Ethnicity and Climate Dissensus in Africa*

Devin Caughey† Preston Johnston‡ Evan Lieberman§

MIT MIT MIT

December 2, 2025

Abstract

The African continent has already experienced severe climate impacts, yet public attitudes toward climate change vary widely within and across countries. Drawing on Afrobarometer surveys from 29 countries, we test whether opinions are divided along ethnic lines. We find evidence of ethnic dissensus in nearly every country, strongest in perceptions of climate hazards but also present in views on policy responses. Using Bayesian multilevel models, we assess three explanations: individual composition of groups, group-level attributes, and geographic context. We find the strongest evidence for the third explanation, specifically that dissensus is greatest where ethnic groups are more regionally segregated. Additionally, wealthier groups tend to be more aware of climate issues yet less concerned about action, though inequality itself does not predict dissensus. These findings underscore the links between ethnicity, regionalism, and climate politics, contributing to research on ethnic politics, public goods provision, and the emerging field of climate-related attitudes.

Keywords: Africa, ethnicity, climate, regionalism, multilevel models, intraclass correlation

*We are grateful to Kate Danahy and Nico Studen for research assistance. We received valuable feedback during presentations at the 2024 annual meeting of the American Political Science Association, the 2024 Working Group on African Political Economy (WGAPE) in Accra, Ghana, the University of Southern California comparative politics workshop, the Boston University comparative politics workshop, the October 2024 meeting of the Boundaries, Membership and Belonging program sponsored by the Canadian Institute for Advanced Research, and especially specific comments from Zainab Mai-Bornu, and Gaea Patrice Morales.

†Department of Political Science, Massachusetts Institute of Technology; Email: caughey@mit.edu

‡Department of Political Science, Massachusetts Institute of Technology; Email: prhj@mit.edu

§Department of Political Science and Center for International Studies, Massachusetts Institute of Technology; Email: evanlieb@mit.edu

Contents

1 Introduction **2**

2 Potential explanations for ethnic dissensus **6**

2.1 Composition of ethnic groups 7

2.2 Intergroup relations 8

2.3 Geography and regionalism 10

3 Research questions and data **11**

3.1 Climate-related survey items 13

3.2 Ethnic categories 16

4 Empirical approach **18**

5 Results **25**

5.1 Is there ethnic dissensus on climate attitudes? If so, how much? 25

5.2 Where does ethnicity matter? Cross-national variation in ethnic dissensus . . 29

5.3 Why does ethnicity matter? Evaluating alternative explanations 33

5.3.1 The correlates of climate attitudes 35

5.3.2 Ethnic dissensus controlling for other factors 39

5.3.3 Country-level predictors of ethnic dissensus 41

6 Conclusion **46**

A Descriptive statistics and figures **56**

B Ethnic Categories - Afrobarometer to EPR translation **58**

C Alternative measures **70**

D Model details **70**

E Additional analyses **72**

1 Introduction

To date, scholarly research on climate politics and climate-related attitudes has focused on the world's wealthiest countries and the biggest emitters of greenhouse gases (Echendu 2025). Yet there is good reason to turn our attention to Africa: While the over one billion people living on the continent have historically had the lowest carbon footprint relative to other world regions, they are among the most vulnerable to a host of climate-related hazards that threaten their livelihoods and well-being (Adelekan et al. 2022; Chen et al. 2023). Moreover, given current low levels of energy consumption, net emissions from Africa will almost surely grow, but the magnitude of such increases will be affected by both private- and public-sector choices regarding energy sources.

In turn, learning how African citizens have come to understand climate change ought to be a key priority for research. Faced with a wide range of needs and priorities, to what extent is there consensus around perceptions of the climate problem and the best solutions? In this paper, we focus on *consensus* rather than simply levels of concern or support for policies. Regardless of which climate-related problems citizens or governments choose to prioritize, where there is disagreement, especially along politically-salient lines, this may contribute to conflict, with potentially negative implications for policy.

In particular, we turn our attention to the influence of ethnic and racial identities. To date, the role of ethnic difference in climate attitudes has been relatively understudied. One meta-study, Hornsey et al. (2016), analyzed the drivers of climate attitudes across 56 countries using 25 different surveys and 171 studies, but the only consideration of an identity-based variable was a binary race indicator (white/non-white), covering just 12 countries. Several recent cross-country meta-analyses (Arıkan and Günay 2021; Bergquist et al. 2022) do not consider race or ethnic variables at all. Yet, there are good reasons to suspect that dissensus on climate attitudes across social categories such as race or ethnicity exist in many countries. The United States offers a motivating example of a case where perceptions, priorities, and policy preferences may differ between social groups, as several studies highlight key racial differences in attitudes about the dangers of climate change and support for government actions on mitigation and adaptation (Ballew et al. 2019a; Benegal et al. 2022).

Given our attention to the African context, we are motivated by a large body of scholarship that has demonstrated various links between ethnic diversity and the challenges of public goods provision (e.g. Easterly and Levine 1997; Posner 2004; Baldwin and Huber 2010; Franck and Rainer 2012; Beiser-McGrath et al. 2021). A key debate within that literature has concerned the mechanisms that link ethnic difference to poor governance outcomes, including whether ethnic groups hold divergent preferences for particular policies (Alesina et al. 1999). Empirical studies basd on public opinion data have generated mixed findings. For example, Habyarimana et al. (2009) reported that they failed to detect ethnically-distinctive preferences for public goods based on original survey of citizens in urban Kampala; while Lieberman and McClendon (2013) identified the prevalence of ethnically distinct policy preferences for a range of (non-climate) policies in a study of 18 African countries.

Only a few studies have so far considered the role of ethnic identity as a predictor of *climate* attitudes in Africa. Collier et al. (2008) claim, but do not empirically demonstrate, that African climate adaptation would likely be impeded by the ethnic fractionalization of the continent. Sanchez et al. (2012) found in a series of focus groups conducted in Benin that although there were no substantial inter-ethnic differences in observations of climate-related changes within climatic zones/latitudes, members of different ethnic groups focused on different consequences of the same changes, and that they used different adaptive strategies to cope. Finally, Honig et al. (2021) study the Kenyan case and conclude that Muslims express lower efficacy with respect to the climate emergency because of perceptions of marginalization by the state. Despite these contributions, we lack synthesized, cross-national empirical evidence of ethnic dissensus on climate attitudes and preferences.

In this article, we seek to contribute to the scholarly literatures on climate attitudes and on the link between ethnic diversity and public policy by investigating whether African citizens from different ethnic groups hold distinct attitudes about various aspects of the climate emergency and about climate policies. We take advantage of Afrobarometer Round 9, a recently released, geo-coded survey fielded in more than 30 countries, comprising a total of over 40,000 respondents. We combine the Afrobarometer data with data on group relations, climate conditions, and other socio-economic indicators. The focus of our analysis is on eight climate-related survey items, which we broadly categorize as either regarding *Literacy* about the climate problem, *Perceptions* of climatic changes, or relating to views on *Actions* that should be taken, such as which actor bears primary responsibility for addressing the crisis, whether emissions reductions ought to be pursued despite potential costs, and whether everyday citizens can make a difference.

When considering this wealth of data, we highlight the challenge of estimating the magnitude of inter-ethnic preference diversity across countries and indicators with existing approaches, and the need for a summary measure that can flexibly handle requirements such as comparability across survey items and countries with different numbers of groups, and can accurately account for uncertainty. We focus on a concept we call *ethnic dissensus*, which is the extent to which politically-salient ethnic groups hold divergent preferences or attitudes on various dimensions of public opinion. We develop an original approach to measuring ethnic dissensus based on statistics derived from the variance of ethnic group intercepts in multilevel Bayesian models. From these models, we can construct estimators for various quantities of interest, including the *level* of ethnic dissensus on a given survey item in a given country.

We find that about half of all countries studied exhibit at least moderate ethnic dissensus on one or more climate-related survey items. However, countries vary significantly on their overall *level* of dissensus and *which* dimensions of climate attitudes exhibit the most dissensus. We find that dissensus is higher on *Perceptions* of the climate rather than on *Action* questions.

Having estimated the extent of dissensus across countries, we turn to asking inferential questions about why we observe such patterns. We leverage observed cross-country and within-country variation to learn more about why ethnic difference may impede consensus around climate change. We adjudicate among three broad sets of explanations: First is the idea that ethnic groups are simply containers for different distributions of individual-level characteristics, such as education, income, occupation, etc., and that the autonomous role of ethnic difference will wash away when we account for those factors. Second is the idea that group-level characteristics and inter-group relations are behind inter-group variability in climate preferences. Accordingly, we investigate whether group power status, relative wealth, or other variables are informative of group-level views. Finally, we consider the spatial location of where citizens reside, particularly as co-ethnics tend to be residentially concentrated. For example, is the coincidence of co-ethnic perspectives on climate a matter of shared experiences in climatic zones? Or, as Boone et al. (2022); Boone (2024) has argued, is ethnic politics itself largely a manifestation of regional inequalities and competition?

Our multi-level analysis allows us to consider such explanations from micro- (individual), meso- (group), and macro- (national) level perspectives. We arrive at several key findings: First, although many individual-level covariates do predict climate attitudes, their inclusion in our models does not substantially reduce the importance of ethnicity as a source of dissensus, so we reject the notion that climate dissensus is due to ethnicity being merely a "bin" for different types of individuals. Alternatively, we find that group resources and especially regional context provide the best explanations for ethnic dissensus. Despite being marginally more likely to have heard about climate change, members of wealthier ethnic groups are less likely to express concerns about climate change, and ethnic disagreement is much more intense across regions than within them. Finally, ethnic dissensus is more prevalent in countries where ethnic groups are more spatially segregated. We speculate that as climate change intensifies, such spatial segregation could be a source of divergent perspectives on policy responses.

We detail our claims and evidence as follows: First, we present a set of theoretical propositions that motivate the idea that ethnicity may structure climate attitudes. Second, we detail our research questions and data sources. Third, we describe our empirical approach, with special attention to the challenge of examining ethnic dissensus across countries using survey data. Fourth, we present estimates of the extent of ethnic dissensus on climate issues, both continent-wide and within each country. We then assess various theoretical explanations for ethnic dissensus. Finally, we conclude, highlighting implications for scholarship and for policy.

2 Potential explanations for ethnic dissensus

An increasingly large scholarly literature has highlighted that climate-related risk perceptions are affected not just by objective experiences with climate-related shocks (e.g. Frondel et al. 2017; Lawrence et al. 2014), but also by social and political factors including an individual's occupational sector (Frank et al. 2011) or value orientations (Leiserowitz 2006; van der Linden 2017). An important recent study, Bush and Clayton (2022), highlights the role of status concerns as a driver of gender differences in climate attitudes. The authors conclude that greater male attachment to the status quo in richer countries has led to a greater gender gap in climate attitudes relative to poorer countries.

Ethnic differences are also important markers of status and power, especially in the African context. In the face of shared hazards or dangers, individuals with different ethnic identities (and here we use a broad definition of ethnicity that includes race, tribe, national origin, or indigenous status[1]) may, in turn, perceive those risks differently and/or differ in the extent to which they value efforts to collectively insure against harm. Decades of research have highlighted the role borders and social boundaries play in various political conflicts as individuals attempt to make sense of their interests and allegiances in struggles for resources, power, and status.[2] Moreover, evidence of the disproportionate effects of

[1]See, for example, Varshney (2003). However, we do not consider religion as an ethnic category in this study because that is not how most African citizens self-identified when asked about their most important cultural group; and we do not consider the category of caste, which is not a salient dimension of perceived difference in the African context.

[2]For key reviews, see, for example, Lamont and Molnár (2002); Kalin and Sambanis (2018).

adverse climate shocks on racial and ethnic minorities in the United States (e.g., Chaganti et al. 2015; Ballew et al. 2019b; Schuldt and Pearson 2016) raises the question of to what extent different national cases exhibit racial inequality in climate exposure and whether such inequalities have impacts on risk perceptions and opinions.

With respect to other global challenges, particularly around global public health threats, ethnic and racial boundaries have routinely formed the basis for contrasting perceptions of danger—including, for example, regarding the HIV/AIDS pandemic (Cohen 1999; Lieberman 2009). In societies with strong ethnic boundaries—also known as "divided societies" (Horowitz 1985)—welfare-enhancing policies and personal protective action are frequently under-provided. This underprovision has plausibly been driven by, among other factors, group-level disparities in preferences, which in turn are the product of unequal distributions of resources and contrasting views about vulnerability, blame, and deservingness. Relatedly, we expect that where ethnic differences map onto key status differences, we will find increasing group-level dissensus on climate attitudes.

Below, we outline three broad categories of mechanisms through which ethnic identity may drive distinct climate perceptions and preferences. While these these dynamics are not mutually exclusive, we discuss some observable implications for each, which we later examine empirically in Section 5.

2.1 Composition of ethnic groups

One possible explanation for why we observe ethnic groups exhibiting distinct average risk appetites or policy preferences is that such groups are *composed* of individuals with distinct distributions of attributes or resources. If compositional mechanisms are operating, we would expect group dissensus in attitudes or other outcomes to be structured by inequalities in resources such as wealth or education, and for estimates of dissensus to vanish once we account for these individual attributes. Of course, such attributes may be *a consequence* of intergroup relations, but a compositional mechanism exists to the extent that there is no *leftover* variation to be explained once we account for individual attributes. For example, if education is the causally relevant factor for climate change awareness and concern, and some groups have more members with education (e.g., due to proximity to schools), then the members of the more educated group may come to exhibit more knowledge and concern for climate change.

2.2 Intergroup relations

Alternatively, inter-group differences in attitudes and perspectives may be structured by group identities themselves in ways that cut across individual-level circumstances. For example, a large scholarly literature has highlighted the various ways in which ethnic group categories can serve as heuristics for citizens to form attitudes about their circumstances and about the relative value of different policies (e.g. Dawson 1994; Akerlof and Kranton 2000). Members of at least some groups may find it difficult to imagine pooling risks with ethnic "outgroups" simply because they understand their relationship in zero-sum terms. Owing to dynamics associated with Social Identity Theory (e.g., Tajfel and Turner 1986; Lieberman 2009), they may perceive that members of other groups are more likely to be blameworthy for climate-related hazards and/or the inability to adapt, and as such, may resist cooperative behavior even if ultimately welfare-depleting.

In turn, groups may come to exhibit persistently distinct responses to various hazards. For example, for over three decades, risk scientists have detected a "white male" effect in the United States—the finding that white men tend to perceive risks as smaller and more acceptable as compared with white women and non-white men and women (Slovic et al. 1994; Siegrist and Árvai 2020, 2194). In one study, the authors found that white men reported substantially lower concerns about risk for all 25 hazards mentioned. Although the authors did not provide evidence for why this might be the case, they offered a plausible hypothesis in their conclusion: "Perhaps white males see less risk in the world because they create, manage, control and benefit from so much of it" (Slovic et al. 1994, 1107).

Applied to the African context, we consider group-level disparities in power and wealth, which have long been noted as sources of conflict. In a multi-country dataset, Cederman et al. (2010) distinguish the relative power status of salient ethnic groups in terms of control of the state. Scholars have found that in many countries, a leader's ethnicity is predictive of distributive and patronage outcomes across a variety of sectors (Franck and Rainer 2012), and in turn it stands to reason that concerns about future hazards and desire for government intervention are likely to be affected by whether a co-ethnic is in power. Individuals' levels of concern about the future and approval of government performance on climate issues may be related to their perception that they will or will not be protected by in-group or out-group leaders.

Disparities in risk-perceptions and degree of reliance on group identity as a heuristic may also be exacerbated by higher levels of between-group inequality (Baldwin and Huber 2010). Between-group inequality may also contribute to the manifestation of ethnic dissensus on policy preferences. The overlap of identity and socio-economic resources may increase the likelihood of coming to understand problems and solutions in group terms, especially as a group's relative standing and experiences with other hazards tends to shape internal narratives about danger (Siegrist and Árvai 2020). Particularly with respect to climate threats, wealthier groups are more likely to live in areas that are less vulnerable and may have more private resources with which to adapt to new challenges. In countries with higher between-group inequalities, intergroup relations theories would posit that risk perceptions and policy preferences would likely adhere more closely to ethnic lines, potentially leading to greater ethnic dissensus. Crucially, if an intergroup relations mechanism is at work, we should expect such dissensus to persist even after adjusting for individual attributes such as wealth or education.

2.3 Geography and regionalism

In contrast with the aforementioned explanations that focus on the relations between and relative positions of ethnic groups in various countries, some scholars have challenged the more foundational notion that we ought to view ethnic groups as primary building blocks of political competition and preference formation in Africa (e.g. Boone et al. 2022; Boone 2024.) These alternative accounts emphasize the causal weight of other factors, specifically residential location or regionalism.

Given the geographically localized manifestation of many climate-related harms, it stands to reason that climate politics may be particularly sensitive to residential patterns across space. A key candidate explanation for why climate-related attitudes and policy preferences might be associated with particular ethnic groups is differential exposure to climate-related hazards. At first blush, this would seem to be the most plausible explanation. For example, certain ethnic groups are concentrated in low-lying areas, which are more vulnerable to rising sea levels, flooding and storms; in areas with extreme temperatures; or in occupational sectors that depend on agricultural production or fishing, which have been strained under climate-related changes. While the residential location of some ethnic and racial groups may be the product of historical accident, there are also several instances where subordinate groups were forcefully restricted to reside in certain areas and/or to work in occupational categories that are particularly exposed to climate shocks through a combination of natural geography and built environment (the cases of American segregation and South African apartheid are extreme examples of such historical practices, with ongoing legacies still evident). From this perspective, individual risk preferences and behavioral outcomes can be understood in terms of a "rationalist paradigm," that builds on logical assessments of likely outcomes, costs and benefits (Lechowska 2022).

However, the literature on climate opinion has found repeatedly that objectively observed shocks have only limited impact on attitudes, either in terms of magnitude, duration, or both. For instance, Simpson et al. (2021), found that African citizens' *perceptions* of drought and flood were only weakly correlated with the meteorological record of drought and heavy precipitation at respondents' locations ($r < 0.2$). As Howe et al. (2019) find from a meta-analysis of studies of climate attitudes, subjective experiences may be at least as important as actual weather events in predicting individual attitudes. Similarly, Arias and Blair (2024) find that the effect of hurricane exposure on mitigation and adaptation opinions attenuates within six months.

Therefore, whether the geographic distribution of groups drives dissensus is an open empirical question. To the extent that this mechanism and not others drive attitudes, we would expect variation in attitudes *within* ethnic groups to the extent that residential and occupational segmentation is incomplete. Alternately, we would expect less variation within regions across groups. We would also expect that more concentration of groups into regions would be associated with higher ethnic dissensus at the country level, since groups would exhibit persistent disagreements about the nature of threats and preferences over solutions.

A related but distinct regionalist explanation focuses on the territorial administration of government in African countries. According to (Boone 2024, 21), such administration can lead to coalitions and alliances at various levels, as state institutions create and/or reproduce regional inequalities, including in terms of government services, resources, and policies. While possibly difficult to disentangle from an explanation focused on localized climate hazards, we claim that to the extent that regional inequalities can account for ethnic-based preferences on climate attitudes, and that such differences are *not* associated with observable climatic conditions or trends, we can conclude that such an explanation offers a plausible account of ethnic group-based dissensus.

3 Research questions and data

The discussion above offers several motivations for the proposition that we should find links between how individuals identify as members of ethnic groups and how they view the dangers of the changing climate. We consider three sets of questions for empirical analysis:

First, *does* ethnicity matter for climate attitudes in Africa? In how many African countries is the phenomenon of ethnic dissensus prevalent? How substantively large are those disparities relative to disparities associated with other matters of public opinion? Second, *where* does ethnicity matter for climate attitudes? Are countries similar to each other in their level of ethnic dissensus, or do they vary significantly? Which dimensions of climate attitudes exhibit the most dissensus? Finally, *why* does ethnicity matter for climate attitudes? We consider the three sets of candidate explanations from the prior section and deploy multiple analytic strategies to estimate their value in accounting for observed variation within and across countries.

We explore these research questions primarily through analysis of public opinion data from the African continent, taking advantage of the ninth round of geolocated Afrobarometer data, collected between October 2021 and October 2023.[3] These data offer extremely broad geographic coverage, including 37 countries and importantly, a detailed battery of relatively high-quality, climate-related survey questions. We remove certain countries from the sample for a variety of data availability reasons,[4] resulting in an effective N of 40,269[5] for 29 countries.[6] We note that the survey has traditionally been timed to avoid enumeration during the rainy season, which may impose some bias on the results to the effect that seasonality, and precipitation, air temperature and other near-term weather-related factors might affect reported attitudes.

[3]Data available at `http://www.afrobarometer.org`.

[4]Due to lack of data on ethnicity, we exclude the countries of Sudan, Lesotho, Tunisia, Burkina Faso, São Tomé and Principe, Cabo Verde, and eSwatini from our dataset. Either these countries had no question asked regarding ethnicity, all ethnicity responses were missing, or, after linking individual responses to the Ethnic Power Relations (EPR) dataset, there was no variation in reported ethnicity.

[5]Not counting missingness in variables.

[6]The included countries are Angola, Benin, Botswana, Cameroon, Cote d'Ivoire, Gabon, Gambia, Ghana, Guinea, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

3.1 Climate-related survey items

To measure climate attitudes, we rely on eight survey items from Afrobarometer Round 9. For each, shortened variable labels are written in italics; we hereafter refer to the outcomes by these labels.

- *Heard About* (Q67A): "Have you heard about climate change or haven't you had the chance to hear about this yet?" (0=No, 1=Yes). Asked to all respondents.
- *Drought Change* (Q66A): "In your experience, over the past 10 years, has there been any change in the severity of the following events in the area where you live? Have they become more severe, less severe, or stayed about the same?—Droughts?" (1–5 scale with 1=Much less severe and 5=Much more severe). Asked to all respondents.
- *Flood Change* (Q66B): "In your experience, over the past 10 years, has there been any change in the severity of the following events in the area where you live? Have they become more severe, less severe, or stayed about the same?—Flooding" (1–5 scale with 1=Much less severe and 5=Much more severe). Asked to all respondents.
- *National Effect* (Q67B): "Do you think climate change is making life in [country] better or worse, or haven't you heard enough to say?" (1–5 scale with 1=Much better and 5=Much worse). Asked only to respondents who reported having heard about climate change.
- *Citizen Efficacy* (Q68A): Asks respondents to rate on a 1–5 scale how much they agree with the statement "Ordinary [country citizens] can play a role in limiting climate change" (1-5 scale with 1 = Strongly Disagree and 5 = Strongly Agree). Asked only to respondents who reported having heard about climate change.
- *Gov't Act Now* (Q68B): Asks respondents to rate on a 1–5 scale how much they agree with the statement "It is important for our government to take steps now to limit climate change in the future, even if it is expensive or causes some job losses or other harm to our economy." (1–5 scale with 1 = Strongly Disagree and 5 = Strongly Agree). Asked only to respondents who reported having heard of climate change.
- *Gov't Responsibility* (Q70): "Who do you think should have primary responsibility for trying to limit climate change and reduce its impact?" The available responses are "Ordinary [country] citizens"; "Business and industry"; "The government of [country]"; and "Rich or developed countries." To capture the degree to which climate concern is expressed in national-level politics, we dichotomize this variable to take a value of 1 if the respondent answered "The government" of their country and 0 if not. Asked only to respondents who reported having heard of climate change.
- *Climate Performance* (Q46P): "How well or badly would you say the current government is handling the following matters, or haven't you heard enough to say: addressing

the problem of climate change?" (1–4 scale where 1 = Very well and 4 = Very badly). Asked to all respondents.

