# Online Appendix
# "Conventional and Unconventional Participation in Latin America: A Hierarchical Latent Class Approach"

This Online Appendix accompanying the paper "Conventional and Unconventional Participation in Latin America: A Hierarchical Latent Class Approach" includes supplementary information aimed at complementing the analyses presented in the research note. Specifically, Section A.1 provides the definition, coding and sources for all the variables included in our empirical analysis, lists the countries covered in our study, and reports sample sizes and summary statistics for the variables. Section A.2 describes the Markov Chain Monte Carlo (MCMC) algorithm used to fit our hierarchical latent class model and provides further details about the estimation procedure. Finally, Section A.3 presents additional estimation results that had to be relegated to this Online Appendix due to space constraints. The "References" section includes supplementary sources consulted for the elaboration of this Online Appendix.

# A.1 Coding, sources and descriptive statistics for the variables included in the analysis

## A.1.1 Dependent variables

Source: 2012 AmericasBarometer survey of the Latin America Public Opinion Project (LAPOP).

Our choice of dependent variables was based on the comprehensive definitions of political participation proposed by Verba and Nie (1972), Norris (2002) and Teorell, Torcal and Montero (2007), among others. Specifically, the 12 political activities taken as outcome variables ($Y_{i,j,k}$, in the model's notation) cover all the quintessential types of activities considered in Verba and Nie (1972) and Teorell, Torcal and Montero (2007).

These twelve activities are:

1. Voting in the last general election (*Voting*);
2. Attending municipal meetings (*Municipal meeting*);
3. Contacting the municipality (*Contacting municipality*);
4. Contacting local authorities (*Contacting local authority*);
5. Contacting national authorities (*Contacting national authority*);
6. Attending meetings of a committee of improvements (*Improvements meeting*);
7. Helping solve problems in the community (*Solving community problems*);
8. Attending meetings of a political party (*Party meeting*);

9. Signing petitions (*Petitioning*);
10. Sharing or reading political information through social media (*Sharing online*);
11. Participating in peaceful protests (*Protesting*);
12. Participating in street or road blockages (*Blocking*).

Each of these is a binary variable. *Voting* is coded as 1 for respondents who voted in the last national election and zero otherwise. The other variables are coded as 1 if respondents participated in the corresponding activity in the 12 months preceding the survey, and 0 otherwise.

As we mention in the "Data" section of the research note, we decided to fit the model to the 2012 AmericasBarometer survey of the Latin America Public Opinion Project because this wave includes items covering a wider range of political activities for a greater number of countries than other waves. By comparison, participants in the 2018 AmericasBarometer survey, for example, only answer questions about 5 activities on average, and only three items - *Voting*, *Municipal meeting*, *Protesting* - are included in the questionnaires administered in more than 10 countries. Hence, adding data from other waves of the Latin America Public Opinion Project would have required us to drastically limit the number of activities and countries considered in order to preserve the temporal comparability of the analysis.[1]

[1]Nonetheless, following a reviewer's suggestion, Section A.3 reports estimates from a model fitted to AmericasBarometer surveys from 2010 to 2018. Given the data restrictions mentioned above, this specification examines a reduced number of political activities (5) and covers a limited number of countries (7). As we show below, the basic patterns discussed in the research note continue to hold.

Compared to Alvarez, Levin and Núñez (2017)'s original work, the main difference in our dependent variables is that we include voting among the set of political activities under study. Since voting is compulsory in Argentina, Alvarez, Levin and Núñez (2017) argued that it made little sense to include individuals' turnout decisions alongside other activities in which participation is voluntary. By contrast, our study covers countries in which voting is not mandatory (e.g., Chile, Colombia, El Salvador, Guatemala, Nicaragua). Furthermore, there is also considerable variation in the enforcement of compulsory voting provisions among those democracies in our sample that do implement mandatory voting, with some countries like Costa Rica, Honduras and Mexico where mandatory voting is not enforced in practice, and others (e.g., Peru, Uruguay) where failing to vote carries rather hefty penalties (see also Section A.1.2.ii below for the definition of *Compulsory Voting*, and Table A.3 for summary statistics for this variable).

### A.1.2 Explanatory variables

#### A.1.2.i Individual-level covariates

Source: 2012 AmericasBarometer survey of the Latin America Public Opinion Project (LAPOP).

*Age*, in years.

*Female*: 1 if the respondent is female, 0 otherwise.

*Education*: Number of years of schooling for each respondent.

*Relative Income*: Since self-reported income has been shown to be plagued by measurement errors, missing values and under-reporting (e.g., see Meyer and Sullivan 2003, 2011, and the references therein), for the analysis presented in the research note we built an income proxy based on the number of goods and services respondents have access to. Like Booth and Seligson (2009, ch. 5), this income proxy is computed from survey participants' responses to a series of binary items asking whether the following appliances and services are available in their house: television; refrigerator; landline/residential phone; cellular telephone; car; washing machine; microwave oven; motorcycle; indoor bathroom; computer; flat panel TV; and connection to the sewage system. Based on the answers to these items, we:

1. Computed a variable, $\textit{Income Proxy}_{i,k}$, for each survey respondent $i$ in country $k$, by adding the number of positive responses to these 12 items:
$$\textit{Income Proxy}_{i,k} = \sum_{l=1}^{12} i'\text{s response to item } l.$$
2. Computed the average value of *Income Proxy* for each of the Latin American countries in our sample, which we called $\textit{Mean Income Proxy}_k$.
3. Deducted $\textit{Mean Income Proxy}_k$ from $\textit{Income Proxy}_{i,k}$ to obtain the value of *Relative Income* for each individual $i$ in country $k$:
$$\textit{Relative Income (proxy)}_{i,k} = \textit{Income Proxy}_{i,k} - \textit{Mean Income Proxy}_k.$$

For robustness, we replicated the analysis using several alternative income measures in lieu of *Relative Income (proxy)* (see Section A.1.2.iii for a description of these additional measures and Section A.3 for a discussion of the results obtained from various sensitivity checks).

*Perceived Corruption*: Ordinal variable capturing respondents' perception of the extent of corruption among their country's public officials. Coded on a four-point ascending scale, with values: (1) "Very uncommon"; (2) "Uncommon"; (3) "Common"; (4) "Very common".

*Crime Victimization*: This variable is built from answers to the following question: "Have you been a victim of any type of crime in the past 12 months? That is, have you been a victim of robbery, burglary, assault, fraud, blackmail, extortion, violent threats or any other type of crime in the past 12 months?" *Crime Victimization* is coded as 1 for respondents who reported being victims of a crime in the previous 12 months, and 0 otherwise.

*Ideological Distance to Incumbent*: Absolute value of the difference between respondents' ideology (self-placement on the 0-10 left-right scale) and the ideology of the incumbent party.[2] Party ideologies were computed using data from Baker (2019), and rescaled to the 0-10 range to match individuals' self-placement, taken from the 2012 AmericasBarometer survey of the Latin America Public Opinion Project.[3] It is worth noting that Baker (2019)'s data

[2]We thank an anonymous reviewer for suggesting this way of defining the variable to better capture the influence of ideology on political participation.

[3]Another commonly used approach is to compute the distance between each respon-

set only covers 17 of the 23 Latin American and Caribbean countries for which individual-level data on political participation is available (see Table A.1). Hence, for robustness, we also replicated the analysis using alternative proxies for individuals' political orientation available for all 23 Latin American and Caribbean countries, described in Section A.1.2.iii below.

#### A.1.2.ii Contextual (country-level) covariates

*Compulsory Voting*: Ordinal variable measuring the existence and enforcement of compulsory voting provisions in a country. Coding: 0 for countries with no compulsory voting; 1 for countries with mandatory voting, but where there are no sanctions or sanctions are not enforced; 2 for countries with mandatory voting where sanctions exist and are enforced, but they impose minimal costs upon the offending citizen; and 3 for countries with mandatory voting where sanctions exist, are enforced, and impose considerable costs upon the offending citizen. The estimates reported in the "Results" section of the research note and Section A.3 of this Online Appendix are based on the ordinal coding of this variable. For robustness, we also estimated models using a dichotomous variant of this variable, with "no compulsory voting" (0) as baseline and indicators for each of the other three categories. The main results remain unchanged. Source: V-Dem, Varieties of Democracy (2019).

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dent's ideological self-placement and the average of the left-right positions that respondents assign to the incumbent party (e.g., van der Meer, van Deth and Scheepers 2009). However, the AmericasBarometer survey does not ask survey participants to locate parties/candidates on the left-right scale.

*Effective Number of Parties (ENPP)*: Continuous variable computed using Laakso and Taagepera (1979)'s formula: $ENPP = \frac{1}{\sum_{i=1}^{n} p_i^2}$, where $n$ represents the number of (national-level) parties in a country, and $p_i$ represents party $i$'s share of the vote in last general election held up to 2012. This variable has been shown to affect not only individuals' turnout decision (e.g., Carreras 2018), but potentially also their propensity to engage in unconventional forms of political participation (Vráablíková 2010; Katz and Levin 2018a,b). Source: Constituency-Level Elections Archive (2017) and Gallagher (2019).

*GDP per capita*: Total annual Gross Domestic Product (GDP) per capita at constant (2010) prices, in thousands of US dollars. This is a key contextual variable in van der Meer, van Deth and Scheepers (2009)'s cross-national analysis of political participation (also Teorell, Torcal and Montero 2007, and Booth and Seligson 2009). Source: Economic Commission for Latin American and the Caribbean (2019).

*Rule of Law*: A measure developed by the World Bank capturing the extent to which citizens in each country abide by the rules of society. The World Bank estimate gives the country's score in units of a standard normal distribution, theoretically ranging from -2.5 to 2.5. This variable is considered as one of the key contextual drivers of unconventional political participation by Dalton and van Sickle (2015), among others. In the case of Latin America, Booth and Seligson (2009) consider *Rule of Law* as a potential determinant of both conventional and unconventional forms of participation. Source: World

Bank (2019).

*Social Spending*: Sum of government spending on health, education and social protection, as a percentage of the country's annual Gross Domestic Product (GDP). For robustness, we also fitted models including government spending on each of these items (health, education or social protection) separately, without affecting the results reported in the research note. The relevance of this macro-variable as a potential determinant of - conventional and unconventional forms of - political participation is highlighted by Grasso and Giugni (2016) and Katz and Levin (2018b), among others. Source: Economic Commission for Latin American and the Caribbean (2019).

We also fitted models including other contextual variables taken from the literature on political participation (Polity IV score, as Carreras and Castañeda-Angarita 2014; the UNDP human development Index, as Espinal and Zhao 2015; Freedom House ratings for political and civic liberties, like Katz and Levin 2018a). Consistent with the findings reported in Figure 3 of the research note, none of these variables had a statistically significant impact on the probabilities of type assignment.

#### A.1.2.iii Additional (individual-level) variables used for robustness checks

Source: 2012 AmericasBarometer survey of the Latin America Public Opinion Project (LAPOP).

*Additional measures of income:* Instead of deducting *Mean Income Proxy*$_k$ from *Income Proxy*$_{i,k}$ (see our description of the operationalization of *Relative Income*), we replicated the analysis using simply the sum of goods and services available in each respondent's home as a proxy for household income, which we denominate *Income (proxy)*.

