Supplementary Material

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A Approaches to modeling ethnic voting

The following section contains formalized descriptions of modeling approaches to ethnic voting in existing work which we compare to the CVR. In the next section, we demonstrate how different approaches suffer from different biases with the help of Monte Carlo simulations.

A.1 Ethnic Voting as Voter-Candidate/Party Identity Correspondence

Assume a setting with two parties P (A, B) and two ethnic groups G (a, b). Party A runs candidates from group a and party B fields candidates from group b (descriptive representation). Alternatively, parties A and B represent groups a and b respectively without fielding candidates of this ethnicity (substantive representation).

More generally, the predominant empirical approach assumes that any voter i receives positive utility from voting for a party $p_i \in P$ that represents their group identity. Based on data on the set of parties $P_G \subset P$ that represent a given group $g \in G$, the probability of ethnic voting EV in this approach is:

$$Pr(EV) = 1/N \sum_i Pr(p_i \in P_{g_i}|g_i) = 1 - 1/N \sum_i Pr(p_i \notin P_{g_i}|g_i) \qquad \text{(A1)}$$

Importantly, to assess Eq. A1, it is necessary for researchers to specify the mapping between groups G and parties (or candidates) P. The choices in this regard are shaped by important conceptual differences in approaches to ethnic voting. Huber (2012) distinguishes between a *group-based* perspective on ethnic voting and a *party-based* view. The former focuses on the degree to which each group votes homogeneously, suggesting few or only one party in each P_G while not paying attention to any overlap between subsets. The latter, in turn, recognizes high levels of ethnic voting if all voters of a given party or candidate come from one group, thus letting party sets P_G to be disjoint subsets of P.

In practice, the predominant approach of using voter-candidate coethnicity to operationalize ethnic voting falls into the party-based approach as each candidate is clearly attributed to only one group.[1] Empirical analyses of ethnic voting that rely on the voter-party correspondence approach thus reach the maximum estimate if all voters from one party come from one ethnic group, i.e., they rely on the party-based approach to ethnic voting. Specifically, they estimate lower levels of ethnic voting if a party draws support from multiple ethnic groups, even if all members of each group support the party. This is directly related to the selection biases highlighted by Ferree (2022) in cases where for some groups g P_g is an empty set or encompasses the full set P.

A.2 Ethnic Voting as Coethnic Covoting

The covoting approach abstracts away from candidate/party identities or claims regarding group representation, and recasts ethnic voting as the tendency of voters

[1] Taking into account candidates' multiple identities could mitigate this slightly.

from the same group to vote for the same party. The probability of ethnic covoting (ECV) can be written as:

$$\begin{aligned} Pr(ECV) =& \frac{1}{N(N-1)} \sum_{ij, i \neq j} Pr(p_i = p_j | g_i = g_j) + \\ & Pr(p_i \neq p_j | g_i \neq g_j) \\ =& 1 - \sum_{ij} Pr(p_i \neq p_j | g_i = g_j) - \\ & Pr(p_i = p_j | g_i \neq g_j) \end{aligned} \tag{A2}$$

As a result, $Pr(ECV)$ is driven by both logics of ethnic voting. It increases as more coethnics vote for the same party (group-based logic) and as fewer non-coethnics find themselves voting together, which makes parties' more ethnically homogeneous (party-based logic).

More formally, we can use the main formulation of the CVR to derive two measures that directly reflect the group- and party-based logics of ethnic voting. First, we can compute the share of covoters among coethnics: If high, in particular high relative to the share of covoters among non-coethnics,[2] groups vote as blocks and Huber's group-based voting fractionalization (GVF) is high. The measure can be computed directly on the basis of the CVR as defined in Eq. (6):

$$\begin{aligned} Pr(\mathsf{covoting} \,|\, \mathsf{coethnicity} = 1) &= \beta_0 + \beta_1 + \gamma \bar{\mathbf{x}} \\ Pr(\mathsf{covoting} \,|\, \mathsf{coethnicity} = 0) &= \beta_0 + \gamma \bar{\mathbf{x}} \end{aligned} \tag{A3}$$

Following the party-based logic, we can compute the share of coethnics among covoters. If high, in particular if high relative the share of coethnics among those who do not covote,[3] parties feature ethnically homogeneous constituencies and Huber's party-based vote fractionalization (PVF) is high. Again, we can compute the measure directly from our model by scaling the previous concept by the relative rate of coethnicity compared to covoting:

$$\begin{aligned} Pr(\mathsf{coethnicity} \,|\, \mathsf{covoting} = 1) &= \frac{\overline{\mathsf{coethnicity}}}{\overline{\mathsf{covoting}}} \; (\beta_0 + \beta_1 + \gamma \bar{\mathbf{x}}) \\ Pr(\mathsf{coethnicity} \,|\, \mathsf{covoting} = 0) &= \frac{\overline{\mathsf{coethnicity}}}{1 - \overline{\mathsf{covoting}}} \; (1 - (\beta_0 + \beta_1 + \gamma \bar{\mathbf{x}})) \end{aligned} \tag{A4}$$

We illustrate the usefulness of the group- and party-based reformulation of the effect of coethnicity on covoting retrieved from a CVR.

Scenario I: A situation in which four groups (size .25 each) vote as blocks first for one party, and then for two parties (Figure A1). The CVR regression coefficient for coethnicity is 0 in the first situation as coethnics do not covote more than non-coethnics, but increases to .667 in the second situation where coethnics pairs covote

[2] This relative expression, e.g., through a ratio, is necessary to account for the base rate of covoting.

[3] This relative expression, e.g., through a ratio, is necessary to account for the base rate of coethnicity.

Situation 1

	Groups			
	A	B	C	D
Party 1	1	1	1	1

$\Longrightarrow$

Situation 2

	Groups			
	A	B	C	D
Party 1	1	1	0	0
Party 2	0	0	1	1

Figure A1: Scenario I

Situation 1

	Groups	
	A	B
Party 1	1	0
Party 2	0	0.5
Party 3	0	0.5

$\Longrightarrow$

Situation 2

	Groups	
	A	B
Party 1	1	0
Party 2	0	1

Figure A2: Scenario II

more often than non-coethnic ones: $Pr(covoting|coethnicity = 0)$ decreases from 1 to 33 percent. Across this scenario, coethnics always covote ($Pr(covoting|coethnicity = 1) = 1$ and $Pr(coethnicity|covoting = 0) = 0$). The coethnicity coefficient changes as a function of the increasing ethnic homogeneity of parties' voters: the chance that two covoters are coethnics $Pr(coethnicity|covoting = 1)$ increases from 25% to 50%.[4]

Scenario II: A scenario in which two groups (size .5 each) vote first for three purely ethnic parties whereby group B splits its vote, and then for two mono-ethnic parties (Figure A2). The CVR regression coefficient for coethnicity is 0.75 in the first situation, and increases to 1 in the second as coethnics always covote. Non-coethnics never covote in either situation ($Pr(covoting|coethnicity = 0) = 0$. Covoters are always coethnics ($Pr(coethnicity|covoting = 1) = 1$), so that the change in the coefficient of coethnicity is driven by the decreasing political fractionalization of group B: the chance that two coethnics covote $Pr(covoting|coethnicity = 1)$ increases from 75% to 100%.[5]

Scenario III: In a third scenario, we compare a first situation in which two groups of equal size each split their votes into two monoethnic parties with a second situation in which four groups vote as homogeneous blocks for two parties (see Figure A3). Here, the CVR estimate for the effect of coethnicity on covoting increases from .5 in situation 1 to .667 in situation 2. This change is the product of the increase of the chance that coethnics covote $Pr(covoting|coethnicity = 1)$ from 50% to 100% and the decrease in the chance that covoters are coethnics $Pr(coethnicity|covoting =$

[4]Both of Huber's indices, GVF and PVF, take values of 0 in situation 1 because ethnic groups do not differ in their choice of the one party. GVF increases to 0.5 in situation 2 while PVF increases to .35.

[5]Huber's GVF increases from .433 in situations 1 to .5 in situtation 2. The PVF index remains at .5 for both situations as parties maintain their average level of ethnic distinctiveness.

Situation 1

	Groups	
	A	B
Party 1	.5	0
Party 2	.5	0
Party 3	0	.5
Party 4	0	.5

$\Longrightarrow$

Situation 2

	Groups			
	A	B	C	D
Party 1	1	1	0	0
Party 2	0	0	1	1

Figure A3: Scenario III

1) from 100% to 50%.[6]

A.3 Voter-Candidate Correspondence versus covoting

If i, j are iid then it is possible to express ethnic covoting expressions in voter-candidate correspondence terms. In our initial example, $Pr(AA|aa) = Pr(A_i|a_i) * Pr(A_j|a_j)$. Similarly, $Pr(AA|bb) = Pr(A_i|b_i) * Pr(A_j|b_j)$. While it is thus principally possible to link voter/candidate correspondence to the covoting approach, it also becomes clear that the two ways of conceptualizing ethnic voting differ. Whereas, for example, $Pr(AA|aa)$ and its constitutive terms $Pr(A_i|a_i)$ and $Pr(A_j|a_j)$ contribute positively to both $Pr(EV)$ and $Pr(ECV)$, $Pr(AA|bb)$ and its constitutive terms $Pr(A_i|b_i)$ and $Pr(A_j|b_j)$ contribute negatively to the probability of ethnic voting but positively to the probability of ethnic covoting (see Eqs. A1 and A2).

This divergence is directly related to the fact that the party-coding in the example prioritizes the party-based approach of ethnic voting over the group-based approach. In contrast, the CVR model captures both group and party-based conceptualizations of ethnic voting. It increases as supporters for one party come increasingly from the group that the party represents ($Pr(AA|aa)$ or $Pr(BB|bb)$). Similarly, the shared ethnicity coefficient in the CVR model increases if members from one group increasingly support one party, even if that party does not represent that group via coethnics ($Pr(AA|bb)$ or $Pr(BB|aa)$). In contrast, ethnic voting would decrease in the voter-party correspondence approach. This is the source of selection bias that arises if voters of a given party do not have coethnics/a party of their own ethnicity on the ballot.

A.4 Individual choice models and the CVR

Most generally, it is possible to reformulate the CVR by bringing together individuals' candidate choice probabilities as typically modelled via a multinomial linear (or logistic) regression:

$$P(party_{p,i}|X_i) = \delta_{0,p} + \theta_p \mathbf{z}_i + \epsilon_{p,i} \tag{A5}$$

where individuals probabilities to vote for parties $party_p \in P$ is affected in a party-specific way by a constant $\delta_{0,p}$ and covariates $\mathbf{z}_i$ scaled by coefficient vector θ_p. The

[6] Huber's GVF increases from .352 to .5 between situations 1 and 2 as groups become more homogeneous in their political preferences. In parallel, PVF decreases from .5 to .353 as parties' voter base become more ethnically diverse.

error $\epsilon_{p,i}$ is in expectation 0 and assumed to be iid. A categorical coding of i's ethnic group among the covariates $\mathbf{z}_i$ can be used to estimate ethnic voting as the effect of a given ethnic identity on the probability of voting for a given party, thus combining a party- and group-centric understanding. A groups' voting homogeneity can be expressed in terms of its deviation from overall vote choices. A party's ethnic makeup is in turn reflected by the extent to which its voters come disproportionally often from a subset of ethnic groups.

Using Eq. A5, we can reformulate the main CVR (Eq. (6)) as the sum of the joint probability that individuals j and i together vote for any party $p \in P$:

$$Pr(covote_{i,j}|\mathbf{z}_i, \mathbf{z}_j) = \sum_{p \in P} Pr(p_i|\mathbf{z}_i)\, Pr(p_j|\mathbf{z}_j) \tag{A6}$$

This formulation can be used to convert the results of a multinomial choice model into covoting probabilities and the effects of cleavages on them. Specifically, we can estimate Eq. A5, generate predicted probabilites at specific values of a predictor of interest such as ethnicity while keeping all other covariates at their sample mean (or any other arbitrary value). Using these predicted probabilities we can, in a second step, compute the overall covariate-adjusted effect of coethnicity on covoting ($\sim \beta_1$ in Eq. (6)) by comparing how likely it is that two coethnics covote as compared to two non-coethnics. We use this approach as a robustness check in Appendix F.2.

Combining Eqs. A5 and A6 yields additional insights as to the potential importance of considering cross-cleavage interactions in addition to the main CVR's segregated treatment of cleavages. In particular, Eq. A6 can be reformulated as

$$= \sum_{p \in P} \big((\delta_{0,p} + \theta_p \mathbf{z}_i)(\delta_{0,p} + \theta_p \mathbf{z}_j)\big) \tag{A7}$$

$$= \sum_{p \in P} (\delta_{0,p}^2 + \delta_{0,p}\theta_p(\mathbf{z}_i + \mathbf{z}_j) + (\theta_p \cdot \theta_p^\intercal) \odot (\mathbf{z}_i \cdot \mathbf{z}_j^\intercal)) \tag{A8}$$

$$= \sum_{p \in P} \delta_{0,p}^2 + \sum_{p \in P} \delta_{0,p}\theta_p(\mathbf{z}_i + \mathbf{z}_j) + \sum_{p \in P} (\theta_p \cdot \theta_p^\intercal) \odot (\mathbf{z}_i \cdot \mathbf{z}_j^\intercal) \tag{A9}$$

Comparing Eq. A9 with the main CVR in Eq. (6) suggests several ways in which its "short" formulation might have to be extended to capture biases originating at the level of individuals' vote choice. In particular, (1) $\sum_{p \in P} \delta_{0,p}\theta_p(\mathbf{z}_i + \mathbf{z}_j)$ suggests adding the sum of covariates $\mathbf{z}_i$ and $\mathbf{z}_j$ to the model, essentially capturing overall covoting rates among certain groups of individuals. The respective coefficient estimates in the CVR would then capture the sum of party-specific coefficients $\sum_{p \in P} \delta_{0,p}\theta_p$.[7]

Adding more complexity, (2) the term $\sum_{p \in P} (\theta_p \cdot \theta_p^\intercal) \odot (\mathbf{z}_i \cdot \mathbf{z}_j^\intercal)$ denotes one additional term for each interaction between each covariate in $\mathbf{z}_i$ and each covariate in $\mathbf{z}_j$. In our case of ethnic cleavages, that includes not only all interactions between all ethnic groups of individuals i and j, but also the interaction of i's ethnicity with all other cleavage measures for j (urban, wealth, etc.), as well as all interactions among these between i and j, and vise-versa. Again, the respective coefficient

[7] The most straightforward and robust way to do so is to add fixed effects for individuals i and j, see Appendix F.

estimates for the cross-cleavage interactions in the CVR would then capture the sum of party-specific coefficients $\sum_{p \in P}(\theta_p \cdot \theta_p^{\intercal})$.[8]

Doing so can be necessary because our measure of pair-wise coethnicity captures the interaction of the ethnicity of i and j. Put differently, it is the mean effect across all interactions where i and j's ethnic identity is the same. To prevent omitted variable bias from affecting the estimate, it is thus potentially necessary to interact the respective control variables with the main cleavage of interest as well as interactions with each other (Beiser-McGrath and Beiser-McGrath 2020). Empirically, this requires the estimation of a large set of interaction terms, in particular where cleavages are based on categorical variables such as ethnicity, religion or occupation. In turn, problems from overfitting and loss of efficiency might result. Using models that identify relevant interactions from the data is one strategy to tackle these issues (see Beiser-McGrath and Beiser-McGrath 2020, for a discussion). We implement such models for a dedicated robustness check discussed in Appendix F.1.

B Monte Carlo Simulations: Selection and ecological inference biases

Based on our discussions in Appendix A, this section presents two sets of Monte Carlo simulations that address (1) selection bias occurring in voter-candidate correspondence models compared to the CVR and (2) omitted variable bias that might affect the CVR and leads to biases from ecological inferences in meso–level approaches.

B.1 Simulating Selection Bias

We simulate two types of selection biases that can affect the voter-correspondence and CVR model. The first consists in selection bias the occurs when researchers code some voting – typically for a coethnic candidate or party – as "ethnic" compared to non-ethnic votes cast for other parties. The second type of selection bias originates in endogenous party entry and exit, which might be causally related to the extent of ethnic voting in one or several ethnic groups. Our simulation shows that the correspondence model is affected by both biases, while the CVR does not incur biases from endogenous coding decisions but is affected by endogenous party exit and entry.

Our simulations presume 3 ethnic groups a, b, and c, each representing 1/3 of the population. Groups a and b exhibit fixed voting behavior towards two parties, A and B: 40% of their members vote "non-ethnically", splitting their vote equally between the two parties.[9] 60% of their members have an "ethnic" preference, voting for their "ethnic" party (a for A and b for B). As a result, members of a cast 80% (20%) of their votes for A (B), and members of b vote for B at a rate of 80%

[8] Because dyads are in principle undirected, we can force interactions to have the same coefficient irrespective of the order of i and j in the data.