We group these climate-related survey items into three categories: *Climate Literacy*, *Climate Perception*, and *Climate Action*. Climate Literacy[7] consists only of the *Heard About* item. While individuals who respond negatively to this question may experience and be aware of changes in environmental conditions that affect their lives, we interpret this question as a measure of awareness of the idea of human-caused climate change. Climate Perception items—*Drought Change, Flood Change,* and *National Effect*—relate to whether respondents have perceived changes to climatic conditions and/or shocks. Climate Action items—*Citizen Efficacy, Gov't Responsibility, Gov't Act Now,* and *Climate Performance*—on the other hand, ask respondents about their degree of concern about climate change, which entity bears responsibility for responding, and whether the government has handled the issue well. Two of the three Perception items are asked to respondents regardless of whether they answered yes to *Heard About*, which gives us leverage to study climate-related perceptions even among those who have not necessarily encountered the term "climate change." On the other hand, all but one of the Climate Action items are asked only to those respondents who answer "Yes" to *Heard About.* It is important to note that this means the set of respondents in the analysis of Climate Action attitudes is distinct from the broader population; in the Round 9 Afrobarometer data, only 51.5% of respondents report having heard of climate change.

We recode all survey item response categories so that higher values reflect more concern, more awareness, or more support for policies combating climate change. We code respondents who answer "don't know" or refuse to answer as missing and remove them from the subsequent analyses for that item.

Together, these eight survey items constitute our primary outcomes of interest. They provide a variety of information about risk perception, prioritization, and direct climate experiences. In the analysis below, we examine the items both individually, and collectively

[7] Simpson et al. (2021) analyze the predictors of climate literacy with data from a prior round of the Afrobarometer survey but do not consider the effects of ethnic difference.

in their respective categories (Literacy, Perception, or Action). Since we wish to use these items to estimate the degree of ethnic dissensus on climate attitudes, however, it is important to also have a benchmark or comparison against which we can assess the magnitude of climate-related dissensus. To contextualize the degree to which ethnicity matters for our climate items, we therefore compare to other areas of public opinion unrelated to climate change where ethnicity may plausibly affect responses. We thus also analyze responses to three non-climate items as a basis for comparison:

Comparison items:

- For a comparison outcome where we ought to detect a strong signal on the importance of respondent ethnicity, providing an "upper bound" on ethnic dissensus, we first consider the item *Ethnic fairness* (Q84B): "How often, if ever, are [respondent's ethnic group] treated unfairly by the government?" (0-3 scale, with 0 = Never and 3 = Always.) Asked to all respondents.

We also consider two other important items which are also plausibly correlated with ethnic group identities:

- First is *Economy Change* (Q5A), selected for its similarity in structure to *Drought Change* and *Flood Change*: "Looking back, how do you rate economic conditions in this country compared to 12 months ago?" (1–5 scale with 1 = Much better and 5 = Much worse).[8] Asked to all respondents.
- Second is *Health Performance* (Q46G): "How well or badly would you say the current government is handling the following matters, or haven't you heard enough to say: improving basic health services?" (1-4 scale with 1 = Very well and 4 = Very badly).[9] Asked to all respondents.

Table 1 summarizes the full set of items (8 climate-related and 3 comparison), listing the original Afrobarometer variable, the question type, outcome scale, and set of possible respondents.

[8]We have inverted the original scale so that higher values reflect more concern, mirroring our climate items.

[9]Again, we inverted the original scale so that higher values reflect more concern.

Item name	**Afrobarometer variable**	**Question type**	**Scale**	**Asked to**
Heard About	Q67A	Literacy	Binary	All respondents
Drought Change	Q66A	Perception	1–5	All respondents
Flood Change	Q66B	Perception	1–5	All respondents
National Effect	Q67B	Perception	1–5	Yes to "Heard About"
Citizen Efficacy	Q68A	Action	1–5	Yes to "Heard About"
Gov't. Act Now	Q68B	Action	1–5	Yes to "Heard About"
Gov't Responsibility	Q70	Action	Binary	Yes to "Heard About"
Climate Performance	Q46P	Action	1–4	All respondents
Ethnic Fairness	Q84B	Comparison	0–3	All respondents
Economy Change	Q5A	Comparison	1-5	All respondents
Health Performance	Q46G	Comparison	1-4	All respondents

Table 1: Summary of survey items analyzed in this study.

It is important to highlight that almost all African countries—with the notable exception of South Africa— have to date contributed a very small share of the greenhouse gases that have led to global warming, and so the idea that African countries ought to play a direct role in mitigating climate change is highly debatable. Nonetheless, it is worth emphasizing that African governments can play an indirect role by pressuring wealthier countries to limit their emissions. Moreover, as African states develop, their energy policies will become increasingly important to the global energy transition. The survey items above also provide information on the role of government in climate *adaptation*, a pressing question for virtually all African countries (Trisos et al. 2022). We believe one can interpret responses to Climate Action questions as indicators of general concern for the climate crisis and an expectation that government ought to act to help protect citizens from its effects.

We present descriptive statistics for all variables used in this study in Table A.1 in the Appendix.

3.2 Ethnic categories

In our efforts to draw broad conclusions about a set of socio-political phenomena across the African continent, we confront the theoretical and empirical challenges posed by the fact that the expression of ethnic categories is itself highly varied across countries. In fact, we suspect that such challenges have contributed to the very gaps in knowledge that motivate our study. The names, relative sizes, and characteristics of groups, let alone the number of salient groups, vary widely across countries; and unlike other commonly-studied sources of social diversity, such as gender, age, level of education, income, and/or wealth, there is far less consensus about how to categorize or to order ethnic groups. Therefore, based on a constructivist understanding of ethnicity—now widely adopted among social scientists (Chandra 2006; Lamont and Molnár 2002; Lieberman and Singh 2012; Wimmer 2008)—we use answers to the self-reported question "What is your ethnic community, cultural group, or tribe?" (Q84). Respondents were broadly free to answer as they saw fit, but responses closely matching commonly recognized ethnic groups received standardized labels in Afrobarometer.

A limitation of simply relying on self-reported ethnicity, however, is that open-ended responses can lead to a proliferation of categories, many of which may not be particularly salient for politics, or which may be nested within larger categories—for example, a clan within a tribe. To address this possible concern, we link self-reported ethnic labels to a smaller set of ethnic groups identified in the Ethnic Power Relations (EPR) dataset (Cederman et al. 2009), which enumerates "politically relevant" groups.[10] In our primary analyses, we consider a respondent's EPR group label as an unordered factor. Later, to examine the possible role of political power as a driver of climate attitudes, we will also consider the EPR-defined "power status,"[11] which is a measure of whether the group is in the governing coalition.

[10]The linking between Afrobarometer group labels and EPR labels was done manually based on review of secondhand sources and the EPR dataset manual, which summarizes the ethnic politics of each included country. A small proportion of Afrobarometer group labels could not be matched to EPR labels (approximately 7% among the 29 countries we include in our sample; these were given values of NA for their EPR group.) More details can be found in Appendix B.

[11]Note that we distinguish only whether a group is in- or out-of-power, and do not consider distinctions between junior and senior coalition partners.

4 Empirical approach

As a first step in our analysis, we ask the question: Does ethnic dissensus *exist* on climate issues? To answer it, we follow previous studies of ethnicity in conducting tests of the joint null hypothesis of no opinion differences between ethnic groups (e.g., Habyarimana et al. 2007; Lieberman and McClendon 2013). We do so by fitting a probit regression model for each item separately in each country, with indicators for ethnic group membership as the only regressors.[12] To test the joint significance of ethnicity dummies, we use a likelihood ratio (LR) test against the null (i.e., intercept-only) model for that country-item. If the likelihood ratio test of the ethnicity-only model versus the null model is significant at the 0.05 level, we can broadly conclude that "ethnicity matters" for that country-item.

Although hypothesis tests are useful for detecting the *existence* of dissensus, they are poorly suited for estimating its *magnitude* and comparing it across contexts (e.g., Gill 1999; Gelman and Stern 2006). To address this need, we turn to Bayesian multilevel regression (Gelman and Hill 2006). Multilevel models are a natural fit for this application because our data have a hierarchical structure: respondents are nested within ethnic groups and enumeration areas, which are in turn nested within countries. By modeling each level of this hierarchy, multilevel regression provides a flexible framework for decomposing the variation in the data and for examining the predictors of that variation. Since the models we employ are fairly complex, we describe them in detail now before reporting the results.

As motivation for our modeling approach, consider Figure 1, which plots Angolan ethnic groups' evaluations of the government's handling of climate change. The fraction of respondents who strongly disapprove of the government's handling of this issue ranges widely, from less than 30% among the Lunda-Chokwe to nearly 70% among the Bakongo. This opinion variation across groups indicates substantial ethnic dissensus on climate change: some ethnic groups are highly dissatisfied with the current approach to the issue, while others are

[12] We use binary probit for dichotomous items and ordered probit for items with three or more ordered responses.

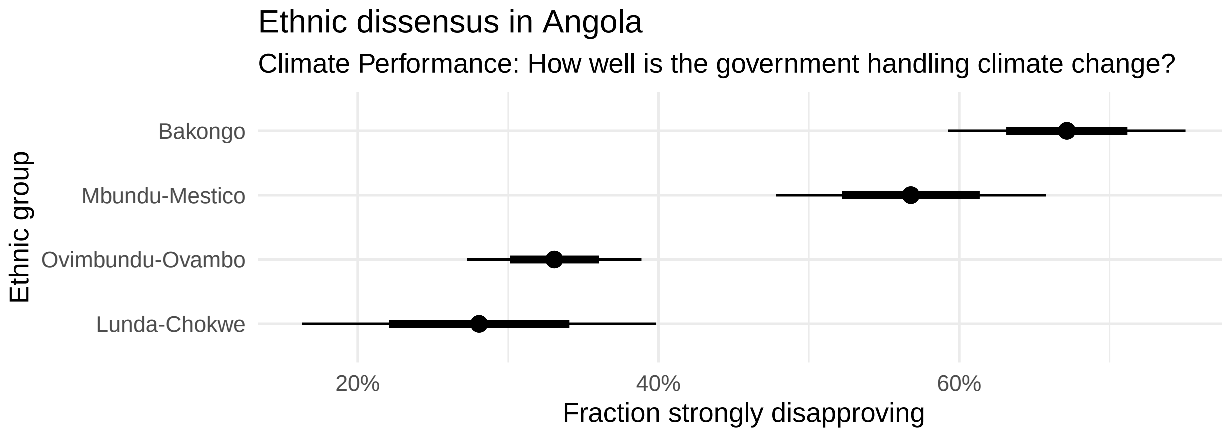

Figure 1: Differences in responses to the survey item *Climate Performance* across Angolan ethnic groups. Points indicate sample means. Thin lines indicate 95% confidence intervals and thick lines 68% intervals (±1 standard error).

much less so. The literature on ethnic politics suggests that such disagreement is likely to undermine collective action on this issue.

Now consider Figure 2, which plots variation in *Climate Performance* across countries as well as ethnic groups. As the black diamonds indicate, the fraction of a country's population that strongly disapproves ranges from 10% to 50%. This is an indicator of *cross-national* dissensus. Note, however, that countries differ not only in their overall level of disapproval (black diamonds), but also in their internal variation across ethnic groups (hollow circles). Angola (AGO) is among the countries with the greatest inter-ethnic variation—that is, the highest ethnic dissensus. By contrast, Mauritius (MUS), in addition to having a lower overall level of disapproval, exhibits much less opinion variation across ethnic groups. In short, countries can differ in both their *average* response to this item and in the *variance* in responses across ethnic groups. The former reflects cross-national dissensus and the latter reflects ethnic dissensus.

As shown above, differences in climate attitudes stem from factors that vary at different levels, including countries and ethnic groups as well as individual respondents. Our multi-level models are designed to account for these different sources of variation. To model the

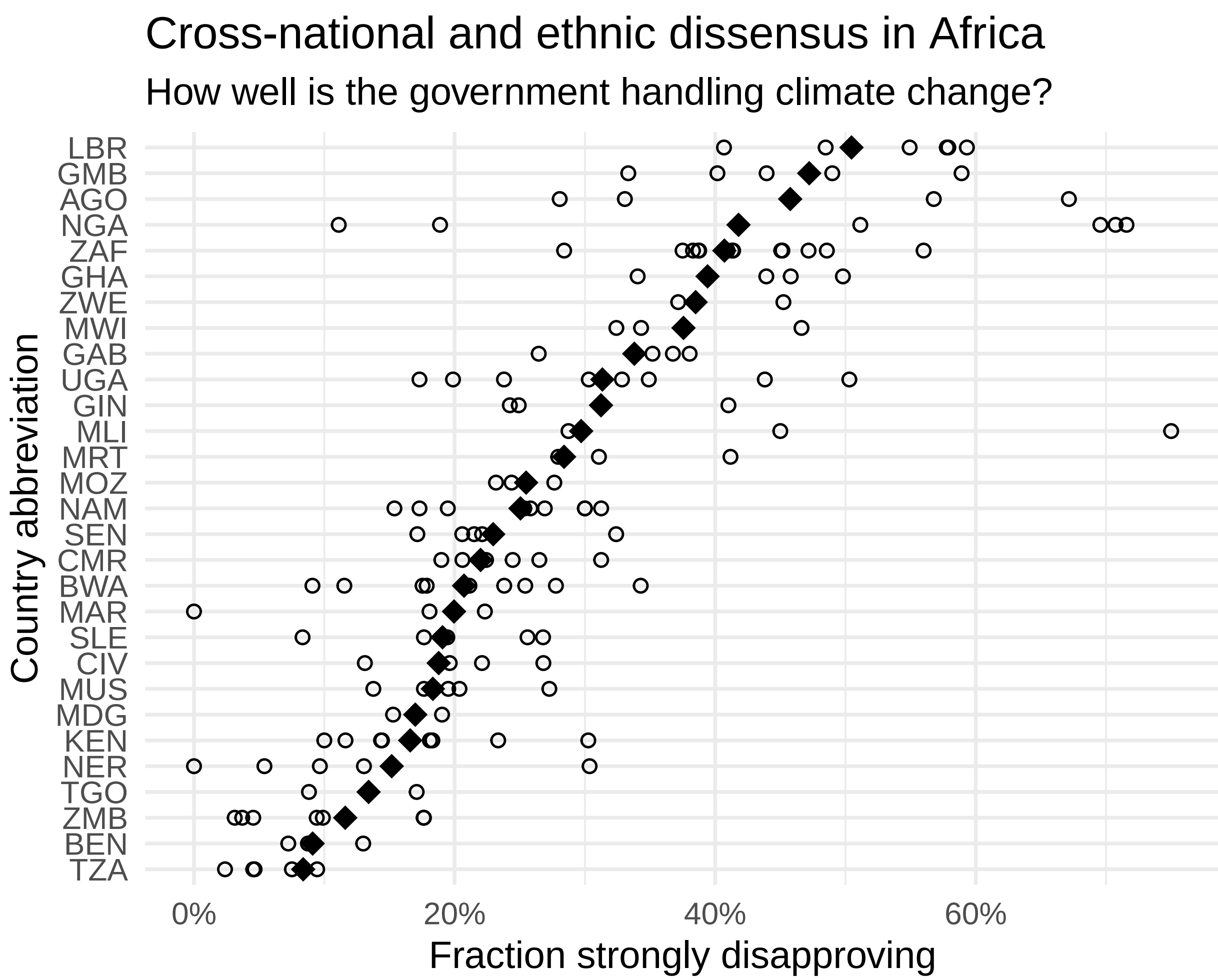

Figure 2: Average response by country (black diamonds) and Afrobarometer ethnic group (hollow circles) to the survey item *Climate Performance*.

responses to each item i, we fit Bayesian generalized linear models (GLMs) of the form

$$\tilde{y}_{ij} = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta}_i + \gamma^{\text{nat}}_{ic[j]} + \gamma^{\text{eth}}_{ie[j]} + \epsilon_{ij}$$
$$y_{ij} = f(\tilde{y}_{ij}), \tag{1}$$

where y_{ij} is person j's observed response, $\tilde{y}_{ij}$ is their latent response, μ_i is the global intercept, $\mathbf{x}_{ij}$ is an optional vector of covariates, $\boldsymbol{\beta}_i$ are their corresponding coefficients, $\gamma^{\text{nat}}_{ic[j]}$ and $\gamma^{\text{eth}}_{ie[j]}$ are random intercepts for j's country $c[j]$ and ethnicity $e[j]$, ϵ_{ij} is the observation-specific error term, and $f(\cdot)$ is a function mapping $\tilde{y}_{ij}$ to the binary or ordinal scale of y_i.[13] We adopt a probit link, which implies the distribution $\epsilon_{ij} \sim \text{N}(0, 1)$ for the residual error term. This baseline model thus includes error terms at three levels: country ($\gamma^{\text{nat}}_{ic[j]}$), ethnic group ($\gamma^{\text{eth}}_{ie[j]}$), and respondent ($\epsilon_{ij}$).

What makes this model multilevel is that we assign hierarchical priors to the random intercepts:

$$\gamma^{\text{nat}}_{ic[j]} \sim \text{N}(0, \tau_i)$$
$$\gamma^{\text{eth}}_{ie[j]} \sim \text{N}(0, \sigma_{ic[j]}),$$

where each of the hyperparameters τ_i and $\sigma_{ic[j]}$ is the standard deviation (SD) of the corresponding batch of intercepts. In a typical multilevel model, the SD of ethnicity intercepts is assumed to be constant across countries (i.e., $\sigma_{ic} = \sigma_i \; \forall c$). Our initial continent-wide analyses are conducted under this assumption. Later, however, we relax it and allow σ_{ic} to vary across countries. This enables us to measure and model variation in ethnic dissensus across countries.

To explore the sources of variation in ethnic dissensus, we use variance function regression

[13] For example, in a binary probit model, $y_{ij} = f(\tilde{y}_{ij}) = \begin{cases} 1 & \text{if } \tilde{y}_{ij} > 0 \\ 0 & \text{otherwise} \end{cases}$. This latent-variable formulation is a common way of representing Bayesian GLMs such as probit models (Gelman et al. 2013, 408).

(Western and Bloome 2009). Specifically, we model σ_{ic} as a log-linear function of a global intercept ν_i, country-specific intercepts ζ_{ic}, and (optionally) centered country-level attributes $\mathbf{w}_{ic}$:

$$\log(\sigma_{ic}) = \nu_i + \mathbf{w}_{ic}\boldsymbol{\delta}_i + \zeta_{ic}, \qquad \zeta_{ic} \sim \mathrm{N}(0, \phi_i).$$

In this model, ν_i is the value of $\log(\sigma_{ic})$ in the average country, ζ_{ic} is country c's deviation from this average, and $\boldsymbol{\delta}_i$ is the vector of log-linear coefficients for country attributes $\mathbf{w}_{ic}$. Figure 3 displays a plate diagram of the complete model.

In addition to yielding estimates of the predictors of ethnic dissensus, this model also permits calculation of a convenient summary measure of ethnic dissensus: the intraclass correlation (ICC) of ethnicity.[14] Ranging from 0 to 1, the ICC is the proportion of variance in the outcome attributable to a given grouping factor. As its name suggests, it can also be interpreted as the expected correlation between the responses of units in the same cluster (Skrondal and Rabe-Hesketh 2004, sec. 3.2.1). Given the ordinal nature of many of our items, we follow Nakagawa et al. (2017) and calculate the ICC on the scale of the latent response $\tilde{y}_{ij}$ rather than the observed outcome y_{ij}.

We consider the ICC at two levels: continent-wide and country-specific. In a model without covariates $\mathbf{x}_{ij}$, the continent-wide ICC of ethnicity is equal to the cross-ethnicity variance (σ_i^2, assumed constant across countries) divided by the sum of the cross-ethnicity variance, the cross-national variance (τ_i^2), and the residual variance (1^2):

$$\mathrm{ICC}_i^{\mathrm{eth}} = \frac{\sigma_i^2}{\sigma_i^2 + \tau_i^2 + 1^2}.$$

The continent-wide ICC of nationality is defined analogously as

$$\mathrm{ICC}_i^{\mathrm{nat}} = \frac{\tau_i^2}{\sigma_i^2 + \tau_i^2 + 1^2}.$$

[14] The ICC has been used for many purposes, such as estimating the reliability of a multi-item scale (Bartko 1966) and quantifying the degree of clustering in an outcome (Masood and Reidpath 2016).

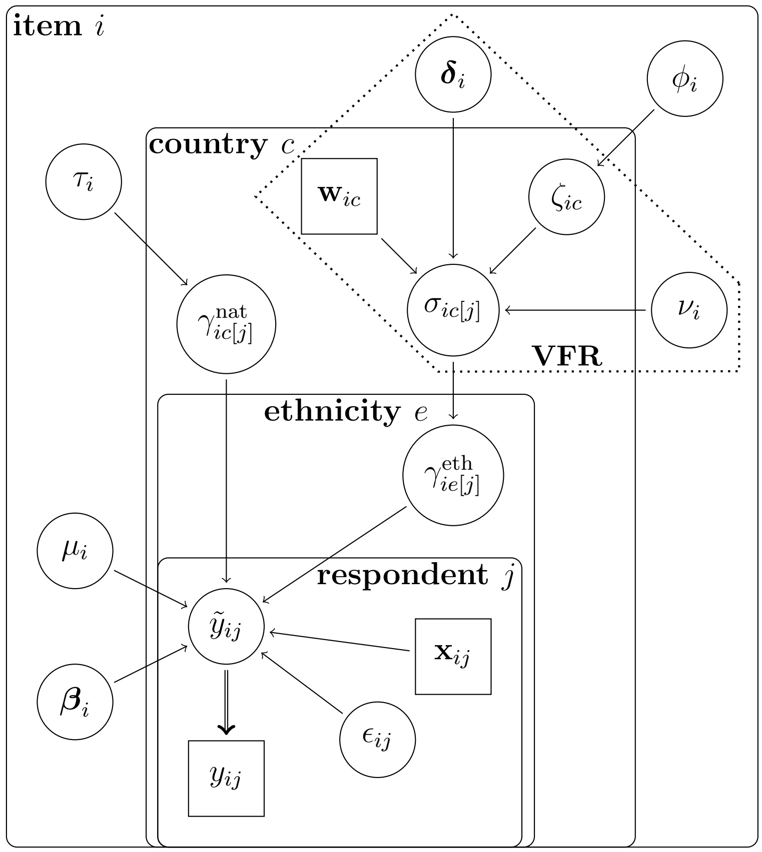

Figure 3: Plate diagram of the baseline multilevel model. Respondents j are nested within ethnic groups e, which are in turn nested within countries c. The model is fit separately to each item i. The model includes respondent/group/country covariates $\mathbf{x}_{ij}$, country intercepts $\gamma^{\text{nat}}_{ic[j]}$, ethnicity intercepts $\gamma^{\text{eth}}_{ie[j]}$, and a variance function regression (VFR) for the country-specific dispersion $\sigma_{ic[j]}$ of the ethnicity intercepts (enclosed in dotted line). Observed variables are enclosed in rectangles and latent variables/parameters in circles. A directed edge between variables indicates that the variable with the arrow pointing at it is modeled as a function of the other variable. The double line between the latent response $\tilde{y}_{ij}$ and the observed response y_{ij} represents the deterministic relationship given by $f(\cdot)$.

