provide a more substantive base for public goods preferences (Baldwin and Huber 2010). This motivates our analysis of between-group inequality in the analyses below. Of course, ethnicity, language, and religion are not the only markers of social identity; there may be further non-economic bases of heterogeneity, such as other group identities, age, or gender. While certain political identities are possibly endogenous to public goods preferences, heterogeneity induced by ethnicity, language, or religion may be the most visible and salient non-economic bases for heterogeneity.

6. The 2021 wave was administered online because of the pandemic. This required dramatically reducing the length of the questionnaire. None of our dependent variables were collected in this wave.

7. We also estimate logistic regressions with country and year fixed effects. The results corroborate our findings and are presented in Tables S5–S7 in the supplement in the online version of the journal.

8. Imagine country A has four groups, each with a 0.25 share. This yields a Herfindahl index of 0.75. Imagine country B has four groups with a 0.24 share, but also four other groups with a 0.01 share. Even though country B has twice as many groups, the Herfindahl index is a similar 0.77. Taking into account that not all groups are equally influential for policymaking, we also test how much being part of the dominant group (the largest ethnic, linguistic, or religious group) influences preferences (see Tables S8–S10 in the online supplement). Results are discussed below.

9. In some countries, Other mainly refers to Chinese ethnicity, so we also keep this category when calculating the Herfindahl index. Results are robust when we drop the Other category.

10. Catholic, Protestant, other non-Christian (Jewish, Muslim), none, Evangelical, Mormon/Jehovah's Witness, and traditional/native religions.

11. Estimation results with the finer-grained religion item generally mirror the results from the seven-category item (available on request).

12. Morgan and Kelly label their BGI estimates as based on income. However, their publicly available code reveals they actually use the same LAPOP wealth measure.

13. In analyses available on request, we include marital status and household size. Limited data availability prevents their inclusion in the main models.

14. For ethnic heterogeneity and BGI as well as religious heterogeneity and BGI, zero cases have negative weights, and we do not violate the treatment effect homogeneity assumption. For linguistic heterogeneity and BGI there is evidence of treatment effect heterogeneity, but the results are robust while dropping cases with negative weights.

15. For all 4 preferences and 3 heterogeneities for the same time period, Figure A5 in the Appendix displays the minimal common time period (2010–2012) (see Figures A6–A7 for other comparisons).

16. This robustness test is motivated by minority threat theory, which might expect only the “dominant” group to be threatened by heterogeneity (e.g., Blumer 1958). However, the only two significant interactions (of eight) are positive, contrary to threat theory (Table S8).

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APPENDIX

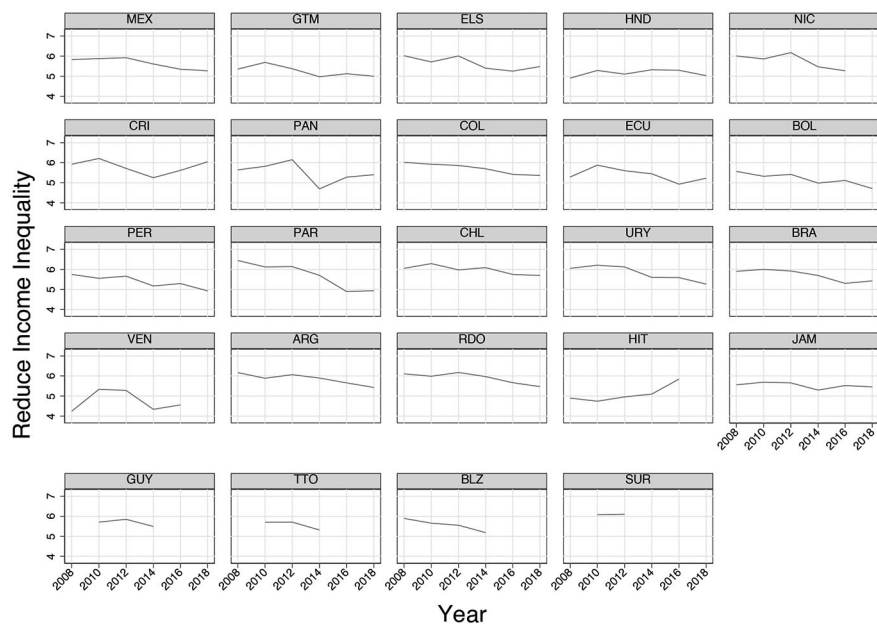


FIGURE A1. Over-time variation of redistribution preferences by country.