[9] This could be due to a second substantive axis of party competition, a cross-cutting cleavage, or even simple indifference between the two parties.

(20%).[10] The third group, c, varies in the degree to which its members vote ethnically between 0 and 100%, thus varying the "true" value of aggregate ethnic voting alongside. Non-ethnic voters in c always split their votes equally between parties A and B.

In a first set of simulations (Scenario 1), ethnic voters from group c vote for a third party C. In the second set (Scenario 2), party C does not exist and ethnic voters from c vote for their "second-best" choice, party B. Here, we assume that B is not regarded as ethnically representative of group c by the researcher following the voter-correspondence approach. Non-ethnic voters from a, b, and c never vote for party C, a choice which is conservative but clarifies the contrast between the scenarios.[11]

For both scenarios, we generate 1000 draws of 1000 "survey respondents" and sample their party choices. We then estimate the average level of ethnic voting according to the voter correspondence model and the effect of coethnicity on covoting in the CVR. In Scenario 2, which does feature party C, we simulate two more researcher choices in the correspondence approach: for one, keeping group c in the analysis (with all members voting non-ethnically); for another, dropping group c due to the inability of voting ethnically.

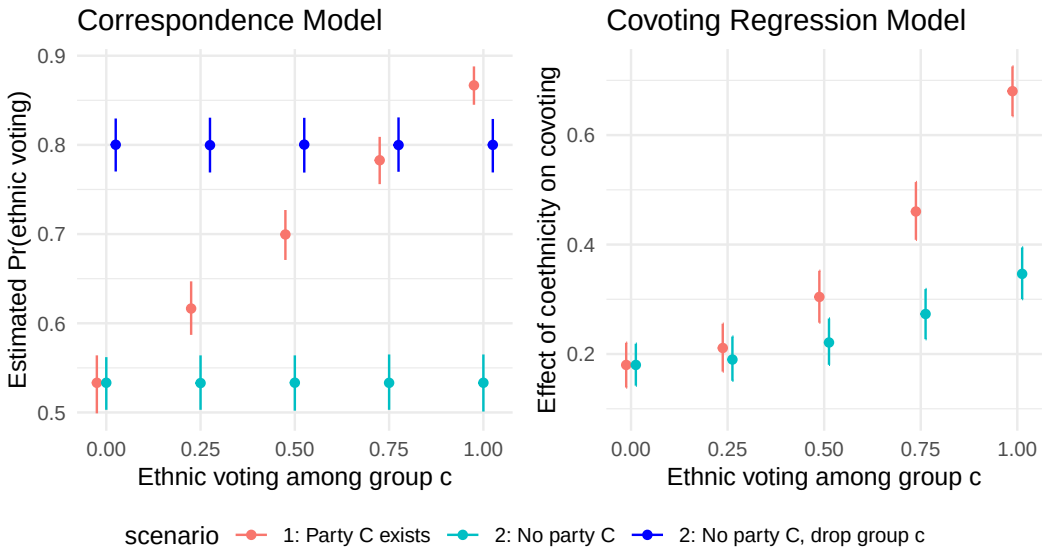


Figure A4: Selection bias in the voter-correspondence model and CVR

Figure A4 presents the results. Recall that the true extent of aggregate ethnic voting varies with the increasing share of members of group c to vote ethnically. In the left panel and for baseline Scenario 1 (red point ranges), we see that the correspondence approach clearly captures the increase of average ethnic voting by 33 percentage points. This is caused by the increasing share of ethnic voters among group c, which party C unambiguously separates from all other voters.

[10] Although only 60% of group members in a and b have an ethnic preference, we obtain an overall rate of 80% voting for their respective party. The discrepancy arises because half of the 40% of members without any ethnic preference split their vote equally between parties A and B.

[11] The entry of C would typically attract at least some "non-ethnic" voters from all groups which would muddy the comparisons.

In Scenario 2, that drops party C, the average rate of ethnic voting in the correspondence approach does not change, regardless of whether we keep (light blue) or drop group c (dark blue). Recall though that group c increases its vote for the "second-best" party B. Keeping group c in the analysis increasingly underestimates ethnic voting as the share of members of c would like to vote ethnically increases. The reason is that correspondence approaches do not consider group-based conceptualizations of ethnic voting. Dropping group c from the analysis overestimates ethnic voting for most parameter values, in particular when fewer members of group c prefer to vote ethnically.

Inportantly, we find that the correspondence approach overestimates the extent of ethnic voting by the share of non-ethnic voters that vote for "their" ethnic party due to chance. Even when dropping group c, we thus overestimate ethnic voting among groups a and b by 20 percentage points at 80 instead of 60 percent. This is because *all voters* for the ethnically corresponding party of a group are coded as "ethnic voters," even those 40% who randomly split their vote between parties A and B. Similarly, the base-rate of ethnic voting in Scenario 1 without ethnic voting by c is overestimated: it should be at 40 instead of 53.3 percent.

Turning to the CVR, the model clearly captures the increase in ethnic voting – expressed as the effect of coethnicity on covoting – in Scenario 1 (red point ranges). When no member of c votes ethnically, the effect of coethnicity on covoting is .18. This is exactly the result expected from the setup, as ethnic voters among a and b disproportionally vote for their parties A and B. The CVR correctly accounts for the covoting among coethnics that occurs due to pure randomness among the non-ethnic voters across all groups which split their votes across A and B. As a result, coethnics covote at a rate of 62 percent, and non-coethnics at a rate of 44 percent, leaving an effect of coethnicity of .18. As expected, this effect increases to a maximum of .68 as members of c shift their votes towards mono-ethnic party C, increasing covoting among coethnics from 62 to 78 percent, while strongly decreasing covoting among non-coethnics to 10 percent.

In Scenario 2, where party C does not exist, the effect of coethnicity on covoting increases with greater ethnic voting among c, but in a less pronounced manner. In this scenario, the rate of covoting among non-coethnics remains constant as voters c shift their votes from A to B. In contrast, however, the rate at which coethnics covote increases strongly from 62 to 78 percent, just as much as in Scenario 1, as the vote share for B increases in group c.

These results show that the CVR avoids the selection bias that comes with the correspondence approach when not all groups have the choice to vote for or against a coethnic. It also accounts for the baseline rate at which we would expect groups to vote for each party without any ethnic voting. Lastly, the coethnicity estimate in the CVR model is not robust to selection from potentially endogenous party entry and exit which remains an issue common to all observational approaches to studying ethnic voting.[12] However, the bias we observe is smaller than in the correspondence approach as the CVR captures the group-based logic of ethnic voting which remains unaffected by the entry/exit of party C. Moreover, assuming

[12]Note that the endogeneous party entry of the sort modeled here would also affect Huber (2012) measures of ethnic voting. Moving from Scenario 1 to 2 at positive levels of ethnic voting in group c would decrease party vote fractionalization as well as group vote fractionalization.

sincere voting and perfectly proportional electoral rules, the bias is largest when high demand of ethnic voting among members of c makes it least likely that no coethnic party would run. This claim rests on other factors not influencing voting decisions. The size of the bias likely varies with country-specific group sizes, the presence or absence of intra-group divisions, and individual candidate characteristics. In plurality or majoritarian electoral systems that incentivize strategic voting, the CVR would most likely suffer from selection bias even if members of group c have strong preferences for coethnic candidates if the latter do not run (or are not voted for) for strategic reasons.

B.2 Simulating the impact of omitted variables and the threat of ecological inference

While group-based measures of ethnic voting, like those proposed by Huber (2012), reduce the problem of selection bias, they potentially create new challenges in the context of multiple cleavages that affect voting decisions. When applying group-based measures, researchers decide that one cleavage is the primary cleavage in their analysis. This may mask relevant political dynamics if this cleavage is correlated with another cleavage dimension, which also decisively influences electoral politics.

We simulate such a situation in a setting with two parties (A, B) and two ethnic groups (1, 2), with a size of .4 and .6, respectively. However, voters have an additional urban/rural status with a mean of .5 and varying degrees of correlation (0 to .9) with their group identity. We model the probability of voting for party B in this Scenario 1 as:

$$Pr(VoteB_i) = .2 + .3\,\mathbb{1}(group_i = 2) + .2\,urban \tag{A10}$$

Table A1: Monte Carlo specifications for four different scenarios to test the influence of omitted confounders/cleavage dimensions.

	Scenario			
	(1)	(2)	(3)	(4)
Parties	2	2	2	4
Ethnic Groups	2	4	4	4
$\beta_{Ethnicity}$	0.3 (Group 2)	0.3 (2&4)	0.3 (2&4)	0.15 (Party B), 0.15 (C), -0.1 (D)
Urban/Rural	Yes (0.5/0.5)	Yes (0.5/0.5)	Yes (0.5/0.5)	Yes (0.5/0.5)
β_{Urban}	0.2	0.2	0.2	0.1 (Party B), 0.05 (C), 0 (D)
Income	No	No	$\mathcal{N}(0.5,\,0.2)$	$\mathcal{N}(0.5,\,0.2)$
β_{Income}			0.1	0.1 (Party B), 0.05 (C), 0 (D)

We extend this setup in three steps to more realistic scenarios. In Scenario 2, we add two more groups, which simply mirror groups 1 and 2, such that group 3

behaves as 1 and group 4 as 2 does in their voting behaviors and urban/rural status.[13] In Scenario 3, we add a second alternative cleavage, say income, which takes on continuous values (normally distributed, mean = .5, sd = .2), increases voting for party B with a coefficient of .1, and correlates with groups to the same extent as urban/rural status. The correlation between urban/rural status and income increases with the one with group identities. In Scenario 4, we add two more parties C and D, and adjust coefficients in Eq. A10 downwards to avoid negative probabilities.[14] Table A1 summarizes the key parameters across the four scenarios

For each scenario, we vary the correlation between group identity and the alternative cleavages in 10 steps between 0 and .9. For each step and scenario, we simulate 1,000 voters 1,000 times. We evaluate the scenarios in three ways. We first compute Huber's (2016) Group Vote Fractionalization index, using ethnic groups and urban/rural status as group determinants. Second, we estimate the CVR models without covariates, with simple controls (joint urban/rural status, income difference), and a fully saturated model with all cross-cleavage interactions (see Appendix A.4). Finally, we show results that aggregate group-specific coefficients from party-specific individual-level analysis of the form of Eq. A10 with and without covariates. As explained in Appendix A.4, we use group- and party-specific predicted voting probabilities at the mean of all covariates to derive the overall, covariate-adjusted difference between covoting among coethnics and non-coethnics.

Figure A5 plots the values of Huber's group vote fractionalization (GVF) computed separately for ethnic groups and urban/rural strata. While we recuperate the true value of ethnic (and urban/rural) GVF (red dotted line) across all scenarios at zero correlation between ethnic groups and the alternative cleavages, both GVF measures increase as the correlation rises, even though the effect of each cleavage on vote choice remains constant by construction. The reason for the overestimation derives from the omitted impact of individuals' urban status (ethnicity) that increasingly feeds into the ethnicity (urban status) estimate with their growing correlation.

Turning to the results of the CVR and individual-level models in Figure A6 we find a similarly over-estimated effect of coethnicity on covoting in models without covariates at increasing levels of correlation between ethnicity and alternative cleavages (red line). Again, this upward bias stems from the impact of the omitted alternative cleavages (rural/urban status and income). In the CVR, this bias can be partially mitigated by adding "simple controls" for shared rural-urban status and income differences between individuals (turquoise line). Once we add all interactions between the characteristics of individuals' i and j in a pair, the CVR recuperates the true effect of coethnicity on covoting, just as the individual-level model does (blue line).

These results show that the CVR provides an unbiased estimate of the effect of coethnicity on covoting when confounders are observable and correctly specified. While the "simple" specification that models cleavages separately can be indicative of the existence of bias when comparing it to a no controls model, it does not necessarily capture all biases to their full extent. To that intent, researchers should

[13] We adjust group sizes of groups 1 to 4 to .2, .3, .1, .4.

[14] Party A is the baseline category. Parties B, C, D have a constant β_0 of .1, .1, .15; effects of groups 2 and 4 of .15, .15, -.1; an effect of urban status of .1, .05, 0; and of income of .1, .05, 0, respectively.

Figure A5: Monte Carlo simulation results: Huber's Group Vote Fractionalization. Ground truth value as red dotted line.

model a fully specified interactive model, which can be reduced to an empirically relevant set of interaction using, e.g., LASSO (see below in Appendix F.1). The results also show that conditional covoting probabilities can be successfully derived from individual-level models as explained in Appendix A.4 though the derivation of correct standard errors proves challenging.[15]

[15]This is because the results depend on separate models for each party.

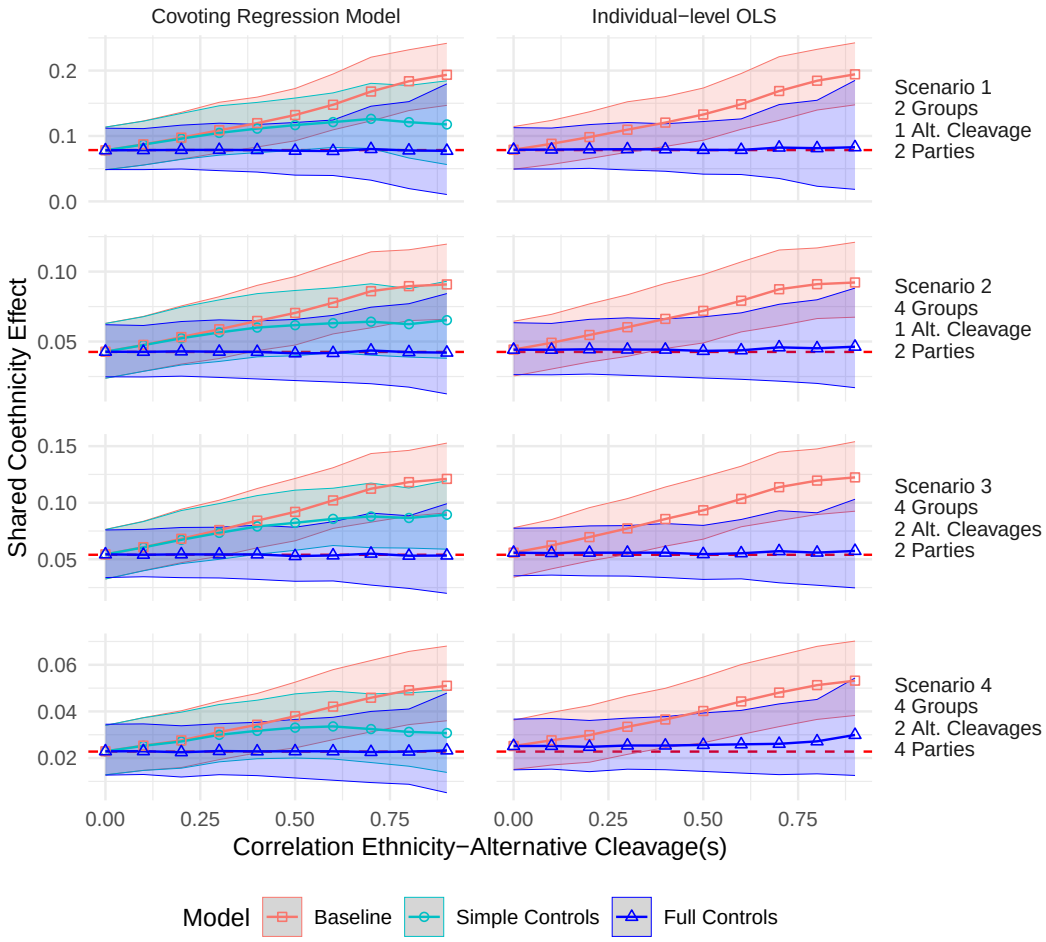


Figure A6: Monte Carlo simulation results: CVR and individual-level approach. Ground truth effects as red dotted line.

C Summary statistics

Table A2: Summary statistics of variables in presidential voting intention data.