We also created three additional variables based on answers to a question included in the 2012 AmericasBarometer survey asking participants to report their household income (in their countries' domestic currency). LAPOP classifies respondents in each country into 17 income categories based on their responses to this question. To build the first of these additional measures, we retrieved the income category each respondent belonged to, computed the average income category for each sample country, and created an indicator, *Above-average (monetary) Income*, for respondents whose income category was above their country's average. We also divided respondents in each country into income quartiles and created indicators for the *Second*, *Third*, and *Fourth* (highest) *Income Quartile*, with respondents in the first (lowest) quartile as the reference group. Finally, since the number of income categories in LAPOP's original variable is quite large, it is possible to treat it as continuous according to some scholars (e.g. Johnson and Creech 1983; Zumbo and Zimmerman 1993; Norman 2010; Sullivan and Artino 2013). Hence, another specification simply includes the "raw" LAPOP measure, which we denominate *Continuous LAPOP Income Variable*, as a predictor.

It is worth noting that the original LAPOP variable based on self-reported monetary income has a higher proportion of missing values (18.90%) than the proxies based on households' access to good and services (which only have 5.26% of missing values). Additionally, differences in purchasing power and exchange rates across countries may render cross-national comparisons of monetary income difficult. Nevertheless, the specifications using *Above-average (monetary) Income*, *Continuous LAPOP Income Variable*, and the indicators for income quartiles as predictors lead to results that are generally similar to those obtained using either *Relative Income (proxy)* or *Income (proxy)* (see Section A.3 of this Online Appendix). Hence, our main substantive findings are not sensitive to the particular operationalization of respondents' relative income.

*Perceived Relative Deprivation*: As pointed out by a reviewer, several authors define relative deprivation primarily - or even exclusively - in terms of perceptions, rather than as a function of actual economic conditions (Lasswell and Kaplan 1950; Gurr 1969, 1970; Majeed 1979, among others). At the empirical level, one of the variables most commonly used to capture perceived relative deprivation in surveys is based on answers to a question asking respondents whether they felt that their household economic conditions had deteriorated in the past few years (e.g., Grasso and Giugni 2016; Asingo 2018; Grasso et al. 2019).[4] Such temporal comparisons - i.e., contrasting individuals' current economic situation to their own situation at some previous point in time - also figure prominently in theoretical analyses of perceived relative deprivation (see Tyler 2001, and the references therein).

[4]Other scholars measure perceived relative deprivation based on questions asking respondents to rate their living conditions vis-á-vis those of other individuals/groups (e.g. Asingo 2018). Unfortunately, no such questions were included in the AmericasBarometer survey.

Drawing on these studies, we fitted another specification that replaced *Relative Income (proxy)* with *Perceived Relative Deprivation*, recording answers to a question asking respondents whether their household income had deteriorated, stayed the same or improved in the two years preceding the 2012 survey. Following Rüdig and Karyotis (2013) and Grasso and Giugni (2016), *Perceived Relative Deprivation* was coded as 1 for respondents who stated that their household income had deteriorated, and 0 otherwise. The results from this alternative specification are also reported in Section A.3 of this Online Appendix, and lead to similar substantive conclusions as those obtained using *Relative Income (proxy)*, *Income (proxy)*, *Above-average (monetary) Income*, *Continuous LAPOP Income Variable*, and the income quartile indicators.

*Additional measures of ideological preferences*: As we noted in Section A.1.2.i, it was only possible to compute the *Ideological Distance to Incumbent* variable for 17 Latin American countries. Hence, we also replicated the analysis alternatively replacing the spatial distance measure with *Government Support*, *Prospective Vote for Incumbent*, and *Close to Incumbent Party*, all of which are available for the 23 Latin American and Caribbean countries for which data on political participation is available from the AmericasBarometer survey. *Government Support* is an ordinal variable measuring how respondents rate the performance of the incumbent government, coded on a five-point scale with values: (1) "Very bad"; (2) "Bad"; (3) "Neither good nor bad"; (4) "Good"; (5) "Very good". *Prospective Vote for Incumbent* is a binary variable coded as 1 if respondents indicate that they would vote for the incumbent candidate or party if elections were held in the week when the survey was administered, and 0 otherwise. *Close to Incumbent Party* is an indicator for respondents who identify with the incumbent party. Estimates from these alternative specifications are reported in Section A.3 of this Online Appendix.

**Table A.1:** Latin American countries covered in our study, with sample sizes

| Country | Abbreviation | Sample Size |
|---|---|---|
| Argentina | ARG | 1,512 |
| Brazil | BRA | 1,500 |
| Chile | CHL | 1,571 |
| Colombia | COL | 1,512 |
| Costa Rica | CRI | 1,498 |
| Dominican Republic | DOM | 1,512 |
| Ecuador | ECU | 1,500 |
| El Salvador | ESV | 1,497 |
| Guatemala | GTM | 1,509 |
| Honduras | HND | 1,728 |
| Mexico | MEX | 1,560 |
| Nicaragua | NIC | 1,686 |
| Panama | PAN | 1,620 |
| Paraguay | PAR | 1,510 |
| Peru | PER | 1,500 |
| Uruguay | URU | 1,512 |
| Venezuela | VEN | 1,500 |
| Observations (main specification) | | 26,227 |
| Belize* | BLZ | 1,512 |
| Guyana* | GUY | 1,529 |
| Haiti* | HTI | 1,836 |
| Jamaica* | JAM | 1,500 |
| Suriname* | SUR | 1,492 |
| Trinidad and Tobago* | TTO | 1,506 |
| Observations (additional specifications) | | 35,602 |

* These countries were only included in specifications using alternative measures of respondents' ideological preferences (*Government Support*, *Prospective Vote for Incumbent* and *Close to Incumbent Party*). Estimates reported in Section A.3.

**Table A.2:** Summary statistics for the dependent variables

| Dependent Variables | Mean | Std. Dev. | Range |
|---|---|---|---|
| Voting | 0.75 | 0.43 | [0, 1] |
| Municipal meeting | 0.11 | 0.31 | [0, 1] |
| Contacting municipality | 0.13 | 0.33 | [0, 1] |
| Contacting local authority | 0.14 | 0.35 | [0, 1] |
| Contacting national authority | 0.09 | 0.29 | [0, 1] |
| Improvements meeting | 0.23 | 0.42 | [0, 1] |
| Solving community problems | 0.34 | 0.48 | [0, 1] |
| Party meeting | 0.15 | 0.36 | [0,1] |
| Petitioning | 0.09 | 0.29 | [0, 1] |
| Sharing online | 0.11 | 0.31 | [0, 1] |
| Protesting | 0.07 | 0.26 | [0, 1] |
| Blocking | 0.02 | 0.16 | [0, 1] |

**Table A.3:** Summary statistics for the explanatory variables

| Variables | Mean | Std. Dev. | Range (in sample) |
|---|---|---|---|
| Main Specification | | | |
| Age | 40.08 | 15.94 | [14, 99] |
| Female | 0.51 | 0.50 | [0, 1] |
| Education | 9.24 | 4.29 | [0, 18] |
| Relative Income (proxy) | -0.09 | 2.52 | [-9, 9] |
| Perceived Corruption | 3.14 | 0.85 | [1, 4] |
| Crime Victimization | 0.17 | 0.38 | [0, 1] |
| Ideological Distance to Incumbent | 3.46 | 2.38 | [0, 9] |
| Compulsory Voting | 0.73 | 0.93 | [0, 3] |
| ENPP | 3.99 | 2.12 | [2.00, 11.25] |
| GDP per capita | 7.13 | 4.48 | [0.70, 16.68] |
| Rule of Law | -0.48 | 0.66 | [-1.69, 1.39] |
| Social Spending | 0.09 | 0.03 | [0.05, 0.14] |
| Alternative income measures[a] | | | |
| Income (proxy) | 6.78 | 3.00 | [0, 12] |
| Above-average (monetary) Income | 0.50 | 0.50 | [0, 1] |
| Second Income Quartile | 0.18 | 0.38 | [0, 1] |
| Third Income Quartile | 0.32 | 0.47 | [0, 1] |
| Fourth Income Quartile | 0.27 | 0.44 | [0, 1] |
| Continuous LAPOP Income Variable | 7.74 | 4.08 | [0, 16] |
| Perceived Relative Deprivation | 0.26 | 0.44 | [0, 1] |
| Alternative measures of ideological preferences[b] | | | |
| Government Support | 3.26 | 0.94 | [1, 5] |
| Prospective Vote for Incumbent | 0.36 | 0.48 | [0, 1] |
| Close to Incumbent Party | 0.43 | 0.49 | [0, 1] |

[a] These variables are not included in the main model reported in the research note. Instead, they replace *Relative Income (proxy)* in additional specifications reported in Section A.3.

[b] These variables are not included in the main model, but used in lieu of *Ideological Distance to Incumbent* in alternative specifications reported in Section A.3.

## A.2 Additional estimation details

Here we describe the Markov chain Monte Carlo (MCMC) algorithm used to fit our hierarchical latent class model.

Starting with initial values for all the model parameters $\Theta = \{T, \alpha, \mu, \sigma^2, \beta, \gamma, \eta, \Sigma_\eta\}$, our proposed MCMC sampler iterates through the following eight steps until convergence:

1. Using data augmentation to sample the latent variables $T_{c,i,k}$ and $T_{u,i,k}$ $\forall i$ from their full conditional distributions, given the other model parameters;

2. Updating the country-specific random intercepts and slopes, $\alpha_{j,k}$, $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ $\forall j, k$;

3. Updating the activity-specific means, $\mu_{\alpha_j}$, $\mu_{\alpha_{c,j}}$ and $\mu_{\alpha_{u,j}}$, $\forall j$;

4. Updating the variances of the country-specific random coefficients, $\sigma^2_{\alpha_j}$, $\sigma^2_{\alpha_{c,j}}$, and $\sigma^2_{\alpha_{u,j}}$ $\forall j$;

5. Updating the coefficients of the individual-level covariates, $\beta_c$ and $\beta_u$;

6. Updating the coefficients of the country-level covariates, $\gamma_c$ and $\gamma_u$;

7. Updating the values of $\eta_k = (\eta_{c,k}, \eta_{u,k})'$, $\forall k$;

8. Updating $\Sigma_\eta$, the variance-covariance matrix of $\eta$.

More concretely, assuming (multivariate) *Normal* priors for the parameters in $\{\alpha, \mu, \beta, \gamma, \eta\}$, conjugate *Inverse Gamma* priors for $\left\{\sigma^2_{\alpha_j}, \sigma^2_{\alpha_{c,j}}, \sigma^2_{\alpha_{u,j}}\right\}$ and an

*Inverse Wishart* prior for $\Sigma_\eta$ (Gelman et al. 2004; Lynch 2007), the algorithm proceeds as follows:

1. The latent variables $T_{c,i,k}$ $\forall i$ are sampled from their full conditional categorical distribution $T_{c,i,k}|\Theta_{-T_{c,i,k}} \sim Cat(p_{c,i,k,low}, p_{c,i,k,high})$, where $|\Theta_{-T_{c,i,k}}$ indicates that all the other model parameters are conditioned on when sampling $T_{c,i,k}$. The probability $p_{c,i,k,high}$ is given by:

$$p_{c,i,k,high} = \frac{P(T_{c,i,k} = high) \times \prod_j^J P(Y_{i,j,k}|T_{c,i,k} = high)}{\sum_{l=low}^{high} P(T_{c,i,k} = l) \times \prod_j^J P(Y_{i,j,k}|T_{c,i,k} = l)}$$

   where:

$$P(T_{c,i,k} = high) = \frac{\exp\left(X'_{i,k}\beta_c + Z'_k\gamma_c + \eta_{c,k}\right)}{1 + \exp\left(X'_{i,k}\beta_c + Z'_k\gamma_c + \eta_{c,k}\right)}$$

   and:

$$P(Y_{i,j,k}|T_{c,i,k} = high) = F\Big(\alpha_{j,k} + \alpha_{c,j,k} + \alpha_{u,j,k}(T_{u,i,k} - 1)\Big)^{Y_{i,j,k}} \times \\ \Big(1 - F\Big(\alpha_{j,k} + \alpha_{c,j,k} + \alpha_{u,j,k}(T_{u,i,k} - 1)\Big)\Big)^{(1-Y_{i,j,k})}$$

   for some cumulative density function (cdf) $F(\cdot)$. $p_{c,i,k,low}$ is simply $1 - p_{c,i,k,high}$.