$\mathrm{ICC}_i^{\mathrm{eth}}$ and $\mathrm{ICC}_i^{\mathrm{nat}}$ indicate the proportion of variation in the entire Afrobarometer sample attributable to respondents' ethnicity and nationality, respectively.

For many purposes, we are more interested in the proportion of variation within a given country that is attributable to ethnicity. The ICC of ethnicity specific to country c is defined as

$$\mathrm{ICC}_{ic}^{\mathrm{eth}} = \frac{\sigma_{ic}^2}{\sigma_{ic}^2 + 1^2}.$$

The country-specific ICC of ethnicity thus differs from its continent-wide counterpart in two ways: (1) the variance of ethnicity intercepts σ_{ic}^2 varies by country, and (2) the denominator does not include the cross-national variance τ_i^2. It therefore provides a measure of the extent of ethnic dissensus *within* countries rather than across them.

The ICC is a useful measure of ethnic dissensus for several reasons. First, it has an intuitive interpretation: the proportion of total variance attributable to a given factor. Second, its normalized 0–1 range enables it (unlike the raw variance) to be compared across items with different scales. Third, the ICC is closely related to a measure of multigroup polarization recently developed by Mehlhaff (2024), the "cluster-polarization coefficient" (CPC). In fact, in the case of a single outcome variable, the ICC and CPC are identical, both being equal to the R-squared of a least-squares regression on dummy variables for groups. Mehlhaff (2024) shows that the CPC has several desirable properties, such as insensitivity to moderate differences in group size. The main advantages of ICC over the CPC are that it can be calculated for ordinal variables and that the multilevel modeling framework used to calculate it can be extended to incorporate covariates at the levels of respondents, groups, and countries. For these reasons we prefer the ICC for this application, but its close relationship to the CPC provides reassurance about ICC's validity as a measure of dissensus.[15]

[15] For a review of measures of related concepts, see Appendix C.

5 Results

5.1 Is there ethnic dissensus on climate attitudes? If so, how much?

We begin by addressing the simple question of whether ethnic dissensus exists with respect to climate change. For almost every country, the unambiguous answer is "yes." The evidence for this conclusion is summarized in Figure 4. For each country, this figure plots the proportion of climate items for which a likelihood-ratio test rejects the null hypothesis of no differences between ethnic groups. For all countries except Botswana (BWA), the null hypothesis can be rejected for at least one climate item. Seventeen countries display statistically significant ethnic dissensus on at least half of climate items. Six countries (Mozambique, Morocco, Madagascar, Kenya, Cameroon, and Uganda) do so on three-quarters or more of items.

These results indicate that the hypothesis of no ethnic dissensus on climate issues can be confidently rejected almost everywhere. However, because p-values are affected by ancillary factors such as sample size, they cannot be interpreted as estimates of the *magnitude* of ethnic dissensus. We therefore now turn to our alternative approach based on Bayesian multilevel models and the ICC.

We begin by asking how much of the variation in African climate attitudes can be attributed to nationality and ethnicity, respectively. As a baseline for comparison, we ask the same question of the three comparison issues: *Ethnic Fairness*, *Economy Change*, and *Health Performance*. Our answers are based on estimates of the continent-wide ICCs of nationality and ethnicity, which are plotted in Figure 5.

First consider the comparison issues (left column). Among these, we would expect *Ethnic Fairness* to be the most strongly related to ethnic membership, and indeed it is. This item's ICC of ethnicity ($\text{ICC}_i^{\text{eth}}$) is $11 \pm 1.5\%$.[16] In other words, ethnic group membership explains

[16]Throughout this paper, we follow the **posterior** package (Bürkner et al. 2025) in reporting parameter estimates in terms of the mean ± standard deviation of the posterior distribution. For normally distributed quantities, this interval covers approximately 68% of the posterior distribution.

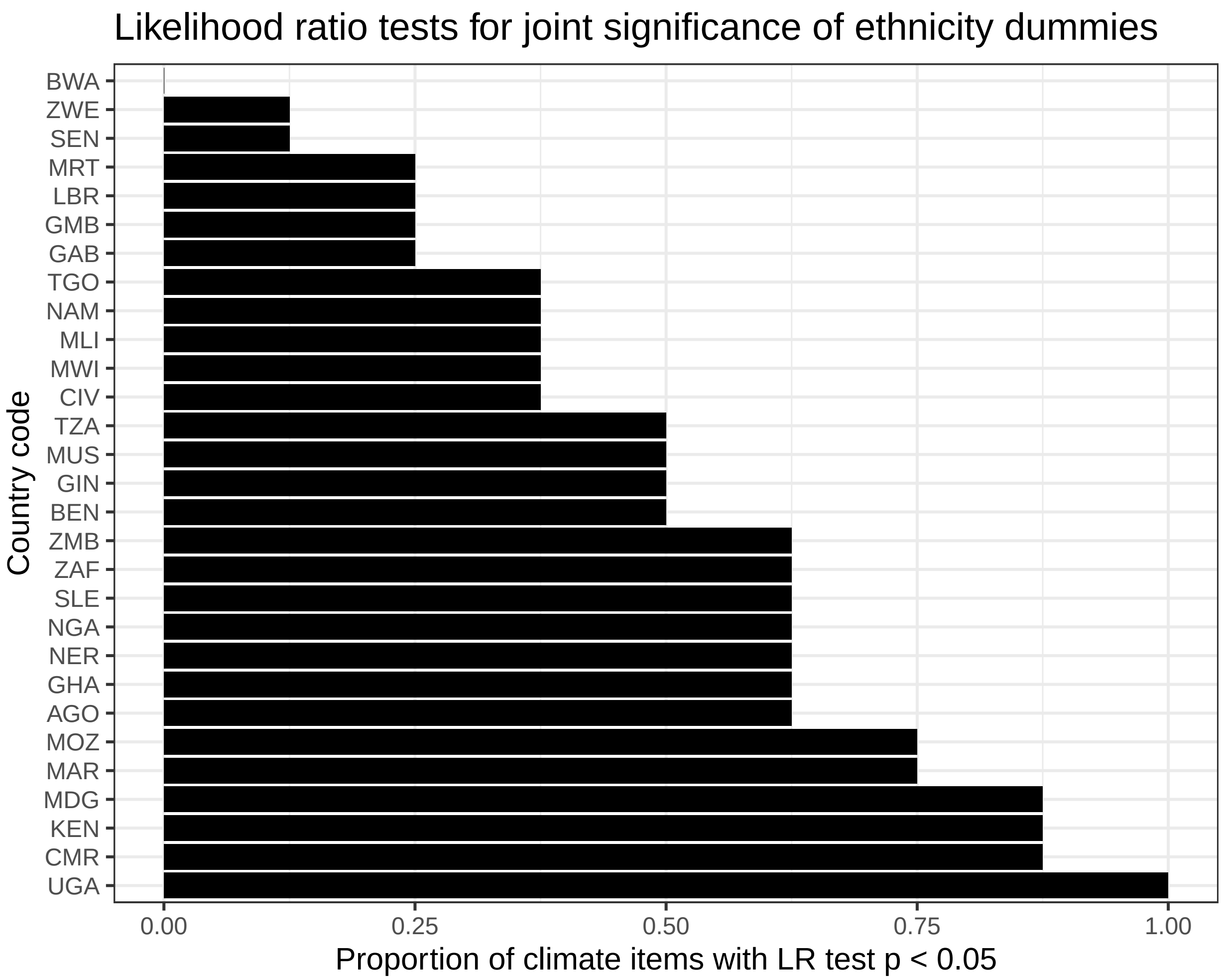

Figure 4: The figure shows for each country the proportion of climate items (out of 8 total) where ethnicity dummies are jointly significant in a likelihood ratio test relative to a null model. Ordered probit models are used for ordinal outcomes; probit models for binary outcomes.

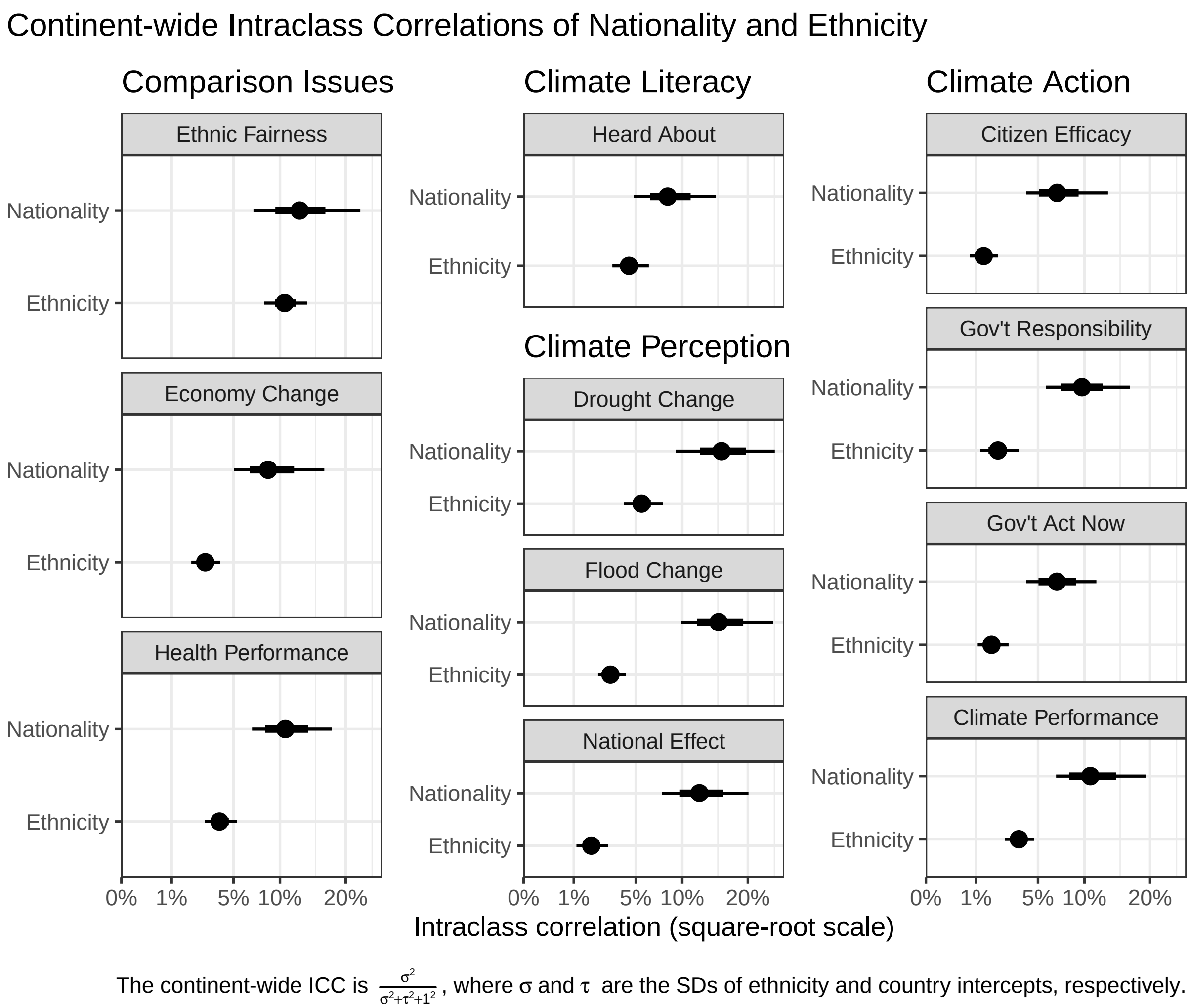

Figure 5: Ethnic and cross-national dissensus, by item. The horizontal axis indicates the continent-wide ICC of nationality/ethnicity. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. Because the distributions are left-skewed, the estimates are plotted on the square-root scale. For full model results underlying these estimates, see Supplementary Materials, "Full Model Results Appendix," Section 2.0.

about 11% of the variation in respondents' perceptions of how fairly their group is treated. This estimate is statistically indistinguishable from the ICC of nationality ($\text{ICC}_i^{\text{nat}}$) for this item. To further contextualize the substantive magnitude of the ICC estimates, consider the two other comparison items, both of whose $\text{ICC}_i^{\text{eth}}$ estimates are less than 5%. By this measure, ethnic dissensus is over twice as severe on *Ethnic Fairness* than on *Economy Change* or *Health Performance*.

Ethnic dissensus also varies substantially across climate items. With $\text{ICC}_i^{\text{eth}}$ estimates of about 5%, both *Heard About* and *Drought Change* exhibit slightly more ethnic dissensus than *Economy Change* and *Health Performance*. On the other end of the spectrum, *Citizen Efficacy*, *National Effect*, *Gov't Responsibility*, and *Gov't Act Now* all have $\text{ICC}_i^{\text{eth}}$ estimates smaller than *Economy Change* and *Health Performance*. Among climate items, Literacy and Perception items have higher levels of ethnic dissensus than Action items. The average climate item has an $\text{ICC}_i^{\text{eth}}$ of 3%—roughly on par with the two comparison items other than *Ethnic Fairness*.

It is worth noting that on no item, even *Ethnic Fairness*, is ethnic dissensus greater than cross-national dissensus. Furthermore, even the combination of ethnicity and nationality still leaves most of the variation on these survey items unexplained, which is not surprising given the potential influence of other respondent characteristics as well as the general prevalence of random error in survey responses. Among other factors, this is a reflection of the degree of random error in individual-level survey responses (Converse 1964). Nevertheless, this analysis indicates that ethnic dissensus in Africans' climate attitudes, though less severe than on issues that relate explicitly to ethnicity, is roughly comparable to that on other non-climate issues, such as health and economic change.

5.2 Where does ethnicity matter? Cross-national variation in ethnic dissensus

The preceding analysis reports ethnic dissensus in the typical country, ignoring cross-national variation in the salience of ethnicity. In this section, we focus on the latter variation.

As noted above, the ICC of item i in country c is the within-country variance in ethnicity intercepts divided by the total within-country variance: $\text{ICC}_{ic}^{\text{eth}} = \sigma_{ic}^2/(\sigma_{ic}^2 + 1^2)$. We estimate $\text{ICC}_{ic}^{\text{eth}}$ using the parameter estimates from the multilevel model described in the previous section, fit to each item. We then take two approaches to summarizing ethnic dissensus on each type of item: averaging the ICC across items (Figure 6) and reporting the largest ICC across items (Figure 7).

As Figure 6 shows, nearly all countries have an average $\text{ICC}_{ic}^{\text{eth}}$ on climate items between 2% and 5%, with an average across countries of $3.2 \pm 0.30\%$. This is on par with *Economy Change*'s cross-country average of $3.3 \pm 0.73\%$ but somewhat below *Health Performance* ($4.9 \pm 1.1\%$) and much smaller than *Ethnic Fairness* ($13 \pm 1.9\%$). By far the largest outlier in terms of climate ICC is Kenya (KEN), with an estimated average of $7.6 \pm 1.5\%$. The next largest estimates are Nigera (NGA) and Uganda (UGA) at around $5 \pm 1\%$, though these are not statistically distinguishable from most other countries.' Similarly, the smallest ICC estimate, Botswana's (BWA) at $1.8 \pm 0.5\%$, is statistically indistinguishable from those of Mauritius (MUS), Gabon (GAB), and a number of other low-dissensus countries.

Figure 7 provides a different perspective, reporting each country's *largest* ICC across climate items—the "high-water mark" of ethnic dissensus. This analysis takes account of the fact that an issue that is contentious in one country may not be in another. For example, a country with high flooding risk and hence high dissensus across ethnic groups about flood perceptions may not also exhibit dissensus on drought risk. "High-water mark" estimates are revealing for our purposes because dissensus over even a single issue can reflect or entrench political conflict, and a lack of polarization on other dimensions may be irrelevant if the one high-dissensus dimension is salient.

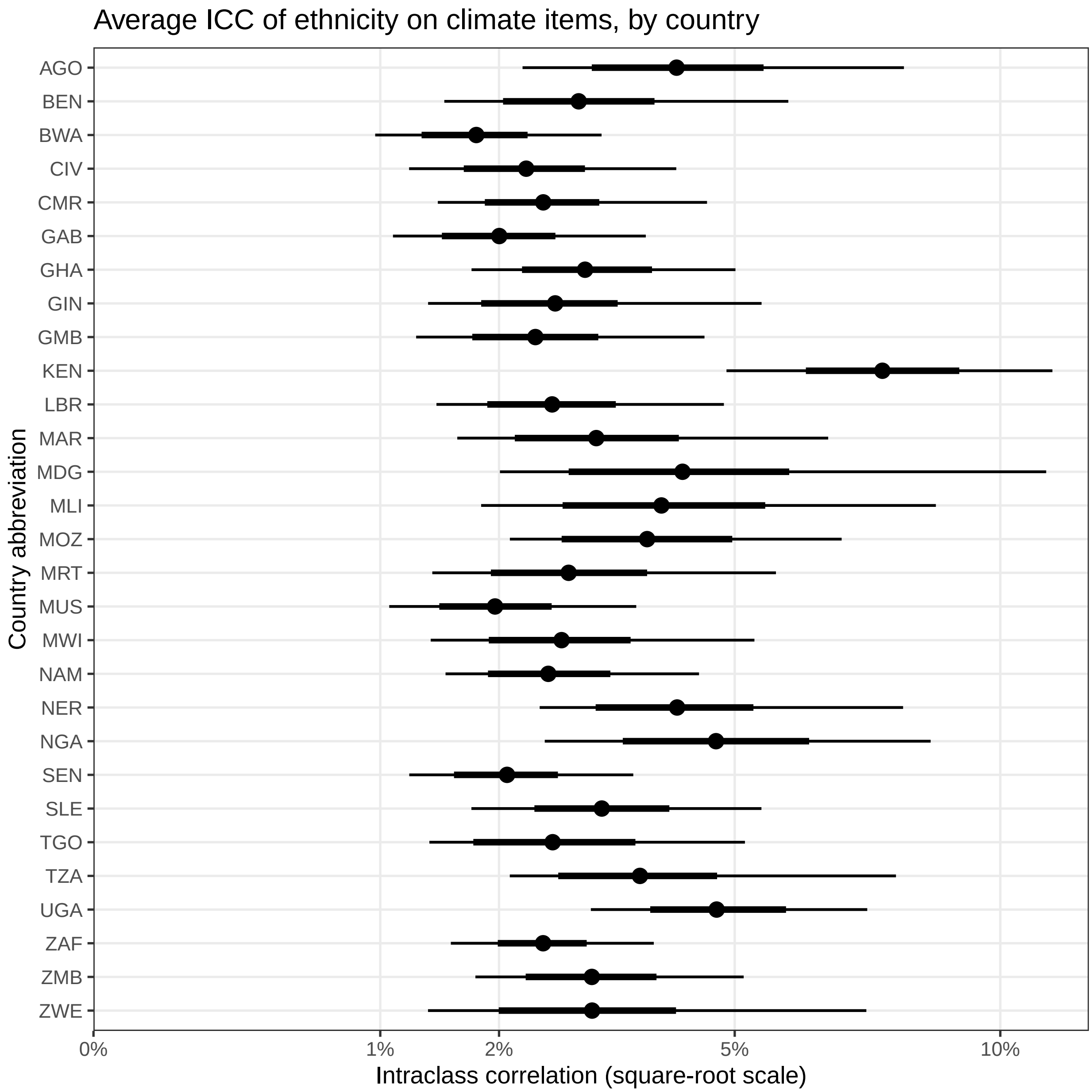

Figure 6: Estimates of the average $\text{ICC}_{ic}^{\text{eth}}$ across climate items in each country. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. Because the distributions are left-skewed, the estimates are plotted on the square-root scale. For full model results underlying these estimates, see Supplementary Materials, "Full Model Results Appendix," Section 2.1.

Among the comparison items (not shown), *Ethnic Fairness* exhibits the greatest ethnic dissensus in every country. Among the climate items (plotted in Figure 7), there is substantially more variation. The three most common highest-ICC items are *Climate Performance* (10 countries), *Heard About* (9 countries), and *Drought Change* (7 countries). These three items constitute the highest-ICC item in all but 3 countries: Benin and Liberia, where *Gov't Responsibility* is highest; and Senegal, where *Flood Change* is highest.

Paralleling the results for average ICCs in Figure 6, Kenya also has the largest maximum ICC estimate: 32.3±9.8% (on *Drought Change*). In several countries, however, a low average ICC conceals a high degree of dissensus on at least one item. Nigeria, for example, has an average ICC of about 5% across all climate items, but on *Climate Performance* its ICC estimate spikes to 16.9±8.9%. Similar things may be said of Angola (12.4±7.8% for *Climate Performance*), Uganda (11.8±5.8% for *Drought Change*), and Madagascar (11.5±13.2% for *Drought Change*). All in all, we estimate that 6.4 ± 2.0 countries have at least one climate item with an $\text{ICC}^{\text{eth}}_{ic}$ above 10% and that 15 ± 2.8 have one above 5%.[17]

In sum, we find that for the typical country and item, the $\text{ICC}^{\text{eth}}_{ic}$ is small to moderate, with ethnicity explaining 1–5% of the total variation in climate attitudes. However, some countries (most notably Kenya) and items (most often *Climate Performance*, *Heard About*, and *Drought Change*) display a much greater degree of ethnic dissensus, with ICC estimates ranging as high as 32%. This suggests that even if ethnic dissensus is typically low in a given country, it often has at least one climate issue over which ethnic groups exhibit substantial disagreement. It also raises the question of why ethnic dissensus is greater in some countries than others. We address this question in the following section.

[17]This is a conservative estimate as it does not take into account uncertainty over which item has the largest $\text{ICC}^{\text{eth}}_{ic}$.