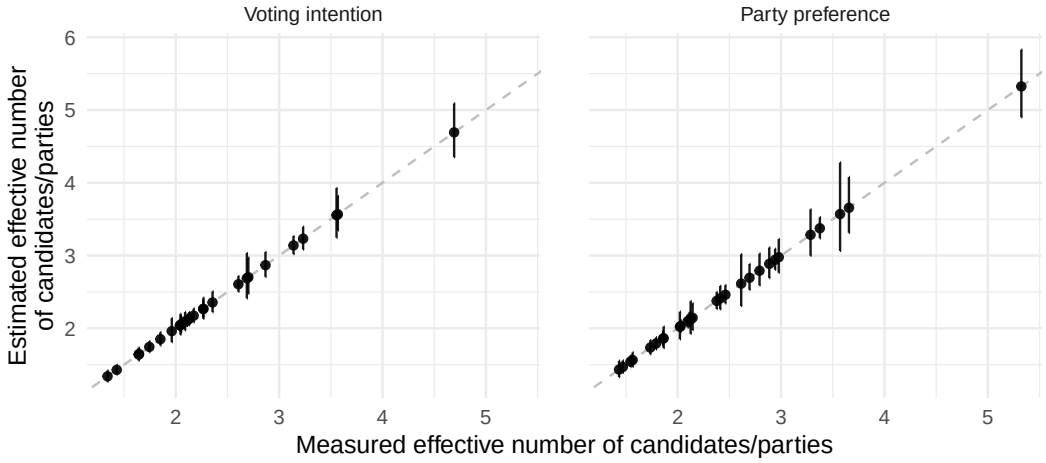
Statistic	N	Mean	St. Dev.	Min	Max
Voting intention	6,506,927	0.460	0.498	0	1
Shared mother tongue	6,506,927	0.216	0.412	0	1
Shared religion	6,506,927	0.334	0.472	0	1
Age similarity	6,506,927	−1.573	1.282	−8.800	0.000
Shared gender	6,506,927	−0.500	0.500	−1	0
Shared education	6,506,927	0.370	0.483	0	1
Wealth similarity	6,506,927	−1.038	0.790	−4.131	0.000
Shared occupation	6,506,927	0.201	0.401	0	1
Geographic proximity	6,506,927	−0.328	0.286	−2.359	0.000
Shared urban/rural	6,506,927	−0.433	0.495	−1	0

Table A3: Summary statistics of variables in party preference data.

Statistic	N	Mean	St. Dev.	Min	Max
Party preference	3,815,492	0.458	0.498	0	1
Shared mother tongue	3,815,492	0.276	0.447	0	1
Shared religion	3,815,492	0.340	0.474	0	1
Age similarity	3,815,492	−1.643	1.317	−8.800	0.000
Shared gender	3,815,492	−0.496	0.500	−1	0
Shared education	3,815,492	0.371	0.483	0	1
Wealth similarity	3,815,492	−1.030	0.781	−4.408	0.000
Shared occupation	3,815,492	0.209	0.407	0	1
Geographic proximity	3,815,492	−0.309	0.268	−2.359	0.000
Shared urban/rural	3,815,492	−0.419	0.493	−1	0

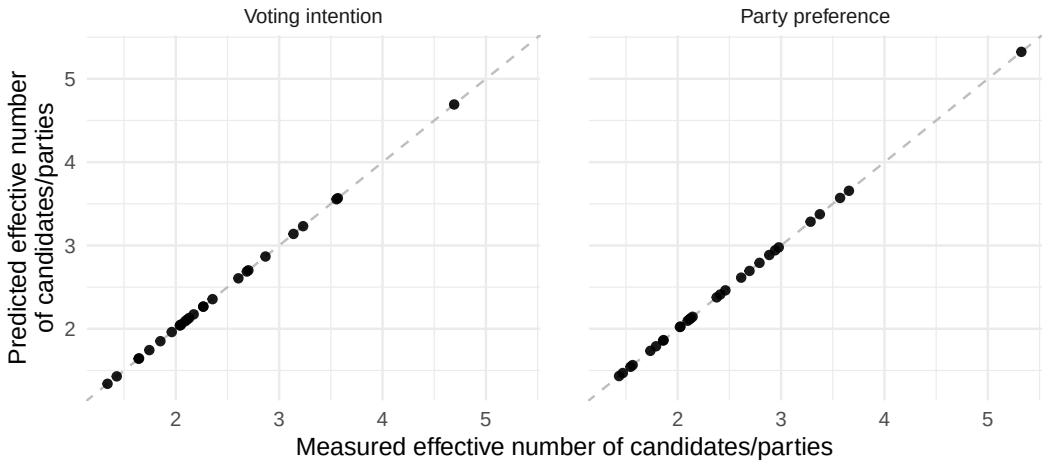
D Empirical relationship to macro-, meso-, and micro-level approaches

D.1 Macro-level: Effective number of parties and ethnic fractionalization



(a) Estimated and measured effective number of parties

Note: Estimates are derived as the inverse intercept of an otherwise empty regression model estimated separately for each country, standard errors are clustered on the level of individuals.



(b) Predicted and measured effective number of parties

Note: Predicted ENP is derived as the inverse average fitted probability of co-voting obtained from the fully specified regression model estimated separately for each country.

Figure A7: Empirical relation between measured Effective Number of Parties and the Linear Probability Model of co-voting

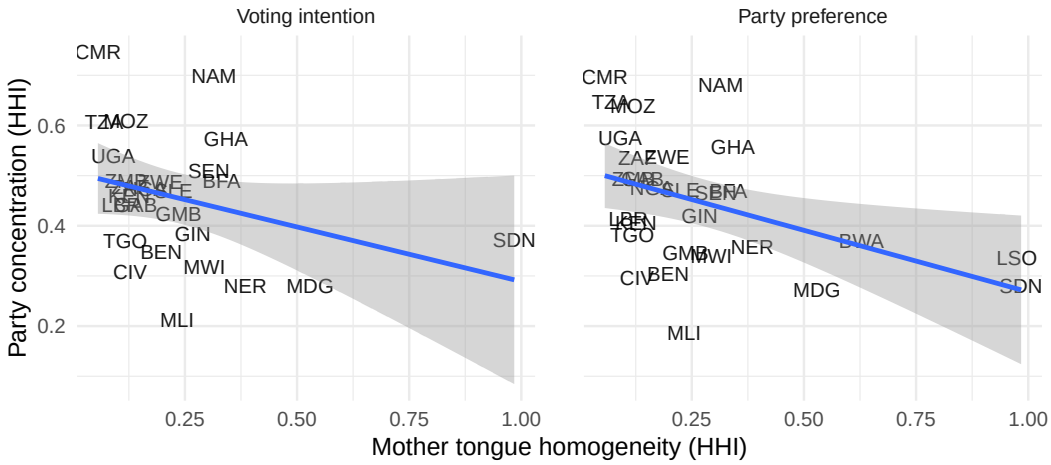


Figure A8: Bi-variate relationship between the national party system concentration and mother tongue homogeneity

Note: Both variables measured as Herfindahl-Hirschman Indices. Based on Afrobarometer Data, round 7.

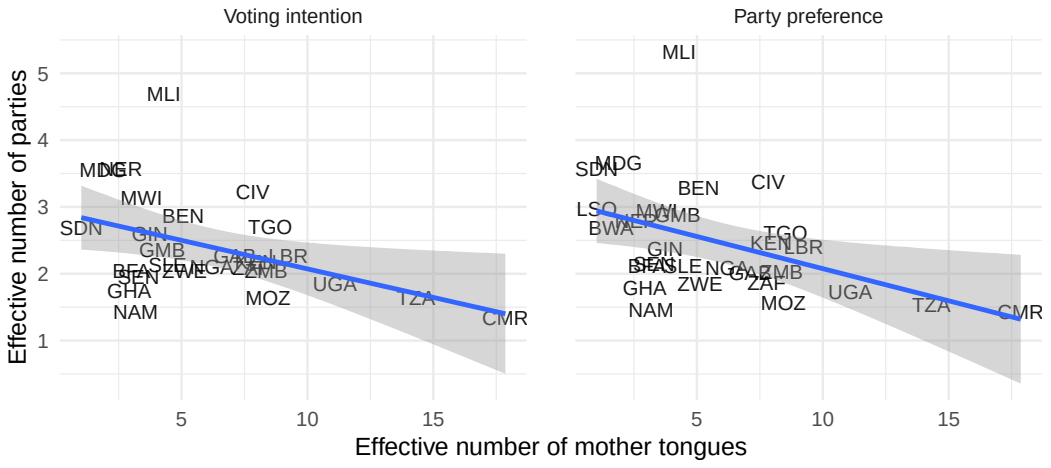


Figure A9: Bi-variate relationship between the national Effective Number of Parties and Effective Number of Mother Tongues

Note: Based on Afrobarometer Data, round 7.

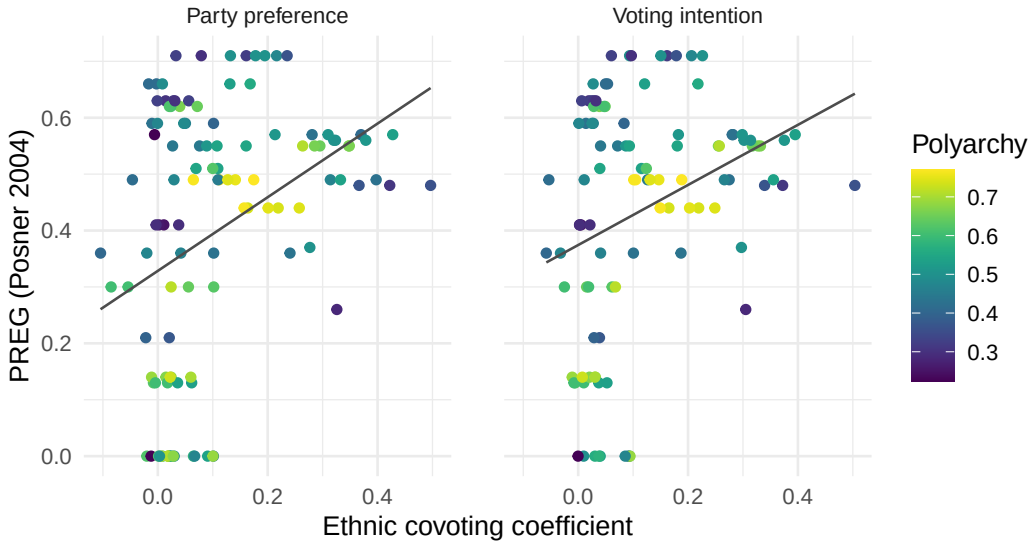


Figure A10: Country-level correlation between effect of shared mother tongues on covoting and PREG Fractionalization Index (Posner 2004).

D.2 Meso-level: Group- and Party-based measures of ethnic voting

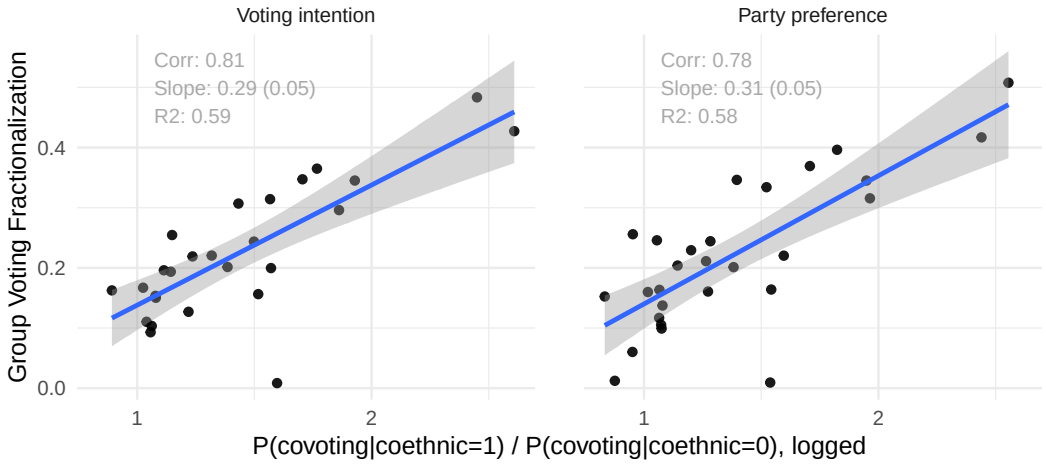


Figure A11: Co-voting among (non-)coethnics and Group Voting Fractionalization (Huber 2012).

Note: Country-level estimates from Afrobarometer Round 7.

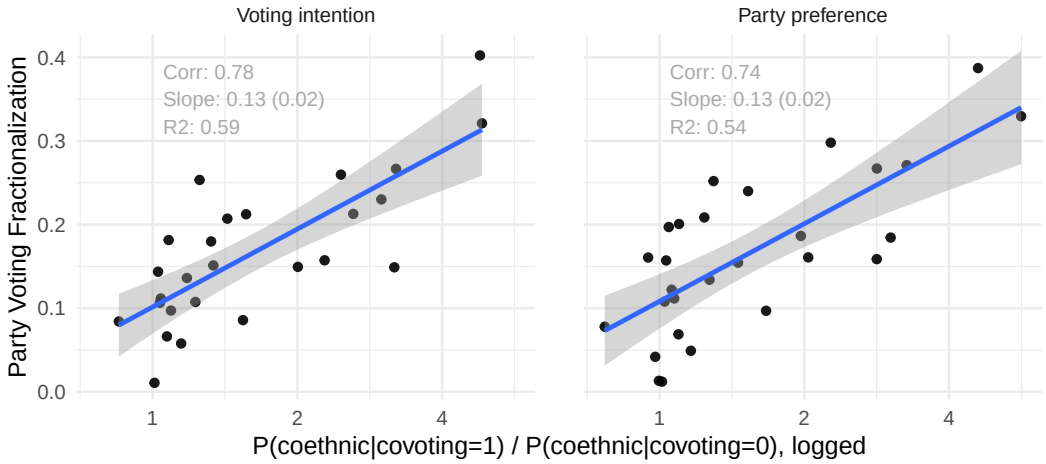


Figure A12: Coethnicity among (non-)covoters and Party Voting Fractionalization (Huber 2012)

Note: Country-level estimates from Afrobarometer Round 7.

E Heterogeneous effects

E.1 Micro-level: Ethnic bias, expected favoritism, and political knowledge

We test the moderating effect of individual-level factors on coethnic covoting in a series of interaction models. We measure the prevalence of ethnic bias, by recurring

to the Linz-Moreno question (Moreno 1995) which asks whether respondents identify in terms of their national as compared to their ethnic identity on a 1 to 5 scale. Expectations of ethnic favoritism from the government is measured in Afrobarometer Round 5.[16] To test the moderating impact of political knowledge, we construct a knowledge index (0-1) based on the respondents' average knowledge of their MP, local government councilor, the Vice President, the largest party, term limits, and the responsibility for constitutional review as well as a news index based on respondents average frequency of getting news from the radio, TV, newspapers, the internet, and social media (rescaled to 0-1).

Table A4: Covoting intentions and shared mother tongue: Ethnic identification and expected favoritism

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.150*		0.117+	
	(0.063)		(0.067)	
Ethnic ID (1-5)	0.008		0.010	
	(0.006)		(0.007)	
Shared mother tongue (0/1) × Ethnic ID (1-5)	0.004		0.011	
	(0.022)		(0.021)	
Shared ethnicity (0/1)		0.128***		0.126***
		(0.032)		(0.032)
Expect Favors (1-5)		0.002		0.001
		(0.003)		(0.003)
Shared ethnicity (0/1) × Expect Favors (1-5)		0.014+		0.016+
		(0.009)		(0.010)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
AB Round	7	5	7	5
Outcome mean	0.465	0.466	0.464	0.475
Countries	25	25	27	28
Respondents	16,744	19,298	13,148	17,477
Dyads	5,910,390	7,730,782	3,480,447	5,823,715
R^2	0.085	0.086	0.086	0.101
Within R^2	0.024	0.019	0.021	0.018

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

The results in Tables A4 and A5 show that ethnic biases, expectations of ethnic

[16]The respective question Q18 asks respondents whether should be "obliged to help their home community or group first" or "should represent everyone [...]," with respondents ranking their agreement with statement 1 vs 2 on a 5-point scale. We recode the variable to capture expected favoritism with higher values.

Table A5: Covoting intentions and shared mother tongue: Political knowledge and news consumption

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared ethnicity (0/1)	0.133^{+}		0.173^{+}	
	(0.077)		(0.091)	
Knowledge (0-1)	0.023		0.074**	
	(0.023)		(0.028)	
Shared ethnicity (0/1) $\times$ Knowledge (0-1)	-0.035		-0.092	
	(0.077)		(0.086)	
Shared mother tongue (0/1)		0.152***		0.146**
		(0.044)		(0.052)
News (0-1)		-0.183***		-0.152***
		(0.020)		(0.024)
Shared mother tongue (0/1) $\times$ News (0-1)		0.047		0.047
		(0.071)		(0.098)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
AB Round	3	7	3	7
Outcome mean	0.515	0.461	0.531	0.459
Countries	14	26	16	28
Respondents	10,579	17,817	10,310	13,885
Dyads	4,123,500	6,492,402	3,535,367	3,810,540
R^2	0.168	0.083	0.155	0.081
Within R^2	0.011	0.027	0.011	0.023

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

favoritism, and political knowledge and news consumption do not significantly moderate the effects of coethnicity on shared voting intentions and party preferences.[17] While the effects of ethnic identification and favoritism expectations in Table A4 point in the expected positive direction, the estimates are not statistically significant. The interaction of coethnicity with political knowledge is as expected negative, but again not statistically significant, while higher news consumption (insignificantly) correlates with greater coethnic covoting (Table A4).