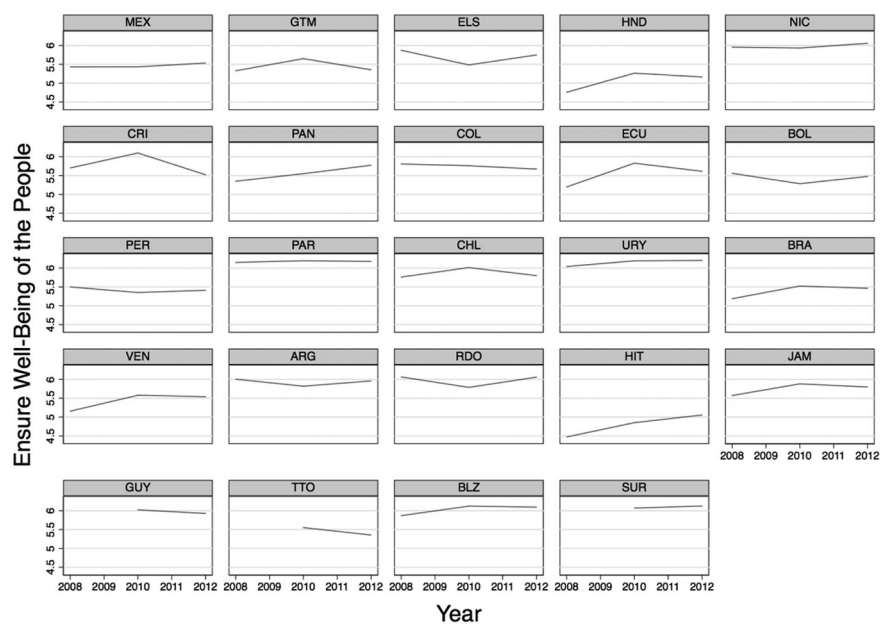


FIGURE A2. Over-time variation of public welfare by country.

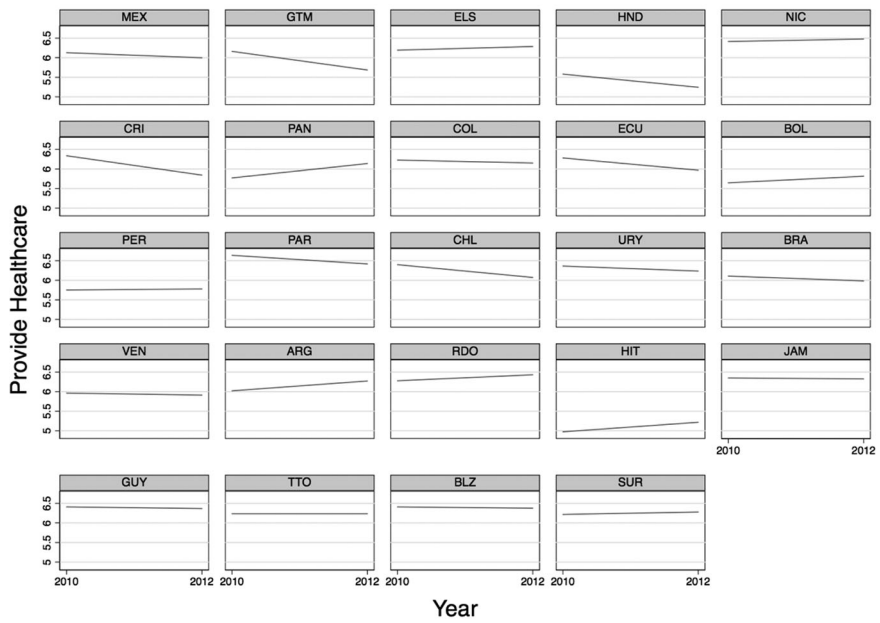


FIGURE A3. Over-time variation of healthcare preferences by country.

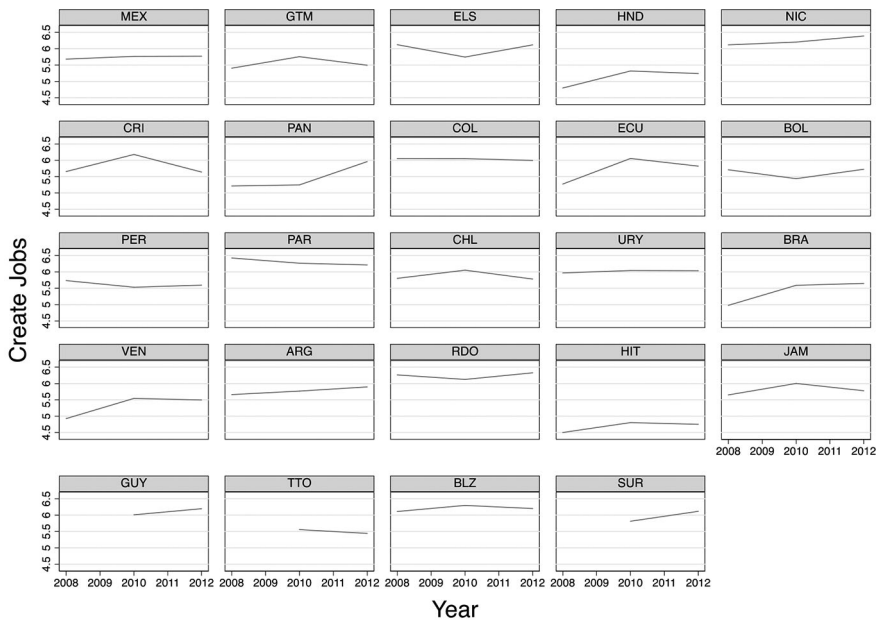


FIGURE A4. Over-time variation of job creation preferences by country.