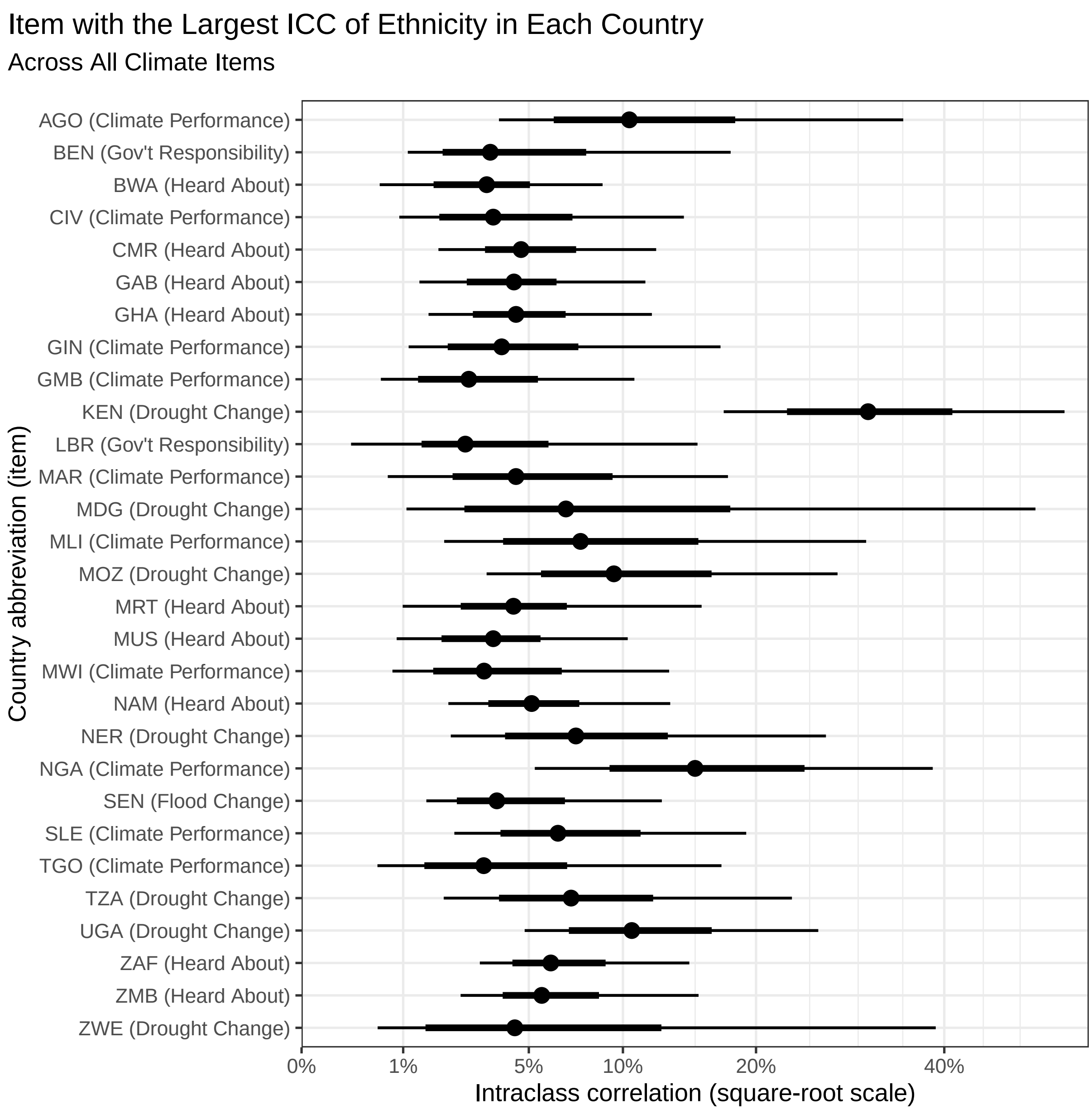

Figure 7: $\text{ICC}_{ic}^{\text{eth}}$ estimates for each country's highest-dissensus climate item. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. Because the distributions are left-skewed, the estimates are plotted on the square-root scale. For full model results underlying these estimates, see Supplementary Materials, "Full Model Results Appendix," Section 2.1.

5.3 Why does ethnicity matter? Evaluating alternative explanations

Having shown that ethnic differences are an important source of dissensus on climate opinion and that countries differ in the extent and content of such dissensus, we now turn to unpacking the predictors of these differences. We examine factors related to three main explanations for ethnic dissensus: *individual-level composition*, *group-level attributes*, and *geographic context*.

As discussed earlier, compositional explanations for ethnic dissensus posit that group differences in opinion are rooted in differences in the distribution of individual-level attributes. For example, if concern for climate change increases with education and education levels are higher in some ethnic groups than others, then compositional differences in education at least partially explain ethnic dissensus on this issue. In this case, ethnic dissensus should be lower when we compare citizens of the same education level, which we can do in practice by estimating dissensus with a model that adjusts for respondent education. In addition to a 10-category ordinal *education* variable, the individual-level covariates that we consider are *age*, *gender*, *wealth*, *religion*, occupation as *farmer*, and *urban* residence.

Group-level attributes are those shared by all group members. For example, if an ethnic group is part of the governing coalition, each group member is also "in power" in this sense, even if they themselves do not support the governing coalition. Explanations rooted in group-level attributes thus locate group differences in the emergent dynamics of the group, not in the sum of the characteristics of its members. To the extent that group-level attributes are an important driver of climate attitudes, including them in a model should reduce the residual variation between groups and thus decrease estimates of ethnic dissensus. The group-level covariates we assess are *group power*,[18] *group wealth* (based on average household wealth),[19]

[18]As measured by whether it is a junior or senior partner in the governing coalition in the country according to the latest edition of the ethnic power relations (EPR) dataset.

[19]An individual's household wealth is the sum of how many assets a respondent reports themselves or anyone in their household to own out of 6 possible listed in Afrobarometer: radio, television, motor vehicle, computer, bank account, and mobile phone. The household wealth index therefore ranges from 0 to 6. We

and an indicator for being the *largest group* in the country.

Geographic context can be understood as a hybrid between an individual-level and group-level attribute. On one hand, within-group variation in geographic context is not only logically possible but empirically prevalent. On the other hand, many ethnic groups are geographically concentrated and thus share common influences stemming from their spatial context. These influences may be especially salient when it comes to climate attitudes, which are likely to be influenced by local environmental and climatic conditions. The work of Boone (2024) suggests, however, that the *political* context created by regional administrative boundaries may be just as important a source of ethnic dissensus. We therefore consider three sets of geographic covariates:

- *Climate covariates*: (1) respondents' agro-ecological zone (AEZ) [20] and (2) climate vulnerability of their country[21]
- *Local covariates*: (1) respondents' survey enumeration area (EA); (2) the economic development of the EA, as measured by a summative index of 13 public goods and services observed to be present there;[22] and (3) the degree of state security presence

then calculate the average for each ethnic group.

[20]We link each respondent to one of 15 zones using geospatial data from the Regional Centre for Mapping of Resources for Development (RCMRD). See `https://rcmrd.africageoportal.com/`. Note that AEZs are often quite granular, with small regions containing multiple zones. Figure A.1 in the Appendix maps AEZs across Africa. He et al. (2024) provides one set of analyses linking climatic vulnerability to ecological zone.

[21]We acquire data on a country's climate vulnerability as measured by the Notre Dame Global Adaptation Initiative (ND GAIN) index. The overall ND GAIN index aims to capture a country's ability to adapt to climate change and is composed of two components: vulnerability and readiness. We examine only the vulnerability measure, which consists of three underlying components: exposure, sensitivity, and adaptive capacity. For full methodological details, see `https://gain.nd.edu/our-work/country-index/methodology/`. We use the vulnerability index in 2022 as a general indicator for how affected a country is (or will be) by climate change.

[22]In particular, we sum the binary values for the Afrobarometer variables `EA_SVC` and `EA_FAC`. Together, there are 13 sub-parts to these questions. Each of these subparts is recorded by the survey enumerator and reflects whether there is the given service or facility in the primary sampling unit/enumeration area. The full list of services and facilities is: electricity grid, piped system, sewage system, mobile phone service, borehole or tubewell, post office, school, police station, health clinic, market stalls, bank, social center/government help center, and paid transport. For example, if a EA has market stalls, a school, and a sewage system, but none of the other facilities or services, it receives a score of 3. For each respondent, we calculate the sum of the services and facilities in their EA.

in the EA, as measured by a summative index of 5 indicators for police, military, or private security/community activity.[23]

- *Regional covariates:* (1) respondents' administrative region and (2) the economic development level of that region, as measured by the regional average of our EA-level development index described above. Administrative regions are defined as the highest-level subnational administrative unit in a given country. For example, "administrative regions" for Ghana are the regions such as Ashanti and Greater Accra. For South Africa, they are the provinces, such as KwaZulu-Natal.

5.3.1 The correlates of climate attitudes

We begin our evaluation of the explanations for ethnic dissensus by examining the predictors of climate attitudes. To do so, we include covariates $\mathbf{x}_{ij}$ that vary at the levels of country, region, enumeration area, ethnic group, and the individual respondent. We also augment our baseline model by adding random effects for EA and region to account for the fact that some predictors vary at these levels. The augmented model thus has the following form:

$$\tilde{y}_{ij} = l;' \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta}_i + \gamma^{\text{nat}}_{ic[j]} + \gamma^{\text{eth}}_{ie[j]} + \gamma^{\text{EA}}_{ia[j]} + \gamma^{\text{region}}_{ir[j]} + \epsilon_{ij}.$$

Figure 8 summarizes the results of fitting this augmented model to each climate item. The items are coded so that larger values indicate greater climate concern. For statistical power and ease of presentation, we average the item-specific coefficients within the Perception and Action categories. We report the Literacy item *Heard About* separately because many of its coefficients are signed oppositely from the other items. The predictors on the vertical axis are grouped according to the level at which they vary. Continuous predictors are scaled so

[23] In particular, we sum the binary values for the Afrobarometer variable `EA_SEC`. The 5 subparts for this question are presence of "any police officers or police vehicles," "any soldiers or army vehicles," "any roadblocks set up by police or army," "any customs checkpoints," and "any roadblocks or booms set up by private security providers or by the local community." For example, if an EA has customs checkpoints and police officers, but none of the others, it receives a score of 2.

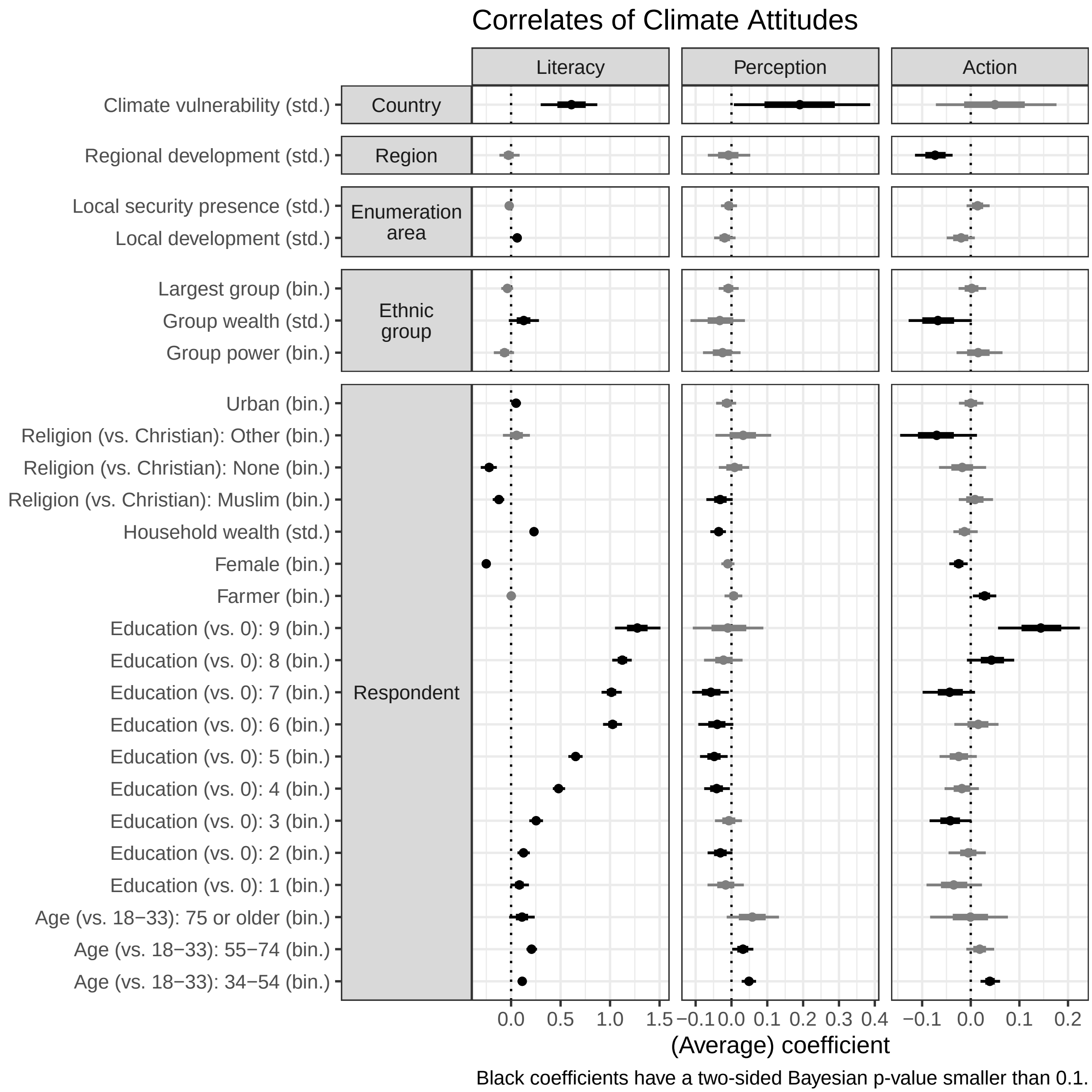

Figure 8: Effects of group-level and regional attributes on climate attitudes. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. Higher values indicate greater climate concern. Each panel indicates the average coefficient within a given category of survey items. Predictors marked "bin." are binary variables, and those marked "std." are continuous variables that have been standardized so that the coefficient represents the effect of a difference of two standard deviations. Fixed effects for agro-ecological zone are omitted from the figure. For full model results underlying these estimates, see Supplementary Materials, "Full Model Results Appendix," Section 2.7.

that the coefficient represents the effect of a difference of two standard deviations, making them roughly comparable to binary predictors (Gelman 2008).[24]

The results provide at least some support for each explanation we consider. Attributes that vary at the level of the individual respondent tend to be the largest in substantive magnitude and statistical significance. Most strikingly, respondents with more education are much more likely to report having "heard about" climate change, but less likely to perceive climate-related changes or to demand action on climate change.[25] Household wealth exhibits the same pattern. Beyond these indicators of socioeconomic status, most remaining associations relate to climate literacy, which tends to be higher among respondents who are older, male, Christian, urban residents, and not farmers. To the extent that the attributes predictive of climate concern are distributed differentially across ethnic groups, these respondent-level associations provide one potential explanation for ethnic dissensus regarding climate change.

What about the characteristics of ethnic groups themselves? The three attributes we examine—*largest group*, *group wealth*, and *group wealth*—are all related to group status and power, and their coefficient estimates mirror those for respondents' socioeconomic status discussed above. The only coefficients that are significant at the 0.1 level, however, are *group wealth*'s positive association with climate literacy and its negative association with Climate Action, the latter of which rivals the largest respondent-level coefficients in magnitude.

The results for measurable features of the geographic context are also mixed. National climate vulnerability strongly predicts both literacy about and perceptions of climate change, though not support for climate action. This suggests that objective climate risks do influence Africans' climate attitudes. It is possible that these attitudes are shaped by more local conditions as well, but unfortunately we do not have subnational measures of climate vulnerability. An indirect measure of climate conditions, which of 15 AEZs the respondent lives in (not

[24]More precisely, the raw coefficient estimates were multiplied by twice their standard deviation across Afrobarometer respondents.

[25]Recall that all but one of the Action items were asked only of respondents who said they had heard about climate change.

shown in Figure 8), have only a few significant associations with climate attitudes.[26] Among non-climate contextual attributes, the only statistically significant coefficients are *local development*'s positive association with climate literacy and *regional development*'s negative association with climate action. As we will see below, however, it is possible that local or regional context matters in other ways not amenable to systematic measurement.

In sum, climate attitudes are correlated with several attributes of respondents, groups, and geographic areas. One throughline is that status, power, and wealth—whether at the individual or aggregate level—are positively associated with climate literacy but negatively with climate perceptions and demand for climate action. Put simply, more-advantaged Africans tend to know more about climate change but are less concerned about it. Respondents' climate concern is also positively associated with their country's objective vulnerability to climate change. Although there are some associations with group and EA/regional attributes, they tend to be smaller and less statistically significant.

On their own, these results may seem to favor compositional over group and geographic explanations for ethnic dissensus. Two caveats are in order, however. First, for composition to explain ethnic dissensus, it must be the case not only that respondent attributes be associated with climate attitudes, but also the distribution of these attributes differ sufficiently across ethnic groups. Second, the relative paucity of significant group and geographic correlates may indicate not that these influences are unimportant, but rather that the relevant attributes are unobserved or cannot be measured systematically across the entire continent. With these caveats in mind, we turn in the next section to an analysis of the sources of ethnic dissensus that makes use of the ICC.

[26] The primary exception is that, relative to the "Tropic - warm / subhumid" areas (the most common AEZ in the survey), residents of "Tropic - warm / humid" and "Tropic - warm / semiarid" areas are more likely to perceive climate-related changes. The Afrobarometer sample contains about 16,000 respondents from the latter two zones, spread across 27 countries.

5.3.2 Ethnic dissensus controlling for other factors

In our baseline model, $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ represents the proportion of variance on item i in country c attributable to ethnic group membership. When we augment the model with additional covariates, the interpretation of $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ changes; it now captures only the variation across respondents with different ethnic identities but similar covariate values. If this variation is smaller than in the baseline model, resulting in a smaller $\mathrm{ICC}_{ic}^{\mathrm{eth}}$, this implies that the additional covariates are partially "responsible for" ethnic dissensus. Conversely, if the $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ estimate remains stable, then interethnic variation is roughly independent of the additional covariates.

This section uses this logic to assess the relative importance of different classes of covariates for explaining ethnic dissensus. Beginning with our baseline specification with only country and ethnicity random effects, we fit a series of models with increasingly rich sets of control variables, culminating in the full "augmented" specification described in Section 5.3.1. We first add respondent-level covariates, then group-level covariates, then climate-related covariates (*AEZ* and *climate vulnerability*), then EA-level covariates and random effects, and finally regional covariates and REs. For each specification and item, we calculate the average $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ across countries.[27]

Figure 9 shows how the ICC of ethnicity for each item changes across specifications. The vertical axis indicates the difference in $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ relative to the baseline model, and the horizontal axis the covariates at each stage. Nearly every item exhibits the same pattern: little change in $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ until regional covariates and random effects are added to the model, when it drops sharply. In particular, notwithstanding the statistical significance of many respondent-level covariates reported in Figure 8, the estimated $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ is generally unaffected by their addition to the model. The only partial exception to this pattern is *heard about*, which exhibits a modest decrease in $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ with the addition of respondent covariates, though

[27] Because the augmented models include fixed as well as random effects, we use the "unadjusted" ICC, which includes the variance explained by the fixed effects in the denominator (Nakagawa et al. 2017, 2).

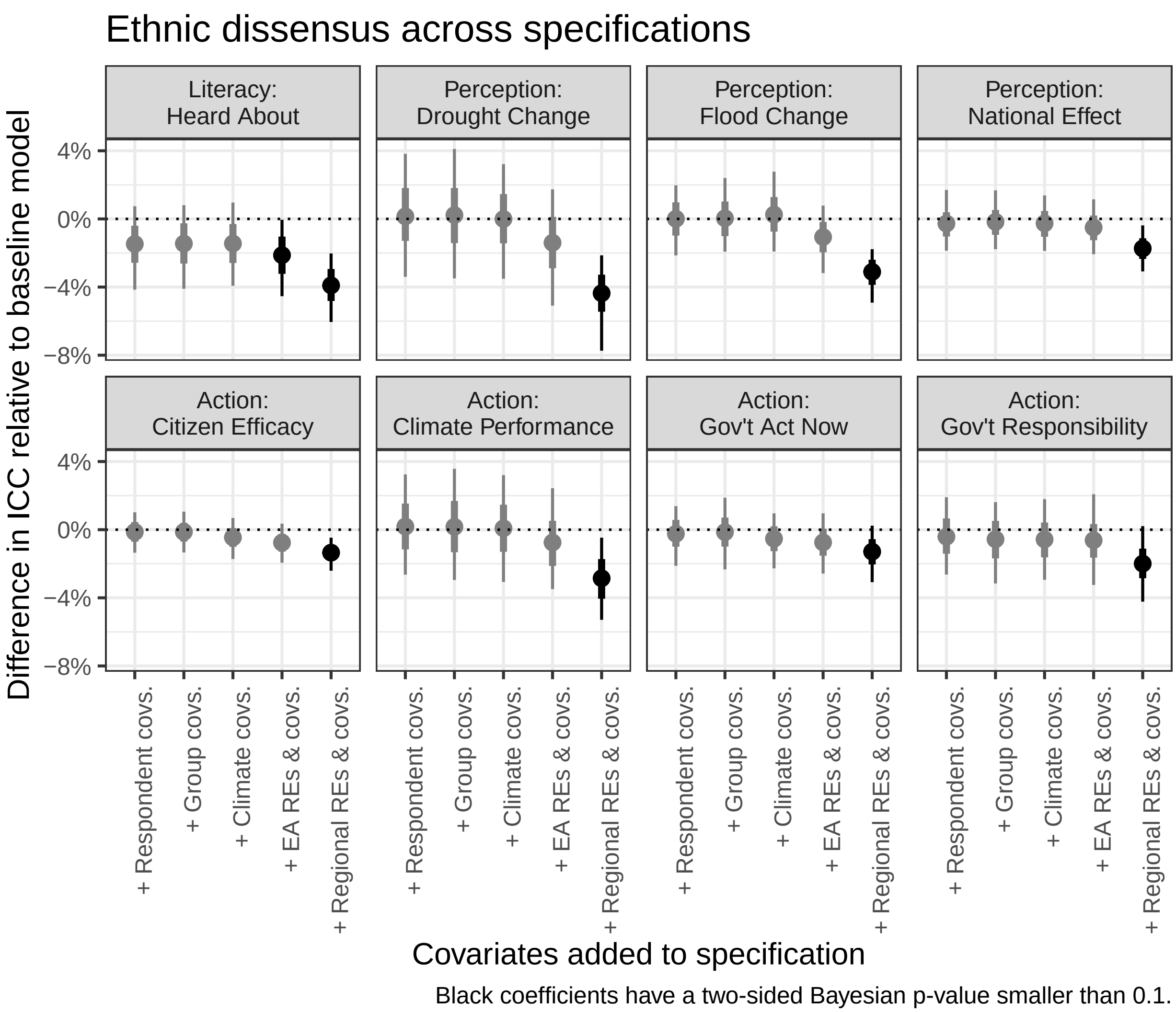

Figure 9: Change in average $\mathrm{ICC}_{ic}^{\mathrm{eth}}$ as covariates are sequentially added to the baseline multilevel model with only ethnicity and country random effects. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. For full model results underlying these estimates, see Supplementary Materials, "Full Model Results Appendix," Sections 2.1, 2.2, 2.3, 2.4, 2.6, and 2.7.

the difference only becomes statistically significant when EA-level variables are added as well.

There is thus substantial tension between the results of this analysis and those reported in Section 5.3.1. On one hand, the most powerful predictors of climate attitudes are attributes of respondents. On the other hand, as Figure 9 shows, controlling for these attributes, or even group- and EA-level attributes, is largely insufficient to substantially reduce the ICC of ethnicity. Rather, even though *regional development* is significantly associated only with Climate Action items (Figure 8), administrative region seems to be the most powerful confounder of the relationship between ethnicity and climate attitudes across all item types.

It is possible to reconcile these divergent findings. Something about administrative region clearly matters: members of ethnic groups living in the same region disagree about climate change much less than those living in different ones. But *regional development* explains at best a portion of these differences, which seem instead to be attributable to unmeasured characteristics of (or correlated with) administrative region. This is a blow to the hypothesis that economic inequality across regions is a major source of ethnic divisions over climate change, but it is consistent with the more general hypothesis that ethnic segregation across regions drives ethnic dissensus. We assess this latter hypothesis directly in the next section.

5.3.3 Country-level predictors of ethnic dissensus

In many African countries, ethnic groups are highly segregated across regions. As illustration, consider our running example of Angola. Figure 10 shows the locations of Angolan respondents in the Afrobarometer data, labeled by their EPR group, overlaid on a map of Angolan provinces.[28] The capital city of Luanda clearly exhibits a high degree of ethnic diversity. The surrounding provinces, however, are much less heterogeneous. Some provinces only have a handful of enumeration areas, which tend to be fairly, but not entirely, ethnically homogeneous.