E.2 Meso-level: Groups and parties

Our analysis of meso-level heterogeneity and mechanisms focuses on the importance of politically relevant ethnic group(ing)s as well as differences in covoting

[17]Note that rounds 3 and 5 do not ask for respondents' mother tongue but only their ethnicity.

patterns for parties with and without ethnic constituencies as coded by the VDEM-Party data (Lührmann et al. 2020).

At the group level, we first match the mother tongues of Afrobarometer respondents to politically relevant ethnic groups as listed in the Ethnic Power Relations data (Vogt et al. 2015) as well as Posner's (2004) PREG data. We do so using the LEDA package which makes use of phylogenetic linguistic treeto provide a consistent mapping of ethnic datasets onto each other (Müller-Crepon, Pengl and Bormann 2022).[18] We then encode, for each respondent pair whether the two respondents belong to a common EPR and PREG group, groups which often encompass multiple mother tongues.[19] This coding then allows us to examine by how much the effect of general shared membership in a politically relevant ethnic group(ing) affects covoting above and beyond the effect of a shared mother tongue. Table A6 and A7present the results for the EPR and PREG data respectively. We find in Models 1 and 3 that joint membership in a politically relevant ethnic groups increases covoting by between 16 and 17 percentage points when modelled without accounting for shared mother tongues. When adding the latter indicator in Models 2 and 4, the effect of joint EPR / PREG membership decreases but remains sizeable and significant at between 9 and 10 percentage points. In turn, the effect of shared mother tongues amounts to 10 to 12 percentage points, significantly smaller than in the main specification. Overall, this shows that (1) there are electorally meaningful linguistic cleavages within politically relevant ethnic groups but (2) that these have effects of approximately half the size of the cleavages between politically relevant ethnic groups.[20]

At the level of parties, we test whether the main effect of shared ethnicity on covoting is driven by covoting for parties with or without ethnic constituencies. To that intent, we turn to Afrobarometer Round 6, for which party labels in the responses to the question on party preferences are linked to the VDEM-Party data (Döring and Regel 2019). We then compute, for each party, the share of VDEM-Party experts that state that "the core membership and supporters of this party" belong to one or several "ethnic or racial group(s)" as an indicator of the degree to which a party can be considered an "ethnic party". We cluster parties in three groups, "high" where the majority of coders code it as being ethnic [.5-1], "medium" where a minority does so (.5-0), and "none" where no coder codes it as such. We use this coding to categorize instances of covoting for a given party into the same categories. This coding enables us, in Table A8 to disaggregated the overall effect of coethnicity[21] on covoting (Model 1) into the three categories. The results show that around 60 percent of the overall effect is driven by parties with a high level of ethnic support and approximately 40 percent by parties with a medium level. Importantly, parties coded by no expert has relying on an ethnic support base do not feature higher levels of coethnic covoting.

[18] While EPR and PREG groups are overwhelmingly coarser than Afrobarometer categories, some are not. We then map respondents to all the relevant groups.

[19] We drop pairs where a respondent is not matched to any EPR/PREG group.

[20] For the latter, we have to sum the effect of shared mother tongue and shared EPR / PREG.

[21] Note that round 6 does not ask for respondents' mother tongue but only their ethnicity.

Table A6: Covoting intentions with politically relevant groups: EPR

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)		0.117***		0.102***
		(0.022)		(0.024)
Shared EPR (0/1)	0.173***	0.097***	0.157***	0.087***
	(0.039)	(0.028)	(0.041)	(0.025)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Outcome mean	0.458	0.458	0.452	0.452
Countries	17	17	19	19
Respondents	10,227	10,227	8,423	8,423
Dyads	3,344,394	3,344,394	2,096,591	2,096,591
R^2	0.099	0.104	0.089	0.092
Within R^2	0.031	0.037	0.023	0.026

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A7: Covoting intentions with politically relevant groups: PREG

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)		0.097***		0.118***
		(0.022)		(0.025)
Shared PREG (0/1)	0.181***	0.102***	0.177***	0.081**
	(0.033)	(0.020)	(0.043)	(0.025)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Outcome mean	0.466	0.466	0.452	0.452
Countries	26	26	28	28
Respondents	11,038	11,038	8,976	8,976
Dyads	2,883,577	2,883,577	1,861,151	1,861,151
R^2	0.112	0.114	0.101	0.104
Within R^2	0.033	0.035	0.027	0.031

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A8: Covoting by parties' reliance on ethnic support groups

Dependent Variables:	Party preference	High	Medium	None
Model:	(1)	(2)	(3)	(4)
Variables				
Shared ethnicity (0/1)	0.152***	0.098***	0.055**	-0.004
	(0.022)	(0.022)	(0.021)	(0.003)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Controls	Yes	Yes	Yes	Yes
Outcome mean	0.427	0.150	0.187	0.087
Dyads	5,887,039	5,855,285	5,855,285	5,855,285
R^2	0.090	0.318	0.360	0.311
Within R^2	0.018	0.017	0.006	0.002

Standard errors clustered at the level of each respondent's ethnicity in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

E.3 Macro-level: Country-level institutions

Electoral system: A large literature suggests that proportional electoral systems politicize ethnic identities as particularistic parties face few obstacles to representation and may even join governing coalitions (e.g., Lijphart 2004). In contrast, some majoritarian electoral rules arguably incentivize cross-ethnic mobilization (e.g., Posner 2005). Using data on electoral systems from Bormann and Golder (2022), our results in Table A9 suggest that there are no large or statistically significant difference in the effect of coethnicity on covoting intentions. While PR systems see slightly less shared support for presidential candidates among coethnics at higher average levels of covoting, this difference is not statistically significant. We note that the share of coethnics among covoters (≈25%) as compared to coethnicity among non-covoters (≈17%) is similar in PR and majoritarian systems. This suggests that the (non-)result does not mask differences in the group- and party-based logics of ethnic voting.

Democracy: Democratic institutions, specifically competitive elections, are frequently associated with ethnic mobilization (Rabushka and Shepsle 1972; Horowitz 1985; Eifert, Miguel and Posner 2010). As described above, political leaders seek to mobilize majorities through clientelism and patronage, which often follows ethnic lines (Bates 1974), and might reinforce the effect of cultural differences on diverging policy preferences (Lieberman and McClendon 2013). While elections within dictatorships might also follow a clientelist logic, they are less likely to reveal divergent policy preferences. Countering these considerations, we find that the effect of coethnicity on covoting preferences is, if at all, smaller in countries with higher levels of democracy measured via V-DEM's polyarchy index (Coppedge et al. 2016, see Table A10). Again, the differences we observe are not statistically significant. We note that democracies have in general a slightly higher share of coethnic dyads among all dyads than non-democracies. This does however not translate into a statistically different extent to which covoters are more often coethnics than non-coethnics. Again, this suggests that the results reflects an alignment of party- and group-based logics of ethnic voting.

Traditional institutions may co-produce local public goods (Baldwin 2016), and act as complements to the state where they are institutionally tied to it (Holzinger et al. 2019; Henn 2022). Therefore, voters have incentives to vote "with their chief" (Baldwin 2013, see also De Kadt and Larreguy 2018). As a result of the entanglement between traditional authorities and ethnic identities, one might expect strong traditional institutions to come with stronger effects of coethnicity on covoting intentions. Using data on the constitutionalization of traditional authorities from (Holzinger et al. 2019), Table A11 shows relatively little and no statistically significant variation in the effect of coethnicity on covoting preferences. As in the previous analyses, further analyses of the group- and party-based interpretations of the CVR suggest that the results reflect both.

Table A9: Covoting and shared mother tongue: By electoral system

Dependent Variables:	Voting intention			Party preference		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shared mother tongue (0/1)	0.204**	0.193***	0.130***	0.196**	0.201**	0.107**
	(0.072)	(0.056)	(0.029)	(0.068)	(0.061)	(0.039)
Shared religion (0/1)	0.006	0.046*	0.004	0.020**	0.025	0.007
	(0.005)	(0.022)	(0.006)	(0.007)	(0.018)	(0.006)
Age similarity (decades)	-0.005*	-0.004+	-0.003	-0.006**	0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Shared gender (0/1)	0.002	-0.002	0.002	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Shared education (0/1)	0.026***	0.016**	0.015+	0.017**	0.014*	0.015+
	(0.007)	(0.005)	(0.008)	(0.005)	(0.007)	(0.009)
Wealth similarity (sd)	0.002	0.004	0.006	0.000	0.001	0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Shared occupation (0/1)	0.036***	0.024**	0.017	0.037***	0.014*	0.013
	(0.009)	(0.008)	(0.011)	(0.010)	(0.006)	(0.009)
Geographic proximity (1'000km)	0.062	0.029	0.036	0.043	0.027	0.033
	(0.042)	(0.033)	(0.028)	(0.048)	(0.027)	(0.027)
Shared urban vs. rural (0/1)	0.036**	0.021***	0.010	0.046***	0.015+	0.003
	(0.013)	(0.006)	(0.009)	(0.012)	(0.008)	(0.006)
Fixed-effects						
Country x Round	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Democracy level	Low	Medium	High	Low	Medium	High
Outcome mean	0.483	0.421	0.474	0.496	0.421	0.469
Countries	10	8	8	10	9	9
Respondents	6,117	5,549	6,161	4,519	4,886	4,487
Dyads	2,054,470	2,010,878	2,434,748	1,181,336	1,440,002	1,192,968
R^2	0.067	0.092	0.075	0.075	0.086	0.068
Within R^2	0.030	0.029	0.015	0.030	0.026	0.011

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A10: Covoting and shared mother tongue: By level of democracy

Dependent Variables:	Voting intention			Party preference		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shared mother tongue (0/1)	0.176***	0.207^{+}	0.120**	0.157***	0.186*	0.143*
	(0.033)	(0.116)	(0.042)	(0.041)	(0.088)	(0.056)
Shared religion (0/1)	0.030*	0.007	0.002	0.025^{+}	0.011	0.006
	(0.013)	(0.016)	(0.006)	(0.013)	(0.007)	(0.009)
Age similarity (decades)	-0.004*	0.001	-0.006*	-0.005***	0.006	-0.008^{+}
	(0.002)	(0.001)	(0.003)	(0.001)	(0.004)	(0.005)
Shared gender (0/1)	0.001	-0.001	0.000	0.002	-0.004	-0.003^{+}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Shared education (0/1)	0.020***	0.031*	0.007	0.018***	0.023^{+}	-0.010
	(0.004)	(0.014)	(0.010)	(0.004)	(0.012)	(0.007)
Wealth similarity (sd)	0.006**	-0.002	0.002	0.007*	-0.008	-0.006
	(0.002)	(0.008)	(0.006)	(0.003)	(0.006)	(0.006)
Shared occupation (0/1)	0.023***	0.023*	0.031*	0.020**	0.026^{+}	0.017^{+}
	(0.007)	(0.011)	(0.015)	(0.007)	(0.013)	(0.009)
Geographic proximity (1'000km)	0.034	0.082	0.049^{+}	0.031	0.065	0.033
	(0.027)	(0.053)	(0.029)	(0.024)	(0.055)	(0.029)
Shared urban vs. rural (0/1)	0.018**	0.042***	0.020	0.018*	0.035*	0.011
	(0.007)	(0.007)	(0.014)	(0.007)	(0.015)	(0.011)
Fixed-effects						
Country x Round	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Electoral system	FPTP	PR	Mixed	FPTP	PR	Mixed
Outcome mean	0.452	0.406	0.515	0.453	0.399	0.585
Countries	15	5	6	16	6	6
Respondents	10,868	2,816	4,143	8,606	2,973	2,313
Dyads	4,143,346	853,843	1,502,907	2,502,968	809,680	501,658
R^2	0.062	0.135	0.082	0.070	0.063	0.072
Within R^2	0.022	0.051	0.014	0.019	0.032	0.018

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A11: Covoting and shared mother tongue: By constitutionalization of traditional institutions

Dependent Variables:	Voting intention			Party preference		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shared mother tongue (0/1)	0.154***	0.176*	0.177***	0.145***	0.187*	0.160*
	(0.034)	(0.069)	(0.051)	(0.031)	(0.080)	(0.064)
Shared religion (0/1)	0.011	0.054**	-0.008*	0.020+	0.058***	-0.009*
	(0.008)	(0.017)	(0.004)	(0.011)	(0.014)	(0.004)
Age similarity (decades)	-0.003	-0.003	-0.005*	-0.002	-0.004*	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Shared gender (0/1)	0.001	-0.002	0.002+	-0.003*	-0.003	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Shared education (0/1)	0.017*	0.023***	0.015*	0.010	0.025***	0.012+
	(0.008)	(0.004)	(0.006)	(0.008)	(0.003)	(0.007)
Wealth similarity (sd)	0.008*	-0.004	0.008*	0.001	-0.005	0.006
	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)
Shared occupation (0/1)	0.019+	0.031***	0.029**	0.008	0.033***	0.026*
	(0.011)	(0.008)	(0.009)	(0.006)	(0.009)	(0.010)
Geographic proximity (1'000km)	0.002	0.048	0.137**	0.006	0.014	0.124**
	(0.020)	(0.033)	(0.042)	(0.023)	(0.029)	(0.042)
Shared urban vs. rural (0/1)	0.016+	0.021***	0.032*	0.017+	0.022***	0.024+
	(0.009)	(0.004)	(0.013)	(0.009)	(0.004)	(0.012)
Fixed-effects						
Country x Round	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Trad. Inst. constitut.	Low	Medium	High	Low	Medium	High
Outcome mean	0.473	0.403	0.507	0.451	0.432	0.484
Countries	9	11	6	9	11	8
Respondents	6,715	6,425	4,687	4,768	4,306	4,818
Dyads	2,585,612	2,068,186	1,846,298	1,339,588	982,545	1,492,173
R^2	0.094	0.087	0.032	0.087	0.114	0.048
Within R^2	0.019	0.029	0.027	0.017	0.032	0.021

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

F Robustness checks

F.1 Interaction models:

Appendix A.4 shows that the CVR as estimated in the main analysis can potentially suffer from omitted variable bias when significant cross-cleavage interactions are left unmodeled. We address this issue here in two steps. We first model the full set of direct effects of individuals' i and j characteristics and all interactions between them (Eq. A9 on page A5).[22] This amounts to 100s, in some cases more than 1,000 additional parameters[23] which can yield to unstable estimates due to multi-collinearity. As a remedy, we reduce the set of potential interaction and control variables through a Least Absolute Shrinkage and Selection Operator (LASSO), adding up to a maximum number of 100 additional terms to the main "controls" specification (cf. Beiser-McGrath and Beiser-McGrath 2020).

We estimate both models for each country covered in round 7 of the Afrobarometer and separately for voting intentions and party preferences. We then compare the results with country-level CVR estimates using the baseline and control specifications. Readers may note that proceeding on a country-by-country basis is a comparatively stringent test, as we introduce significantly more flexibility than in the pooled sample. The approach has the further advantage of facilitating empirical estimation which is challenging as a pooled context comes with many more interaction terms to be estimated on a much larger sample.

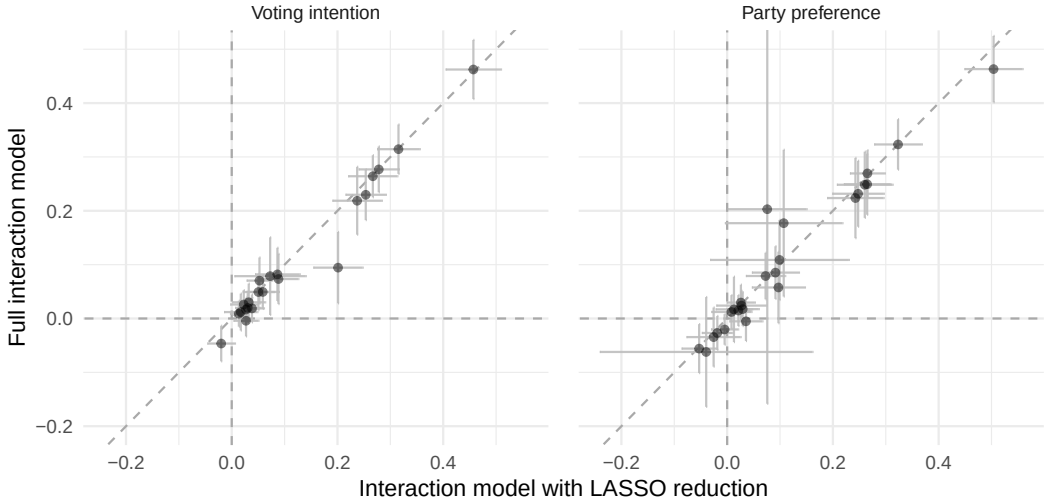


Figure A13: Comparison of country-level effects of coethnicity on covoting from interaction models with the fully set of interactions and LASSO-selected interactions.