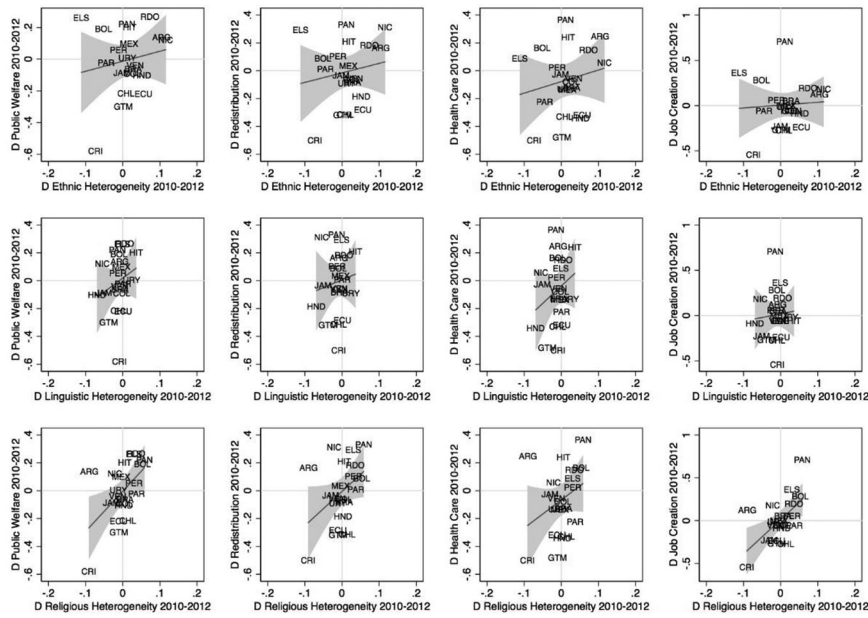


FIGURE A5. Bivariate correlations of changes in preferences and heterogeneity, 2010–2012 only.

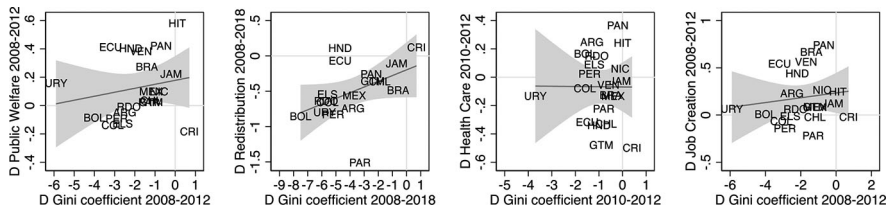


FIGURE A6. Bivariate correlations of changes in preferences and the Gini coefficient for the maximum time span (Solt 2019, version 8-9).

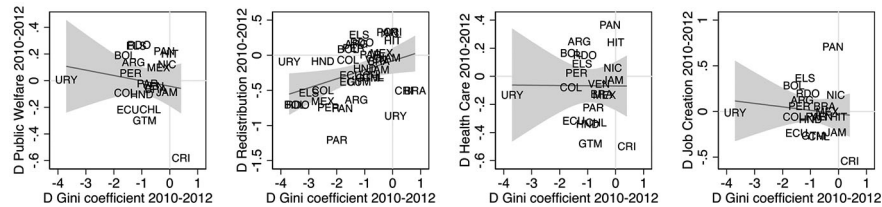


FIGURE A7. Bivariate correlations of changes in preferences and the Gini coefficient, 2010–2012 only (Solt 2019, version 8-9).