The regional segregation visible in Figure 10 can be quantified with a measure called the

[28]At the time of the Round 9 data, Angola had 18 provinces, the number shown in Figure 10; since then, that number has expanded to 21.

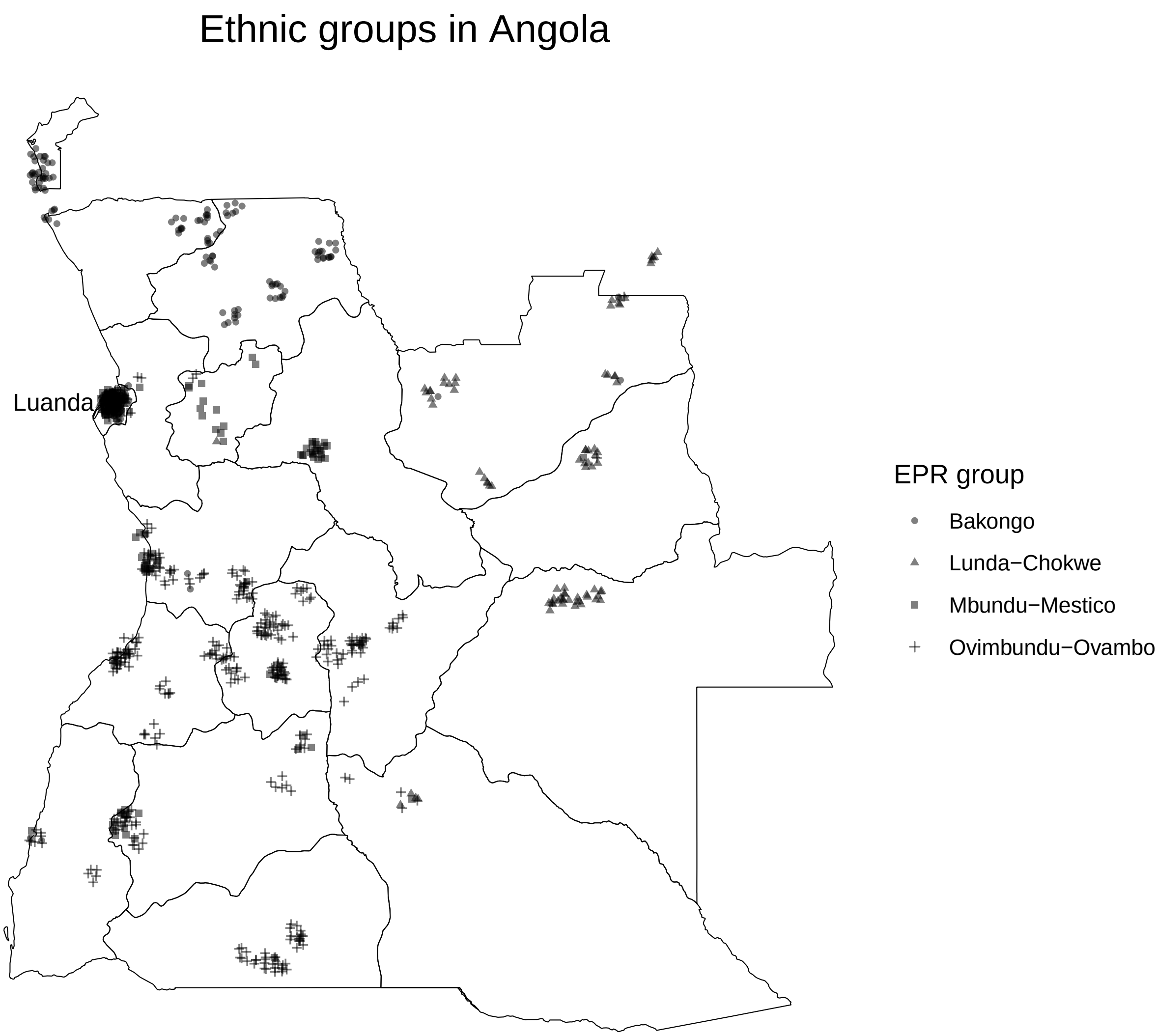

Figure 10: The figure shows the spatial distribution of respondents by ethnic group and province (administrative region) in Angola.

Theil index, which ranges between 0 and 1.[29] According to our survey data, Angola's Theil index value is approximately 0.6, making it the sixth-most segregated country in Africa by this measure. Angola also has higher-than-average ethnic dissensus on most climate items, which is what we should expect if ethnic segregation is a driver of ethnic dissensus.

As Figure 11 shows, the positive relationship between these two variables generalizes beyond Angola. In each panel of this figure, the horizontal axis indicates a country's degree of ethnic segregation. The vertical axis indicates each country's estimated intercept ζ_{ic} from our baseline multilevel model with just country and group intercepts. As Section 4 describes, ζ_{ic} represents country c's deviation from the expected value of $\log(\sigma_{ic})$ for item i. A positive value of ζ_{ic} indicates a higher level of ethnic dissensus than the typical country, and vice versa for a negative value. The bivariate relationship between ethnic dissensus and ethnic segregation is positive for all but one climate item (*Gov't Act Now* being the exception). Among comparison items (not shown), ethnic segregation is correlated with higher dissensus on *Ethnic Fairness* and *Economy Change* but not on *Health Performance.*

For a more formal assessment of the relationship between ethnic segregation and ethnic dissensus, we employ the variance function regression described in Section 4. Since the dependent variable in this regression is $\log(\sigma_{ic})$, the effective sample size of this regression is the number of countries (29). We therefore include only a few country-level predictors $\mathbf{w}_{ic}$:

- *Ethnic segregation* across regions, as measured by the Theil index (centered at 0)
- *Regional inequality*, as measured by the Baldwin-Huber between-region inequality in household wealth[30] (centered at 0)
- *Ethnic segregation* $\times$ *regional inequality*

[29] Reardon and Firebaugh (2002) provides an overview of multigroup segregation measures and studies their performance with respect to several desired properties. They settle on the Theil index as their recommended segregation measure. With M groups and J regions, the Theil index is defined as $H \equiv \sum_{m=1}^{M} \sum_{j=1}^{J} \frac{t_j}{TE} \pi_{jm} \ln \frac{\pi_{jm}}{\pi_m}$ where T is the total number of individuals, t_j is the number of individuals in region j, π_{jm} is the proportion of individuals in both group m and region j, π_m is the proportion of individuals in group m, and E is the entropy index, defined as $E \equiv \sum_{m=1}^{M} \ln \left(\frac{1}{\pi_m} \right)$.

[30] For this variable, we use the Baldwin-Huber BGI formula but applied to regions rather than ethnic groups.

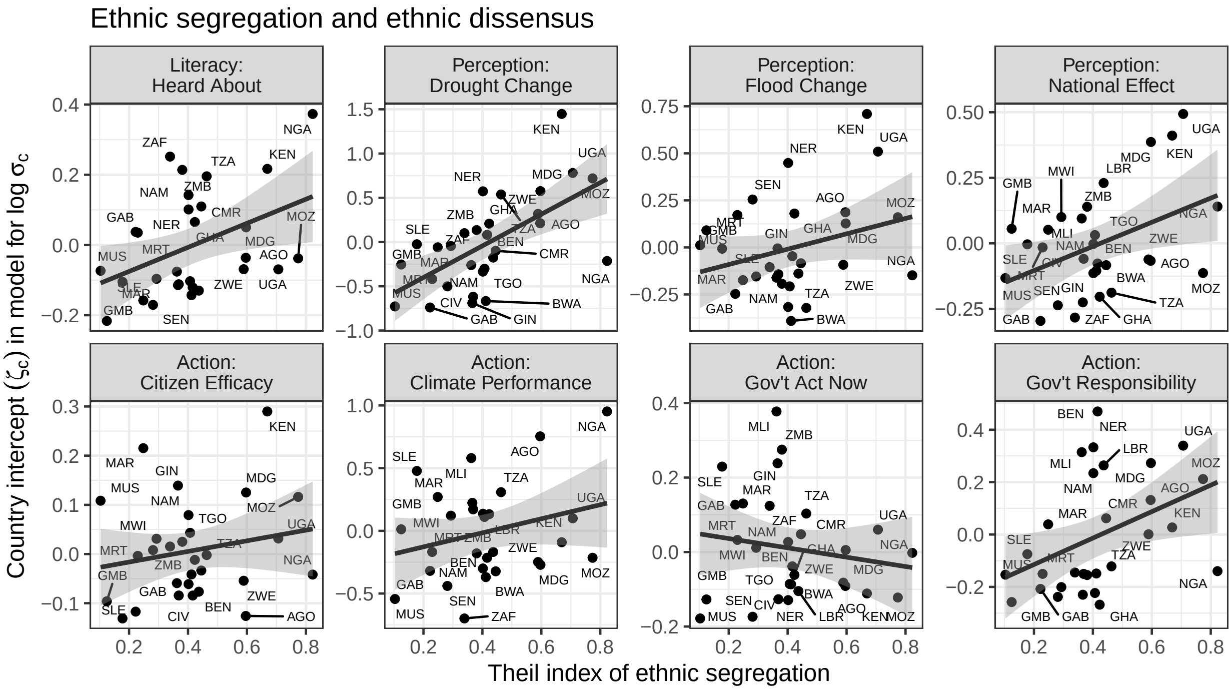

Figure 11: Bivariate relationship between the ethnic segregation and the country intercept ζ_c from a variance function regression for $\log(\sigma_c)$. For further details on these models, see Supplementary Materials, "Full Model Results Appendix," Section 2.1.

- *Ethnic inequality*, as measured by the Baldwin-Huber between-group inequality in household wealth (centered at 0)[31]
- *Climate vulnerability* (centered and standardized by twice the cross-country SD)
- *Log GDP per capita* (centered and standardized by twice the cross-country SD)

Because *ethnic segregation* and *regional inequality* are centered at 0, each of their main effects can be interpreted as the effect at the other variable's mean.

We use these variables to evaluate three hypotheses—one derived from the intergroup relations (IR) perspective and two from different variants of geographic (G) explanations:

- H_{IR}: If disagreements between ethnic groups are rooted in between-group differences

[31]Following Baldwin and Huber, we calculate the between-group inequality (BGI) index using our measure of household wealth. We define the between-group inequality index for a country as: BGI $\equiv \frac{1}{2\bar{y}} \sum_{i=1}^{n} \sum_{j=1}^{n} |p_i p_j (\bar{y}_i - \bar{y}_j)|$, where $\bar{y}$ is the mean level of household wealth in the country, $\bar{y}_k$ is the mean level of household wealth in group k, and p_k is the proportion of individuals belonging to group k.

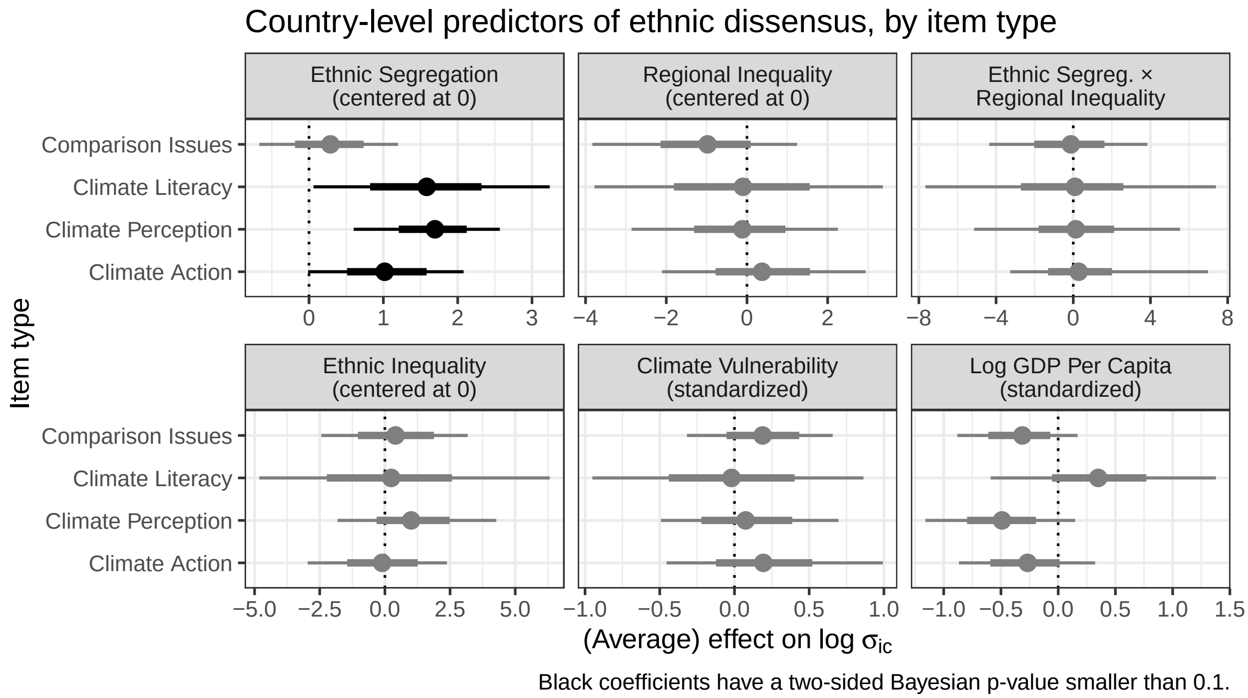

Figure 12: Predictors of dissensus, as estimated by a variance function regression for log σ_{ic}. For each item type (vertical axis), the horizontal axis indicates the coefficient δ_{ip} of predictor w_{icp}. Points indicate posterior means, and lines indicate 95% and 68% credible intervals. For full model results, see Supplementary Materials, "Full Model Results Appendix," Section 2.11.

in economic resources, ethnic dissensus should be positively associated with *ethnic inequality*.

- H_{G1}: If ethnic dissensus is rooted in groups' uneven distribution across regions, ethnic dissensus should be positively associated with *ethnic segregation*.

- H_{G2}: If ethnic dissensus is rooted in groups' uneven distribution across regions *with different levels of wealth*, ethnic dissensus should be positively associated with the interaction of *ethnic segregation* and *regional inequality*.[32]

We test these hypotheses by fitting variance function regressions to all survey items, including comparison items. Figure 12 reports the results, again averaging coefficients within

[32]This hypothesis stems from Boone (2024), who argues that regional inequalities have driven political conflicts often perceived as following ethnic lines in Africa.

item type for greater precision. As the leftmost panel shows, ethnic segregation is robustly associated with ethnic dissensus on climate issues. Segregation is strongly positively associated with dissensus on Literacy and Perception items. It is also positively related to dissensus on Action items, though the 95% credible interval just barely covers 0.[33] By contrast, the comparison items display no such relationship, nor do any of the coefficient estimates for other variables, including the interaction term.

Given that this analysis is based on just 29 country-level observations, the dearth of significant coefficients is perhaps unsurprising. This makes the clarity of the relationship between ethnic segregation and ethnic dissensus on climate items—and just climate items—all the more striking. The correlational nature of this analysis cautions against a causal interpretation. Nevertheless, this result suggests that for climate issues specifically, the uneven geographic distribution of different ethnic groups exacerbates ethnic dissensus, but not for reasons related to economic inequality between regions.

6 Conclusion

Using an original approach to the study of group-based dissensus, this paper systematically examines climate-related attitudes in 29 African countries. In over half of the countries, we find evidence of substantial differences between ethnic groups in terms of at least one dimension of how individuals perceive various aspects of climate-related outcomes. In only a few countries do we find substantial differences across ethnic groups in terms of views about actions to take on climate change. The latter may reflect the fact that the politicization of climate policy, including literacy about the problem (Trisos et al. 2022), is still nascent even as citizens are already experiencing the effects of climate change. We find that wealthier ethnic groups tend to express lower support for climate action, as do residents of more developed regions. Across countries, we find that ethnic dissensus is greater where ethnic

[33] There is a 97% posterior probability that the average coefficient of *ethnic segregation* for Climate Action items is positive.

segregation is more pronounced.

These findings make several contributions. With respect to extant scholarship on climate attitudes, we contribute to a set of studies (e.g., Bush and Clayton 2022; Honig et al. 2021; Trisos et al. 2022; Simpson et al. 2021) that focus or substantially draw on African perspectives. To our knowledge, this paper represents the first attempt to study the role of ethnicity as construed in a general sense in structuring climate opinion across a large number of countries on the continent. We highlight that ethnic dissensus is likely to be greater where ethnicities are segregated into administrative regions. Resonating with other studies that do not consider ethnicity, we find that even though increased education may lead to more awareness about climate change, group-based power and wealth may dampen relative concern because members of such groups perceive themselves as relatively less precarious. The idea that climate change is something that "affects all of us," quickly runs up against the reality of unequal ability to adapt.

Second, we contribute to a now extensive scholarly literature on ethnic politics in Africa, including research that focuses on the relationship between ethnic identities and policy-related perceptions and priorities. Although this study does not attempt to establish a link between citizen attitudes and government policies, it does lend plausibility to studies that theorized that a source of conflict over policies is the different preferences of different ethnic groups. Within this literature, our findings also speak to a recent debate regarding the relative roles of region and ethnicity in African politics. We find that ethnic dissensus is in part spatial: there is much more dissensus between groups in different regions than within the same region, even when controlling for a host of other factors; and countries with more regionally-segregated ethnic groups demonstrate significantly more ethnic dissensus on climate change. This echoes the claims of Boone (2024), at least in the sense of reminding us of the extent to which a characteristic feature of ethnic groups is their concentration in particular locations, and that conflict that appears as "ethnic" may have roots and manifestations in regional inequalities. Nevertheless, we do not find that ethnicity is fully reducible to regional context. Even when controlling for regional random effects and regional wealth, we find nonzero levels of ethnic dissensus. Further, one implication of the argument from Boone et al. (2022) that regional *inequalities* are important for driving observed ethnic politics could be that ethnicities only exhibit significantly different views when clustered into regions with unequal levels of wealth. We tested this hypothesis by examining the relationship between our estimates of dissensus and the interaction of ethnic segregation and regional inequality, but found null results. Regional inequality itself is also not a significant predictor of dissensus. Therefore, although spatial variables are important, ethnic dissensus at the country level is not explained exclusively by regional dynamics.

Third, we provide a new, flexible methodological tool for studying group-based dissensus, especially when the number, size, and salience of groups differ across countries. As scholars increasingly study the question of how to measure polarization on multiple dimensions and across multiple groups (Mehlhaff 2024; Huber 2012; Esteban and Debraj 1994), we offer multilevel model-based quantities such as the standard deviation of group intercepts and the intraclass correlation coefficient as estimators of dissensus with attractive properties. These include the ability to compare across dimensions with different scales, the natural incorporation of both within- and between-group variances, the ability to estimate dissensus for a certain grouping while controlling for other groupings and covariates, the ability to readily calculate uncertainty estimates, and the ability to explicitly model the predictors of dissensus, all in a single modeling framework.

We note, however, certain limitations to the study and the degree to which we can make inferences about climate politics in Africa from these analyses. First, citizen-reported survey attitudes may be "noisy" and may not reflect deeply-held perspectives, and they do not necessarily map onto political mobilization or the policy-making process. Relatedly, we have not established a link between attitudes and private actions. The relationship between climate-related attitudes and behaviors in Africa ought to be an important focus for future research.

Moreover, the evidence we provide for adjudicating among hypothesized drivers of climate attitudes is primarily suggestive rather than causal. As scholars of identity politics know well, we cannot assume that ethnic identities are fully exogenous. In fact, the changing climate is likely to be a driving factor shaping patterns of attachment to particular identities, most notably but not exclusively in terms of the effects on migration (Abel et al. 2019). Broader or more narrow categories of attachment may arise from people's shared experiences and understanding of the climate. Nonetheless, ethnic identities are relatively sticky, and at least in the short-term, are not likely to be a *consequence* of climate-related attitudes and behaviors. For the countries characterized by high levels of ethnic group-based dissensus, the fundamental dilemma of coordination around climate action may pose a great challenge for effective national policy-making.

Given the substantive significance of climate change and ethnic politics across many parts of the African continent, and our findings relating the two, more work is needed to better understand these evolving phenomena, and the role citizens and governments might play in building resilience in the face of continued challenges.

References

Abel, G. J., Brottrager, M., Crespo Cuaresma, J., and Muttarak, R. (2019). Climate, conflict and forced migration. *Global Environmental Change*, 54:239–249.

Adelekan, I. O., Simpson, N. P., Totin, E., and Trisos, C. H. (2022). IPCC Sixth Assessment Report (AR6): Climate Change 2022-Impacts, Adaptation and Vulnerability: Regional Factsheet Africa. Publisher: IPCC: Intergovernmental Panel on Climate Change.

Akerlof, G. A. and Kranton, R. E. (2000). Economics and Identity. *The Quarterly Journal of Economics*, 115(3):715–753.

Alesina, A., Baqir, R., and Easterly, W. R. (1999). Public Goods and Ethnic Divisions. *Quarterly Journal of Economics*, 114(4):1243–1284.

Arias, S. and Blair, C. (2024). In the Eye of the Storm: Hurricanes, Climate Migration, and Climate Attitudes. *American Political Science Review*, pages 1–21.

Arıkan, G. and Günay, D. (2021). Public attitudes towards climate change: A cross-country analysis. *The British Journal of Politics and International Relations*, 23(1):158–174. Publisher: SAGE Publications.

Baldwin, K. and Huber, J. D. (2010). Economic versus Cultural Differences: Forms of Ethnic Diversity and Public Goods Provision. *American Political Science Review*, 104(4):644–662. Publisher: Cambridge University Press.

Ballew, M., Goldberg, M. H., Rosenthal, S. A., Cutler, M. J., and Leiserowitz, A. (2019a). Climate Change Activism Among Latino and White Americans. *Frontiers in Communication*, 3:58.

Ballew, M., Leiserowitz, A., Roser-Renouf, C., Rosenthal, S. A., Kotcher, J. E., Marlon, J. R., Lyon, E., Goldberg, M. H., and Maibach, E. W. (2019b). Climate Change in the American Mind: Data, Tools, and Trends. *Environment: Science and Policy for Sustainable Development*, 61(3):4–18.

Bartko, J. J. (1966). The Intraclass Correlation Coefficient as a Measure of Reliability. *Psychological Reports*, 19(1):3–11.

Beiser-McGrath, J., Müller-Crepon, C., and Pengl, Y. I. (2021). Who Benefits? How Local Ethnic Demography Shapes Political Favoritism in Africa. *British Journal of Political Science*, 51(4):1582–1600.

Benegal, S., Azevedo, F., and Holman, M. R. (2022). Race, ethnicity, and support for climate policy. *Environmental Research Letters*, 17(11):114060. Publisher: IOP Publishing.

Bergquist, M., Nilsson, A., Harring, N., and Jagers, S. C. (2022). Meta-analyses of fifteen determinants of public opinion about climate change taxes and laws. *Nature Climate*

Change, 12(3):235–240. Publisher: Nature Publishing Group.

Boone, C. (2024). *Inequality and Political Cleavage in Africa: Regionalism by Design*. Cambridge University Press, Cambridge, UK ; New York.

Boone, C., Wahman, M., Kyburz, S., and Linke, A. (2022). Regional cleavages in African politics: Persistent electoral blocs and territorial oppositions. *Political Geography*, 99:102741.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. 80(1):26–35.