Note: Based on Afrobarometer round 7.

[22] We adjust all additional interaction terms to have a mean of zero, such that we can continue to directly interpret the coefficient of coethnicity. To the same intent, interactions between ethnic groups of i and j are shifted such that they have a mean of zero among coethnic pairs if i and j are coethnics and a mean of 0 among non-coethnics if i and j are not coethnic.

[23] This is the case, e.g., in Nigeria where many mother tongues of i interact, e.g., with the many religions and occupations of j.

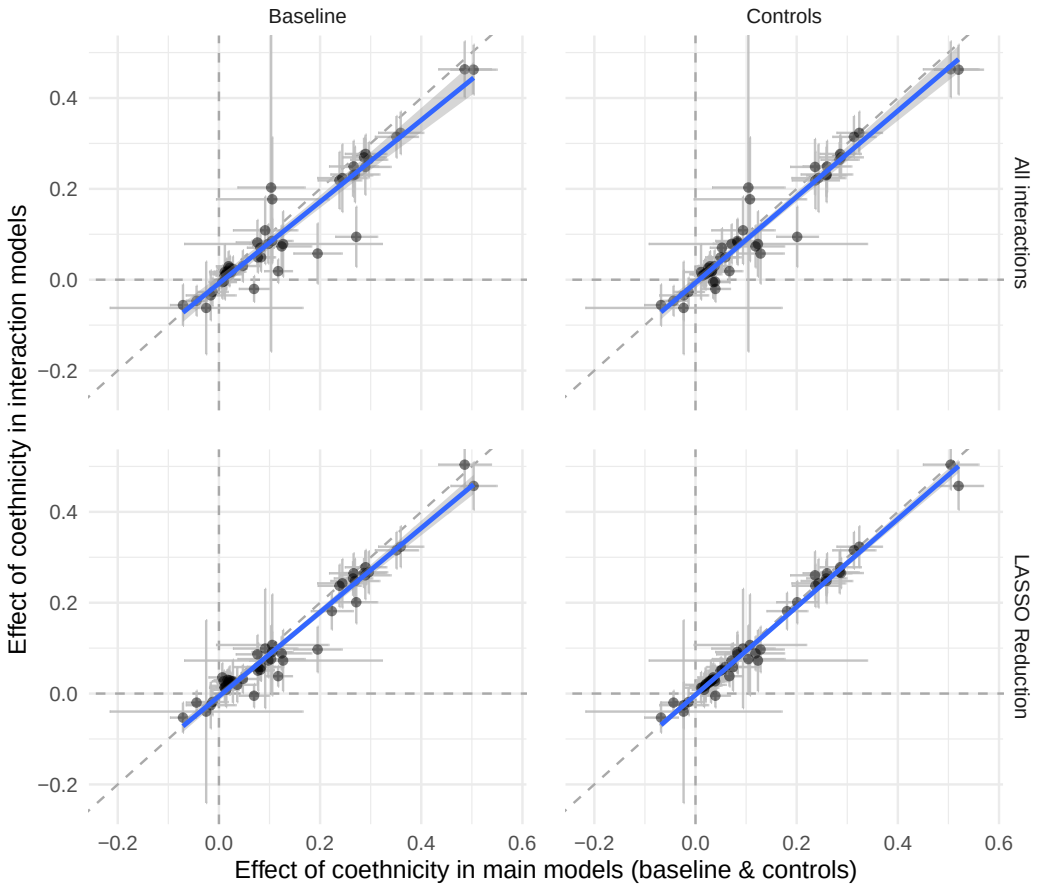


Figure A14: Comparison of country-level effects of coethnicity on covoting from baseline and control specifications and interaction models.

Note: Data from Afrobarometer round 7, separate models for voting intentions and party preference.

We first note the strong overlap between the fully specified and LASSO-reduced models which is shown in Figure A13. In fact, the main divergence consists in a set of one outlier produced through the full interaction model which is due to uncaptured multi-collinearity issues. These results suggest that the LASSO-reduction is successful in streamlining the otherwise overly complicated interaction model.

Figure A14 then plots the results of the interaction models that account for cross-cleavage interactions and our main, country-level results. We first note the close alignment of estimates of the effect of coethnicity with each other as visible in their clustering around the 45-degree line. As to be expected, we observe slightly larger deviations with the empty baseline model than the main "controls" specification. The interaction models yield an effect of coethnicity that amount on average to .89 times the baseline coefficient. In turn, the interaction results are closely aligned with the estimates for the effects of coethnicity using the main controls. Here, estimates from the interaction models on average correspond to .95 times the effects from the models with controls.

F.2 Estimates from multinomial voting models

Based on the discussion in Appendix A.4, we estimate, for each country-round and party $p \in P$, a separate OLS model of the probability that survey respondents intend to vote for that party or has a preference for it:[24]

$$P(p_i) = \delta_{0,p} + \theta_p \mathbf{z}_i \tag{A11}$$

where δ_0 denotes a party-specific constant and θ_p captures the vector of party-specific effects of the covariate vector $\mathbf{z}_i$. $\mathbf{z}_i$ captures individual-level characteristics, in particular i mother-tongue $g \in G$ and control variable $\mathbf{z}'$ used in the main analysis.[25] We use this model to derive for each group, party-specific voting probability $Pr(p|g, \bar{\mathbf{z}}')$ setting all controls $\mathbf{z}'$ to their country-specific mean value. We adjust predicted probabilities to 0 where they are < 0 and to 1 where they are > 1. Using these predicted voting probabilities, we can derive the effect of coethnicity on covoting as the difference between the expected probabilities that a representative pair of coethnics and non-coethnics covote. Doing so only necessitates weighting group-dyadic covoting probabilities by group's share in the survey population w_g:

$$\beta_{coeth} = Pr(p_i = p_j | g_i = g_j, \bar{\mathbf{z}}'_{i,j}) - Pr(p_i = p_j | g_i \neq g_j, \bar{\mathbf{z}}'_{i,j}) \tag{A12}$$

$$= \frac{1}{\sum_g^G w_g^2} \sum_p^P \sum_g^G (w_g^2 \, Pr(p|g, \bar{\mathbf{z}}')^2) - \frac{1}{\sum_{g_i, g_j, g_i \neq g_j}^G w_{g_i} \, w_{g_j}} \sum_p^P \sum_{g_i, g_j, g_i \neq g_j}^G (w_{g_i} \, w_{g_j} \, Pr(p|g_i, \bar{\mathbf{z}}') \, Pr(p|g_j, \bar{\mathbf{z}}')) \tag{A13}$$

Essentially, Eq. A13 takes the size-weighted, covoting probability within each ethnic group and substracts from it the size-weighted, pairwise covoting probabilities between all non-identical ethnic groups, all adjusted to the average control values $\bar{\mathbf{z}}$.

This approaches comes with two disadvantages compared to the CVR. First and most importantly, the aggregation of voting probabilities across independently estimated models does not allow for recovering adequate uncertainty estimates. Second, the estimation procedure is comparatively inefficient, as voting probabilities for each party and group have to be computed even though the quantity of interest is based on an average across parties and pairs of groups.

We recover β_{coeth} as defined in Eq. A13 for voting intentions and party preferences in each country in round 7 of the Afrobarometer using a baseline model without any control variables as well as the full vector of control defined above. This allows us to directly contrast the results with results from estimating the CVR separately for each country and outcome with the baseline and control specifica-

[24] Note that $P(p_i)$ cal also be estimates using a multinomial logistic regression. Yet, in our case, many ethnic groups are small and do not exhibit positive outcomes for each party, which leads to singularities in the estimation procedure.

[25] Individuals' religious identity (categorical), their age, gender, education level (categorical), wealth index, occupation (categorical), urban status, and latitude and longitude.

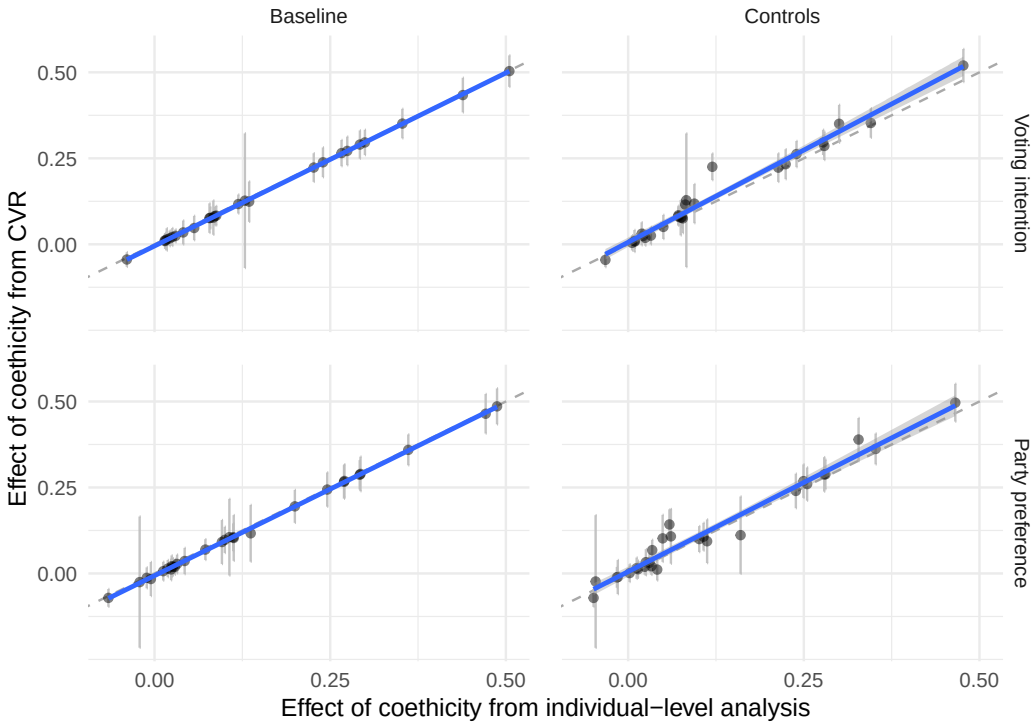


Figure A15: Comparison of country-level effects of coethnicity on covoting from main models compared with estimates recovered from party-by-party "multinomial" OLS estimates of individuals' voting propensities.

Note: Data from Afrobarometer round 7, separate models for voting intentions and party preference. For the individual-level estimation approach, see discussion in text.

tions.

Figure A15 shows the results. Importantly, the baseline specification without controls of the individual-level estimation and the CVR yield almost exactly the same results, thus showing that the aggregation procedure of covariate-adjusted party-level probabilities across groups works as intended. Second, once we include additional control variables the results still coincide substantively with only two country-level estimates deviating significantly from the 45-degree line. Overall, there is a strong linear relationship between the two sets of estimates with only minimal effect overestimation by the CVR, a deviation that is similar to that observed in the fully specified interaction model (Appendix F.1).

F.3 Accounting for potentially endogenous ethnicity

One threat to inference consists in endogenous ethnic change or identity misreporting among respondents. For example, minority members might be incentivized to report membership in a powerful majority group (Green 2021) or economic incentives might shape political preferences and ethnic groups in parallel (Pengl, Roessler and Rueda 2022). In Appendix F.3, we implement two strategies to gauge in how far such processes can explain our main findings.

First, we leverage differences in the malleability of different ethnic markers.

Beyond respondents mother tongue, interviewers in Afrobarometer round 7 also asked respondents about (a) the language spoken in their homes *now* and (b) their "ethnic community, cultural group, or tribe". Both are more malleable than reported mother tongues, with the current language at home being most susceptible to change and strategic reporting. Yet, in particular the ethnicity item is also more precise in reflecting their current ethnic identification than information about individuals' mother tongue, thus reducing measurement error and related downward bias. Re-estimating the CVR using these two variables to construct the indicator of pairwise coethnicity, we find the smallest effect (12 percentage point) for shared language spoken at home. The more precise indicator of shared ethnicity has a slightly larger effect (19 percentage points) than our baseline specification.

Our second strategy draws on the assumption that misreporting and assimilation is least likely to affect pairs of respondents with very distinct and linguistically unrelated mother tongues. We thus estimate the effect of the pairwise linguistic proximity between respondents and find that shared covoting intentions are least likely among respondents who grew up speaking unrelated languages.[26]

As an alternative approach, we vary the coding of coethnicity depending on the level of the language tree on which two mother tongues share the first common node. Very distinct languages come from different languages families (e.g., Khosian or Nilo-Saharan) and share no common root, whereas more closely related languages – such as Bambara and Fulanke in Mali – share a common node on level 9 of the Mande branch of the Niger-Congo language tree. Recoding coethnicity at the levels of the language tree and reestimating the main specification for each recoding shows that we recover positive effects of coethnicity on covoting no matter how coarse our classification of ethnic groups is. While effect estimates decrease with coarser levels (reaching 5 percentage points at level 1), we note that they do so nonlinearly and remain constant above level 5, which already reclassifies many respondent pairs as coethnics which are classified as non-coethnics in the main analysis which is based on the most fine-grained classification of languages. These patterns are well inline with the previous finding that covoting increases with linguistic differences. In combination, these results suggest that strategic misreporting or endogenous ethnic change are unlikely to substantively affect our results.

[26] We compute linguistic distance through the ethnic linkages data from Müller-Crepon, Pengl and Bormann (2022).

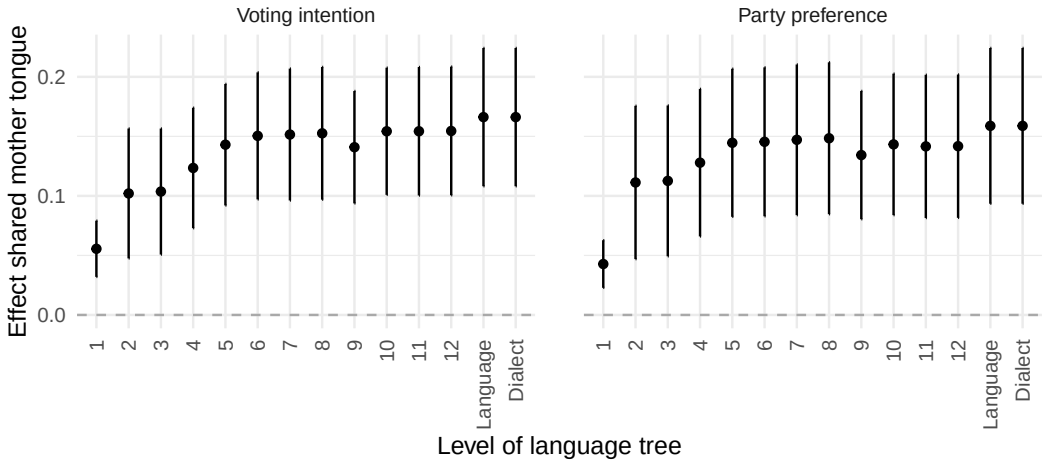


Figure A16: Shared level on language tree, separate models

Table A12: Covoting intentions and shared home language

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared language (0/1)	0.133***	0.124***	0.133***	0.125***
	(0.029)	(0.028)	(0.030)	(0.029)
Shared religion (0/1)		0.023**		0.021**
		(0.007)		(0.007)
Age similarity (decades)		-0.005**		-0.003
		(0.001)		(0.002)
Shared gender (0/1)		0.000		0.000
		(0.001)		(0.001)
Shared education (0/1)		0.018***		0.015***
		(0.004)		(0.004)
Wealth similarity (sd)		0.004+		0.002
		(0.002)		(0.003)
Shared occupation (0/1)		0.028***		0.025***
		(0.006)		(0.006)
Geographic proximity (1'000km)		0.052*		0.045*
		(0.022)		(0.021)
Shared urban vs. rural (0/1)		0.022***		0.022***
		(0.006)		(0.006)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.460	0.460	0.458	0.458
Countries	26	26	28	28
Respondents	17,709	17,709	13,803	13,803
Dyads	6,421,172	6,421,172	3,772,319	3,772,319
R^2	0.070	0.073	0.072	0.074
Within R^2	0.014	0.017	0.014	0.016

Clustered (lang.round.to & lang.round.from) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A13: Covoting intentions and shared ethnicity

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared ethnicity (0/1)	0.199***	0.192***	0.194***	0.187***
	(0.030)	(0.029)	(0.031)	(0.031)
Shared religion (0/1)		0.017*		0.016*
		(0.008)		(0.007)
Age similarity (decades)		-0.004**		-0.002+
		(0.001)		(0.001)
Shared gender (0/1)		0.000		0.000
		(0.001)		(0.001)
Shared education (0/1)		0.018***		0.015***
		(0.004)		(0.003)
Wealth similarity (sd)		0.004+		0.001
		(0.002)		(0.002)
Shared occupation (0/1)		0.026***		0.021***
		(0.005)		(0.005)
Geographic proximity (1'000km)		0.033+		0.027
		(0.019)		(0.017)
Shared urban vs. rural (0/1)		0.023***		0.022***
		(0.005)		(0.005)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.460	0.460	0.459	0.459
Countries	26	26	28	28
Respondents	17,519	17,519	13,648	13,648
Dyads	6,294,664	6,294,664	3,693,742	3,693,742
R^2	0.081	0.083	0.081	0.083
Within R^2	0.025	0.027	0.024	0.025