TABLE A1. Available LAPOP samples from countries and years							
Country	2008	2010	2012	2014	2016	2018	Total
Argentina	1,486	1,410	1,512	1,512	1,528	1,528	8,976
Belize	1,552	1,504	1,512	1,533	0	0	6,101
Bolivia	3,003	3,018	3,029	3,066	1,691	1,682	15,489
Brazil	1,497	2,482	1,499	1,500	1,532	1,498	10,008
Chile	1,527	1,965	1,571	1,571	1,625	1,638	9,897
Colombia	1,503	1,506	1,512	1,496	1,563	1,663	9,243
Costa Rica	1,499	1,500	1,498	1,537	1,514	1,501	9,049
Ecuador	1,507	1,498	1,512	1,520	1,518	1,516	9,071
El Salvador	3,000	2,999	1,500	1,489	1,545	1,533	12,066
Guatemala	1,549	1,550	1,497	1,512	1,551	1,511	9,170
Guayana	1,538	1,494	1,509	1,506	1,546	1,596	9,189
Haiti	0,000	1,540	1,529	1,557	1,576	0	6,202
Honduras	1,536	1,752	1,836	1,512	2,221	0	8,857
Jamaica	1,522	1,596	1,728	1,561	1,560	1,560	9,527
Mexico	1,499	1,504	1,500	1,503	1,515	1,513	9,034
Nicaragua	1,560	1,562	1,560	1,535	1,563	1,580	9,360
Panama	1,539	1,540	1,686	1,546	1,560	1,547	9,418
Paraguay	1,536	1,536	1,620	1,508	1,521	1,559	9,280
Peru	1,166	1,501	1,510	1,503	1,528	1,515	8,723
Dominican Republic	1,500	1,500	1,500	1,500	2,647	1,521	10,168
Suriname	0	1,516	1,490	4,000	0	0	7,006
Trinidad and Tobago	0	1,503	1,506	4,203	0	0	7,212
Uruguay	1,500	1,500	1,512	1,512	1,514	1,581	9,119
Venezuela	1,500	1,500	1,500	1,500	1,558	0	7,558
Total	34,519	40,976	38,628	43,182	34,376	28,042	219,723

Source: LAPOP 2008-2018.

Note: KNA, VCT, ATG, DMA, LCA, GRD, BRB, BHS are excluded from the sample, as none of the four DVs was asked in these countries.

TABLE A2. Religion categories in LAPOP as of 2010 (Q3c, Q3cn)

Category	Name
1	Catholic
2	Protestant, Mainline Protestant, or Protestant non-Evangelical (Christian; Calvinist; Lutheran; Methodist; Presbyterian; Disciple of Christ; Anglican; Episcopalian; Moravian)
3	Non-Christian Eastern religions (Islam; Buddhist; Hinduism; Taoist; Confucianism; Baha'i)
4	None (believes in a Supreme Entity but does not belong to any religion)
5	Evangelical and Pentecostal (Evangelical; Pentecostals; Church of God; Assemblies of God; Universal Church of the Kingdom of God; International Church of the Foursquare Gospel; Christ Pentecostal Church; Christian Congregation; Mennonite; Brethren; Christian Reformed Church; Charismatic non-Catholic; Light of World; Baptist; Nazarene; Salvation Army; Adventist; Seventh-Day Adventist; Sara Nossa Terra)
6	Church of Jesus Christ of Latter-Day Saints (Mormon)
7	Traditional religions or native religions (Santería, Candomblé, Voodoo, Rastafarian, Mayan Traditional Religion; Umbanda; Maria Lanza; Inti; Kardecista, Santo Daime, Esoterica)
8	Jewish (Orthodox; Conservative; Reform)
9	Agnostic, atheist (does not believe in God)
10	Jehovah's Witness

Source: LAPOP, 2010–2018.

TABLE A3. Descriptive statistics

	Obs.	Mean	Std. Dev.	Min.	Max.
DV					
Welfare	110,819	5.647	1.591	1	7
Redistribution	206,695	5.549	1.696	1	7
Health Care	78,232	6.075	1.370	1	7
Jobs	111,306	5.738	1.567	1	7
Heterogeneity indicators					
Ethnic heterogeneity	219,723	0.533	0.168	0.014	0.823
Linguistic heterogeneity	134,921	0.199	0.237	0.001	0.807
Religious heterogeneity	219,723	0.540	0.145	0.210	0.786
Ethnicity BGI	219,723	0.016	0.010	0.000	0.049
Language BGI	134,921	0.013	0.014	0.000	0.047

(continued)

TABLE A3. Descriptive statistics (*continued*)

	Obs.	Mean	Std. Dev.	Min.	Max.
Religion BGI	219,723	0.008	0.004	0.002	0.025
Controls					
Language	134,346	10.615	14.833	1	55
<i>Ethnicity</i>					
White	212,772	0.231	0.421	0	1
Mestizo	212,772	0.420	0.494	0	1
Indigenous	212,772	0.059	0.235	0	1
Black	212,772	0.149	0.356	0	1
Mulatto	212,772	0.054	0.225	0	1
Moreno	212,772	0.014	0.119	0	1
Other	212,772	0.021	0.142	0	1
<i>Religion</i>					
Catholic	212,882	0.580	0.494	0	1
Protestant	212,882	0.087	0.282	0	1
Other non-christian	212,882	0.028	0.166	0	1
None	212,882	0.102	0.303	0	1
Evangelical	212,882	0.177	0.000	0	1
Jehova	212,882	0.015	0.123	0	1
Traditional religion	212,882	0.009	0.096	0	1
Female	219,706	0.508	0.500	0	1
Age	218,961	3.965	1.601	16	112
Age squared	218,961	1.828	1.457	256	12,544
Wealth	219,588	5.639	1.145	0.007	8.860
Education years	217,371	9.488	4.338	0	18
<i>Employment status</i>					
Employed	216,325	0.452	0.498	0	1
Public employee	216,325	0.076	0.266	0	1
Unemployed	216,325	0.088	0.283	0	1
Non-employed	216,325	0.316	0.465	0	1
Retired	216,325	0.068	0.252	0	1
Religiosity	170,809	3.028	1.403	1	5

Source: LAPOP 2008–2018.