Bush, S. S. and Clayton, A. (2022). Facing Change: Gender and Climate Change Attitudes Worldwide. *American Political Science Review*, pages 1–18.

Bürkner, P.-C., Gabry, J., Kay, M., and Vehtari, A. (2025). posterior: Tools for working with posterior distributions. R package version 1.6.1.

Cederman, L.-E., Min, B., and Wimmer, A. (2009). Ethnic power relations dataset.

Cederman, L.-E., Wimmer, A., and Min, B. (2010). Why Do Ethnic Groups Rebel? New Data and Analysis. *World Politics*, 62(01):87–119.

Chaganti, S., Waddell, J., Chaganti, S., and Waddell, J. (2015). Employment Change among Hurricane Katrina Evacuees: Impacts of Race and Place. *Journal of Public Management and Social Policy*, 22(2).

Chandra, K. (2006). What is ethnic identity and does it matter? *Annu. Rev. Polit. Sci.*, 9:397–424.

Chen, Noble, I., Hellmann, J., Coffee, J., Murillo, M., and Chawla, N. (2023). University of Notre Dame Global Adaptation Initiative, Country Index Technical Report. Technical report, University of Notre Dame.

Cohen, C. J. (1999). *The Boundaries of Blackness: AIDS and the Breakdown of Black Politics*. University of Chicago Press, Chicago.

Collier, P., Conway, G., and Venables, T. (2008). Climate change and Africa. *Oxford Review of Economic Policy*, 24(2):337–353.

Converse, P. E. (1964). The nature of belief systems in mass publics. In Apter, D. E., editor, *Ideology and Discontent*, pages 206–261. Free Press, London.

Dawson, M. (1994). *Behind the mule: Race and class in African-American politics*. Princeton Univ Pr.

Desmet, K., Weber, S., and Ortuño-Ortín, I. (2009). Linguistic Diversity and Redistribution. *Journal of the European Economic Association*, 7(6):1291–1318.

Easterly, W. and Levine, R. (1997). Africa's Growth Tragedy: Policies and Ethnic Divisions. *The Quarterly Journal of Economics*, 112(4):1203–1250.

Echendu, A. J. (2025). It has not always been like this: public opinion of climate change in Port Harcourt, Nigeria. *Integrated Environmental Assessment and Management*, 21(2):314–325.

Esteban, J.-M. and Debraj, R. (1994). On the Measurement of Polarization. *Econometrica*, 62(4):819–851.

Franck, R. and Rainer, I. (2012). Does the Leader's Ethnicity Matter? Ethnic Favoritism, Education, and Health in Sub-Saharan Africa. *American Political Science Review*, 106(02):294–325.

Frank, E., Eakin, H., and López-Carr, D. (2011). Social identity, perception and motivation in adaptation to climate risk in the coffee sector of Chiapas, Mexico. *Global Environmental Change*, 21(1):66–76.

Frondel, M., Simora, M., and Sommer, S. (2017). Risk Perception of Climate Change: Empirical Evidence for Germany. *Ecological Economics*, 137:173–183.

Gabry, J., Češnovar, R., Johnson, A., and Bronder, S. (2024). *cmdstanr: R Interface to CmdStan*. R package version 0.8.0, https://discourse.mc-stan.org.

Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine*, 27:2865–2873.

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., and Rubin, D. B. (2013). *Bayesian Data Analysis*. CRC Press, 3 edition.

Gelman, A. and Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press.

Gelman, A. and Stern, H. (2006). The difference between "significant" and "not significant" is not itself statistically significant. *The American Statistician*, 60(4):328–331.

Gill, J. (1999). The insignificance of null hypothesis significance testing. *Political Research Quarterly*, 52(3):647–674.

Habyarimana, J., Humphreys, M., Posner, D. N., and Weinstein, J. M. (2007). Why Does Ethnic Diversity Undermine Public Goods Provision? *American Political Science Review*, 101(4):709–725. Publisher: Cambridge University Press.

Habyarimana, J., Humphreys, M., Posner, D. N., and Weinstein, J. M. (2009). *Coethnicity: Diversity and the Dilemmas of Collective Action*. Russell Sage Foundation Press.

He, M., Cui, J., Yi, Y., Chen, H. W., Zhang, Q., Li, L., Huang, L., and Hong, S. (2024).

Vegetation increases global climate vulnerability risk by shifting climate zones in response to rising atmospheric CO2. *Science of The Total Environment*, 949:174810.

Honig, L., Smith, A. E., and Bleck, J. (2021). What Stymies Action on Climate Change? Religious Institutions, Marginalization, and Efficacy in Kenya. *Perspectives on Politics*, pages 1–18. Publisher: Cambridge University Press.

Hornsey, M. J., Harris, E. A., Bain, P. G., and Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature Climate Change*, 6(6):622–626. Number: 6 Publisher: Nature Publishing Group.

Horowitz, D. L. (1985). *Ethnic Groups in Conflict*. University of California Press, Berkeley.

Howe, P. D., Marlon, J. R., Mildenberger, M., and Shield, B. S. (2019). How will climate change shape climate opinion? *Environmental Research Letters*, 14(11):113001.

Huber, J. D. (2012). Measuring Ethnic Voting: Do Proportional Electoral Laws Politicize Ethnicity? *American Journal of Political Science*, 56(4):986–1001.

Kalin, M. and Sambanis, N. (2018). How to Think About Social Identity. *Annual Review of Political Science*, 21(1):239–257.

Lamont, M. and Molnár, V. (2002). The Study of Boundaries in the Social Sciences. *Annual Review of Sociology*, 28:167–195.

Lawrence, J., Quade, D., and Becker, J. (2014). Integrating the effects of flood experience on risk perception with responses to changing climate risk. *Natural Hazards*, 74(3):1773–1794.

Lechowska, E. (2022). Approaches in research on flood risk perception and their importance in flood risk management: a review. *Natural Hazards*, 111(3):2343–2378.

Leiserowitz, A. (2006). Climate Change Risk Perception and Policy Preferences: The Role of Affect, Imagery, and Values. *Climatic Change*, 77(1):45–72.

Lieberman, E. and Singh, P. (2012). Conceptualizing and Measuring Ethnic Politics: An Institutional Complement to Demographic, Behavioral, and Cognitive Approaches. *Studies in Comparative International Development*, 47(3):255–286.

Lieberman, E. S. (2009). *Boundaries of contagion : how ethnic politics have shaped government responses to AIDS*. Princeton University Press, Princeton.

Lieberman, E. S. and McClendon, G. H. (2013). The Ethnicity-Policy Preference Link in Sub-Saharan Africa. *Comparative Political Studies*, 46(5 %U http://cps.sagepub.com/content/46/5/574.abstract):574–602.

Masood, M. and Reidpath, D. D. (2016). Intraclass correlation and design effect in BMI, physical activity and diet: a cross-sectional study of 56 countries. *BMJ Open*, 6(1):e008173.

Mehlhaff, I. D. (2024). A Group-Based Approach to Measuring Polarization. *American Political Science Review*, 118(3):1518–1526.

Nakagawa, S., Johnson, P. C. D., and Schielzeth, H. (2017). The coefficient of determination r^2 and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of The Royal Society Interface*, 14(134):20170213.

Posner, D. (2004). Measuring Ethnic Fractionalization in Africa. *American Journal of Political Science*, 48(4):849–863.

Reardon, S. F. and Firebaugh, G. (2002). Measures of multigroup segregation. *Sociological methodology*, 32(1):33–67.

Sanchez, A. C., Fandohan, B., Assogbadjo, A. E., and Sinsin, B. (2012). A countrywide multi-ethnic assessment of local communities' perception of climate change in Benin (West Africa). *Climate and Development*, 4(2):114–128. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/17565529.2012.728126.

Schuldt, J. P. and Pearson, A. R. (2016). The role of race and ethnicity in climate change polarization: evidence from a U.S. national survey experiment. *Climatic Change*, 136(3):495–505.

Siegrist, M. and Árvai, J. (2020). Risk Perception: Reflections on 40 Years of Research. *Risk Analysis*, 40(S1):2191–2206. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/risa.13599.

Simpson, N. P., Andrews, T. M., Krönke, M., Lennard, C., Odoulami, R. C., Ouweneel, B., Steynor, A., and Trisos, C. H. (2021). Climate change literacy in Africa. *Nature Climate Change*, 11(11):937–944. Number: 11 Publisher: Nature Publishing Group.

Skrondal, A. and Rabe-Hesketh, S. (2004). *Generalized Latent Variable Modeling*. CRC Press.

Slovic, P., Flynn, J., and Mertz, C. K. (1994). Gender, Race, and Perception of Environmental Health Risks. *Risk Analysis*, 14:1101–1108.

Tajfel, H. and Turner, J. C. (1986). The Social Identity Theory of Intergroup Behavior. In Worchel, S. and Austin, W. G., editors, *Psychology of Intergroup Relations*, pages 7–24. Nelson-Hall, Chicago.

Trisos, C., Adelekan, I., Totin, E., Ayanlade, A., Efitre, J., Gemeda, A., Kalaba, K., Lennard, C., Masao, C., Mgaya, Y., and others (2022). Africa. In *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Publisher: Cambridge university press.

van der Linden, S. (2017). Determinants and Measurement of Climate Change Risk Perception, Worry, and Concern. SSRN Scholarly Paper ID 2953631, Social Science Research Network, Rochester, NY.

Varshney, A. (2003). Nationalism, Ethnic Conflict, and Rationality. *Perspective on Politics*, 1(1):85–99.

Vehtari, A., Gelman, A., Simpson, D., Carpenter, B., and Bürkner, P.-C. (2021). Rank-normalization, folding, and localization: An improved rhat for assessing convergence of mcmc (with discussion). *Bayesian Analysis*, 16(2):667–718.

Western, B. and Bloome, D. (2009). Variance Function Regressions for Studying Inequality. *Sociological Methodology*, 39(1):293–326.

Wimmer, A. (2008). The Making and Unmaking of Ethnic Boundaries: A Multilevel Process Theory. *American Journal of Sociology*, 113(4):970–1022.

A Descriptive statistics and figures

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Drought Change	38805	3.31	1.42	1.00	2.00	5.00	5.00
Flood Change	38869	2.80	1.42	1.00	1.00	4.00	5.00
Heard About	39113	0.51	0.50	0.00	0.00	1.00	1.00
National Effect	19434	3.96	1.18	1.00	4.00	5.00	5.00
Citizen Efficacy	19677	2.13	1.17	1.00	1.00	2.00	5.00
Gov't Act Now	19692	3.88	1.21	1.00	4.00	5.00	5.00
Gov't Responsibility	19727	0.48	0.50	0.00	0.00	1.00	1.00
Climate Performance	33941	2.75	0.94	1.00	2.00	4.00	4.00
Ethnic Fairness	38535	1.65	0.92	1.00	1.00	2.00	4.00
Economy Change	40062	3.61	1.14	1.00	3.00	5.00	5.00
Health Performance	39964	2.77	0.97	1.00	2.00	4.00	4.00
Age	40250	37.59	14.72	18.00	26.00	47.00	100.00
Female	40269	0.50	0.50	0.00	0.00	1.00	1.00
Household wealth	40269	3.53	1.77	0	2.00	5.00	6
Education	40174	3.53	2.24	0.00	2.00	5.00	9.00
Urban	39685	0.45	0.50	0.00	0.00	1.00	1.00
Occupation farmer	39914	0.27	0.44	0.00	0.00	1.00	1.00
Religion	38429						
... Christian	23239	60%					
... Muslim	12157	32%					
... Nonreligious, athiest, or agnostic	1891	5%					
... Other	1142	3%					
Avg. group wealth	37359	3.59	0.86	1.00	2.86	4.23	5.76
Largest group	37359	0.50	0.50	0.00	0.00	1.00	1.00
Group in power	40269	0.63	0.48	0.00	0.00	1.00	1.00
Local (EA) development	40269	7.20	3.28	0.00	5.00	10.00	13.00
Local (EA) security presence	40269	0.56	0.99	0.00	0.00	1.00	5.00
Regional development	40269	7.22	2.02	1.26	5.99	8.54	13.00
ND GAIN Climate vulnerability	40269	0.50	0.061	0.37	0.46	0.53	0.63
GDP per capita	40269	2425.14	2417.90	471.26	954.15	2292.89	10241.88
Theil segregation index	40269	0.44	0.18	0.10	0.34	0.59	0.82
Between-group inequality	40269	0.042	0.03	0.000049	0.022	0.052	0.13
Number of groups	40269	5.24	2.55	2	3.00	6.00	13
Between-region inequality	40269	0.12	0.049	0.037	0.076	0.15	0.23

Table A.1: Summary statistics. The first variables listed are our outcome items. Then, we list individual-level covariates, group-level covariates, EA-level covariates, the region-level covariate, and finally country-level covariates.

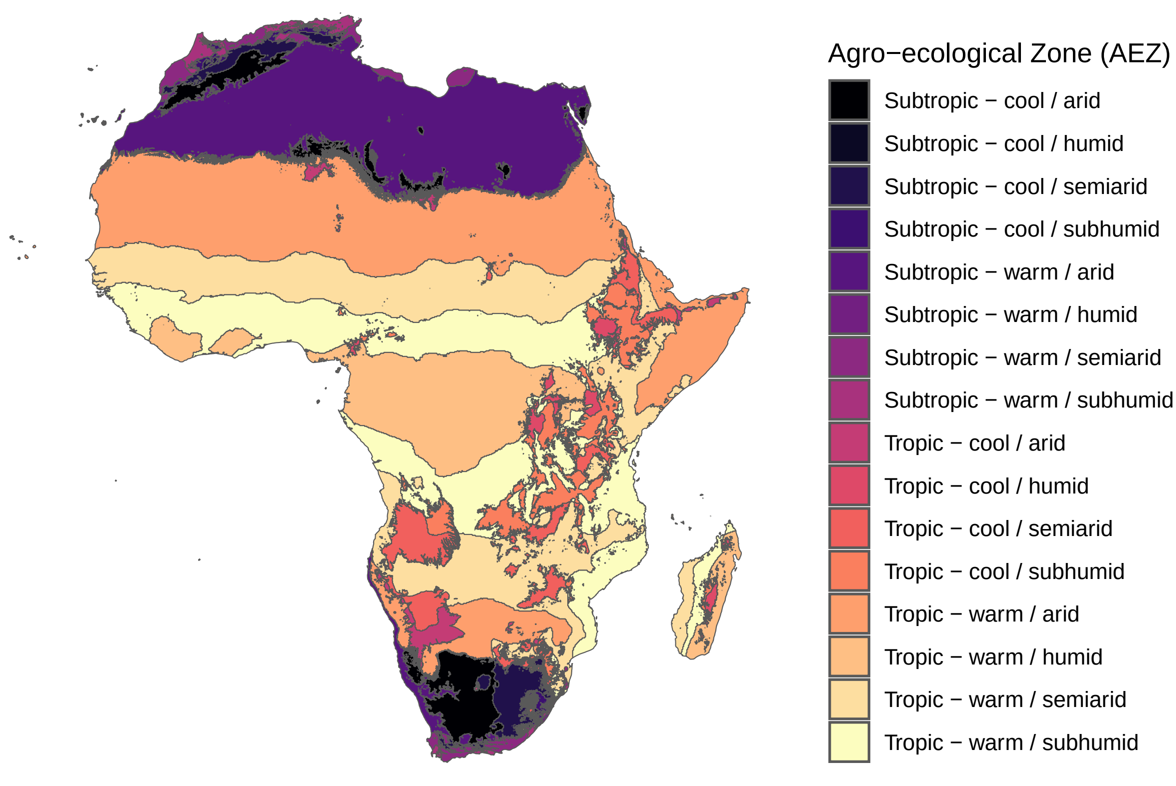

Figure A.1: Map of Africa's agro-ecological zones from the Regional Centre for Mapping of Resources for Development (RCMRD), an intergovernmental organization in Nairobi, Kenya. See `https://rcmrd.africageoportal.com/`.

B Ethnic Categories - Afrobarometer to EPR translation

As discussed in the paper, we sought to classify respondents' self-reported ethnic groups in terms of "politically-relevant" ethnic groups. To do so, we looked for matches between the group names reported in the Afrobarometer survey (and associated codes) with groups listed in the dataset of politically-relevant ethnic groups (EPR). We consider corresponding groups as well as nested groups to be matches (that is, if the respondent identified a group that was a sub-group reported in EPR, we matched on the superordinate EPR group.)

We generated a spreadsheet in which all groups associated with all African countries were listed. In the column next to the country name there was a column with the Afrobarometer ethnic code, and next to that a third column with the Afrobarometer ethnic group name. When comparing it to the EPR code, first, country names were matched, and then ethnic group names were examined for a match. If one was found, the respective ethnic group name would be recorded, along with the EPR group ID, size, and status.

Sometimes the ethnic group names were similar in EPR and Afrobarometer, but not an exact match. In such cases, the identification was crosschecked via web search that this was indeed the same group. Determination of matches was made via looking for conflation of names and via looking at the languages spoken by the group. For example, the Yom group in Benin speaks Yoa-Lokpa, and since Yoa-Lokpa is an EPR group, the match was determined to be valid.

When a match was not certain, a notation was made. The uncertain match was then researched to determine whether this was truly a match. By doing this, the number of uncertain matches dropped to only a few. Many remaining uncertain matches were in Tanzania, which classified groups differently when compared with other countries. The 2021 EPR classifications for Tanzania was predominately based on religion and where people lived (i.e. "Mainland Muslims," "Others Mainland (Christian and traditional religions") which differed from the ethnic group classifications of the Afrobarometer. While some matches could be determined by location and predominant religion, others could not.

Occasionally a match could not be found. Research was also conducted on these groups, and it was found that unmatched groups were most commonly either quite small in terms of number of respondents or appeared to be pastoralist/dispersed/not "politicized" groups.

There were also challenges matching groups in Nigeria and Mozambique in particular, as the classification of groups has changed over time. This was not particularly surprising, as EPR's document on Nigeria notes: "Any other of the hundreds of minority ethnic groups were not included as there was no evidence of any political representation of them at the national level. The communal violence these minority groups have engaged in is normally targeted against each other - for local reasons (e.g. land, local political positions etc.) (see e.g. group code 3957) - and does not stem from a national struggle over the access to political power."

Our final crosswalk is below. Values of "*NA*" in the EPR label column indicate no match for this group could be found. These unmatched groups amount to about 7.2% of all Afrobarometer respondents.

Country	Afrobarometer label	EPR label	EPR group power status
Angola	Bakongo	Bakongo	Powerless
Angola	Kwanhama	Ovimbundu-Ovambo	Powerless
Angola	Luanda	*NA*	*NA*
Angola	Lunda Chokwe ou Catchokwe	Lunda-Chokwe	Powerless
Angola	Malanjinho	*NA*	*NA*
Angola	Mbundu-Kimbundu	Mbundu-Mestico	Dominant
Angola	Mucubal	*NA*	*NA*
Angola	Nhaneka-Humbe	*NA*	*NA*
Angola	Ovanganguela	*NA*	*NA*
Angola	Ovimbundu	Ovimbundu-Ovambo	Powerless
Benin	Aja	Southwestern (Adja)	Junior partner
Benin	Bariba	Southwestern (Adja)	Junior partner
Benin	Dendi	Southwestern (Adja)	Junior partner
Benin	Fon	Southwestern (Adja)	Junior partner
Benin	Lopka	Northern (Bariba, Peul, Ottamari, Yoa-Lokpa, Dendi, Gourmanchéma)	Junior partner
Benin	Otamari	Northern (Bariba, Peul, Ottamari, Yoa-Lokpa, Dendi, Gourmanchéma)	Junior partner
Benin	Peulh	Northern (Bariba, Peul, Ottamari, Yoa-Lokpa, Dendi, Gourmanchéma)	Junior partner
Benin	Yoruba	Southeastern (Yoruba/Nagot and Goun)	Junior partner
Botswana	Mmirwa	Birwa	Powerless
Botswana	Moherero	Herero/Mbanderu	Powerless
Botswana	Mohurutshe	Tswana	Senior partner
Botswana	Mokalaka/Mokalanga	Kalanga	Junior partner
Botswana	Mokgalagadi	Kgalagadi	Powerless
Botswana	Mokgatla	Tswana	Senior partner
Botswana	Mokhurutshe	Tswana	Senior partner
Botswana	Mokwena	Tswana	Senior partner
Botswana	Molete	Tswana	Senior partner
Botswana	Mombukushu	Mbukushu	Powerless
Botswana	Mongologa	Kgalagadi	Powerless
Botswana	Mongwaketse	Tswana	Senior partner
Botswana	Mongwato	Tswana	Senior partner
Botswana	Morolong	Tswana	Senior partner
Botswana	Mosarwa	San	Powerless
Botswana	Mosubeya	Mbukushu	Powerless
Botswana	Motawana	Tswana	Senior partner
Botswana	Motlhaping	Tswana	Senior partner
Botswana	Motlharo	Tswana	Senior partner
Botswana	Motlokwa	Tswana	Senior partner
Botswana	Motswapong	Tswapong	Powerless
Botswana	Moyeyi/Moyei	Yeyi	Powerless
Cameroon	Arabe choua	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Bafia	Bamileke	Junior partner
Cameroon	Bafut	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Bakassi	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Bakundu	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Bakweri	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Bali Gashu	Northwestern Anglophones (Grassfielders)	Junior partner

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Cameroon	Balikumbat	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Bamileke	Bamileke	Junior partner
Cameroon	Bamoun	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Bangwa	Bamileke	Junior partner
Cameroon	Bassa	Bassa/Duala	Junior partner
Cameroon	Batanga	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Batibo	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Bayangi	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Beti	Beti (and related peoples)	Senior partner
Cameroon	Daba	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Dii	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Fali	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Gbaya	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Guider	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Guiziga	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Haoussa	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Hina	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Kapsiki	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Kotoko	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Mada	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Mafa	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Maka	Beti (and related peoples)	Senior partner
Cameroon	Mandara	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Mankon	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Massa	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Mbamois	Bamileke	Junior partner
Cameroon	Mbo	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Mboum	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Moudan	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Mousgoum	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Njikwa	Bamileke	Junior partner
Cameroon	Nso	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Oku	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Peule	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Sawa	Bassa/Duala	Junior partner
Cameroon	Tikari	Southwestern Anglophones (Bakweri etc.)	Junior partner
Cameroon	Toupouri	Fulani (and other northern Muslim peoples)	Junior partner
Cameroon	Wimbum	Northwestern Anglophones (Grassfielders)	Junior partner
Cameroon	Yamba	Northwestern Anglophones (Grassfielders)	Junior partner
Cote d'Ivoire	Akan	Other Akans	Junior partner
Cote d'Ivoire	Gur (Voltaique)	Northerners (Mande and Voltaic/Gur)	Senior partner
Cote d'Ivoire	Koua Lagunaire	*NA*	*NA*
Cote d'Ivoire	Krou	Kru	Powerless
Cote d'Ivoire	Mande du Nord	Northerners (Mande and Voltaic/Gur)	Senior partner
Cote d'Ivoire	Mande du Sud	Southern Mande	Junior partner
Gabon	Fang	Fang	Junior partner
Gabon	Kele	*NA*	*NA*