   Similarly, the values of $T_{u,i,k}$ $\forall i$ are sampled from $T_{u,i,k}|\Theta_{-T_{u,i,k}} \sim Cat(p_{u,i,k,low}, p_{u,i,k,high})$, with:

$$p_{u,i,k,high} = \frac{P(T_{u,i,k} = high) \times \prod_j^J P(Y_{i,j,k}|T_{u,i,k} = high)}{\sum_{l=low}^{high} P(T_{u,i,k} = l) \times \prod_j^J P(Y_{i,j,k}|T_{u,i,k} = l)}$$

$$P(T_{u,i,k} = high) = \frac{\exp\left(X'_{i,k}\beta_u + Z'_k\gamma_u + \eta_{u,k}\right)}{1 + \exp\left(X'_{i,k}\beta_u + Z'_k\gamma_u + \eta_{u,k}\right)}$$

$$P(Y_{i,j,k}|T_{u,i,k} = high) = F\big(\alpha_{j,k} + \alpha_{c,j,k}(T_{c,i,k} - 1) + \alpha_{u,j,k}\big)^{Y_{i,j,k}} \times \\ \Big(1 - F\big(\alpha_{j,k} + \alpha_{c,j,k}(T_{c,i,k} - 1) + \alpha_{u,j,k}\big)\Big)^{(1-Y_{i,j,k})}$$

and $p_{u,i,k,low} = 1 - p_{u,i,k,high}$.

Based on the sampled values of $T_{c,i,k}$ and $T_{u,i,k}$, each iteration of the algorithm classifies $i$ as an "activist" if $\{T_{c,i,k}, T_{u,i,k}\} = \{high, high\}$; as "conventional" when $\{T_{c,i,k}, T_{u,i,k}\} = \{high, low\}$; as an "agitator" if $\{T_{c,i,k}, T_{u,i,k}\} = \{low, high\}$; and as an "outsider" if $\{T_{c,i,k}, T_{u,i,k}\} = \{low, low\}$. Note that $T_{c,i,k}$ and $T_{u,i,k}$ may vary across iterations, and thus $i$'s type may vary as well.

2. Specifying a standard normal cdf for $F(\cdot)$, we can resort to Gibbs sampling (Lynch 2007, ch. 4) to draw the country-specific random effects from their conditional posterior distributions:

$$p(\alpha_{j,k}|\Theta_{-\alpha_{j,k}}) \propto Normal(a_{\alpha_{j,k}}, A_{\alpha_{j,k}})$$

$$a_{\alpha_{j,k}} = \frac{\sigma^2_{\alpha_j} \sum_{i:i\in k} \Big(Y^*_{i,j,k} - \alpha_{c,j,k}(T_{c,i,k} - 1) - \alpha_{u,j,k}(T_{u,i,k} - 1)\Big) + \mu_{\alpha_j}}{\sigma^2_{\alpha_j} N_k + 1}$$

$$A_{\alpha_{j,k}} = \frac{\sigma^2_{\alpha_j}}{\sigma^2_{\alpha_j} N_k + 1}$$

$$p(\alpha_{c,j,k}|\Theta_{-\alpha_{c,j,k}}) \propto \textit{Truncated Normal}(a_{\alpha_{c,j,k}}, A_{\alpha_{c,j,k}}, 0, \infty)$$

$$a_{\alpha_{c,j,k}} = \frac{\sigma^2_{\alpha_{c,j}} \sum_{i:i\in k} (T_{c,i,k} - 1) \times \Big(Y^*_{i,j,k} - \alpha_{j,k} - \alpha_{u,j,k}(T_{u,i,k} - 1)\Big) + \mu_{\alpha_{c,j,k}}}{\sigma^2_{\alpha_{c,j}} \sum_{i:i\in k} (T_{c,i,k} - 1)^2 + 1}$$

$$A_{\alpha_{c,j,k}} = \frac{\sigma^2_{\alpha_{c,j}}}{\sigma^2_{\alpha_{c,j}} \sum_{i:i\in k} (T_{c,i,k} - 1)^2 + 1}$$

$$p(\alpha_{u,j,k}|\Theta_{-\alpha_{u,j,k}}) \propto \textit{Truncated Normal}(a_{\alpha_{u,j,k}}, A_{\alpha_{u,j,k}}, 0, \infty)$$

$$a_{\alpha_{u,j,k}} = \frac{\sigma^2_{\alpha_{u,j}} \sum_{i:i\in k}(T_{u,i,k}-1) \times \Big(Y^*_{i,j,k} - \alpha_{j,k} - \alpha_{c,j,k}(T_{c,i,k}-1)\Big) + \mu_{\alpha_{u,j,k}}}{\sigma^2_{\alpha_{u,j}} \sum_{i:i\in k}(T_{u,i,k}-1)^2 + 1}$$

$$A_{\alpha_{u,j,k}} = \frac{\sigma^2_{\alpha_{u,j}}}{\sigma^2_{\alpha_{u,j}} \sum_{i:i\in k}(T_{u,i,k}-1)^2 + 1}$$

where $N_k$ is the number of respondents from country $k$ and $Y^*_{i,j,k}$ is respondent $i$'s latent probit score for activity $j$.

When a logistic cdf is specified for $F(\cdot)$, the conditional distributions $p(\alpha_{j,k}|\Theta_{-\alpha_{j,k}})$, $p(\alpha_{c,j,k}|\Theta_{-\alpha_{c,j,k}})$ and $p(\alpha_{u,j,k}|\Theta_{-\alpha_{u,j,k}})$ no longer have closed-form solutions. For instance, the posterior distribution for $\alpha_{j,k}$ becomes:

$$p(\alpha_{j,k}|\Theta_{-\alpha_{j,k}}) \propto p(\alpha_{j,k}|\mu_{\alpha_j}, \sigma^2_{\alpha_j}) \times \prod_{i:i\in k} \left( \frac{\exp\big(\alpha_{j,k} + \alpha_{c,j,k}(T_{c,i,k}-1) + \alpha_{u,j,k}(T_{u,i,k}-1)\big)}{1 + \exp\big(\alpha_{j,k} + \alpha_{c,j,k}(T_{c,i,k}-1) + \alpha_{u,j,k}(T_{u,i,k}-1)\big)} \right)^{Y_{i,j,k}}$$

which has no standard distribution - regardless of the prior chosen for $p(\alpha_{j,k}|\mu_{\alpha_j}, \sigma^2_{\alpha_j})$.

Hence, the country-specific random effects cannot be updated using Gibbs sampling when $F(\cdot)$ is the cumulative density function of a standard logistic distribution. Still, their values can be updated using random-walk Metropolis steps with Student-t proposals, adjusting the scaling parameters to achieve an acceptance rate of $\approx 25\%$ (Robert and Casella 2010). The algorithm takes longer to run in this case (see footnote 5 below), although this is contingent on the starting values of the parameters and the particular details of the proposal density (Lynch 2007, ch. 6). Nonetheless, the substantive results remain broadly similar (see Section A.3.2 of this Online Appendix).

3. The activity-specific means can be updated using a standard Gibbs sampler. For instance, assuming a *Normal*(0, 1000) prior, we obtain draws from the conditional posterior distribution of $\mu_{\alpha_j}$ $\forall j$:

$$p(\mu_{\alpha_j}|\Theta_{-\mu_{\alpha_j}}) \propto Normal\left(\frac{1000\sum_k \alpha_{j,k}}{1000K + \sigma^2_{\alpha_j}}, \frac{1000\sigma^2_{\alpha_j}}{1000K + \sigma^2_{\alpha_j}}\right)$$

where $K$ is the number of countries in our sample.

4. The variances of the country-specific random coefficients are updated from their posterior distributions:

$$p(\sigma^2_{\alpha_j}|\Theta_{-\sigma^2_{\alpha_j}}) \propto Inverse\ Gamma\left(0.1 + \frac{K}{2}, 0.1 + \frac{\sum_k(\alpha_{j,k} - \mu_{\alpha_j})^2}{2}\right)$$

$$p(\sigma^2_{\alpha_{c,j}}|\Theta_{-\sigma^2_{\alpha_{c,j}}}) \propto Inverse\ Gamma\left(0.1 + \frac{K}{2}, 0.1 + \frac{\sum_k(\alpha_{c,j,k} - \mu_{\alpha_{c,j}})^2}{2}\right)$$

$$p(\sigma^2_{\alpha_{u,j}}|\Theta_{-\sigma^2_{\alpha_{u,j}}}) \propto Inverse\ Gamma\left(0.1 + \frac{K}{2}, 0.1 + \frac{\sum_k(\alpha_{u,j,k} - \mu_{\alpha_{u,j}})^2}{2}\right)$$

where the shape and scale parameters of the prior *Inverse Gamma* distributions are equal to 0.1.

5. The coefficients of the individual-level covariates are updated from their

full conditional distributions:

$$p(\beta_c|\Theta_{-\beta_c}) \propto \prod_{k=1}^{K}\prod_{i=1}^{N_k} \frac{\exp\left(X'_{i,k}\beta_c + Z'_k\gamma_c + \eta_{c,k}\right)}{1+\exp\left(X'_{i,k}\beta_c + Z'_k\gamma_c + \eta_{c,k}\right)} Normal(\beta_c, 0, (9/4)I)$$

$$p(\beta_u|\Theta_{-\beta_u}) \propto \prod_{k=1}^{K}\prod_{i=1}^{N_k} \frac{\exp\left(X'_{i,k}\beta_u + Z'_k\gamma_u + \eta_{u,k}\right)}{1+\exp\left(X'_{i,k}\beta_u + Z'_k\gamma_u + \eta_{u,k}\right)} Normal(\beta_u, 0, (9/4)I)$$

where the priors for $\beta_c$ and $\beta_u$ are multivariate normal distributions with zero mean and variance-covariance matrix equal to $(9/4)I$, with $I$ being the identity matrix. This yields relatively flat priors for $P(T_{d,i,k} = high)$, $d = c, u$, centered around 0.5 (Garrett and Zeger 2000).