TABLE A4. Full table: fixed effects (FE) and multilevel (ML) models of preferences on ethnic heterogeneity variables in 24 countries in LAPOP data, 2008–2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Welfare</i>	<i>Welfare</i>	<i>Redist.</i>	<i>Redist.</i>	<i>Healthcare</i>	<i>Healthcare</i>	<i>Jobs</i>	<i>Jobs</i>
	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>
Ethnic heterogeneity	1.241 (0.778)	1.155*** (0.158)	−0.106 (0.907)	−0.073 (0.136)	0.832 (0.688)	0.715*** (0.184)	1.532 (0.848)	1.440*** (0.155)
Ethnic BGI	−5.432 (6.027)	−5.167*** (1.461)	−8.122 (6.406)	−7.899*** (1.035)	−1.303 (6.047)	−2.764 (1.947)	−11.734 (6.812)	−11.319*** (1.426)
White	−0.036 (0.034)	−0.032* (0.014)	−0.111*** (0.023)	−0.109*** (0.012)	−0.041 (0.039)	−0.035* (0.015)	−0.051 (0.033)	−0.052*** (0.014)
Indigenous	0.023 (0.060)	0.031 (0.023)	0.069 (0.067)	0.060** (0.020)	0.046 (0.048)	0.023 (0.024)	−0.039 (0.054)	−0.047* (0.022)
Black	0.007 (0.035)	0.008 (0.023)	−0.044 (0.034)	−0.042* (0.020)	0.010 (0.029)	0.002 (0.023)	−0.001 (0.042)	−0.007 (0.023)
Mulatto	0.019 (0.042)	0.026 (0.028)	−0.052 (0.037)	−0.050* (0.023)	0.032 (0.044)	0.023 (0.028)	0.043 (0.051)	0.039 (0.028)
Moreno	−0.029 (0.025)	−0.027 (0.050)	−0.018 (0.024)	−0.018 (0.053)	−0.008 (0.025)	−0.010 (0.051)	0.085** (0.023)	0.082 (0.049)
<i>Individual-level controls</i>								
Female	−0.034* (0.014)	−0.037*** (0.011)	−0.012 (0.010)	−0.014 (0.009)	−0.014 (0.015)	−0.019 (0.011)	0.017 (0.016)	0.012 (0.010)
Age	0.009* (0.004)	0.010*** (0.002)	0.008** (0.003)	0.007*** (0.001)	0.008 (0.005)	0.009*** (0.002)	−0.000 (0.003)	−0.000 (0.002)
Age squared	−0.000 (0.000)	−0.000*** (0.000)	−0.000** (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Wealth	−0.041** (0.014)	−0.038*** (0.006)	−0.033** (0.011)	−0.031*** (0.005)	−0.032* (0.013)	−0.031*** (0.006)	−0.067*** (0.012)	−0.064*** (0.006)
Education years	−0.001 (0.003)	−0.000 (0.001)	0.011** (0.004)	0.011*** (0.001)	0.003 (0.004)	0.002 (0.001)	−0.015** (0.005)	−0.015*** (0.001)
Public employee	0.069* (0.029)	0.072*** (0.019)	0.098** (0.026)	0.100*** (0.017)	0.026 (0.032)	0.028 (0.019)	0.064* (0.029)	0.066*** (0.019)
Unemployed	0.004 (0.019)	0.007 (0.020)	0.040 (0.027)	0.045** (0.015)	0.017 (0.022)	0.021 (0.020)	0.039 (0.029)	0.045* (0.019)
Non-employed	−0.012 (0.016)	−0.004 (0.013)	−0.032* (0.014)	−0.022* (0.011)	−0.008 (0.025)	0.001 (0.013)	−0.005 (0.015)	0.009 (0.012)

(continued)