Clustered (eth.round.to & eth.round.from) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A14: Covoting intentions and linguistic proximity

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Mother tongue proximity (0-1)	0.150***	0.082***	0.150***	0.083***
	(0.028)	(0.019)	(0.030)	(0.019)
Shared religion (0/1)	0.024***	0.018*	0.023***	0.018**
	(0.007)	(0.007)	(0.006)	(0.007)
Age similarity (decades)	-0.004***	-0.004**	-0.003	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Shared gender (0/1)	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Shared education (0/1)	0.016***	0.016***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Wealth similarity (sd)	0.004+	0.004	0.002	0.001
	(0.003)	(0.002)	(0.003)	(0.003)
Shared occupation (0/1)	0.025***	0.024***	0.021***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
Geographic proximity (1'000km)	0.053*	0.026	0.051*	0.020
	(0.020)	(0.018)	(0.021)	(0.018)
Shared urban vs. rural (0/1)	0.021***	0.021***	0.021***	0.021***
	(0.005)	(0.005)	(0.006)	(0.006)
Shared mother tongue (0/1)		0.139***		0.133***
		(0.027)		(0.030)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.460	0.460	0.459	0.459
Countries	26	26	28	28
Respondents	17,619	17,619	13,748	13,748
Dyads	6,359,590	6,359,590	3,745,650	3,745,650
R^2	0.074	0.083	0.074	0.082
Within R^2	0.016	0.026	0.015	0.024

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

F.4 Accounting for geographic variation

A second threat to inference originates in the geography of ethnic groups. Many ethnic groups' inhabit regionally distinct homelands. Coethnic voting intentions might simply emerge from an alignment of political preferences of individuals who live in the same administrative region or even location based on joint economic interests (Boone et al. 2022; Boone 2024), an argument that dovetails with findings of non-ethnic voting of local minorities in presidential elections (Ichino and Nathan 2013). This risk is further compounded by previous findings that the drawing of subnational borders has partially shaped ethnic geography itself (Posner 2005; Müller-Crepon 2025). Yet, we note that ethnic geography likewise affects individuals' migration decisions and place of residence (Müller-Crepon 2025, see also Marbach 2021) as well as countries' division into administrative units (Muller-Crepon 2024).

We address this threat in two steps. First, Table A15 assess whether controlling for more finegrained geographical commonalities affects the estimated effect of coethnicity and whether the geography and coethnicity interact. Models 1 and 4 show, for voting intentions and party preferences, respectively, that geographic proximity has a non-linear association with covoting, with covoting becoming increasingly less common the more distant to respondents are. Accounting for this pattern does however not substantively change the effect of coethnicity. Models 2 and 5 then show that adding dummy variables for respondents who live in the same enumeration area, district, and region does not impact the estimate of coethnicity either, even though individuals from the same areas tends to covote more often. Lastly, we do not find substantively large or consistent interaction effects between joint residence patterns and coethnicity. If at all, the effect of coethnicity is reduced by about 4 percentage points within the same enumeration area,[27] yet this pattern does not replicate for the district or regional level. Overall then, accounting for additional nuances of shared geographic backgrounds between respondents does not explain our results.

In a second step, we excluding variation between administrative regions or single localities from our data altogether. We do so by constructing our dyadic comparisons *after* splitting each country-round into disjoint samples from (a) administrative regions and (b) enumeration areas (EAs).[28] The resulting data then features no dyads that span across these spatial units, leaving only comparisons among respondents who live in the same region/EA. Doing so increases the rate of shared mother tongues from 24 percent in the full sample to 43 percent within regions and 66 percent within enumeration areas.[29] Equally important, we note that *non-coethnic* dyads within regions and EAs are not representative of the overall distribution of respondent pairs. In particular, they feature greater linguistic proximity (average distance of .2 compared to .5), which should increase covoting among non-coethnics and water down the effect of coethnicity.

[27] This coincides with earlier findings by Ichino and Nathan (2013) and findings below.

[28] For countries for which we subsample large Afrobarometer surveys to 1'200 respondents, we repeat this procedure, but sampling enumeration areas in a block-wise manner to maintain as large a sample as possible. Typically, there are 8 respondents per EA.

[29] Similarly, covoting intentions increase from 46 percent to 52 and 59 percent within regions and enumeration areas, respectively.

Table A15: Co-voting intentions and shared mother tongue: Distance and administrative geography

Dependent Variables:	Voting intention			Party preference		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shared mother tongue (0/1)	0.164***	0.163***	0.162***	0.159***	0.157***	0.158***
	(0.030)	(0.030)	(0.030)	(0.033)	(0.033)	(0.035)
Geographic proximity (1'000km)	0.114**	0.054*	0.054*	0.092*	0.028	0.028
	(0.040)	(0.023)	(0.024)	(0.036)	(0.023)	(0.023)
Geographic proximity (1'000km) square	0.054**			0.045*		
	(0.021)			(0.021)		
Shared enum. area		0.043**	0.065***		0.026	0.048***
		(0.015)	(0.010)		(0.017)	(0.012)
Shared district (adm2)		-0.033*	-0.042***		-0.020	-0.026**
		(0.013)	(0.009)		(0.013)	(0.009)
Shared region (adm1)		0.032*	0.033*		0.047**	0.050**
		(0.015)	(0.015)		(0.017)	(0.018)
Shared mother tongue (0/1) × Shared enum. area			-0.043*			-0.036+
			(0.018)			(0.021)
Shared mother tongue (0/1) × Shared district (adm2)			0.022			0.014
			(0.015)			(0.017)
Shared mother tongue (0/1) × Shared region (adm1)			-0.001			-0.008
			(0.015)			(0.018)
Fit statistics						
Country-Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Outcome mean	0.460	0.461	0.461	0.459	0.466	0.466
Countries	26	26	26	28	27	27
Respondents	17,827	17,758	17,758	13,892	13,224	13,224
Dyads	6,500,096	6,446,025	6,446,025	3,814,306	3,596,229	3,596,229
R^2	0.079	0.080	0.080	0.079	0.081	0.081
Within R^2	0.023	0.024	0.024	0.021	0.023	0.023

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

While decreasing in size, the estimated effects of a shared mother tongue remain sizeable even within regions (12-14ppts) and enumeration areas (10-12ppts) when using country-round fixed effects. Once we add region and EA fixed effects, estimates decrease by another 2-4 percentage points to 10-11 percentage pints within regions and 7-8 percentage points within EAs. This decrease from the main effect suggests more frequent alignment of electoral preferences across ethnic lines within small geographic radii within which coethnicity and covoting are both generally more common. Yet, we note that respondent pairs within EAs (regions) only make up a small fraction of around 6 (15) percent of the full data, thus having only relatively minor impact on the overall results.

Figure A17 investigates whether the drop in the estimated effect of shared mother tongues varies between countries. The results show that country-level estimates are quite closely aligned across specifications. Similar to the results shown in Table A17, the EA-level specifications lead to a drop in effect sizes by around 35 percent when using country FEs and by around 55 percent when using EA FEs. While in states such as Kenya the EA-specific effect of coethnicity is almost as large as that in the overall sample, Zambia for example sees a drop from around .2 to 0, but only once we include EA FEs wich soak up most of the variation in covoting, which stands at an average of 70 percent within EAs but 35 percent nationwide.

Table A16: Covoting intentions and shared mother tongue: Within Administrative Regions

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.137***	0.107***	0.116***	0.100***
	(0.020)	(0.017)	(0.022)	(0.019)
Shared religion (0/1)	0.020*	0.016*	0.023*	0.015+
	(0.008)	(0.006)	(0.011)	(0.008)
Age similarity (decades)	-0.007***	-0.005**	-0.007**	-0.005*
	(0.002)	(0.001)	(0.003)	(0.002)
Shared gender (0/1)	0.002	0.003+	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Shared education (0/1)	0.024***	0.019***	0.018***	0.012**
	(0.006)	(0.004)	(0.005)	(0.004)
Wealth similarity (sd)	0.009*	0.007+	0.004	0.004
	(0.004)	(0.004)	(0.005)	(0.004)
Shared occupation (0/1)	0.020*	0.009	0.017+	0.012
	(0.009)	(0.008)	(0.009)	(0.008)
Geographic proximity (1'000km)	0.013	0.124	0.080	0.148
	(0.065)	(0.098)	(0.072)	(0.094)
Shared urban vs. rural (0/1)	0.022**	0.028***	0.024*	0.031***
	(0.007)	(0.005)	(0.010)	(0.008)
Fixed-effects				
Country x Round	Yes		Yes	
Region		Yes		Yes
Fit statistics				
Outcome mean	0.517	0.517	0.521	0.521
Regions	324	324	358	358
Respondents	17,825	17,825	13,890	13,890
Dyads	1,007,404	1,007,404	600,974	600,974
R^2	0.079	0.135	0.081	0.138
Within R^2	0.021	0.013	0.016	0.012

*Standard errors clustered at the level of each respondent's mother tongue in parentheses. Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A17: Covoting intentions and shared mother tongue: Within Enumeration Areas

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.113***	0.063***	0.098***	0.076***
	(0.016)	(0.017)	(0.015)	(0.017)
Shared religion (0/1)	0.031**	0.025**	0.030**	0.020+
	(0.010)	(0.008)	(0.011)	(0.010)
Age similarity (decades)	-0.008***	-0.002	-0.004	0.000
	(0.002)	(0.002)	(0.003)	(0.003)
Shared gender (0/1)	0.001	0.000	-0.008	-0.009
	(0.005)	(0.004)	(0.006)	(0.005)
Shared education (0/1)	0.035***	0.023***	0.027**	0.017*
	(0.007)	(0.006)	(0.009)	(0.008)
Wealth similarity (sd)	0.016**	0.015**	0.008	0.008
	(0.005)	(0.005)	(0.006)	(0.006)
Shared occupation (0/1)	0.045***	0.008	0.049***	0.016*
	(0.009)	(0.007)	(0.010)	(0.008)
Fixed-effects				
Country x Round	Yes		Yes	
Enum. Area		Yes		Yes
Fit statistics				
Outcome mean	0.594	0.594	0.590	0.590
Enum. areas	3,690	3,690	3,375	3,375
Respondents	17,681	17,681	13,293	13,293
Dyads	39,408	39,408	23,666	23,666
R^2	0.074	0.367	0.081	0.416
Within R^2	0.018	0.005	0.014	0.006

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

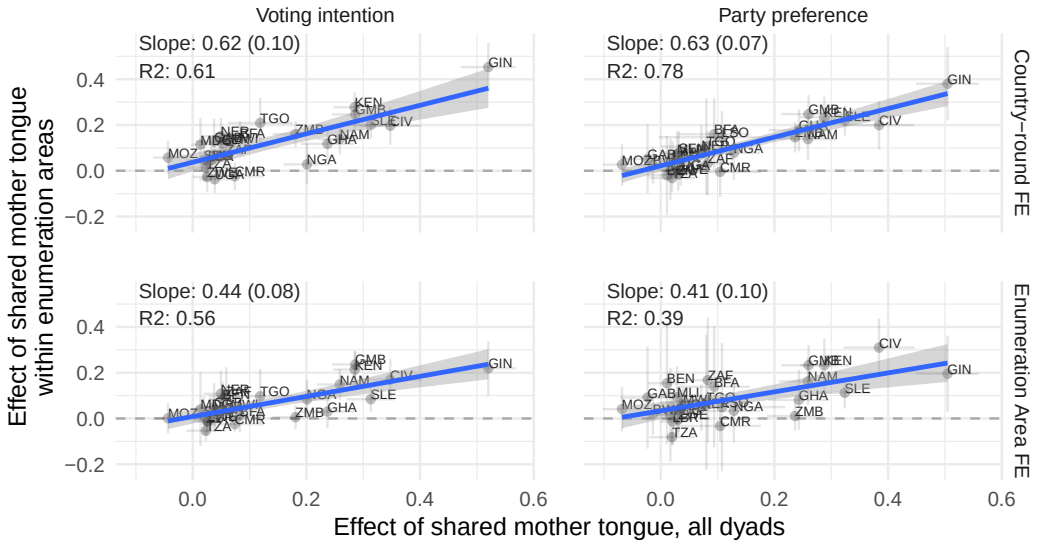


Figure A17: Country-wise estimate of effect of shared mother tongue on covoting across the whole sample (x-axis) and within enumeration areas only (y-axis)

Note: Coefficients result from the fully specified model in Equation (10) estimated by country. Specifications within Enumeration Areas correspond to models in Table A17. We drop Sudan which features an outlier estimates of .4 in the EA-level analysis due to low variation in coethnicity in the mostly Arabic-speaking country.

F.5 Expanding the economic wealth index

We compute a more expansive measure of economic class by including, in addition to the economic factors used to compute the main wealth indicator, respondents' level of education, whether they are fully or partially and informally or formally employed, as well as whether they had adequate access to fuel in the past year. Results in Table A18 show that the estimated effect of this expanded measure of socio-economic status does not differ from the main results (which we keep due to the lack of some of the added variables in earlier rounds).

Table A18: Covoting and shared mother tongue: Expanded Class Index

Dependent Variables:	Voting intention	Party preference
Model:	(1)	(2)
Variables		
Shared mother tongue (0/1)	0.168***	0.162***
	(0.030)	(0.034)
Shared religion (0/1)	0.020**	0.019**
	(0.007)	(0.007)
Age similarity (decades)	-0.004**	-0.002
	(0.001)	(0.002)
Shared gender (0/1)	0.000	0.000
	(0.001)	(0.001)
Shared education (0/1)	0.018***	0.015***
	(0.004)	(0.003)
Wealth similarity (extended, sd)	0.002	0.001
	(0.002)	(0.003)
Shared occupation (0/1)	0.026***	0.022***
	(0.006)	(0.005)
Geographic proximity (1'000km)	0.042*	0.035+
	(0.020)	(0.019)
Shared urban vs. rural (0/1)	0.022***	0.021***
	(0.005)	(0.006)
Fixed-effects		
Country x Round	Yes	Yes
Fit statistics		
Outcome mean	0.460	0.459
Countries	26	28
Respondents	17,827	13,892
Dyads	6,500,096	3,814,306
R^2	0.079	0.079
Within R^2	0.023	0.021

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

F.6 Data construction

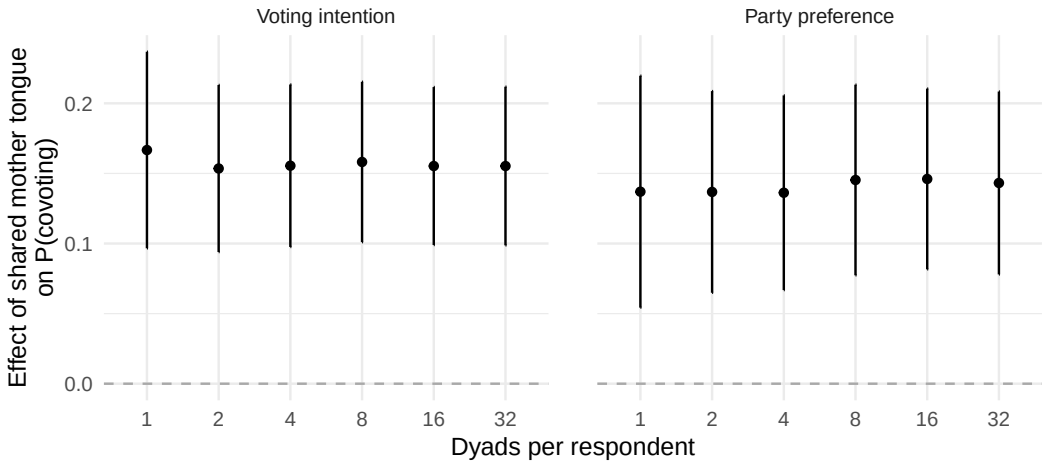


Figure A18: Effect of shared mother tongue by number of comparisons per respondent

Note: Coefficients result from the fully specified model in Equation (10) estimated with different number of dyadic pairings for each respondents, and using respondents' self-identified ethnicity to construct the co-ethnicity indicator. The estimated are thus equivalent to Models 2 and 4 in Table 1 in all respects except for the construction of dyads.