These conditional distributions do not have a closed form. However, $\beta_c$ and $\beta_u$ can be updated through random-walk Metropolis steps with a multivariate $Student{-}t_3(s_\beta B)$ proposal, using the empirical covariance matrix of $\beta_c$ and $\beta_u$ from an extended burn-in period to tune $B$ and improve mixing (Haario et al. 2004), and adjusting the scaling parameter $s_\beta$ to achieve an acceptance rate of $\approx 25\%$ (Robert and Casella 2010).

6. Random-walk Metropolis steps similar to those described in 5 are used to update the values of the coefficients of the country-level covariates, $\gamma_c$ and $\gamma_u$.

7. The full conditional distribution for $\eta_k = (\eta_{c,k}, \eta_{u,k})'$ is:

$$p(\eta_k|\Theta_{-\eta_k}) \propto \prod_{i=1}^{N_k} P(T_{c,i,k} = high|\eta_{c,k}) \times P(T_{u,i,k} = high|\eta_{u,k}) \times Normal(\eta_k, 0, \Sigma_\eta)$$

which does not have a closed form. We thus update $\eta_k$ $\forall k$ using random-walk Metropolis steps with a bivariate $Student - t_3(s_\eta R_\eta)$ proposal centered at the previous values of $\eta_k$ – i.e., the values of $\eta_{c,k}$ and $\eta_{u,k}$ sampled from the prior iteration of the MCMC algorithm. The scale matrix $R_\eta$ can be estimated using the inverse information matrix obtained from a frequentist fit of the model (Neelon, O'Malley and Normand 2011), and the scaling factor $s_\eta$ is adjusted to achieve optimal acceptance rates.

8. Finally, $\Sigma_\eta$ is updated from its full conditional Inverse-Wishart distribution via Gibbs sampling:

$$p(\Sigma_\eta|\Theta_{-\Sigma_{eta}}) \propto Inverse\ Wishart\bigg(K+3, I+\eta^{'}\eta\bigg)$$

A well-known difficulty with MCMC estimation of latent class models is "label switching", which stems from the fact that permutations of the class assignments are not necessarily identifiable because the likelihood may be unchanged under these permutations (Redner and Walker 1984). In other words, this means that draws of the class-specific parameters may be associated with different labels (types) during the course of the MCMC algorithm. Label switching is not a problem in our model, though, given that, as we noted in the "Data" section of the research note, we imposed the constraints $\alpha_{c,Blocking,k} = \alpha_{u,Municipal\ Meeting,k} = 0$ $\forall k$ for identification purposes. Visual inspection of the MCMC chains showed no evidence of label switching, and application of the decision-theoretic post-processing algorithm proposed by Stephens (2000) to deal with this potential problem did not result in changes in the type assignments.

Given the complexity of the model, the MCMC algorithm was coded in C++ and called from R through Rcpp (Eddelbuettel 2013), and executed it via the University of Exeter High Performance Computing (HPC) cluster to maximize computational efficiency. We ran three parallel chains for 400,000 cycles with a 125,000 burn-in period for each of the models reported in the "Results" section of the research note and in Section A.3 of this Online Appendix; execution time for our benchmark model was 3 days and 18 hours.[5] Visual inspection of the trace-plots indicated that the chains reached the stationary state already after the first 100,000 iterations; we experimented with alternative burn-in periods (e.g., 100,000; 150,000; 175,000; 200,000), with no change in the results.

To ensure that inferences were data-dependent, several alternative values for the hyper-parameters were tried, yielding essentially similar findings. All the continuous predictors included in our model were centered to speed convergence (Gelman and Hill 2007; Jackman 2009), which was assessed according to Gelman and Rubin (1992)'s diagnostic. The posterior summaries – on which the findings reported in the "Results" section of the research note and in Section A.3 below are based – were computed from the pooled convergent samples.

[5] Using a logistic cdf for $F(\cdot)$ increased the execution time to 5 and a half days.

## A.3 Additional estimation results

We now report additional results obtained from the application of our hierarchical latent class model of participation to Latin American survey data. Specifically, Section A.3.1 presents supplementary estimates from our baseline model complementing the information reported in the "Results" section of the research note. Section A.3.2 reports estimates from a variant of our baseline model using a standard logistic instead of a standard normal cumulative distribution function for $F(\cdot)$. Sections A.3.3 and A.3.4 present results from additional specifications that resort to alternative operationalizations of individuals' economic situation and ideological preferences, respectively. In Section A.3.5 we report estimates from a model fitted to AmericasBarometer survey data covering the period 2010-2018. Finally, Section A.3.6 summarizes results obtained from a factor-analytic version of our model specifying $T_{c,i,k}$ and $T_{u,i,k}$ as continuous latent variables, without imposing restrictions on the number of participatory types.

### A.3.1 Additional results from our main specification

Figure A.1 reports posterior summarizes for the country-specific random slopes, $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$, obtained from our main specification.

Consistent with the findings reported in Table 2 of the research note, the estimated values of $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ are statistically indistinguishable for most activities and countries, indicating that participation in the majority of these activities is fueled by both conventional and unconventional inclinations towards political action in much of the region. As we mentioned in the research note, this poses a challenge for the sort of dichotomous (and largely arbitrary) classifications of activities that prevail in the literature on political participation.

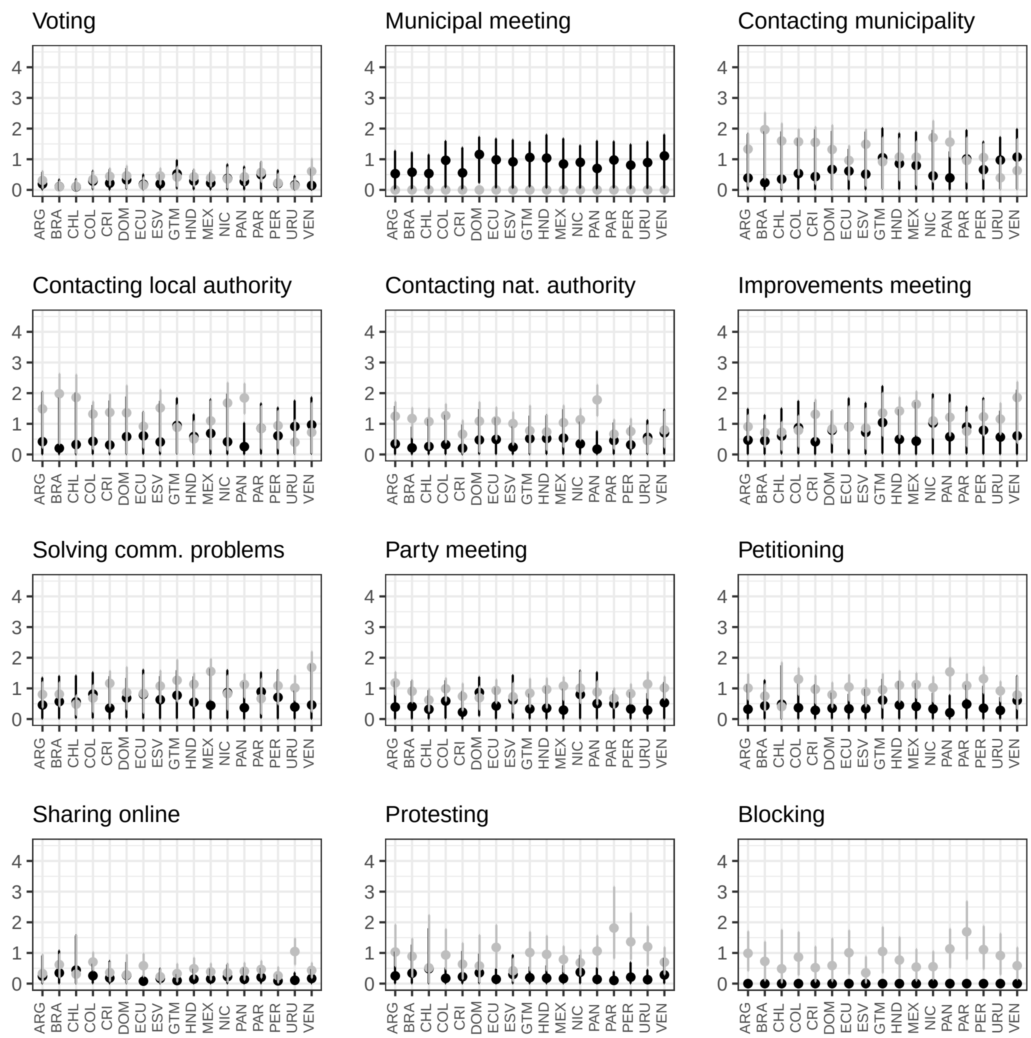


**Figure A.1: Posterior summaries for $\alpha_{c,j,k}$ (in black) and $\alpha_{u,j,k}$ (in gray) $\forall$ $j$, $k$.** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals.

Also interestingly, the values of $\alpha_{c,\text{Voting}}$ and $\alpha_{u,\text{Voting}}$ are quite low in the vast majority of the nations. This finding is again consistent with the average estimates reported in Table 2.

Despite these common regional patterns, Figure A.1 also reveals some cross-national variations in the magnitude of $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ and, in some cases, differences in the relative strength of the relationship between activity $j$ and the latent participatory dimensions. For instance, *Petitioning* is as likely to reflect conventional as unconventional participatory predispositions throughout most of the region, but in Panama (PAN) signing a petition is primarily an unconventional form of political engagement. Similarly, sharing or reading political information through social media is a predominantly unconventional form of participation in Uruguay (URU), while in the other Latin American countries this activity is equally likely to express conventional and unconventional tendencies.

Figure A.2, which plots $\alpha_{j,k}\ \forall\ j,\ k$, also shows some differences in the magnitude of the estimated activity-specific intercepts across countries. These cross-national differences highlight the importance of letting the average probability of partaking in each activity as well as the relationship between each activity and dimension vary across polities, providing support for our decision to specify $\alpha_{j,k}$, $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ as country-specific random effects. This modeling choice is further justified by the goodness-of-fit statistics reported in Table 3 of the research note, which compares our approach vis-á-vis more restrictive specifications assuming metric or scalar invariance - i.e., equality of activity-specific slopes or slopes and intercepts - across all countries. As we note in the main text, relaxing these invariance constraints yields a large improvement in fit according to a variety of model selection criteria.