TABLE A4. Full table: fixed effects (FE) and multilevel (ML) models of preferences on ethnic heterogeneity variables in 24 countries in LAPOP data, 2008–2018 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Welfare</i>	<i>Welfare</i>	<i>Redist.</i>	<i>Redist.</i>	<i>Healthcare</i>	<i>Healthcare</i>	<i>Jobs</i>	<i>Jobs</i>
	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>
Retired	−0.046 (0.034)	−0.032 (0.024)	0.044 (0.024)	0.055** (0.021)	−0.027 (0.036)	−0.009 (0.024)	−0.021 (0.026)	−0.010 (0.024)
Religiosity	−0.004 (0.008)	−0.003 (0.004)	−0.011 (0.007)	−0.010** (0.003)	0.011 (0.009)	0.010** (0.004)	0.004 (0.007)	0.004 (0.004)
<i>Country-level controls</i>								
GDP per capita	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000*** (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)
Inflation	0.005 (0.005)	0.004** (0.002)	0.007 (0.006)	0.007*** (0.001)	0.007 (0.005)	0.006*** (0.001)	0.006 (0.006)	0.006*** (0.001)
Gov't effectiveness	−0.201 (0.316)	−0.074 (0.061)	−0.457 (0.305)	−0.401*** (0.033)	−0.044 (0.375)	0.141* (0.070)	0.103 (0.322)	0.181** (0.060)
Gini	0.033 (0.035)	0.022** (0.008)	0.038 (0.027)	0.033*** (0.005)	0.028 (0.052)	−0.004 (0.010)	0.056 (0.041)	0.038*** (0.008)
Country fixed effects	yes		yes		yes		yes	
Year-fixed effects	yes		yes		yes		yes	
Constant	3.571 (2.028)	4.044*** (0.424)	4.771** (1.314)	4.548*** (0.304)	4.060 (3.193)	5.887*** (0.521)	2.703 (2.629)	3.776*** (0.417)
Var(Constant)		−1.033*** (0.159)		−0.374* (0.153)		−1.313*** (0.156)		−1.005*** (0.154)
Var(Residual)		0.435*** (0.002)		0.486*** (0.002)		0.277*** (0.003)		0.412*** (0.002)
N	103,523	103,523	154,033	154,033	73,753	73,753	103,963	103,963
Countries	24	24	24	24	24	24	24	24
Years	2008– 2012	2008– 2012	2008– 2018	2008– 2018	2010– 2012	2010– 2012	2008– 2012	2008– 2012
BIC	384,204.3	384,532.0	587,007.5	587,579.6	250,246.9	250,684.0	380,853.7	381,400.3

*** $p < .001$, ** $p < .01$, * $p < .05$.

Note: The numbers in parentheses are standard errors. The reference categories are Mestizo and private employment. All models are fully specified.

TABLE A5. Fixed effects (FE) and multilevel (ME) models of preferences on linguistic heterogeneity variables in 24 countries in LAPOP Data, 2008–2018

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	<i>Welfare</i>	<i>Welfare</i>	<i>Redist.</i>	<i>Redist.</i>	<i>Healthcare</i>	<i>Healthcare</i>	<i>Jobs</i>	<i>Jobs</i>
	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>
Linguistic hetero.	−0.478 (0.491)	−0.396 (0.213)	0.382 (0.552)	0.365 (0.209)	−0.818 (1.572)	−1.190*** (0.349)	−0.062 (0.525)	−0.099 (0.206)
Linguistic BGI	18.948* (8.367)	18.080*** (2.964)	0.094 (8.627)	0.306 (2.922)	26.870* (12.102)	28.830*** (3.622)	10.489 (9.340)	11.303*** (2.858)
Language indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Individual-level controls</i>								
Female	−0.033* (0.014)	−0.035** (0.012)	−0.012 (0.013)	−0.013 (0.012)	−0.017 (0.015)	−0.021* (0.011)	0.013 (0.016)	0.009 (0.011)
Age	0.009* (0.004)	0.010*** (0.002)	0.008* (0.003)	0.008*** (0.002)	0.009 (0.005)	0.009*** (0.002)	−0.000 (0.003)	0.000 (0.002)
Age squared	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Wealth	−0.039* (0.014)	−0.038*** (0.006)	−0.069*** (0.013)	−0.066*** (0.006)	−0.036* (0.014)	−0.034*** (0.006)	−0.068*** (0.014)	−0.067*** (0.006)
Education years	−0.001 (0.004)	−0.001 (0.002)	0.003 (0.003)	0.002 (0.002)	0.002 (0.004)	0.002 (0.001)	−0.015** (0.005)	−0.015*** (0.002)
Public employee	0.057 (0.032)	0.060** (0.021)	0.075* (0.031)	0.078*** (0.021)	0.023 (0.031)	0.026 (0.019)	0.054 (0.034)	0.055** (0.020)
Unemployed	0.039* (0.018)	0.042* (0.021)	0.053 (0.029)	0.063** (0.021)	0.019 (0.022)	0.023 (0.019)	0.069* (0.025)	0.076*** (0.020)
Non-employed	−0.011 (0.018)	−0.006 (0.014)	−0.010 (0.019)	0.001 (0.014)	−0.006 (0.024)	0.004 (0.013)	−0.001 (0.018)	0.012 (0.013)
Retired	−0.046 (0.040)	−0.030 (0.027)	−0.003 (0.038)	0.017 (0.027)	−0.027 (0.038)	−0.007 (0.024)	−0.031 (0.028)	−0.015 (0.026)
Religiosity	−0.005 (0.008)	−0.003 (0.004)	−0.014 (0.010)	−0.012** (0.004)	0.010 (0.009)	0.009* (0.004)	0.006 (0.007)	0.008 (0.004)
<i>Country-level controls</i>								
GDP per capita	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)
Inflation	0.006 (0.005)	0.006*** (0.002)	0.006 (0.004)	0.005** (0.002)	0.004 (0.005)	0.003* (0.001)	0.009 (0.006)	0.008*** (0.002)