Table A19: Covoting intentions and shared mother tongue: Country-weights

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.189***	0.181***	0.190***	0.183***
	(0.031)	(0.031)	(0.041)	(0.042)
Shared religion (0/1)		0.015**		0.009
		(0.006)		(0.006)
Age similarity (decades)		-0.004**		-0.003
		(0.001)		(0.002)
Shared gender (0/1)		0.001		0.001
		(0.001)		(0.001)
Shared education (0/1)		0.018***		0.017***
		(0.004)		(0.003)
Wealth similarity (sd)		0.005*		0.003
		(0.002)		(0.003)
Shared occupation (0/1)		0.025***		0.022***
		(0.006)		(0.006)
Geographic proximity (1'000km)		0.039+		0.036+
		(0.021)		(0.021)
Shared urban vs. rural (0/1)		0.020***		0.023**
		(0.006)		(0.007)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.460	0.460	0.459	0.459
Countries	26	26	28	28
Respondents	17,827	17,827	13,892	13,892
Dyads	6,500,096	6,500,096	3,814,306	3,814,306
R^2	0.076	0.078	0.076	0.077
Within R^2	0.023	0.025	0.024	0.026

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

Table A20: Covoting intentions and shared mother tongue: Recoding 'other' parties as single parties

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.162***	0.155***	0.166***	0.159***
	(0.030)	(0.029)	(0.033)	(0.033)
Shared religion (0/1)		0.019**		0.020**
		(0.007)		(0.007)
Age similarity (decades)		-0.003*		-0.002
		(0.001)		(0.002)
Shared gender (0/1)		0.000		-0.001
		(0.001)		(0.001)
Shared education (0/1)		0.018***		0.016***
		(0.004)		(0.004)
Wealth similarity (sd)		0.003		0.001
		(0.002)		(0.002)
Shared occupation (0/1)		0.024***		0.023***
		(0.006)		(0.005)
Geographic proximity (1'000km)		0.034+		0.033+
		(0.019)		(0.019)
Shared urban vs. rural (0/1)		0.023***		0.021***
		(0.006)		(0.006)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.423	0.423	0.448	0.448
Countries	28	28	28	28
Respondents	18,720	18,720	14,130	14,130
Dyads	7,076,708	7,076,708	3,912,652	3,912,652
R^2	0.085	0.088	0.081	0.083
Within R^2	0.018	0.020	0.018	0.020

*Standard errors clustered at the level of each respondent's mother tongue in parentheses. Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

F.7 Model specification

Table A21: Covoting intentions and shared mother tongue: Logistic regression

Dependent Variables:	Voting intention		Party preference	
Model:	(1)	(2)	(3)	(4)
Variables				
Shared mother tongue (0/1)	0.770***	0.733***	0.737***	0.705***
	(0.133)	(0.132)	(0.147)	(0.147)
Shared religion (0/1)		0.087**		0.082**
		(0.033)		(0.031)
Age similarity (decades)		-0.017**		-0.011
		(0.005)		(0.008)
Shared gender (0/1)		0.002		0.000
		(0.003)		(0.005)
Shared education (0/1)		0.081***		0.066***
		(0.017)		(0.015)
Wealth similarity (sd)		0.018+		0.007
		(0.010)		(0.011)
Shared occupation (0/1)		0.112***		0.095***
		(0.024)		(0.023)
Geographic proximity (1'000km)		0.188*		0.162+
		(0.087)		(0.083)
Shared urban vs. rural (0/1)		0.095***		0.091***
		(0.024)		(0.025)
Fixed-effects				
Country x Round	Yes	Yes	Yes	Yes
Fit statistics				
Outcome mean	0.460	0.460	0.459	0.459
Countries	26	26	28	28
Respondents	17,827	17,827	13,892	13,892
Dyads	6,500,096	6,500,096	3,814,306	3,814,306

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

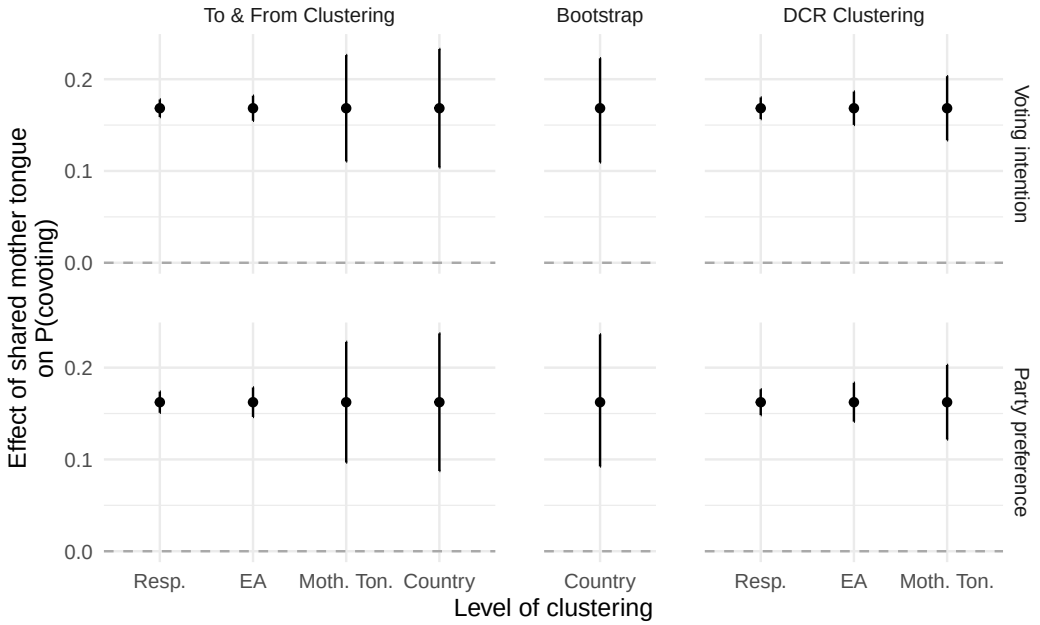


Figure A19: Varying the clustering of standard errors

Note: Coefficients result from the fully specified model in Equation (10) estimated with different standard errors, and using respondents' self-identified ethnicity to construct the co-ethnicity indicator. The estimated models are thus equivalent to Models 2 and 4 in Table 1 in all respects except for the standard errors.

Table A22: Covoting intentions and shared mother tongue: Fixed effects specification

Dependent Variables:	Voting intention			Party preference		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Shared mother tongue (0/1)	0.155***	0.151***	0.151***	0.171***	0.158***	0.170***
	(0.032)	(0.032)	(0.033)	(0.036)	(0.034)	(0.037)
Shared religion (0/1)	0.016*	0.020**	0.026**	0.014+	0.016*	0.020**
	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)	(0.008)
Age similarity (decades)	-0.004***	-0.002+	0.002***	-0.002	-0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Shared gender (0/1)	0.001	0.002*	0.002**	0.000	0.002+	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Shared education (0/1)	0.018***	0.014***	0.009***	0.013***	0.010***	0.008***
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Wealth similarity (sd)	0.004+	0.004**	0.005***	0.003	0.005**	0.006***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Shared occupation (0/1)	0.024***	0.007*	0.003+	0.022***	0.006**	0.002
	(0.005)	(0.003)	(0.001)	(0.005)	(0.002)	(0.001)
Geographic proximity (1'000km)	0.063**	0.118***	0.117***	0.061**	0.108***	0.101***
	(0.022)	(0.032)	(0.030)	(0.022)	(0.030)	(0.028)
Shared urban vs. rural (0/1)	0.017***	0.002	0.002	0.016**	0.003	0.004
	(0.005)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Fit statistics						
Fixed Effects	Lang.	EA	Resp.	Lang.	EA	Resp.
Outcome mean	0.460	0.460	0.460	0.459	0.459	0.459
Countries	26	26	26	28	28	28
Respondents	17,827	17,827	17,827	13,892	13,892	13,892
Dyads	6,500,096	6,500,096	6,500,096	3,814,306	3,814,306	3,814,306
R^2	0.122	0.225	0.426	0.124	0.247	0.437
Within R^2	0.016	0.020	0.025	0.018	0.021	0.028

Standard errors clustered at the level of each respondent's mother tongue in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, +: 0.1*

F.8 Network-based partition model

We here apply the recently developed *Probabilistic Spatial Partition Model* (Müller-Crepon, Schvitz and Cederman 2025) to the case of the partitioning of voters into parties. The model was originally developed to partition geographical space into state territory. We transform the understanding of space to extend to a multi-dimensional electoral space. To apply the model we need to understand voters as the nodes of a network which is divided into partitions (candidates or parties) based on dyadic differences and similarities between voter characteristics, in short, electoral cleavages.

Probabilistic Partition Model

Following Müller-Crepon, Schvitz and Cederman (2025), we model the partitioning of voters as a Boltzman distribution

$$Pr(P = p_k) = \frac{e^{-\epsilon_k}}{\sum_{k=1}^{|\mathbb{P}|} e^{-\epsilon_k}}, \tag{A14}$$

where the chance that a given partitioning p_k is realized decreases with its "energy" ϵ_k. This energy can be interpreted as political tensions in a given division of voters into parties: the more voters are dissatisfied with the party they vote for in a given partitioning, the higher the tension and the less likely the partitioning emerges. Partitionings' energy ϵ_k results from attractive and repulsive forces $\epsilon_{i,j}$ between voters i and j. These forces are only realized when i and j support the same party ($\mathbb{1}_{i,j} = 1$) and not otherwise:

$$\epsilon_k = \sum_{i,j \in L} \mathbb{1}_{i,j} \epsilon_{i,j}, \tag{A15}$$

$$\epsilon_{i,j} = \beta_0 + \gamma \, \mathbf{x}_{i,j}, \tag{A16}$$

The political attraction and/or repulsion between pairs L of voters i and j is determined on the one hand by a constant baseline attraction β_0, as well as a vector of dyadic comparisons $\mathbf{x}_{i,j}$ between them. These comparisons can include binary indicators of differing ethnicity or gender, as well as distance measures, such as their wealth difference or geographic distance between them. Intuitively, we expect individuals with different ethnic backgrounds or vastly different incomes to be less likely to vote for the same party – indeed, were the same party trying to attract them, it might end up not succeeding or splitting. The vector of γ parameters indicates the effect of each dyadic voter comparison on the attraction and repulsion between voters and thus ultimately the partitioning of voters into parties. Estimating parameters in γ is therefore our ultimate goal.

As can be seen, similar to our setup in the baseline analysis, this formulation of vote choice is entirely dependent on comparisons between voters and does therefore not pre-suppose the existence of any party or set of parties. These emerge endogenously as the result of co-voting between voters. This allows for estimating the model across countries or country-periods with differing sets of parties and candidates.

We estimate Eq. A16 using the same data as used in the main analysis. In fact, the set of dyadic comparisons constructed for each country-round of the Afrobarometer can be represented as a graph $G_{c,t}$ of voters $i, j \in N$ who are associated with party or candidate preferences. The edges L of G encode the covariates $\mathbf{x}_{i,j}$ in Eq. A16 that determine whether voters i and j are likely to vote for the same (attraction) or two different (repulsion) parties. These co-variates are the same as used in the main analysis. Instead of a separate fixed effect for each country, we add one variable which stores the average attraction between nodes from each country. This is derived as the intercept of an otherwise empty model estimated separately for each country.

Results

Table A23 presents the main estimates from the partition model, derived – as in the main analysis – from unconditional and conditional models of the effect of share mother tongues on respondents' joint support for presidential candidates and legislative parties. We find relatively large estimates which are stable across specifications and outcomes and associated with little uncertainty. Importantly and as in our main analysis, the effect associated with a shared mother tongue does not significantly change with the introduction of other covariates

Table A23: Shared mother tongue and respondents' partitioning into candidates and parties

	Presidential candidates		Party support	
	(1)	(2)	(3)	(4)
Constant	0.0001	-0.0044^*	0.0009^*	-0.0031
	$[-0.0008; 0.0012]$	$[-0.0060; -0.0013]$	$[0.0002; 0.0026]$	$[-0.0059; 0.0005]$
By-country intercept	0.8121^*	0.7914^*	0.9116^*	0.9242^*
	$[0.6964; 0.9560]$	$[0.6570; 0.9777]$	$[0.8307; 1.0234]$	$[0.8157; 1.0672]$
Shared mother tongue	-0.0085^*	-0.0081^*	-0.0074^*	-0.0073^*
	$[-0.0112; -0.0060]$	$[-0.0109; -0.0055]$	$[-0.0149; -0.0040]$	$[-0.0147; -0.0044]$
Shared religion		-0.0001		-0.0004
		$[-0.0019; 0.0009]$		$[-0.0032; 0.0012]$
Age similarity		-0.0001		-0.0004
		$[-0.0003; 0.0001]$		$[-0.0006; 0.0000]$
Shared gender		-0.0068^*		-0.0064
		$[-0.0090; -0.0035]$		$[-0.0098; 0.0001]$
Shared education		-0.0017^*		-0.0014^*
		$[-0.0027; -0.0007]$		$[-0.0024; -0.0005]$
Wealth similarity		-0.0003		-0.0002
		$[-0.0006; 0.0001]$		$[-0.0007; 0.0002]$
Shared occupation		-0.0009^*		-0.0020^*
		$[-0.0015; -0.0000]$		$[-0.0027; -0.0008]$
Geographic proximity		-0.0012		-0.0009
		$[-0.0038; 0.0001]$		$[-0.0056; 0.0020]$
Shared urban/rural		-0.0020^*		-0.0018^*
		$[-0.0028; -0.0011]$		$[-0.0034; -0.0005]$
Countries	26	26	28	28
Respondents	17827	17827	13892	13892
Edges	6500096	6500096	3814306	3814306

Notes: 95% confidence intervals from country-level bootstrap in parenthesis. * Statistically significant at the 95% level.

We take two additional steps to gauge the comparability between the results from the partition model with our main results. First, we sequentially decrease the connectivity in graph G that underlies the model to the point where each respondent is connected only to one other respondent. We ensure that each respondent is connected to a uniform number of edges by constructing the sparse graphs G as

the union of ring graphs. Each ring graph contains the full set of respondents in a random order and connects each respondent to their two ring-neighbours. Respondent orders are sampled such that the ring graphs do not contain overlapping edges.

Estimates from the disjoint graph of one dyad per respondent without any overarching network structure (see Figure A20) are very close to the estimates obtained from a logistic regression model using the main specification (see Table A21 above). The partition model indeed reduces to a simple edge-wise logistic regression where edges are not connected to each other. Deviations can be explained by the sampling error incurred when sparsening the graph.

Once the density of the network increases, coefficient estimates naturally decrease – this reflects that the importance (or 'energy') of any one edge in influencing the partition membership of each node decreases with the number of its edges. Yet, Figure A20 shows that the *ratio* between the effect of shared mother tongue and the remaining coefficients remains remarkably stable. We take this as further evidence that the network estimator closely mirrors our main results.

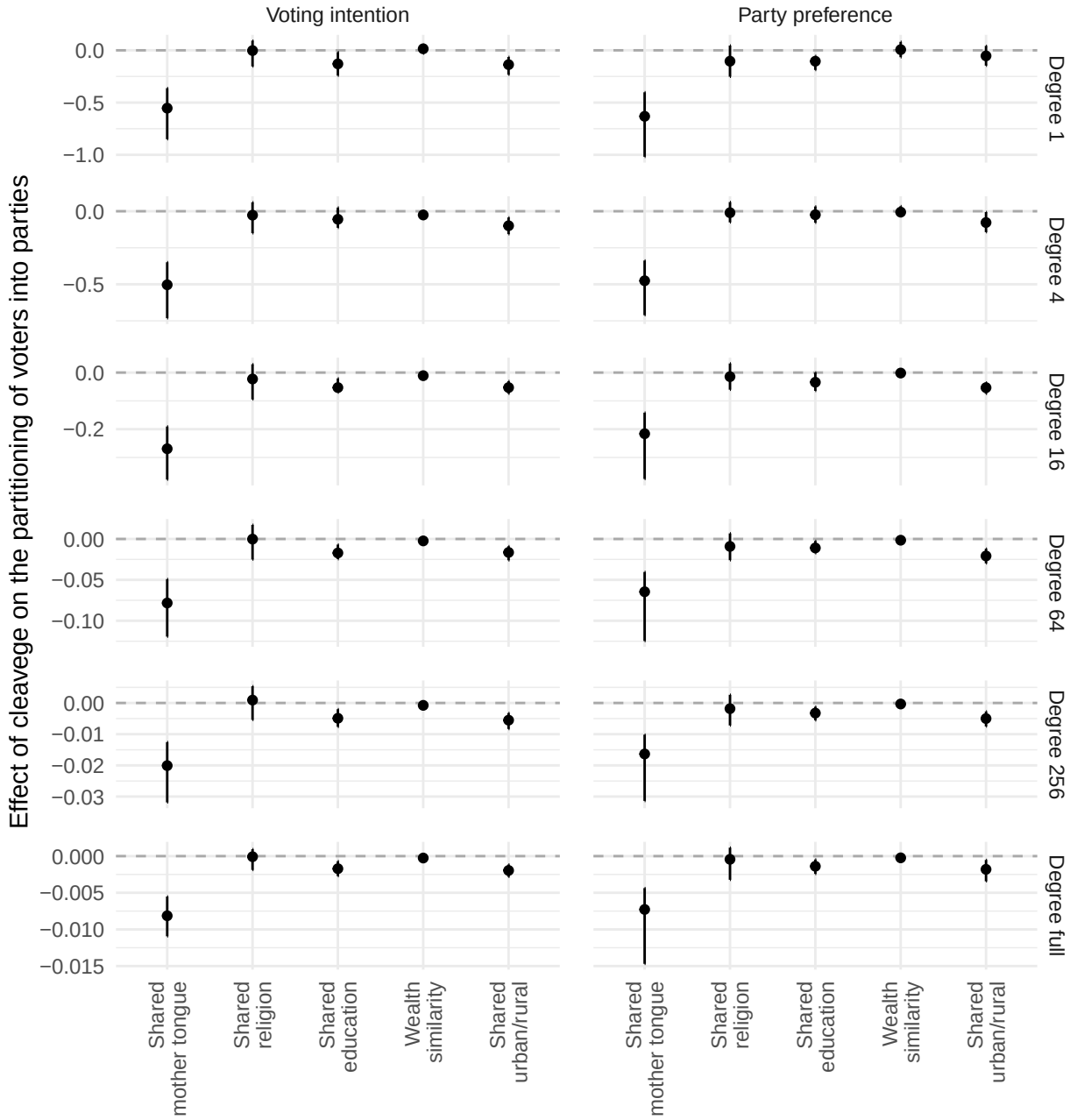


Figure A20: Partition model estimates by degree of connectivity

Note: The figure plots the most important predictors of the partitioning of respondents into presidential candidates and parties, by degree of network connectivity. Each set of coefficients results from estimating Eq. A16 using the full set of control variables. The estimated models are thus equivalent to Models 2 and 4 in Table A23 in all respects except for variation in network connectivity.