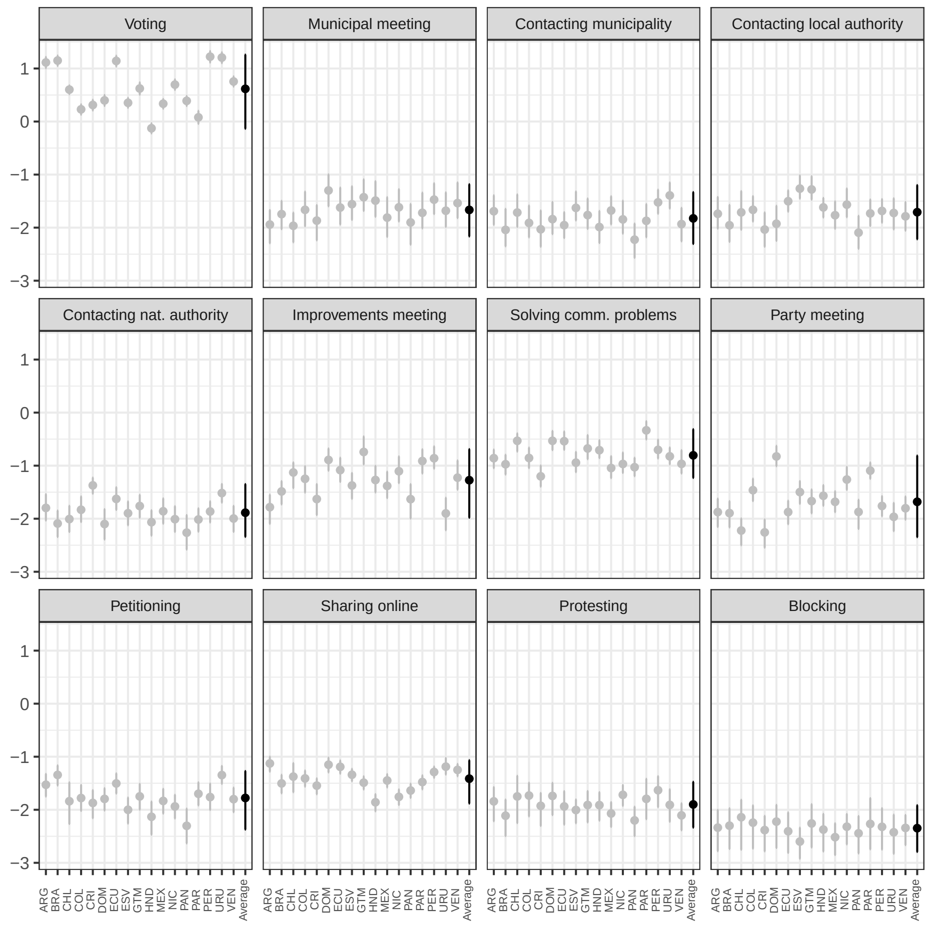


**Figure A.2: Posterior summaries for $\alpha_{j,k}$ $\forall$ $j$, $k$.** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals. Country-specific estimates for each activity are displayed in gray; activity-specific means averaged across countries are displayed in black.

Figures A.3 and A.4 complement the information presented in Figure 1 of the research note. Figure A.3 plots the posterior probabilities of scoring highly on the conventional (left column) and unconventional (right column) participatory dimensions among individuals assigned a high (upper row) and low (bottom row) type. For instance, the upper-left (bottom-left) panel of the figure shows that, among individuals assigned a high (low) conventional type based on the modal value of $T_{c,i,k}$ across iterations of the MCMC algorithm, the mean posterior probability $P(T_{c,i,k} = 2)$ is 0.73 (0.16), while the mean posterior probability $P(T_{c,i,k} = 1)$ is 0.27 (0.84). The upper-right (bottom-right) panel shows that, among individuals assigned a high (low) unconventional type based on their modal value of $T_{u,i,k}$, the mean posterior probability $P(T_{u,i,k} = 2)$ is 0.74 (0.09), while the mean posterior probability $P(T_{u,i,k} = 1)$ is 0.26 (0.91).

In sum, the model's average posterior class probabilities (AvePPs), defined as the mean of the posterior probabilities of assigning a high (low) conventional/unconventional type to individuals whose maximum posterior probability is $P(T_{d,i,k} = 2)(P(T_{d,i,k} = 1))$, $d = c, u$, are all quite high.[6] Nagin (2005) argues that models for which all the AvePPs are above 0.70 exhibit good class separation and high accuracy in the assignment of individuals to classes; this is clearly the case in our application. Similar conclusions hold using alternative measures of class separation (see Masyn 2013, and the references therein).

[6]More formally, denoting by $\hat{p}_{i,k}$ the estimated probability of assigning individual $i$ to class $k$, $\text{AvePP}_k = \text{Mean}\,\{\hat{p}_{i,k}, \forall i : \text{modal class}_i = k\}$ (see Masyn 2013, p. 570).

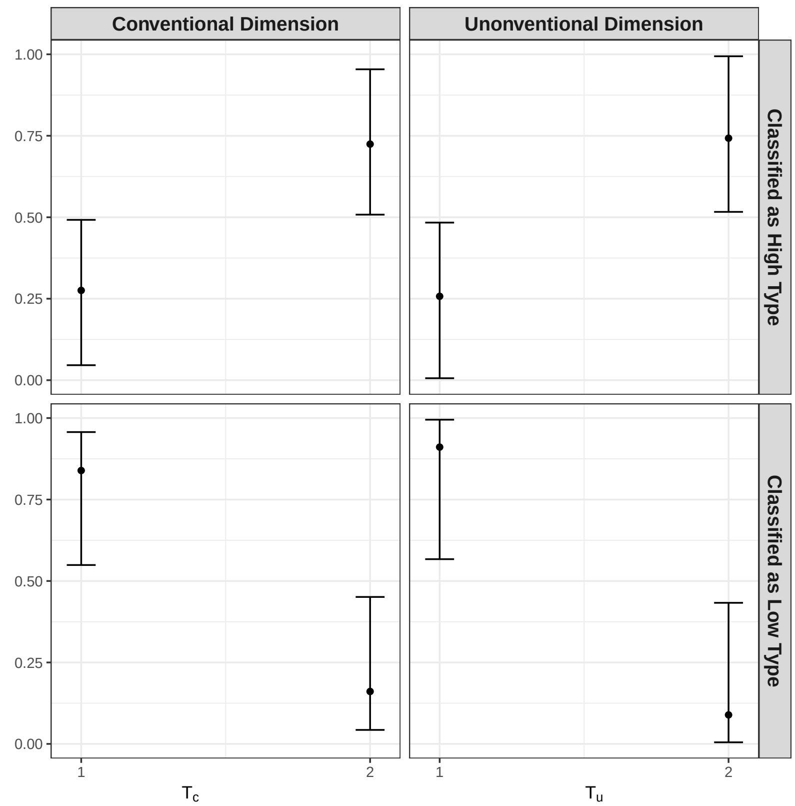


**Figure A.3: Posterior summaries for $P(T_{d,i,k} = l)$, $d = c, u$, $l = 1, 2$, for respondents assigned high/low conventional and unconventional types.** The left column of the figure reports posterior summaries for the probabilities $P(T_{c,i,k} = 1)$ and $P(T_{c,i,k} = 2)$ among respondents assigned a high (upper row) and low (bottom row) conventional type based on the modal value of $T_{c,i,k}$ across MCMC simulations. The right column of the figure reports posterior summaries for the probabilities $P(T_{u,i,k} = 1)$ and $P(T_{u,i,k} = 2)$ among respondents assigned a high (upper row) and low (bottom row) unconventional type based on the modal value of $T_{u,i,k}$ across MCMC simulations. Circles represent posterior means. Vertical lines give the 95% credible intervals (as is well known, Bayesian credible intervals are not necessarily equal-tailed – e.g., Kruschke 2015; Bekker-Nielsen et al. 2019).

Figure A.4 plots the posterior distributions of type assignment (the lower panel of Figure 1 in the research note presents posterior summaries - means and 95% credible intervals - for these distributions). The figure shows that the "Outsider" and "Activist" classes are clearly separated from the rest. While there is more overlap between agitators and conventionals, the difference between the highest and second-highest probabilities of type assignment for the average respondent exceeds 0.5. In fact, this difference is larger than 25 percentage points for more than 99% of the respondents.

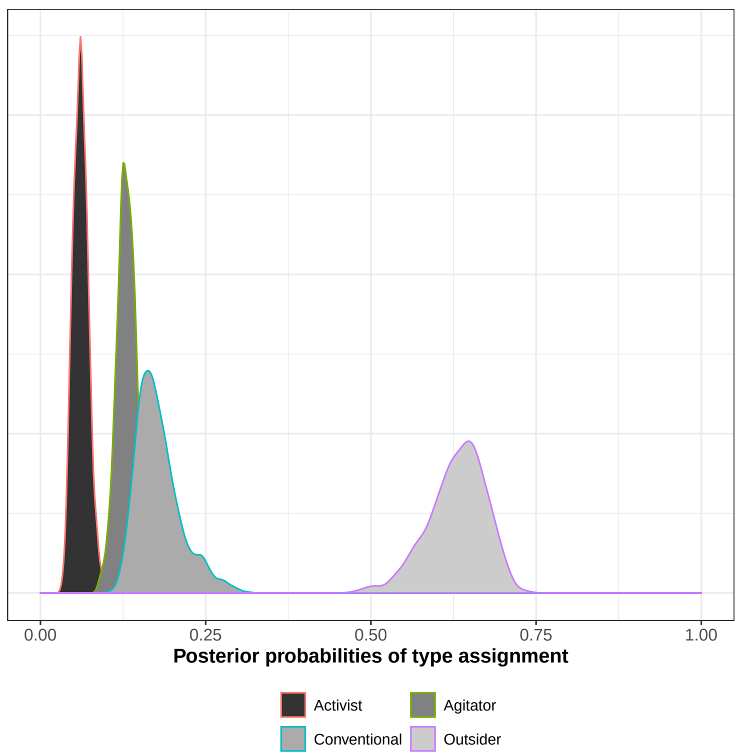


**Figure A.4: Distribution of the posterior probabilities of type assignment in our sample.**

Table A.4 complements the information displayed in Figure 2 of the paper, reporting posterior summaries – posterior means and 95% credible intervals (in parentheses) – for the probabilities of type assignment in every country, in percentage points. As noted in the research note, respondents in each of the Latin American democracies are significantly more likely to be classified as outsiders than to be allocated to the other three participatory types.