(continued)

TABLE A5. Fixed effects (FE) and multilevel (ME) models of preferences on linguistic heterogeneity variables in 24 countries in LAPOP Data, 2008–2018 (*continued*)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	<i>Welfare</i>	<i>Welfare</i>	<i>Redist.</i>	<i>Redist.</i>	<i>Healthcare</i>	<i>Healthcare</i>	<i>Jobs</i>	<i>Jobs</i>
	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>
Gov't effectiveness	−0.579** (0.202)	−0.461*** (0.067)	−0.317 (0.229)	−0.168** (0.064)	−0.217 (0.324)	0.014 (0.073)	−0.403 (0.244)	−0.304*** (0.065)
Gini	0.001 (0.047)	−0.002 (0.011)	0.020 (0.053)	0.013 (0.011)	0.011 (0.053)	−0.019 (0.011)	0.034 (0.065)	0.017 (0.011)
Country fixed effects	yes		yes		yes		yes	
Year fixed effects	yes		yes		yes		yes	
Constant	5.665 (2.992)	5.467*** (0.592)	5.149 (3.339)	5.099*** (0.544)	5.230 (3.389)	6.708*** (0.570)	3.527 (4.374)	4.644*** (0.565)
Var(Constant)		−0.593** (0.183)		−1.029*** (0.170)		−1.092*** (0.161)		−0.704*** (0.158)
Var(Residual)		0.426*** (0.002)		0.431*** (0.002)		0.274*** (0.003)		0.395*** (0.002)
<i>N</i>	85,434	85,434	86,421	86,421	75,058	75,058	85,828	85,828
Countries	24	24	24	24	24	24	24	24
Years	2008- 2012	2008- 2012	2008- 2014	2008- 2014	2010- 2012	2010- 2012	2008- 2012	2008- 2012
BIC	315,652.6	316,282.7	319,985.2	320,732.2	254,273.1	255,068.6	311,464.4	312,371.7

*** $p < .001$, ** $p < .01$, * $p < .05$.

Note: The numbers in parentheses are standard errors. The reference categories are Spanish and private employment. Mother tongue was missing in 2016 and 2018. All models are fully specified.

TABLE A6. Fixed effects (FE) and multilevel (ML) models of preferences on religious heterogeneity (seven categories) variables in 24 countries in LAPOP data, 2008–2018

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	<i>Welfare</i>	<i>Welfare</i>	<i>Redist.</i>	<i>Redist.</i>	<i>Healthcare</i>	<i>Healthcare</i>	<i>Jobs</i>	<i>Jobs</i>
	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>	<i>FE</i>	<i>ML</i>
Religious hetero.	1.230 (0.634)	1.180*** (0.150)	1.047 (0.533)	1.091*** (0.115)	2.507 (1.844)	2.482*** (0.277)	1.904* (0.783)	1.853*** (0.148)
Religion BGI	1.877 (9.518)	0.383 (2.607)	−0.797 (12.569)	−1.560 (1.922)	−3.926 (12.928)	−7.135* (3.091)	−3.281 (10.020)	−4.904 (2.541)
Protestant	−0.002 (0.036)	−0.001 (0.019)	−0.016 (0.031)	−0.016 (0.016)	0.004 (0.023)	−0.001 (0.019)	−0.006 (0.027)	−0.004 (0.018)
Other non-Christian	−0.012 (0.048)	−0.029 (0.037)	−0.030 (0.040)	−0.034 (0.034)	0.004 (0.032)	−0.013 (0.033)	0.045 (0.062)	0.028 (0.036)
None	0.023 (0.027)	0.019 (0.020)	0.068** (0.023)	0.068*** (0.016)	0.010 (0.029)	0.007 (0.019)	−0.004 (0.027)	−0.007 (0.019)
Evangelical	0.075** (0.025)	0.077*** (0.015)	0.068* (0.027)	0.066*** (0.012)	0.057 (0.028)	0.052*** (0.015)	0.057** (0.017)	0.060*** (0.014)
Jehovah's Witness	−0.050 (0.047)	−0.039 (0.039)	0.011 (0.037)	0.000 (0.035)	0.006 (0.039)	−0.012 (0.042)	−0.062 (0.054)	−0.044 (0.038)
Traditional religion	−0.012 (0.103)	−0.014 (0.052)	0.276*** (0.045)	0.265*** (0.045)	0.287* (0.117)	0.252*** (0.060)	0.090 (0.071)	0.073 (0.051)
<i>Individual-level controls</i>								
Female	−0.038** (0.013)	−0.042*** (0.011)	−0.016 (0.011)	−0.018 (0.009)	−0.018 (0.015)	−0.022* (0.011)	0.013 (0.016)	0.006 (0.010)
Age	0.009* (0.004)	0.010*** (0.002)	0.007** (0.003)	0.007*** (0.001)	0.008 (0.005)	0.009*** (0.002)	0.000 (0.003)	0.000 (0.002)
Age squared	−0.000 (0.000)	−0.000*** (0.000)	−0.000** (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000*** (0.000)	−0.000 (0.000)	−0.000 (0.000)
Wealth	−0.044** (0.014)	−0.041*** (0.006)	−0.039* (0.014)	−0.037*** (0.005)	−0.034* (0.014)	−0.032*** (0.006)	−0.067*** (0.012)	−0.064*** (0.006)
Education years	−0.000 (0.003)	−0.000 (0.001)	0.011** (0.004)	0.011*** (0.001)	0.003 (0.004)	0.002 (0.001)	−0.016** (0.005)	−0.015*** (0.001)
Public employee	0.070* (0.027)	0.073*** (0.019)	0.100** (0.027)	0.101*** (0.017)	0.022 (0.029)	0.024 (0.019)	0.062* (0.027)	0.065*** (0.019)
Unemployed	0.004 (0.020)	0.007 (0.020)	0.037 (0.028)	0.041** (0.016)	0.019 (0.024)	0.024 (0.020)	0.046 (0.031)	0.052** (0.019)
Non-employed	−0.007 (0.016)	0.001 (0.012)	−0.033* (0.014)	−0.023* (0.011)	−0.009 (0.024)	0.002 (0.013)	0.001 (0.015)	0.017 (0.012)