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Gabon	Kota	*NA*	*NA*
Gabon	Mbede	Mbede (Nzebi, Bateke, Obamba)	Senior partner
Gabon	Myene	Myene	Junior partner
Gabon	Nzebi/Metie	Mbede (Nzebi, Bateke, Obamba)	Senior partner
Gabon	Punu/Merie	Eshira/Bapounou	Junior partner
Gabon	Tsogho	*NA*	*NA*
Gambia	Aku	Aku (Creoles)	Irrelevant
Gambia	Bambara	Mandinka	Irrelevant
Gambia	Fula, Tukulor or Lorobo	Fula	Irrelevant
Gambia	Jahanka	Mandinka	Irrelevant
Gambia	Jola	Diola	Irrelevant
Gambia	Koroninka	Diola	Irrelevant
Gambia	Mandinka	Mandinka	Irrelevant
Gambia	Manjago	Diola	Irrelevant
Gambia	Serahuleh	Mandinka	Irrelevant
Gambia	Serer	Fula	Irrelevant
Gambia	Wolof	Wolof	Irrelevant
Ghana	Akan	Asante (Akan)	Senior partner
Ghana	Dagaati	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Dagomba	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Ewe/Anlo	Ewe	Junior partner
Ghana	Frafri	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Ga/Adangbe	Ga-Adangbe	Junior partner
Ghana	Gonja	*NA*	*NA*
Ghana	Grusi	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Guan	*NA*	*NA*
Ghana	Gurma	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Hausa	*NA*	*NA*
Ghana	Konkonba	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Kusasi	Northern Groups (Mole-Dagbani, Gurma, Grusi)	Junior partner
Ghana	Mande	*NA*	*NA*
Ghana	Wale	*NA*	*NA*
Guinea	Guerze	Susu	Junior partner
Guinea	Kissien	Peul	Powerless
Guinea	Malinke	Malinke	Senior partner
Guinea	Peulh	Peul	Powerless
Guinea	Sossou	Susu	Junior partner
Guinea	Toma	Susu	Junior partner
Kenya	Borana	*NA*	*NA*
Kenya	Kalenjin	Kalenjin-Masai-Turkana-Samburu	Senior partner
Kenya	Kamba	Kamba	Powerless
Kenya	Kikuyu	Kikuyu-Meru-Emb	Senior partner
Kenya	Kisii	Kisii	Junior partner
Kenya	Kuria	*NA*	*NA*
Kenya	Luhya	Luhya	Powerless

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Kenya	Luo	Luo	Powerless
Kenya	Masai/Samburu	Kalenjin-Masai-Turkana-Samburu	Senior partner
Kenya	Meru/Embu	Kalenjin-Masai-Turkana-Samburu	Senior partner
Kenya	MijiKenda	Mijikenda	Junior partner
Kenya	Orma	*NA*	*NA*
Kenya	Pokot	Kalenjin-Masai-Turkana-Samburu	Senior partner
Kenya	Somali	Somali	Discriminated
Kenya	Swahili	*NA*	*NA*
Kenya	Taita	*NA*	*NA*
Kenya	Teso	*NA*	*NA*
Kenya	Turkana	Kalenjin-Masai-Turkana-Samburu	Senior partner
Liberia	Bassa	Indigenous Peoples	Discriminated
Liberia	Belle	Indigenous Peoples	Discriminated
Liberia	Dei	Indigenous Peoples	Discriminated
Liberia	English	*NA*	*NA*
Liberia	Gbandi	Indigenous Peoples	Discriminated
Liberia	Gio	Gio	Junior partner
Liberia	Gola	Indigenous Peoples	Discriminated
Liberia	Grebo	Indigenous Peoples	Discriminated
Liberia	Kissi	Indigenous Peoples	Discriminated
Liberia	Kpelle	Indigenous Peoples	Discriminated
Liberia	Krahn	Krahn (Guere)	Powerless
Liberia	Kru	Kru	Senior partner
Liberia	Lorma	Indigenous Peoples	Discriminated
Liberia	Mandingo	Mandingo	Powerless
Liberia	Mano	Mano	Junior partner
Liberia	Mende	Indigenous Peoples	Discriminated
Liberia	Vai	Mandingo	Powerless
Madagascar	Antakarana	Cotiers	Irrelevant
Madagascar	Antandroy	Cotiers	Irrelevant
Madagascar	Antanosy	Cotiers	Irrelevant
Madagascar	Antefasy	Highlanders	Irrelevant
Madagascar	Antembahoaka	Cotiers	Irrelevant
Madagascar	Antemoro	Highlanders	Irrelevant
Madagascar	Antesaka	Cotiers	Irrelevant
Madagascar	Bara	Cotiers	Irrelevant
Madagascar	Betsileo	Highlanders	Irrelevant
Madagascar	Betsimisaraka	Cotiers	Irrelevant
Madagascar	Bezanozano	Highlanders	Irrelevant
Madagascar	Mahafaly	Cotiers	Irrelevant
Madagascar	Masikoro	Cotiers	Irrelevant
Madagascar	Merina	Highlanders	Irrelevant
Madagascar	Sakalava	Cotiers	Irrelevant
Madagascar	Sihanaka	Highlanders	Irrelevant
Madagascar	Tanala	Highlanders	Irrelevant
Madagascar	Tsimihety	Cotiers	Irrelevant
Madagascar	Vezo	Cotiers	Irrelevant

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Malawi	Chewa	Central (Chewa)	Senior partner
Malawi	Khokhola	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Lambya	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Lomwe	Southerners (Lomwe, Mang'anja, Nyanja, Yao)	Junior partner
Malawi	Mang'anja	Southerners (Lomwe, Mang'anja, Nyanja, Yao)	Junior partner
Malawi	Ndali	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Ngoni	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Nkhonde	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Nyanja	Central (Chewa)	Senior partner
Malawi	Sena	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Senga	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Tonga	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Tumbuka	Northerners (Tumbuka, Tonga, Ngonde)	Junior partner
Malawi	Yao	Southerners (Lomwe, Mang'anja, Nyanja, Yao)	Junior partner
Mali	Arabic	Arabs/Moors	Junior partner
Mali	Bambara	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Bella	Tuareg	Junior partner
Mali	Bobo	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Bozo	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Dogon	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Haoussa	Arabs/Moors	Junior partner
Mali	Kakolo	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Khassonke	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Malinke	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Maure	Arabs/Moors	Junior partner
Mali	Minianka	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Mossi	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Peulh / Fulfude	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Samogo	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Senufo	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Soninke / Sarakolle	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Sonrhai	Blacks (Mande, Peul, Voltaic etc.)	Senior partner
Mali	Tamasheq	Tuareg	Junior partner
Mauritania	Maure	White Moors (Beydan)	Senior partner
Mauritania	Pular	Haratins (Black Moors)	Junior partner
Mauritania	Soninke	Black Africans	Powerless
Mauritania	Wolof	Black Africans	Powerless
Mauritius	Afro-Mauricien (Creole)	Creoles	Powerless
Mauritius	Chinois	*NA*	*NA*
Mauritius	Euro-Mauricien (Blanc)	*NA*	*NA*
Mauritius	Hindou	Hindi-speaking Hindus	Senior partner
Mauritius	Marathi	Marathis	Powerless
Mauritius	Musulman	Muslims	Junior partner
Mauritius	Tamoul	Tamils and Telugus	Powerless
Mauritius	Telegou	Tamils and Telugus	Powerless

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Morocco	Amazigh	Berbers	Powerless
Morocco	Arab	Arabs	Dominant
Morocco	Sahraoui	Sahrawis	Discriminated
Mozambique	Ajaua	Makonde-Yao	Senior partner
Mozambique	Bitonga	Tsonga-Chopi	Senior partner
Mozambique	Changana	Tsonga-Chopi	Senior partner
Mozambique	Chichewa	Shona-Ndau	Powerless
Mozambique	Chope	Tsonga-Chopi	Senior partner
Mozambique	Chuabo	Makonde-Yao	Senior partner
Mozambique	Cinyungwe	Shona-Ndau	Powerless
Mozambique	Ciyao	Makonde-Yao	Senior partner
Mozambique	Ekoti	Makonde-Yao	Senior partner
Mozambique	Kimwani	*NA*	*NA*
Mozambique	Lomue	Makonde-Yao	Senior partner
Mozambique	Lomwe	Makonde-Yao	Senior partner
Mozambique	Makonde	Makonde-Yao	Senior partner
Mozambique	Makua	Makonde-Yao	Senior partner
Mozambique	Manhaua	*NA*	*NA*
Mozambique	Matewe	*NA*	*NA*
Mozambique	Ndau	Shona-Ndau	Powerless
Mozambique	Nyanja	Shona-Ndau	Powerless
Mozambique	Portuguese	*NA*	*NA*
Mozambique	Sena	Shona-Ndau	Powerless
Mozambique	Shona	Shona-Ndau	Powerless
Mozambique	Xironga	*NA*	*NA*
Mozambique	Xitswa	Tsonga-Chopi	Senior partner
Namibia	Afrikaaner	Whites	Junior partner
Namibia	Baster	Baster	Powerless
Namibia	Caprivian	*NA*	*NA*
Namibia	Coloured	Coloreds	Junior partner
Namibia	Damara	Damara	Senior partner
Namibia	English	Whites	Junior partner
Namibia	German	Whites	Junior partner
Namibia	Herero	Herero, Mbanderu	Junior partner
Namibia	Kavango (Rukwangali/Rumanyo/Hambukushu)	Kavango	Junior partner
Namibia	Lozi	*NA*	*NA*
Namibia	Nama	Nama	Junior partner
Namibia	Portuguese	Whites	Junior partner
Namibia	San	*NA*	*NA*
Namibia	Subia	Basubia	Junior partner
Namibia	Tswana	*NA*	*NA*
Namibia	Wambo	Ovambo	Senior partner
Niger	Arabe	Tuareg	Junior partner
Niger	Haoussa	Hausa	Senior partner
Niger	Kanouri	Kanouri	Junior partner

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Niger	Peulh	*NA*	*NA*
Niger	Tamasheq	Tuareg	Junior partner
Niger	Toubou	Toubou	Powerless
Niger	Zarma/Songhay	Djerma-Songhai	Junior partner
Nigeria	Bade	*NA*	*NA*
Nigeria	Bassa	*NA*	*NA*
Nigeria	Bette	*NA*	*NA*
Nigeria	Birom	*NA*	*NA*
Nigeria	Bura	*NA*	*NA*
Nigeria	Ebira	*NA*	*NA*
Nigeria	Edo	*NA*	*NA*
Nigeria	Efik	Ogoni	Powerless
Nigeria	Etulo	*NA*	*NA*
Nigeria	Fulani	*NA*	*NA*
Nigeria	Gwari	*NA*	*NA*
Nigeria	Hausa	Hausa-Fulani and Muslim Middle Belt	Senior partner
Nigeria	Ibibio	Ogoni	Powerless
Nigeria	Idoma	*NA*	*NA*
Nigeria	Igala	Yoruba	Junior partner
Nigeria	Igbo	Igbo	Junior partner
Nigeria	Ijaw	Ijaw	Powerless
Nigeria	Ikwere	Igbo	Junior partner
Nigeria	Isoko	*NA*	*NA*
Nigeria	Jibu	*NA*	*NA*
Nigeria	Jukun	*NA*	*NA*
Nigeria	Kalabari	Ijaw	Powerless
Nigeria	Kanuri	*NA*	*NA*
Nigeria	Nupe	*NA*	*NA*
Nigeria	Oron	*NA*	*NA*
Nigeria	Tarok	*NA*	*NA*
Nigeria	Tiv	Tiv	Powerless
Nigeria	Urhobo	*NA*	*NA*
Nigeria	Yoruba	Yoruba	Junior partner
Senegal	Bainouk	*NA*	*NA*
Senegal	Diola	Diola	Junior partner
Senegal	Mandinka/Bambara	Mandingue (and other eastern groups)	Junior partner
Senegal	Manjack	Diola	Junior partner
Senegal	Pulaar/Toucouleur	Pulaar (Peul, Toucouleur)	Senior partner
Senegal	Serer	Serer	Junior partner
Senegal	Soninke	Mandingue (and other eastern groups)	Junior partner
Senegal	Wolof	Wolof	Junior partner
Sierra Leone	Fullah	Limba	Junior partner
Sierra Leone	Kissi	Temne	Junior partner
Sierra Leone	Kono	Kono	Junior partner
Sierra Leone	Koranko	Mende	Senior partner
Sierra Leone	Krio	Creole	Irrelevant

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Sierra Leone	Limba	Limba	Junior partner
Sierra Leone	Loko	Mende	Senior partner
Sierra Leone	Madingo	Kono	Junior partner
Sierra Leone	Mende	Mende	Senior partner
Sierra Leone	Sherbro	Temne	Junior partner
Sierra Leone	Susu	Kono	Junior partner
Sierra Leone	Themne	Temne	Junior partner
Sierra Leone	Yalunka	Mende	Senior partner
South Africa	Afrikaans/ Afrikaner / Boer	Afrikaners	Senior partner
South Africa	Coloured	Coloreds	Senior partner
South Africa	English	English	Senior partner
South Africa	Indian	Asians	Senior partner
South Africa	Ndebele	Ndebele	Senior partner
South Africa	Pedi/North Sotho	Pedi (North Sotho)	Senior partner
South Africa	Shangaan/Tsonga	Tsonga	Senior partner
South Africa	Sotho/South Sotho	South Sotho	Senior partner
South Africa	Swazi	Swazi	Senior partner
South Africa	Tswana	Tswana	Senior partner
South Africa	Venda	Venda	Senior partner
South Africa	White / European	English	Senior partner
South Africa	Xhosa	Xhosa	Senior partner
South Africa	Zulu	Zulu	Senior partner
Tanzania	Chaga	Mainland Muslims	Junior partner
Tanzania	Digo	Mainland Africans	Dominant
Tanzania	Fipa	Mainland Africans	Dominant
Tanzania	Gogo	Mainland Africans	Dominant
Tanzania	Haya	Mainland Africans	Dominant
Tanzania	Hehe	Mainland Africans	Dominant
Tanzania	Iraki	Zanzibar Arabs	Powerless
Tanzania	Kurya	Mainland Africans	Dominant
Tanzania	Kwere	Mainland Africans	Dominant
Tanzania	Luguru	Mainland Africans	Dominant
Tanzania	Makonde	Mainland Africans	Dominant
Tanzania	Manyema	Mainland Africans	Dominant
Tanzania	Masai	Maasai	Powerless
Tanzania	Mbena	Mainland Africans	Dominant
Tanzania	Mbugwe	Mainland Africans	Dominant
Tanzania	Meru	Mainland Africans	Dominant
Tanzania	Mjaruo	Mainland Africans	Dominant
Tanzania	Mjita	Mainland Africans	Dominant
Tanzania	Mkaguru	Mainland Africans	Dominant
Tanzania	Mkerewe	Shirazi (Zanzibar Africans)	Powerless
Tanzania	Mkinga	Mainland Africans	Dominant
Tanzania	Mmakuwa	Mainland Africans	Dominant
Tanzania	Mndendeule	Mainland Africans	Dominant
Tanzania	Mnyambo	Mainland Africans	Dominant
Tanzania	Mpemba	Mainland Africans	Dominant

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Tanzania	Mpogoro	Mainland Africans	Dominant
Tanzania	Mrangi	Mainland Africans	Dominant
Tanzania	Msambaa	Mainland Africans	Dominant
Tanzania	Msandawe	Mainland Africans	Dominant
Tanzania	Mshirazi	Shirazi (Zanzibar Africans)	Powerless
Tanzania	Mshubi	*NA*	*NA*
Tanzania	Mtumbatu	Shirazi (Zanzibar Africans)	Powerless
Tanzania	Muha	Mainland Africans	Dominant
Tanzania	Mwera	Mainland Africans	Dominant
Tanzania	Myao	Mainland Muslims	Junior partner
Tanzania	Mzanzibar	Shirazi (Zanzibar Africans)	Powerless
Tanzania	Mzaramo	Mainland Muslims	Junior partner
Tanzania	Mzigua	Mainland Muslims	Junior partner
Tanzania	Ndali	Shirazi (Zanzibar Africans)	Powerless
Tanzania	Ndengereko	Mainland Muslims	Junior partner
Tanzania	Ngindo	Mainland Muslims	Junior partner
Tanzania	Ngoni	Mainland Muslims	Junior partner
Tanzania	Nguu	Mainland Muslims	Junior partner
Tanzania	Nyakyusa	Mainland Africans	Dominant
Tanzania	Nyamwezi	Mainland Africans	Dominant
Tanzania	Nyaturu	Mainland Africans	Dominant
Tanzania	Nyika	Mainland Africans	Dominant
Tanzania	Nyiramba	Mainland Muslims	Junior partner
Tanzania	Pare	Mainland Africans	Dominant
Tanzania	Safwa	Mainland Africans	Dominant
Tanzania	Sukuma	Mainland Africans	Dominant
Togo	Adja	Ewe (and related groups)	Powerless
Togo	Akebou	Ewe (and related groups)	Powerless
Togo	Ben, Moba	Kabre (and related groups)	Dominant
Togo	Ewe	Ewe (and related groups)	Powerless
Togo	Fon	Ewe (and related groups)	Powerless
Togo	Gourma	Kabre (and related groups)	Dominant
Togo	Haoussa	*NA*	*NA*
Togo	Ife, Ana	Ewe (and related groups)	Powerless
Togo	Ikposso, Akposso	Ewe (and related groups)	Powerless
Togo	Kabye	Kabre (and related groups)	Dominant
Togo	Konkomba	Kabre (and related groups)	Dominant
Togo	Lama, Lamba	Kabre (and related groups)	Dominant
Togo	Mina, Guen	Ewe (and related groups)	Powerless
Togo	N'Tcha, Bassar	Kabre (and related groups)	Dominant
Togo	Nawdem, Losso	Kabre (and related groups)	Dominant
Togo	Ngam-Gam	Kabre (and related groups)	Dominant
Togo	Ouatchi	Ewe (and related groups)	Powerless
Togo	Tchamba	Kabre (and related groups)	Dominant
Togo	Tchokossi, Anoufom	Ewe (and related groups)	Powerless
Togo	Tem, Kotokoli	Kabre (and related groups)	Dominant
Uganda	Acholi	Langi/Acholi	Powerless

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Uganda	Alur	Far North-West Nile (Kakwa-Nubian, Madi, Lugbara, Alur)	Irrelevant
Uganda	Ateso	Teso	Powerless
Uganda	Japhadhola	Langi/Acholi	Powerless
Uganda	Kakwa	Far North-West Nile (Kakwa-Nubian, Madi, Lugbara, Alur)	Irrelevant
Uganda	Karamajong	Karamojong	Irrelevant
Uganda	Kumam	Langi/Acholi	Powerless
Uganda	Langi	Langi/Acholi	Powerless
Uganda	Lugbara	Far North-West Nile (Kakwa-Nubian, Madi, Lugbara, Alur)	Irrelevant
Uganda	Madi	Far North-West Nile (Kakwa-Nubian, Madi, Lugbara, Alur)	Irrelevant
Uganda	Mufumbira	Banyarwanda	Discriminated
Uganda	Muganda	Baganda	Junior partner
Uganda	Mugishu	*NA*	*NA*
Uganda	Mugwere	*NA*	*NA*
Uganda	Mukhonzo	*NA*	*NA*
Uganda	Mukiga	South-Westerners (Ankole, Banyoro, Toro)	Senior partner
Uganda	Munyankole	South-Westerners (Ankole, Banyoro, Toro)	Senior partner
Uganda	Munyarwanda	Banyarwanda	Discriminated
Uganda	Munyole	*NA*	*NA*
Uganda	Munyoro	South-Westerners (Ankole, Banyoro, Toro)	Senior partner
Uganda	Musamia	*NA*	*NA*
Uganda	Musoga	Basoga	Junior partner
Uganda	Mutooro	South-Westerners (Ankole, Banyoro, Toro)	Senior partner
Uganda	Sabini	Far North-West Nile (Kakwa-Nubian, Madi, Lugbara, Alur)	Irrelevant
Zambia	Bemba	Bemba speakers	Senior partner
Zambia	Bisa	Bemba speakers	Senior partner
Zambia	Bwile	*NA*	*NA*
Zambia	Chewa	Nyanja speakers (Easterners)	Senior partner
Zambia	Chishinga	*NA*	*NA*
Zambia	Chokwe	Luvale (NW Province)	Junior partner
Zambia	Ila	Tonga-Ila-Lenje (Southerners)	Powerless
Zambia	Kaonde	Kaonde (NW Province)	Junior partner
Zambia	Kunda	Nyanja speakers (Easterners)	Senior partner
Zambia	Lala	Bemba speakers	Senior partner
Zambia	Lamba	Bemba speakers	Senior partner
Zambia	Lenje	Tonga-Ila-Lenje (Southerners)	Powerless
Zambia	Lozi	Lozi (Barotse)	Junior partner
Zambia	Lunda	Luanda (NW Province)	Junior partner
Zambia	Lungu	*NA*	*NA*
Zambia	Luvale	Luvale (NW Province)	Junior partner
Zambia	Mambwe	*NA*	*NA*
Zambia	Mbunda	Luvale (NW Province)	Junior partner
Zambia	Namwanga	Bemba speakers	Senior partner
Zambia	Ngoni	Nyanja speakers (Easterners)	Senior partner
Zambia	Ngumbo	Bemba speakers	Senior partner
Zambia	Nkoya	Kaonde (NW Province)	Junior partner
Zambia	Nsenga	Nyanja speakers (Easterners)	Senior partner
Zambia	Nyanja	Nyanja speakers (Easterners)	Senior partner
Zambia	Nyika	Bemba speakers	Senior partner

(continued)

Country	Afrobarometer label	EPR label	EPR group power status
Zambia	Senga	Bemba speakers	Senior partner
Zambia	Soli	Tonga-Ila-Lenje (Southerners)	Powerless
Zambia	Tabwa	Bemba speakers	Senior partner
Zambia	Tokaleya	Tonga-Ila-Lenje (Southerners)	Powerless
Zambia	Tonga	Tonga-Ila-Lenje (Southerners)	Powerless
Zambia	Tumbuka	Nyanja speakers (Easterners)	Senior partner
Zambia	Ushi	Bemba speakers	Senior partner
Zimbabwe	Kalanga	Ndebele-Kalanga-(Tonga)	Junior partner
Zimbabwe	Karanga	Shona	Senior partner
Zimbabwe	Korekore	Shona	Senior partner
Zimbabwe	Manyika	Shona	Senior partner
Zimbabwe	Ndau	Shona	Senior partner
Zimbabwe	Ndebele	Ndebele-Kalanga-(Tonga)	Junior partner
Zimbabwe	Shona	Shona	Senior partner
Zimbabwe	Tonga	Ndebele-Kalanga-(Tonga)	Junior partner
Zimbabwe	Venda	*NA*	*NA*
Zimbabwe	Zezuru	Shona	Senior partner

C Alternative measures

There is an extensive literature on measuring polarization, fractionalization, diversity, and other concepts similar to dissensus (e.g., Esteban and Debraj 1994; Desmet et al. 2009; Huber 2012). As Desmet et al. (2009) show, many of the most commonly used measures can be written as weighted sums of the pairwise distances between group means. They are therefore very similar to the mean absolute difference and other measures of statistical dispersion, such as the variance. (If there are G groups and $\bar{y}_g$ is the mean of y in group g, then the mean absolute difference is $\frac{1}{G^2}\sum_{ig=1}^{G}\sum_{ik=1}^{G}|\bar{y}_g - \bar{y}_k|$. The variance can be written analogously as $\frac{1}{2G^2}\sum_{ig=1}^{G}\sum_{ik=1}^{G}(\bar{y}_g - \bar{y}_k)^2$.) This gives them an intuitive interpretation along the lines of, "What is the typical distance between two groups?" This interpretation also points to a crucial limitation of these measures: their sensitivity to scale. Due to this sensitivity, estimates cannot be compared across survey items with different scales unless the distances are standardized in some way. Desmet et al. (2009, 1294) solve this comparability problem by assuming that the pairwise distances are standardized to lie between 0 and 1. This limitation is not a problem for Huber (2012) because his focus is vote share, which naturally ranges from 0 to 1.