G Country-level estimates

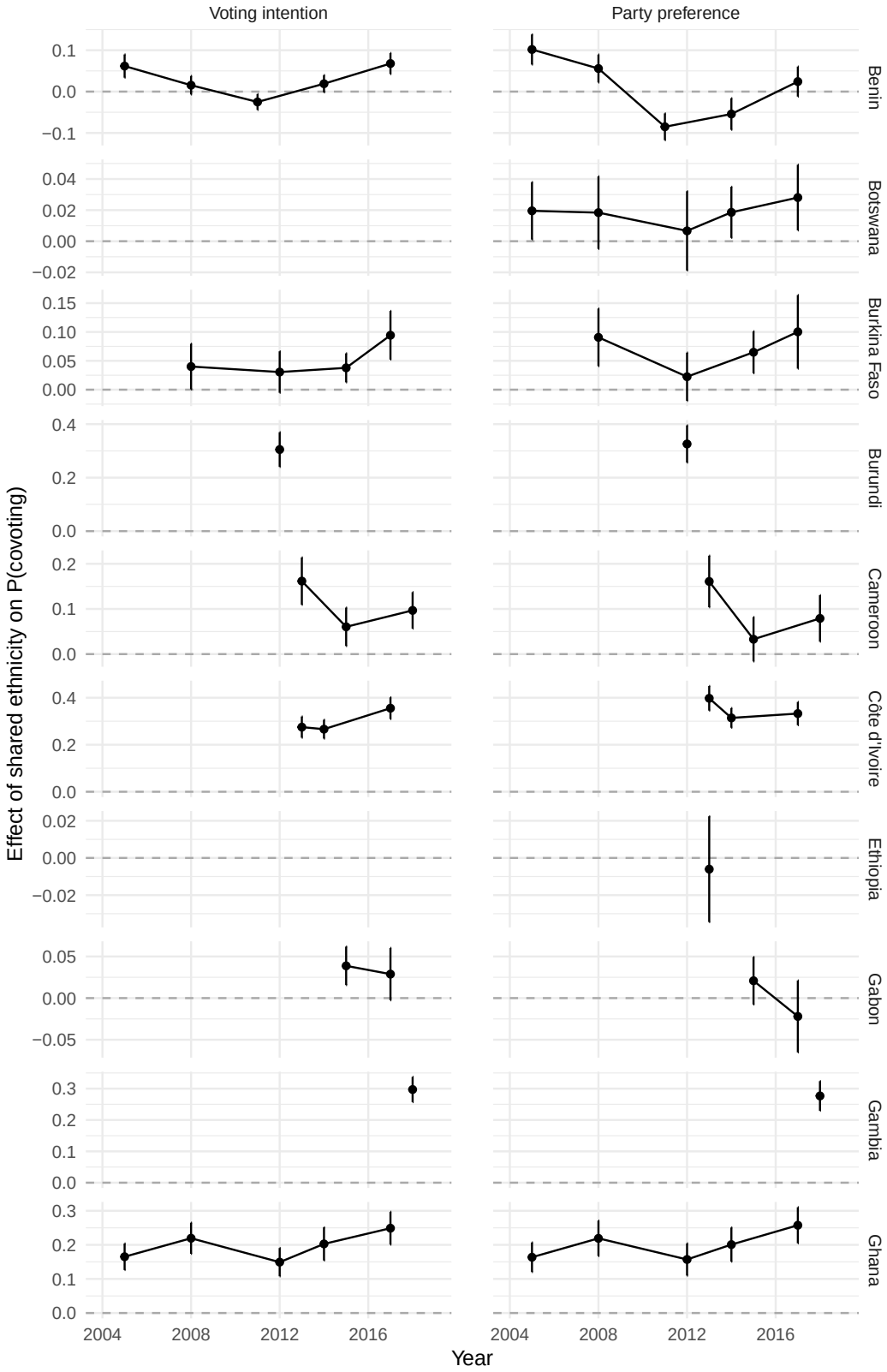


Figure A21: By country, over time, I

Note: Coefficients result from the fully specified model in Eq. (10) estimated separately for each Afrobarometer survey round since Round 3 with respondents' self-identified ethnicity as ethnicity indicator. The estimated models are thus equivalent to Models 2 and 4 in Table 1 in all respects except for the sample which varies by country-survey round.

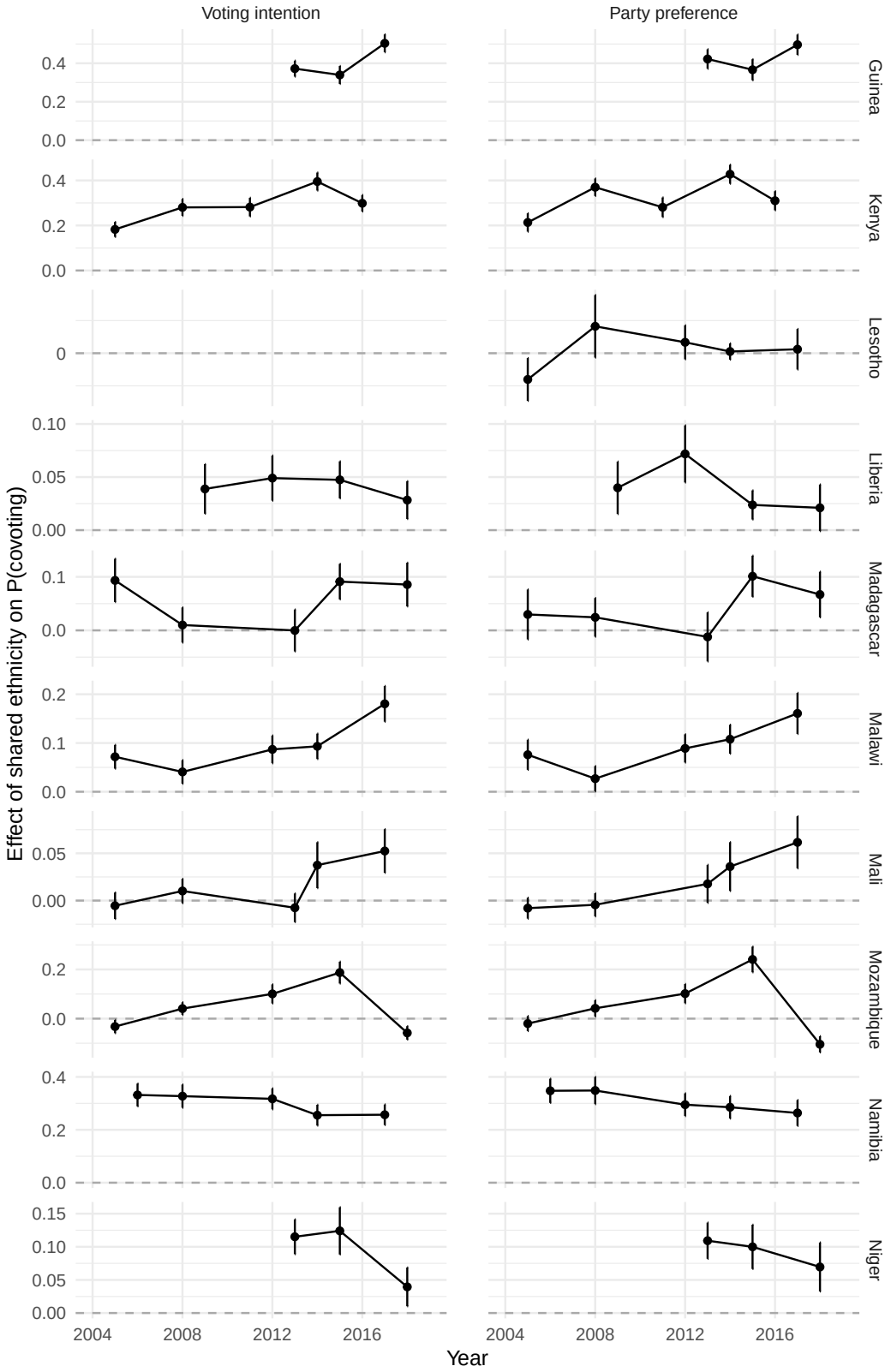


Figure A22: By country, over time, II

Note: Coefficients result from the fully specified model in Eq. (10) estimated separately for each Afrobarometer survey round since Round 3 with respondents' self-identified ethnicity as ethnicity indicator. The estimated models are thus equivalent to Models 2 and 4 in Table 1 in all respects except for the sample which varies by country-survey round.

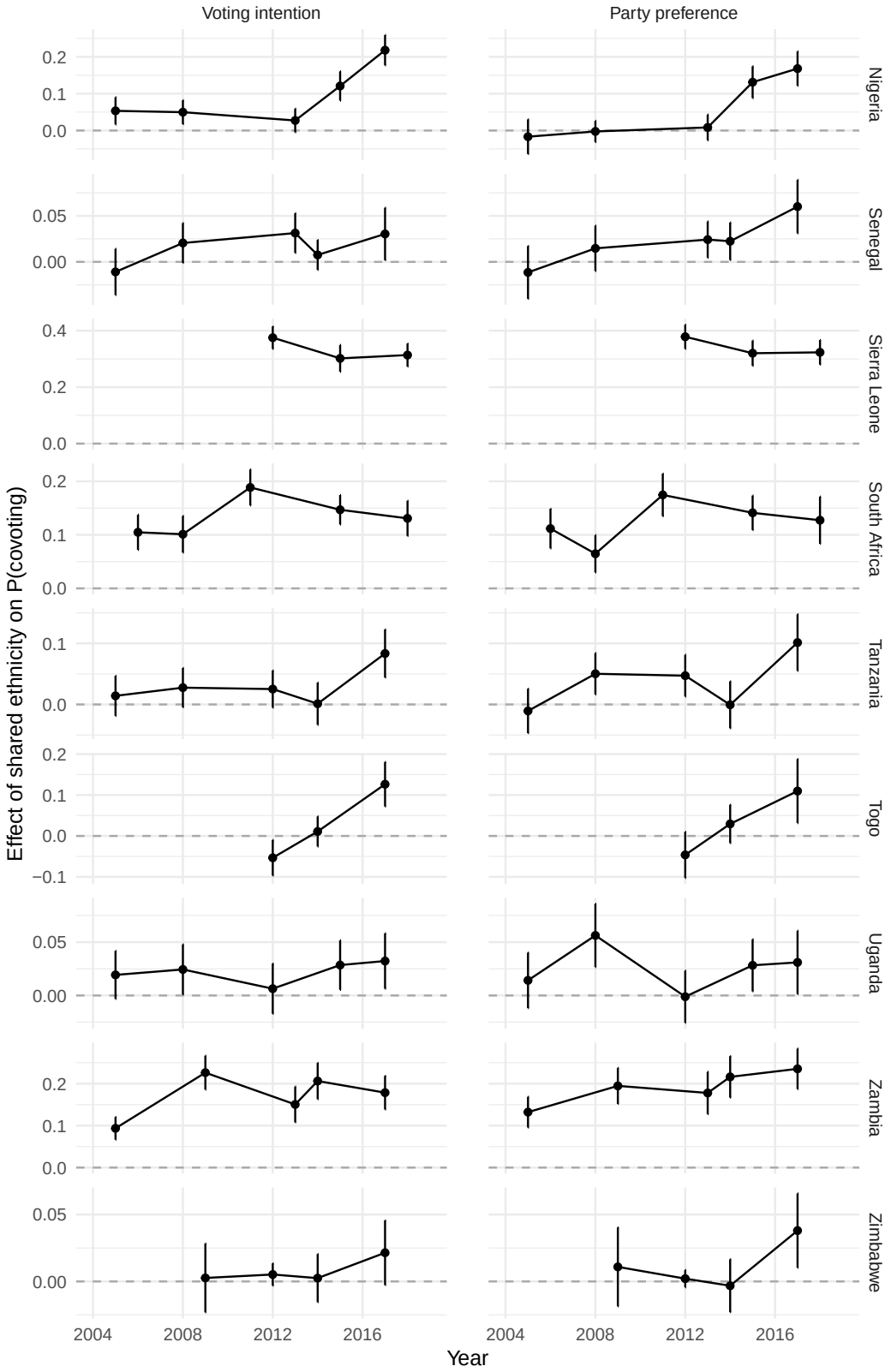


Figure A23: By country, over time, III

Note: Coefficients result from the fully specified model in Eq. (10) estimated separately for each Afrobarometer survey round since Round 3 with respondents' self-identified ethnicity as ethnicity indicator. The estimated models are thus equivalent to Models 2 and 4 in Table 1 in all respects except for the sample which varies by country-survey round.

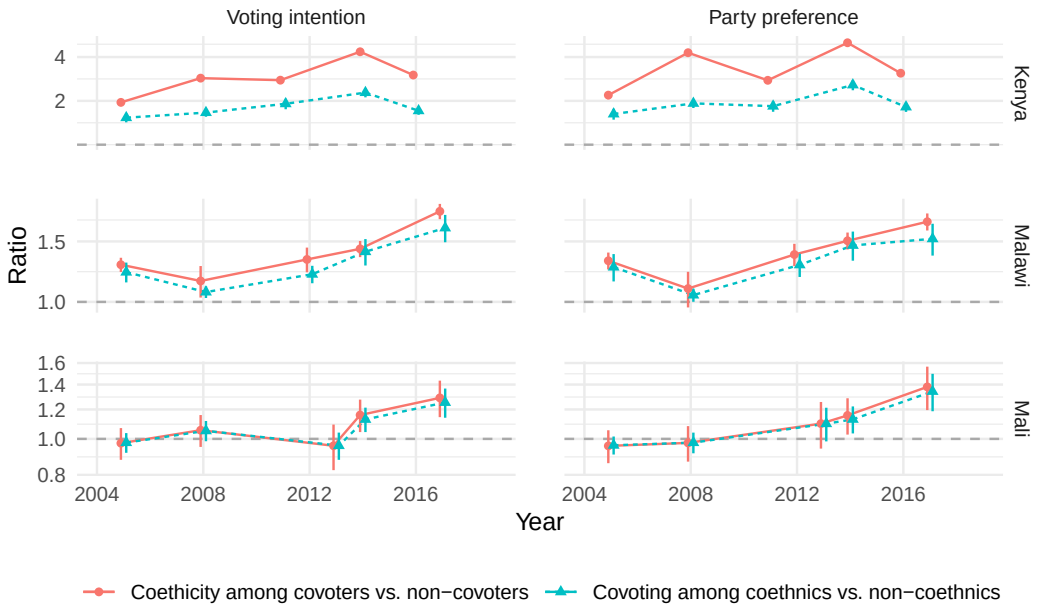


Figure A24: Group and Party driven changes in coethnic covoting in selected cases

Note: Odds ratios are computed by dividing the covariate-adjusted rate of coethnicity among covoters by the rate of coethnicity of non-covoters (red) and the rate of covoting among coethnics divided by the rate of covoting among non-coethnics (blue).

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