(continued)

TABLE A6. Fixed effects (FE) and multilevel (ML) models of preferences on religious heterogeneity (seven categories) variables in 24 countries in LAPOP data, 2008–2018
(continued)

	(17) <i>Welfare</i> FE	(18) <i>Welfare</i> ML	(19) <i>Redist.</i> FE	(20) <i>Redist.</i> ML	(21) <i>Healthcare</i> FE	(22) <i>Healthcare</i> ML	(23) <i>Jobs</i> FE	(24) <i>Jobs</i> ML
Retired	–0.040 (0.034)	–0.027 (0.024)	0.040 (0.026)	0.051* (0.020)	–0.026 (0.038)	–0.007 (0.024)	–0.015 (0.024)	–0.004 (0.023)
Religiosity	–0.006 (0.010)	–0.007 (0.004)	–0.008 (0.009)	–0.006 (0.004)	0.008 (0.010)	0.008 (0.004)	0.001 (0.009)	0.001 (0.004)
<i>Country-level controls</i>								
GDP per capita	–0.000 (0.000)	–0.000 (0.000)	–0.000 (0.000)	–0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Inflation	0.005 (0.005)	0.004** (0.002)	0.007 (0.005)	0.007*** (0.001)	0.006 (0.005)	0.005** (0.001)	0.006 (0.006)	0.006*** (0.001)
Gov't effectiveness	–0.398 (0.309)	–0.255*** (0.063)	–0.463 (0.262)	–0.408*** (0.033)	–0.186 (0.346)	–0.005 (0.084)	–0.171 (0.310)	–0.056 (0.062)
Gini	0.041 (0.033)	0.032*** (0.008)	0.048 (0.033)	0.043*** (0.005)	0.044 (0.046)	0.013 (0.012)	0.066 (0.036)	0.051*** (0.008)
Country fixed effects	yes		yes		yes		yes	
Year fixed effects	yes		yes		yes		yes	
Constant	3.347 (1.823)	3.427*** (0.459)	3.784* (1.632)	3.333*** (0.308)	2.960 (2.837)	3.972*** (0.668)	2.357 (2.272)	2.664*** (0.454)
Var(Constant)		–0.703*** (0.164)		–0.361* (0.152)		–0.724*** (0.168)		–0.611*** (0.150)
Var(Residual)		0.435*** (0.002)		0.485*** (0.002)		0.274*** (0.003)		0.411*** (0.002)
Observations	104,341	104,341	154,599	154,599	73,918	73,918	104,816	104,816
Countries	24	24	24	24	24	24	24	24
Years	2008– 2012	2008– 2012	2008– 2018	2008– 2018	2010– 2012	2010– 2012	2008– 2012	2008– 2012
BIC	387,084.5	387,273.4	588,900.6	589,213.6	250,503.6	250,769.1	383,726.6	384,105.8

*** $p < .001$, ** $p < .01$, * $p < .05$.

Note: The numbers in parentheses are standard errors. The reference categories are Catholic and employed. All models are fully specified.