**Table A.4:** Posterior summaries for the probabilities of type assignment, by country

| Country | $P(i = \text{"Outsider"})$ | $P(i = \text{"Agitator"})$ | $P(i = \text{"Conventional"})$ | $P(i = \text{"Activist"})$ |
|---|---|---|---|---|
| ARG | 62.82 | 13.29 | 17.87 | 6.02 |
| | (47.28, 74.85) | (5.75, 22.59) | (8.96, 32.38) | (2.50, 12.22) |
| BRA | 63.36 | 12.96 | 18.17 | 5.50 |
| | (47.25, 75.66) | (5.50, 22.22) | (8.62, 32.83) | (1.85, 11.31) |
| CHL | 63.11 | 13.27 | 18.55 | 5.07 |
| | (46.93, 75.43) | (5.69, 22.38) | (9.16, 33.85) | (1.75, 10.80) |
| COL | 62.86 | 13.23 | 17.44 | 6.47 |
| | (48.25, 75.35) | (6.14, 21.97) | (8.19, 30.81) | (2.38, 12.80) |
| CRI | 62.66 | 13.51 | 18.13 | 5.70 |
| | (47.48, 74.82) | (6.80, 23.30) | (8.90, 31.59) | (1.96, 11.58) |
| DOM | 62.80 | 12.83 | 18.26 | 6.11 |
| | (48.29, 75.13) | (5.32, 22.32) | (8.90, 33.15) | (2.26, 12.19) |
| ECU | 62.55 | 12.57 | 18.25 | 6.63 |
| | (47.42, 74.63) | (5.72, 21.25) | (9.12, 32.28) | (2.77, 12.53) |
| ESV | 63.24 | 12.93 | 17.48 | 6.35 |
| | (48.27, 74.85) | (5.81, 20.71) | (9.12, 31.08) | (2.47, 12.31) |
| GTM | 61.08 | 13.64 | 18.57 | 6.70 |
| | (46.33, 73.62) | (5.43, 22.39) | (9.55, 33.08) | (2.60, 14.08) |

*Continued on next page*

Table A.4 – *Continued from previous page*

| Country | $P(i =$ "Outsider"$)$ | $P(i =$ "Agitator"$)$ | $P(i =$ "Conventional"$)$ | $P(i =$ "Activist"$)$ |
|---|---|---|---|---|
| HND | 63.59 | 13.19 | 17.09 | 6.13 |
| | (47.61, 75.61) | (6.14, 21.70) | (8.10, 30.01) | (2.30, 12.34) |
| MEX | 63.76 | 13.18 | 17.06 | 6.00 |
| | (49.03, 74.99) | (6.30, 22.15) | (8.54, 30.73) | (2.18, 11.27) |
| NIC | 62.36 | 13.17 | 17.88 | 6.58 |
| | (46.12, 74.75) | (6.22, 22.69) | (8.21, 32.07) | (2.29, 13.35) |
| PAN | 64.92 | 11.90 | 17.87 | 5.31 |
| | (49.97, 76.55) | (5.74, 19.71) | (7.88, 32.91) | (1.94, 10.41) |
| PAR | 62.97 | 11.95 | 18.83 | 6.25 |
| | (48.03, 74.31) | (5.56, 20.70) | (8.71, 32.14) | (247, 12.30) |
| PER | 62.27 | 13.10 | 18.21 | 6.42 |
| | (45.81, 74.64) | (6.07, 22.94) | (8.86, 33.15) | (2.34, 13.22) |
| URU | 63.54 | 12.94 | 18.02 | 5.50 |
| | (47.82, 76.45) | (6.05, 21.93) | (8.63, 33.68) | (2.07, 11.26) |
| VEN | 63.07 | 14.16 | 16.08 | 6.68 |
| | (46.71, 75.43) | (6.42, 23.10) | (7.35, 29.59) | (2.52, 13.79) |

The posterior probabilities of assignment to the "Agitator", "Conventional" and "Activist" types are statistically indistinguishable in these nations. Nonetheless, the overlapping coefficients (Inman and Bradley 1988) between the posterior densities of "Activist" and those of the other two classes are quite low in all countries ($< 0.2$), so the degree of separation between activists and agitators and between activists and conventionals is still reasonably high (Nasserinejad et al. 2017).

Furthermore, Table A.5 shows that the AvePPs are very high for all the sample countries.

**Table A.5:** Average posterior probabilities (AvePPs) by country

| Country | AvePP | | |
|---|---|---|---|
| | $T_c$ | $T_u$ | $T_c$ & $T_u$ |
| ARG | 0.80 | 0.89 | 0.84 |
| BRA | 0.79 | 0.90 | 0.85 |
| CHL | 0.80 | 0.87 | 0.83 |
| COL | 0.83 | 0.88 | 0.86 |
| CRI | 0.80 | 0.87 | 0.84 |
| DOM | 0.85 | 0.86 | 0.85 |
| ECU | 0.83 | 0.88 | 0.86 |
| ESV | 0.82 | 0.87 | 0.84 |
| GTM | 0.85 | 0.86 | 0.86 |
| HND | 0.83 | 0.88 | 0.86 |
| MEX | 0.82 | 0.90 | 0.86 |
| NIC | 0.83 | 0.89 | 0.86 |
| PAN | 0.80 | 0.92 | 0.86 |
| PAR | 0.85 | 0.91 | 0.88 |
| PER | 0.82 | 0.89 | 0.86 |
| URU | 0.84 | 0.89 | 0.86 |
| VEN | 0.86 | 0.90 | 0.88 |

The first column of the table displays the average posterior probabilities of assigning respondents in each country a high (low) conventional type, among those whose maximum posterior probability is $P(T_{c,i,k} = 2)(P(T_{c,i,k} = 1))$. The second column displays the same information for the assignment of a high/low unconventional type. The third column displays the mean posterior probabilities of assigning respondents in each country a high/low value of $T_c$ and $T_u$, among those with high/low values of both latent variables. In all cases, the AvePPs exceed 0.7, indicating that the latent classes are well separated in every Latin American democracy, and that our model does a good job classifying respondents from each of these nations along the two participatory dimensions (Nagin 2005).

Next, we take a closer look at the impact of individual and contextual variables on type assignment. As we showed in Figure 3 of the research note, none of the country-level covariates has a statistically significant influence on the probabilities of type assignment. In fact, as illustrated in Figure A.5, none of the macro-level factors has a statistically significant "marginal effect" on these probabilities even after removing all the individual-level variables from the model. These results thus reinforce our conclusion that the contextual variables have no direct impact on individuals' allocation to participatory types.

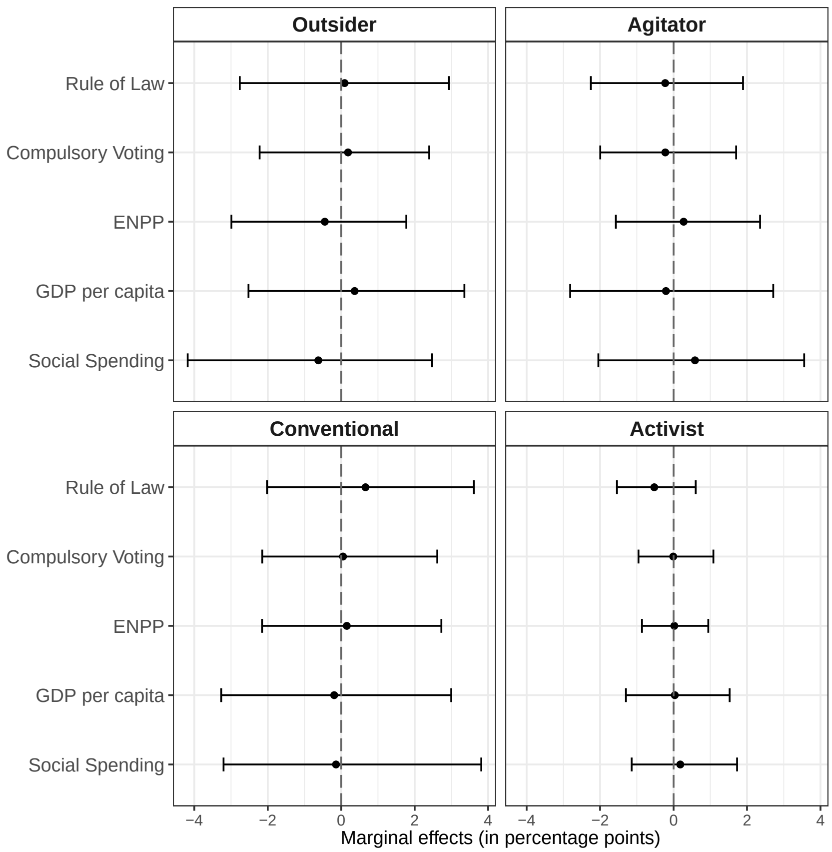


**Figure A.5: "Marginal effect" of contextual variables, estimated from a model without individual-level covariates.** Circles represent point estimates (posterior means), in percentage points. Horizontal lines give 95% credible intervals.

Moreover, Figure A.6 reveals that the probabilities of type assignment are also not systematically related to unobserved country characteristics (captured in our model by $\eta$).

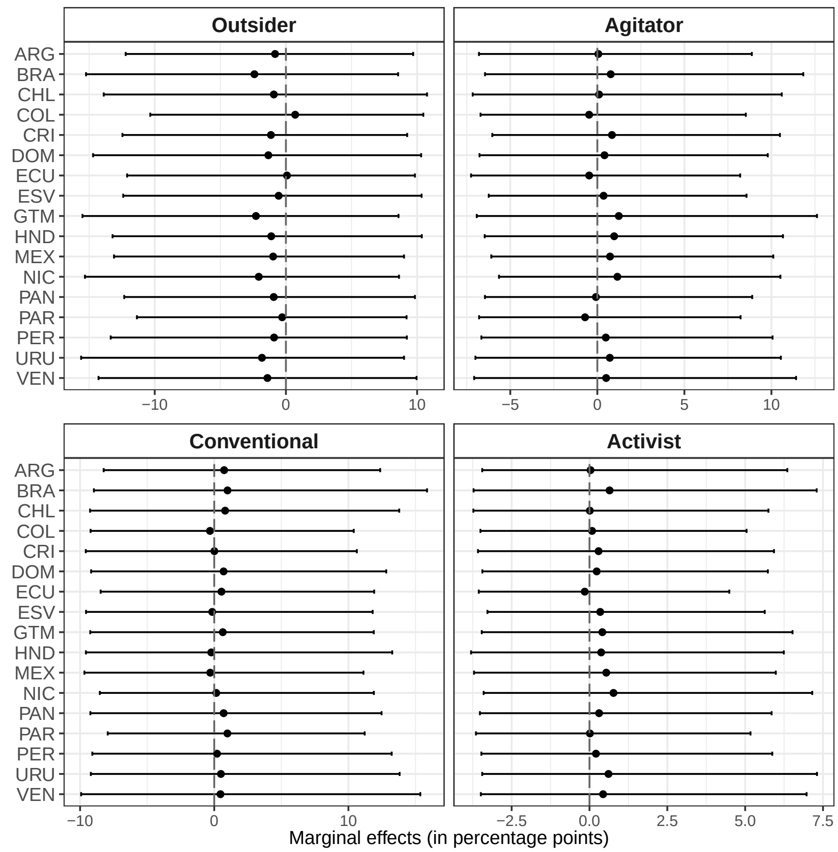


**Figure A.6: Unobserved country-specific differences in type assignment.** Circles represent point estimates (posterior means), in percentage points. Horizontal lines give 95% credible intervals.

However, we mentioned in the discussion of these results that including contextual variables improves the overall model fit. This is illustrated in Table A.6, which uses Dean and Raftery (2010)'s approach to computing Bayes Factors for latent class models to contrast three specifications: (i) our baseline model, including both micro- and macro-level variables as correlates of $P(T_{c,i,k} = high)$ and $P(T_{u,i,k} = high)$; (ii) a model including only individual-level variables as correlates of $P(T_{d,i,k} = high)$, $d = c, u$; and (iii) a model that includes no - individual or contextual - predictors.[7]

The cells of the table report twice the logarithm of the Bayes factor comparing Model A (rows) against Model B (columns). If $2 \times log(\mathcal{B}_{\text{Model A, Model B}})$ is greater than zero, the evidence supports Model A; otherwise it supports Model B (Dean and Raftery 2010; Fop, Smart and Murphy 2017).