D Model details

The analyses reported in this paper are based on 99 fitted models (9 specifications for each of the 11 survey items). We fit the models with the R package **brms** (Bürkner 2017), which relies on **cmdstanr** (Gabry et al. 2024) to sample from the posterior distribution using Hamiltonian Monte Carlo (HMC). We ran 4 chains with 2,000 iterations each, the first 1,000 being warmup draws. The average model run took 2.6 hours; the longest took 17.5 hours.

Some of the more complicated models proved challenging to fit, and we had to refit them multiple times to achieve satisfactory convergence. Four of the 99 models exhibited divergent transitions—an indication of poor sampling behavior—in a subset of chains. We dropped these chains from the analysis, with the result that one model had only two usable chains and three models had only one. Convergence diagnostics (Vehtari et al. 2021) for the remaining (non-divergent) chains were generally good but not perfect. All fits had a median $\hat{R}$ below 1.1, and 83% had a maximum $\hat{R}$ below 1.2. Across all fits and parameters, the largest $\hat{R}$ value was 1.6. Trace plots did not reveal major mixing or convergence problems in the non-divergent chains (see Figure D.1 for a random sample of trace plots).

To ease the computational burden of analyzing the Monte Carlo draws, we randomly subsampled 500 draws for each model (from the non-divergent chains). We based our analyses on these subsampled draws.

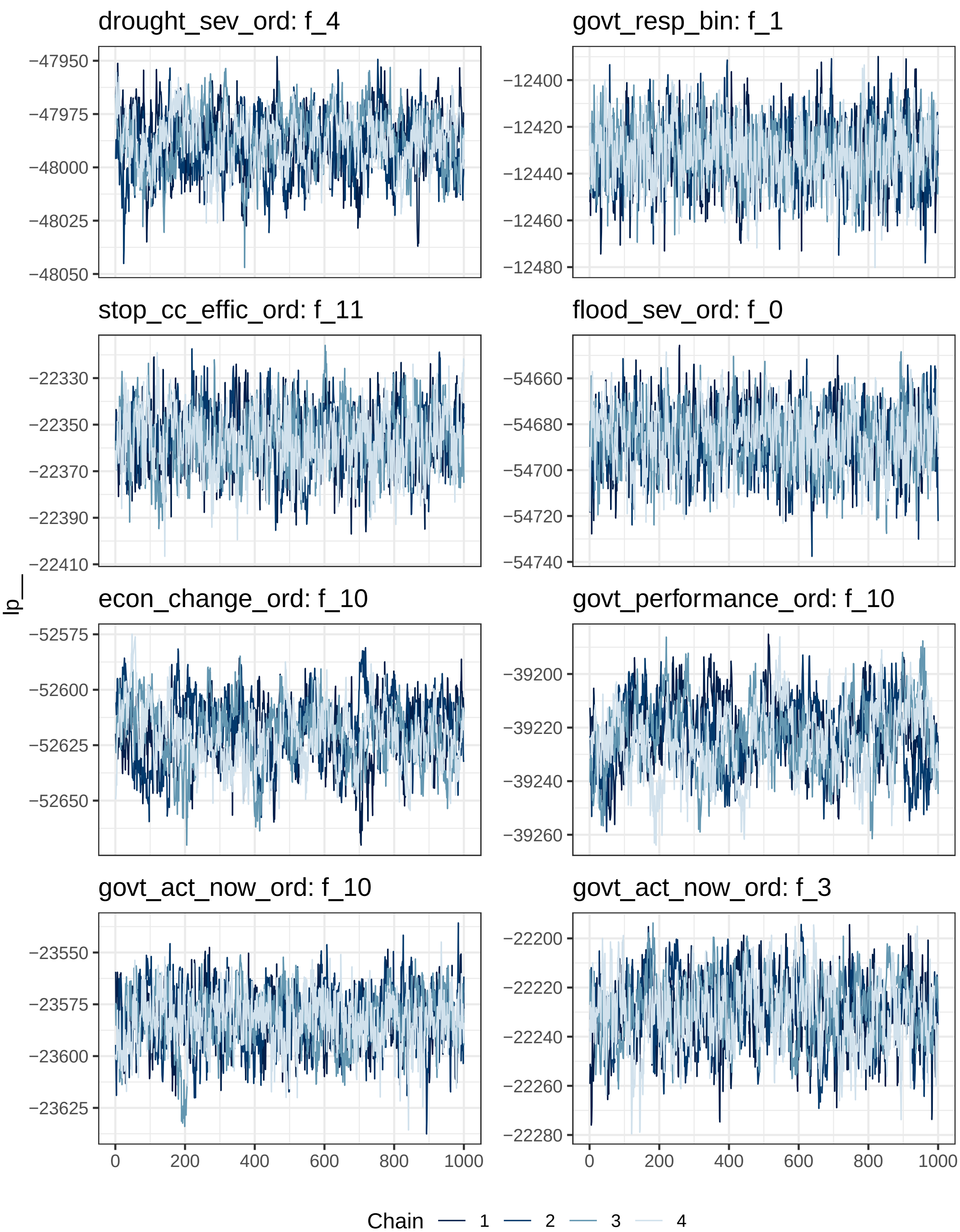

Figure D.1: Trace plots of the log posterior density (`lp__`) for eight randomly sampled models

E Additional analyses

Table E.1: Associations between climate attitudes and agro-ecological zone (AEZ), as estimated by the model described in Section 5.3.1 of the main text. The "Estimate" column contains each zone's probit regression coefficient estimate (posterior mean ± standard deviation). The omitted category is "Tropic - warm / subhumid", which has the largest number of respondents. The estimates for "Subtropic - warm / humid" are unreliable because this category contains only 11 respondents, most of whose responses are missing.

AEZ	Item	Item Type	Estimate	$p < 0.1$
Subtropic - cool / arid	Heard About	Literacy	$-6.9 \times 10^{-2} \pm 0.176$	No
Subtropic - cool / semiarid	Heard About	Literacy	$-5.4 \times 10^{-2} \pm 0.111$	No
Subtropic - cool / subhumid	Heard About	Literacy	$-2.7 \times 10^{-1} \pm 0.219$	No
Subtropic - warm / arid	Heard About	Literacy	$2.4 \times 10^{-1} \pm 0.159$	No
Subtropic - warm / humid	Heard About	Literacy	$9.8 \times 10^{-3} \pm 0.459$	No
Subtropic - warm / semiarid	Heard About	Literacy	$1.6 \times 10^{-1} \pm 0.137$	No
Subtropic - warm / subhumid	Heard About	Literacy	$-7.9 \times 10^{-3} \pm 0.132$	No
Tropic - cool / arid	Heard About	Literacy	$-8.0 \times 10^{-1} \pm 0.253$	Yes
Tropic - cool / humid	Heard About	Literacy	$1.7 \times 10^{-2} \pm 0.073$	No
Tropic - cool / semiarid	Heard About	Literacy	$-1.2 \times 10^{-2} \pm 0.066$	No
Tropic - cool / subhumid	Heard About	Literacy	$-5.8 \times 10^{-2} \pm 0.058$	No
Tropic - warm / arid	Heard About	Literacy	$-9.8 \times 10^{-2} \pm 0.095$	No
Tropic - warm / humid	Heard About	Literacy	$-3.0 \times 10^{-2} \pm 0.051$	No
Tropic - warm / semiarid	Heard About	Literacy	$1.9 \times 10^{-3} \pm 0.052$	No
Subtropic - cool / arid	Drought Change	Perception	$2.1 \times 10^{-2} \pm 0.154$	No
Subtropic - cool / semiarid	Drought Change	Perception	$2.1 \times 10^{-1} \pm 0.094$	Yes
Subtropic - cool / subhumid	Drought Change	Perception	$-3.5 \times 10^{-2} \pm 0.185$	No
Subtropic - warm / arid	Drought Change	Perception	$-2.5 \times 10^{-1} \pm 0.141$	Yes
Subtropic - warm / humid	Drought Change	Perception	$-4.7 \times 10^{-2} \pm 0.349$	No
Subtropic - warm / semiarid	Drought Change	Perception	$-2.2 \times 10^{-1} \pm 0.129$	Yes
Subtropic - warm / subhumid	Drought Change	Perception	$-3.6 \times 10^{-2} \pm 0.112$	No
Tropic - cool / arid	Drought Change	Perception	$2.8 \times 10^{-1} \pm 0.196$	No
Tropic - cool / humid	Drought Change	Perception	$-2.3 \times 10^{-1} \pm 0.069$	Yes
Tropic - cool / semiarid	Drought Change	Perception	$3.9 \times 10^{-2} \pm 0.057$	No
Tropic - cool / subhumid	Drought Change	Perception	$-8.5 \times 10^{-2} \pm 0.052$	No
Tropic - warm / arid	Drought Change	Perception	$1.5 \times 10^{-1} \pm 0.097$	No
Tropic - warm / humid	Drought Change	Perception	$6.6 \times 10^{-2} \pm 0.050$	No
Tropic - warm / semiarid	Drought Change	Perception	$1.0 \times 10^{-1} \pm 0.047$	Yes
Subtropic - cool / arid	Flood Change	Perception	$-2.2 \times 10^{-2} \pm 0.173$	No
Subtropic - cool / semiarid	Flood Change	Perception	$-4.5 \times 10^{-2} \pm 0.101$	No
Subtropic - cool / subhumid	Flood Change	Perception	$1.2 \times 10^{-1} \pm 0.182$	No
Subtropic - warm / arid	Flood Change	Perception	$-1.7 \times 10^{-1} \pm 0.157$	No
Subtropic - warm / humid	Flood Change	Perception	$1.9 \times 10^{-1} \pm 0.371$	No

Subtropic - warm / semiarid	Flood Change	Perception	$-1.2 \times 10^{-1} \pm 0.139$	No
Subtropic - warm / subhumid	Flood Change	Perception	$-2.6 \times 10^{-3} \pm 0.121$	No
Tropic - cool / arid	Flood Change	Perception	$-1.8 \times 10^{-2} \pm 0.221$	No
Tropic - cool / humid	Flood Change	Perception	$3.4 \times 10^{-2} \pm 0.068$	No
Tropic - cool / semiarid	Flood Change	Perception	$4.6 \times 10^{-4} \pm 0.059$	No
Tropic - cool / subhumid	Flood Change	Perception	$-1.1 \times 10^{-1} \pm 0.056$	Yes
Tropic - warm / arid	Flood Change	Perception	$-1.7 \times 10^{-2} \pm 0.095$	No
Tropic - warm / humid	Flood Change	Perception	$8.9 \times 10^{-2} \pm 0.045$	Yes
Tropic - warm / semiarid	Flood Change	Perception	$8.6 \times 10^{-2} \pm 0.047$	Yes
Subtropic - cool / arid	National Effect	Perception	$-2.5 \times 10^{-1} \pm 0.230$	No
Subtropic - cool / semiarid	National Effect	Perception	$9.1 \times 10^{-2} \pm 0.128$	No
Subtropic - cool / subhumid	National Effect	Perception	$3.2 \times 10^{-1} \pm 0.307$	No
Subtropic - warm / arid	National Effect	Perception	$2.8 \times 10^{-1} \pm 0.167$	No
Subtropic - warm / humid	National Effect	Perception	$-4.5 \times 10^{-1} \pm 0.649$	No
Subtropic - warm / semiarid	National Effect	Perception	$3.3 \times 10^{-1} \pm 0.164$	Yes
Subtropic - warm / subhumid	National Effect	Perception	$1.4 \times 10^{-1} \pm 0.156$	No
Tropic - cool / arid	National Effect	Perception	$-2.6 \times 10^{-1} \pm 0.341$	No
Tropic - cool / humid	National Effect	Perception	$6.4 \times 10^{-2} \pm 0.079$	No
Tropic - cool / semiarid	National Effect	Perception	$6.4 \times 10^{-2} \pm 0.073$	No
Tropic - cool / subhumid	National Effect	Perception	$1.3 \times 10^{-1} \pm 0.070$	Yes
Tropic - warm / arid	National Effect	Perception	$2.9 \times 10^{-2} \pm 0.105$	No
Tropic - warm / humid	National Effect	Perception	$4.1 \times 10^{-2} \pm 0.057$	No
Tropic - warm / semiarid	National Effect	Perception	$7.1 \times 10^{-2} \pm 0.055$	No
Subtropic - cool / arid	Citizen Efficacy	Action	$-1.7 \times 10^{-1} \pm 0.221$	No
Subtropic - cool / semiarid	Citizen Efficacy	Action	$4.1 \times 10^{-2} \pm 0.131$	No
Subtropic - cool / subhumid	Citizen Efficacy	Action	$4.2 \times 10^{-1} \pm 0.300$	No
Subtropic - warm / arid	Citizen Efficacy	Action	$-1.7 \times 10^{-1} \pm 0.156$	No
Subtropic - warm / humid	Citizen Efficacy	Action	$2.2 \times 10^{3} \pm 2055.221$	Yes
Subtropic - warm / semiarid	Citizen Efficacy	Action	$-9.9 \times 10^{-2} \pm 0.159$	No
Subtropic - warm / subhumid	Citizen Efficacy	Action	$-2.7 \times 10^{-2} \pm 0.155$	No
Tropic - cool / arid	Citizen Efficacy	Action	$-2.1 \times 10^{-2} \pm 0.352$	No
Tropic - cool / humid	Citizen Efficacy	Action	$1.5 \times 10^{-1} \pm 0.077$	Yes
Tropic - cool / semiarid	Citizen Efficacy	Action	$9.0 \times 10^{-3} \pm 0.071$	No
Tropic - cool / subhumid	Citizen Efficacy	Action	$6.7 \times 10^{-2} \pm 0.070$	No
Tropic - warm / arid	Citizen Efficacy	Action	$-1.9 \times 10^{-1} \pm 0.096$	Yes
Tropic - warm / humid	Citizen Efficacy	Action	$-7.8 \times 10^{-2} \pm 0.053$	No
Tropic - warm / semiarid	Citizen Efficacy	Action	$-6.9 \times 10^{-2} \pm 0.052$	No
Subtropic - cool / arid	Climate Performance	Action	$-1.9 \times 10^{-2} \pm 0.171$	No
Subtropic - cool / semiarid	Climate Performance	Action	$-9.6 \times 10^{-3} \pm 0.102$	No
Subtropic - cool / subhumid	Climate Performance	Action	$-1.7 \times 10^{-1} \pm 0.185$	No
Subtropic - warm / arid	Climate Performance	Action	$-3.4 \times 10^{-1} \pm 0.140$	Yes
Subtropic - warm / humid	Climate Performance	Action	$-8.3 \times 10^{-1} \pm 0.374$	Yes

Subtropic - warm / semiarid	Climate Performance	Action	$-1.7 \times 10^{-1} \pm 0.125$	No
Subtropic - warm / subhumid	Climate Performance	Action	$4.9 \times 10^{-2} \pm 0.121$	No
Tropic - cool / arid	Climate Performance	Action	$-3.5 \times 10^{-2} \pm 0.207$	No
Tropic - cool / humid	Climate Performance	Action	$-1.1 \times 10^{-1} \pm 0.063$	Yes
Tropic - cool / semiarid	Climate Performance	Action	$-1.3 \times 10^{-1} \pm 0.061$	Yes
Tropic - cool / subhumid	Climate Performance	Action	$-6.3 \times 10^{-2} \pm 0.050$	No
Tropic - warm / arid	Climate Performance	Action	$9.1 \times 10^{-2} \pm 0.089$	No
Tropic - warm / humid	Climate Performance	Action	$5.6 \times 10^{-4} \pm 0.048$	No
Tropic - warm / semiarid	Climate Performance	Action	$-6.4 \times 10^{-2} \pm 0.047$	No
Subtropic - cool / arid	Gov't Act Now	Action	$-2.9 \times 10^{-1} \pm 0.199$	No
Subtropic - cool / semiarid	Gov't Act Now	Action	$1.7 \times 10^{-1} \pm 0.119$	No
Subtropic - cool / subhumid	Gov't Act Now	Action	$1.6 \times 10^{-1} \pm 0.266$	No
Subtropic - warm / arid	Gov't Act Now	Action	$-9.6 \times 10^{-2} \pm 0.165$	No
Subtropic - warm / humid	Gov't Act Now	Action	$1.8 \times 10^{4} \pm 15\,705.034$	Yes
Subtropic - warm / semiarid	Gov't Act Now	Action	$2.3 \times 10^{-2} \pm 0.141$	No
Subtropic - warm / subhumid	Gov't Act Now	Action	$-1.9 \times 10^{-1} \pm 0.134$	No
Tropic - cool / arid	Gov't Act Now	Action	$3.0 \times 10^{-1} \pm 0.351$	No
Tropic - cool / humid	Gov't Act Now	Action	$4.0 \times 10^{-2} \pm 0.073$	No
Tropic - cool / semiarid	Gov't Act Now	Action	$3.8 \times 10^{-2} \pm 0.065$	No
Tropic - cool / subhumid	Gov't Act Now	Action	$5.2 \times 10^{-3} \pm 0.065$	No
Tropic - warm / arid	Gov't Act Now	Action	$-8.5 \times 10^{-2} \pm 0.100$	No
Tropic - warm / humid	Gov't Act Now	Action	$-1.0 \times 10^{-1} \pm 0.052$	Yes
Tropic - warm / semiarid	Gov't Act Now	Action	$3.5 \times 10^{-2} \pm 0.047$	No
Subtropic - cool / arid	Gov't Responsibility	Action	$1.2 \times 10^{-1} \pm 0.233$	No
Subtropic - cool / semiarid	Gov't Responsibility	Action	$6.6 \times 10^{-2} \pm 0.135$	No
Subtropic - cool / subhumid	Gov't Responsibility	Action	$4.9 \times 10^{-1} \pm 0.330$	No
Subtropic - warm / arid	Gov't Responsibility	Action	$-3.2 \times 10^{-3} \pm 0.170$	No
Subtropic - warm / humid	Gov't Responsibility	Action	$2.3 \times 10^{-1} \pm 0.758$	No
Subtropic - warm / semiarid	Gov't Responsibility	Action	$3.1 \times 10^{-1} \pm 0.172$	No
Subtropic - warm / subhumid	Gov't Responsibility	Action	$2.6 \times 10^{-1} \pm 0.163$	No
Tropic - cool / arid	Gov't Responsibility	Action	$-2.6 \times 10^{-1} \pm 0.436$	No
Tropic - cool / humid	Gov't Responsibility	Action	$1.4 \times 10^{-2} \pm 0.076$	No
Tropic - cool / semiarid	Gov't Responsibility	Action	$1.4 \times 10^{-2} \pm 0.072$	No
Tropic - cool / subhumid	Gov't Responsibility	Action	$7.2 \times 10^{-2} \pm 0.069$	No
Tropic - warm / arid	Gov't Responsibility	Action	$-8.8 \times 10^{-2} \pm 0.117$	No
Tropic - warm / humid	Gov't Responsibility	Action	$8.9 \times 10^{-2} \pm 0.057$	No
Tropic - warm / semiarid	Gov't Responsibility	Action	$1.2 \times 10^{-3} \pm 0.057$	No

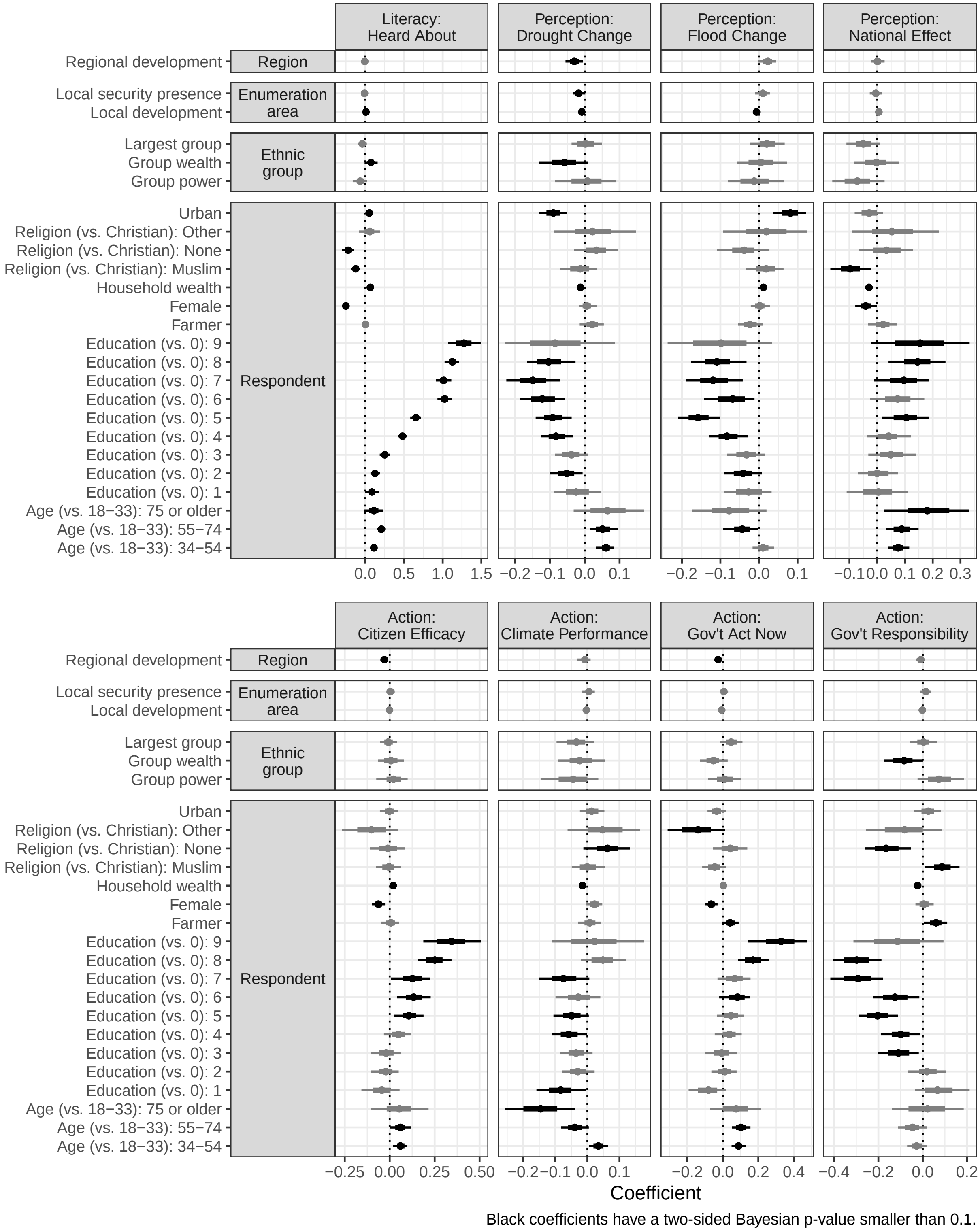

Figure E.1: Correlates of climate attitudes, separately by item