**Table A.6:** Comparing specifications including different sets of covariates using Bayes Factors

| | Baseline model | Individual-level covariates only | No covariates |
|---|---|---|---|
| Baseline model | | 5,112.68 | 22,191.85 |
| Individual-level covariates only | | | 17,079.17 |

The values in the cells correspond to twice the logarithm of the Bayes factor comparing Model A (rows) against Model B (columns). The Bayes factors are computed using Dean and Raftery (2010)'s approach for latent class analysis.

[7] All the specifications account for unobserved heterogeneity and intra-country correlation.

Both our baseline specification and the model including only individual-level covariates as correlates of $P(T_{d,i,k} = high)$, $d = c, u$, outperform the model assuming that the probability of scoring highly on the two participatory dimensions is not systematically related to either individual or contextual factors. In addition, $2 \times log(\mathcal{B}_{\text{Baseline model, Individual-level covariates only}})$ is clearly greater than 0, indicating that incorporating contextual variables improves the explanatory power of the model.

Finally, Figure A.7 displays covariate "marginal effects" estimated from a model that ignores classification uncertainty, as is the standard practice in conventional cluster analysis. Specifically, for this exercise, instead of including individual and contextual variables in the model - see equations (6)-(7) in the research note – we implement a two-step estimation approach. In the first step, we: (i) specify uniform Dirichlet priors for $P(T_{d,i,k} = l)$, $d = c, u$, $l = 1, 2$, as in Alvarez, Levin and Núñez (2017); (ii) sample the values of $T_{c,i,k}$ and $T_{u,i,k}$ $\forall$ $i$ from their full conditional categorical distributions (analogous to equation 8 in the main text) at each iteration of the MCMC algorithm; and (iii) classify $i$ into one of the four participatory types based on these sampled values.[8] We then use individuals' modal type assignment

[8]We could have simply conducted a cluster analysis instead of fitting an unconditional latent class model (i.e., without covariates) for this first step. However, as we noted in the introductory section of the research note, applying standard cluster analysis to cross-country data sets requires imposing the assumption that all the survey items about political participation are interpreted and understood in the same manner by respondents from the different Latin American countries. This is a very strong assumption (see De Jong, Steenkamp and Fox, 2007, Stegmueller, 2011 and Saiegh, 2015, among others), which our hierarchical latent class model - even the simpler unconditional version - avoids.

across iterations as the outcome in a second-step multinomial logit model including individual and contextual variables as predictors, clustering the standard errors to accommodate heteroskedasticity and arbitrary correlation in types at the country-level.

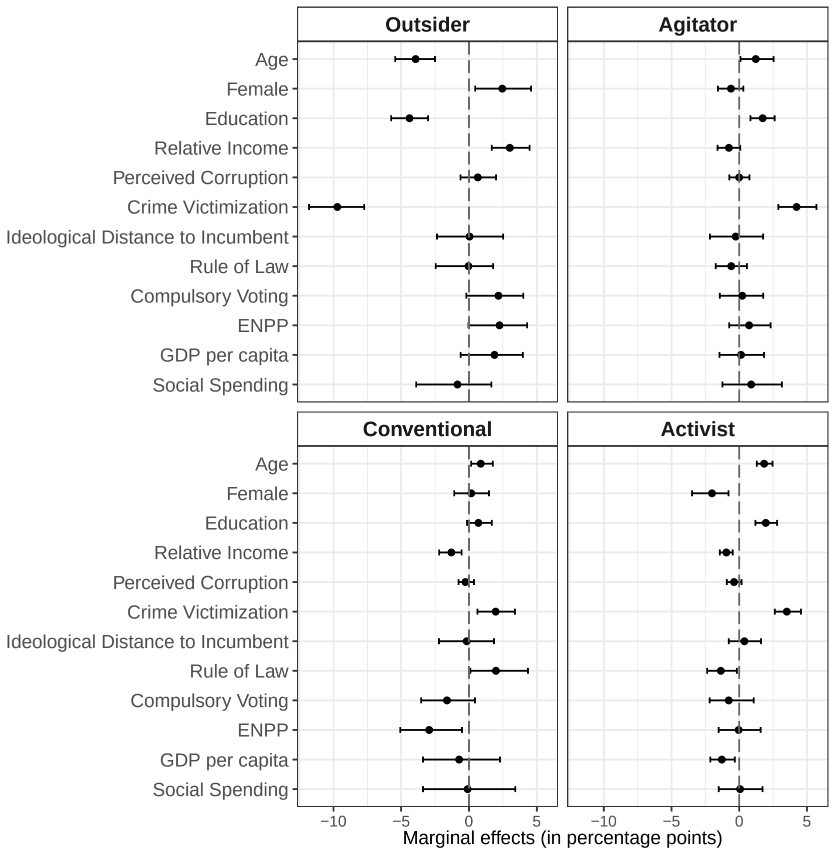


**Figure A.7: "Marginal effect" of individual and contextual variables, ignoring measurement error in type assignments.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

Figure A.7 shows that, while many of the estimates remain similar, the “marginal effects” of some of the individual and contextual variables change when the measurement error of classifications is neglected. For instance, *Relative Income* is positively and significantly correlated with the probability that the average respondent is assigned to the outsider type, and negatively and significantly associated with the probability that she is allocated to the conventional and activist categories. These correlations were all statistically indistinguishable from zero in Figure 3 of the main text.

The main difference concerns the estimates for the country-level covariates, though. In our benchmark model, none of these contextual factors has a statistically significant impact on type assignment. By contrast, Figure A.7 shows that *Rule of Law*, *ENPP* and *GDP per capita* are all systematically related to the probability of allocating survey respondents to certain participatory types. For example, each increase in the World Bank's measure of respect for the *Rule of Law* is associated with a reduction in the probability that the average survey participant is allocated to the activist type, and with a simultaneous increase in the likelihood that she is classified as conventional. A larger effective number of parties, by contrast, is negatively correlated with the probability of being assigned to the conventional type. Each standard deviation increase in *GDP per capita*, in turn, is associated with a 0.88 percentage point drop in the probability that the average respondent belongs to the activist type.

### A.3.2 Results from a model specifying $F(\cdot)$ as a standard logistic cumulative density function

This section presents estimates from a model similar to the one used in the research note and in Section A.3.1, but specifying $F(\cdot)$ as the cumulative density function of a standard logistic distribution.

Table A.7 reports posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ obtained from this model, averaged across countries. Although there are differences in the magnitude of the parameter estimates vis-á-vis those presented in Table 2 of the research note, the basic substantive conclusions are largely aligned with those drawn from our benchmark specification. The posterior distributions of $\alpha_c$ and $\alpha_u$ are statistically indistinguishable for most of the activities considered. This confirms the results of our benchmark specification, in the sense that participation in these activities is fueled by both conventional and unconventional inclinations towards political action.[9]

In other words, the conclusion that simplistic dichotomous - yet widely used - classifications of activities into either conventional or unconventional ignore the "dual nature" of various forms of political participation in Latin America continues to hold when using a logistic cumulative distribution function for $F(\cdot)$.

[9] It is also worth noting that *Voting* exhibits comparatively low values (posterior means) of both $\alpha_c$ and $\alpha_u$ in this alternative specification – as was the case for our benchmark model.

**Table A.7:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries using a logit link in Equation (2)

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.661 | 0.414 |
| | (0.072, 1.377) | (0.014, 1.124) |
| Municipal meeting | 1.967 | 0.000 |
| | (0.575, 2.893) | (0.000, 0.000) |
| Contacting municipality | 2.552 | 0.780 |
| | (0.495, 3.929) | (0.042,2.910) |
| Contacting local authority | 2.536 | 0.731 |
| | (0.414, 4.115) | (0.025, 3.274) |
| Contacting national authority | 1.840 | 0.740 |
| | (0.314, 3.144) | (0.048, 2.486) |
| Improvements meeting | 1.868 | 0.938 |
| | (0.485, 2.990) | (0.112, 2.401) |
| Solving community problems | 1.554 | 0.906 |
| | (0.443, 2.535) | (0.132, 2.197) |
| Party meeting | 1.506 | 1.134 |
| | (0.352, 2.418) | (0.192, 2.302) |

*Continued on next page*

Table A.7 – *Continued from previous page*

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Petitioning | 1.343 | 1.713 |
| | (0.144, 2.330) | (0.506, 3.021) |
| Sharing online | 0.477 | 0.962 |
| | (0.032, 1.145) | (0.104, 2.220) |
| Protesting | 0.598 | 3.890 |
| | (0.043, 1.516) | (0.500, 6.992) |
| Blocking | 0.000 | 3.361 |
| | (0.000, 0.000) | (0.376, 6.035) |

The table reports posterior means and 95% credible intervals (in parentheses) for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ for each activity $j$ averaged across all $k$, estimated from an alternative specification using a standard logistic distribution for $F(\cdot)$.

A similar pattern emerges from Figure A.8, which plots posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ for each sample country. *Municipal meeting*, *Contacting municipality* and *Contacting local authority* tend to exhibit higher values for $\alpha_c$ than for $\alpha_u$ in all nations, while the opposite is true for *Protesting* and *Blocking*. For most activities, though, the difference between the slopes of $T_c$ and $T_u$ are not statistically significant. Moreover, as in our benchmark model, we observe cross-national differences in the relative strength of the association between many of the activities and the latent participatory dimensions.

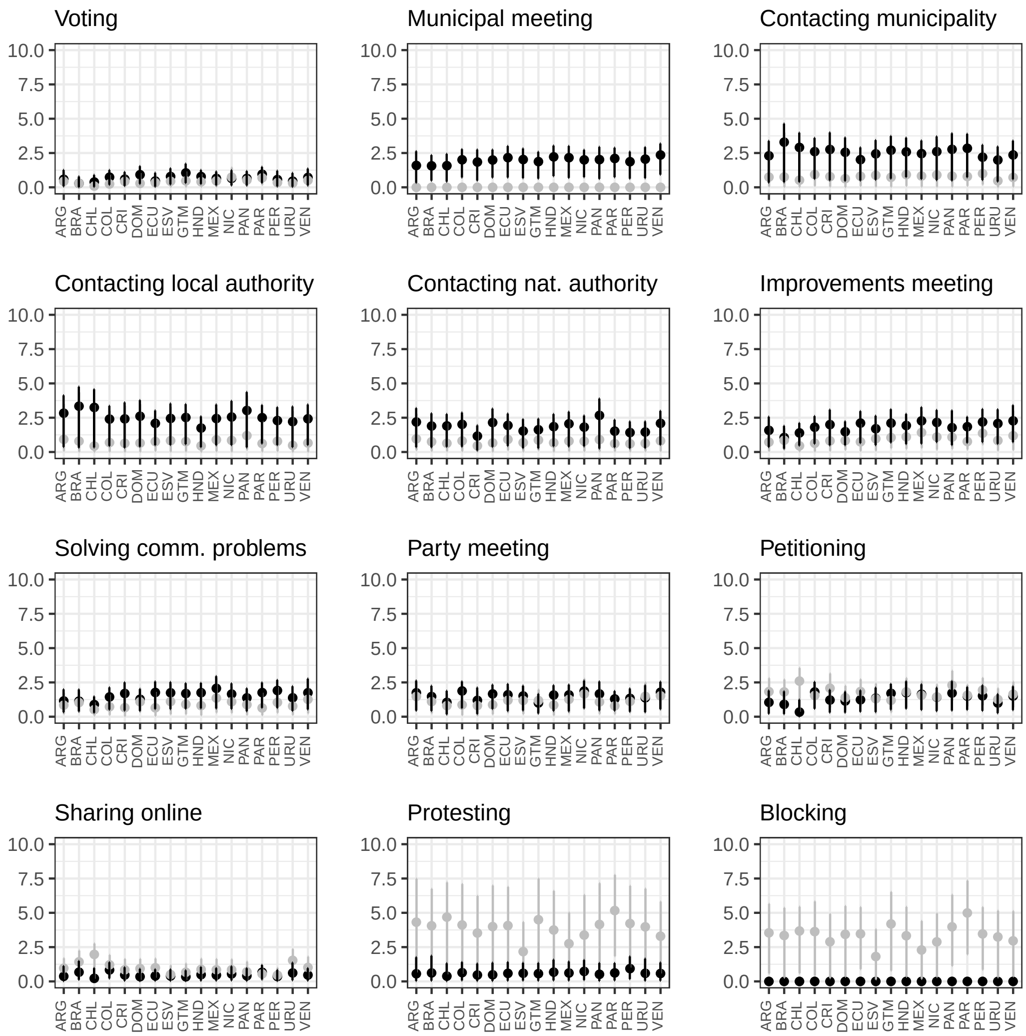


**Figure A.8: Posterior summaries for $\alpha_{c,j,k}$ (in black) and $\alpha_{u,j,k}$ (in gray) $\forall$ $j$, $k$, estimated from the model specifying a standard logistic cdf for $F(\cdot)$.** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals.

For completeness, Figure A.9 plots the activity-specific intercepts $\alpha_{j,k}$ for each country. The patterns emerging from the figure are again broadly in line with those from our baseline model, presented in Figure A.2 above.

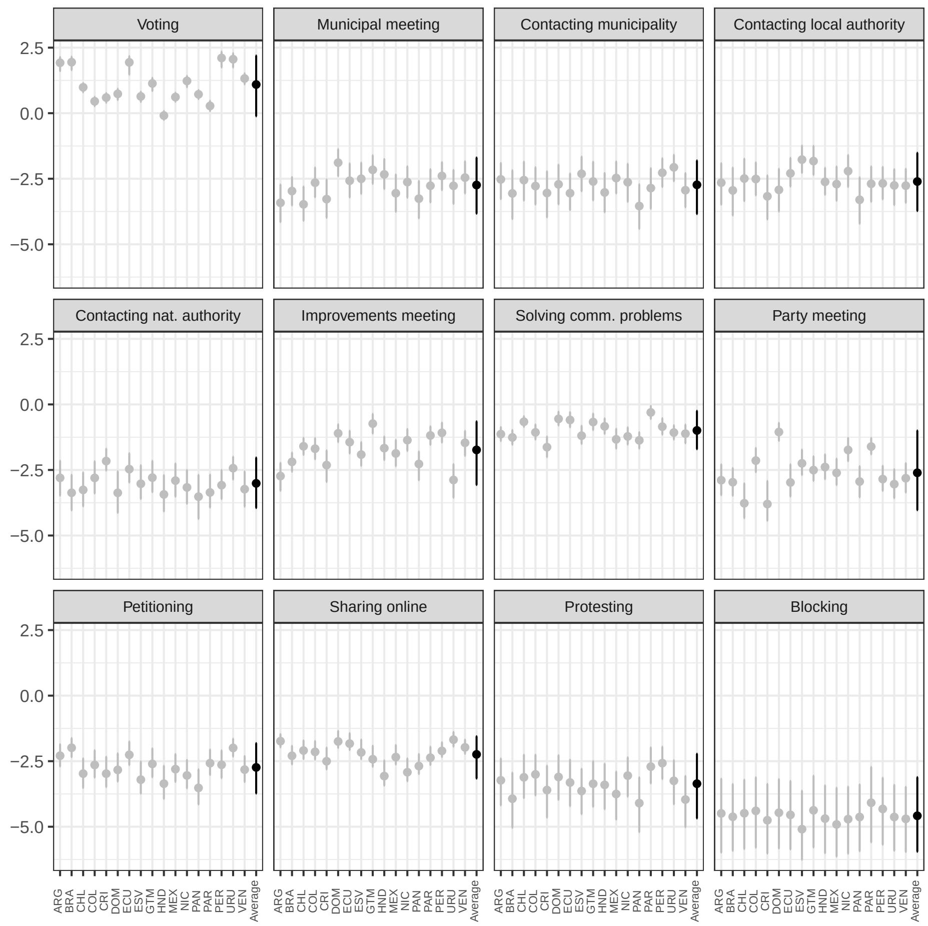


**Figure A.9: Posterior summaries for $\alpha_{j,k}$ $\forall$ $j$, $k$, estimated from the model specifying a standard logistic cdf for $F(\cdot)$.** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals. Country-specific estimates for each activity are displayed in gray; activity-specific means averaged across countries are displayed in black.

Figure A.10 summarizes the posterior probabilities of type assignment obtained from this model, averaged across countries. The average probabilities that a survey respondent scores highly on the conventional and unconventional dimensions are 0.14 and 0.07, respectively. The mean posterior probabilities of allocating respondents to each of the four participatory types are: 0.82 for "outsiders", 0.12 for "conventionals", 0.05 for "agitators", and 0.01 for "activists". Although these probabilities differ from those reported in Figure 1 of the research note, the substantive conclusions emerging from the upper panel of Figure A.10 are analogous to those drawn from our benchmark specification: Latin Americans are most likely to belong to the outsider group, and least likely to be classified as activists.

The lower panel of Figure A.10 shows that, as in our baseline model, the probabilities of type assignment are precisely estimated.

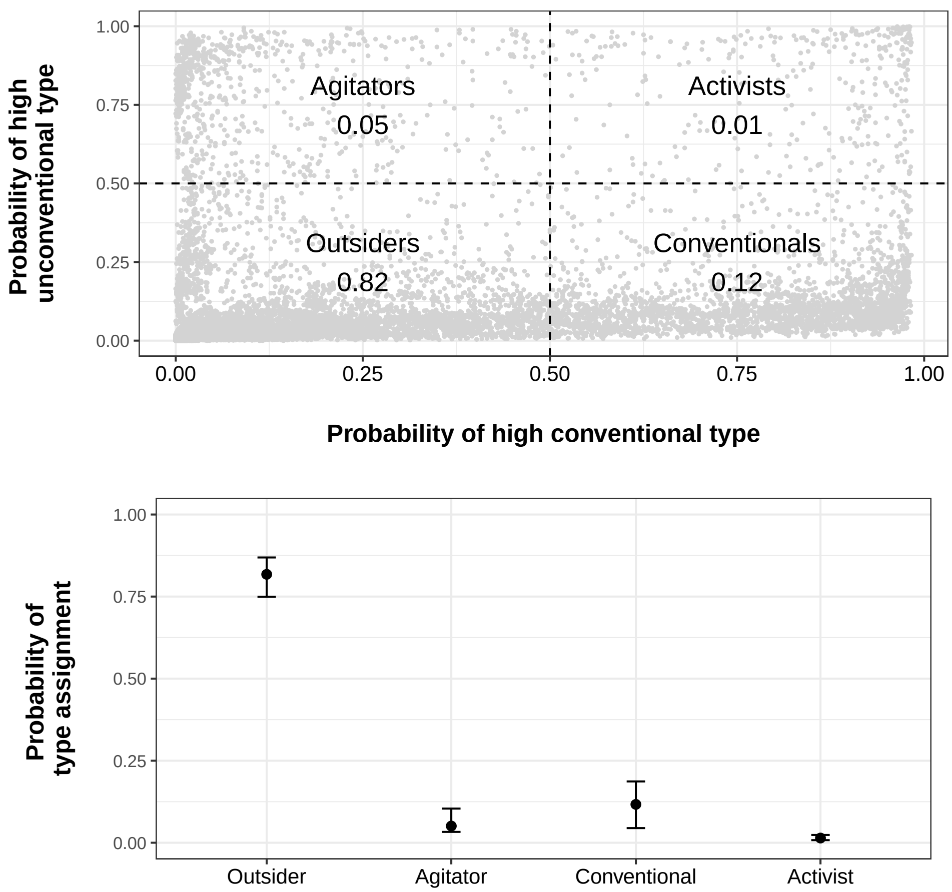


**Figure A.10: Posterior probabilities of type assignment averaged across countries, using a logit link.** The upper panel depicts the relationship between the probability of being assigned a high conventional and high unconventional type obtained from the alternative specification using a standard logistic distribution for $F(\cdot)$. Circles represent survey respondents. The lower panel reports posterior means (dots) and 95% credible intervals for the probabilities of type assignment, averaged across countries.

Figure A.11 complements the information presented in Figure A.10, plotting the posterior distributions of type assignment.

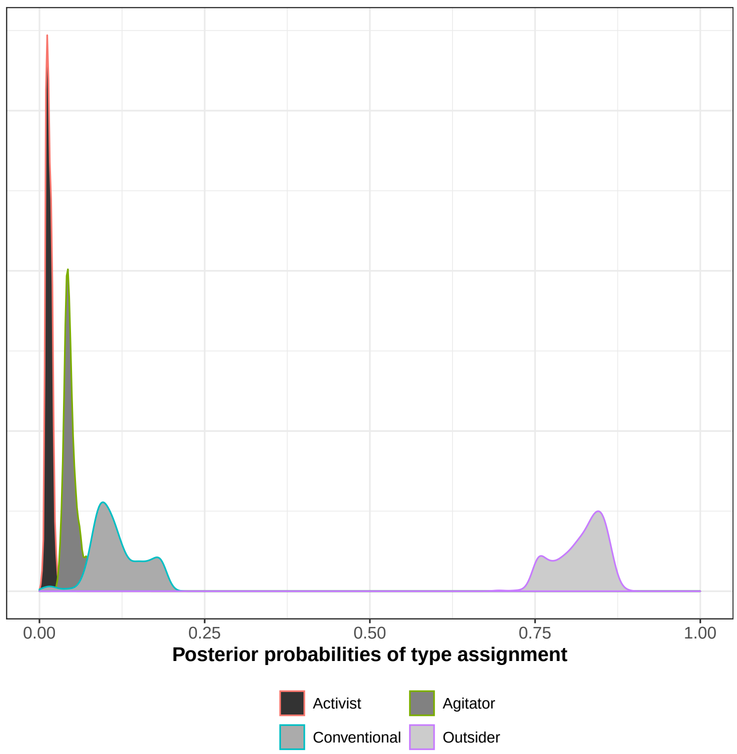


**Figure A.11: Distribution of the posterior probabilities of type assignment in our sample, estimated from the model using a logit link.**

Consistent with the findings reported in Figure A.4 (Section A.3.1) above, we observe that the "Outsider" and "Activist" classes are clearly separated from the rest. Although there is more overlap between agitators and conventionals, the latent classes are well separated in every country in our sample. This is illustrated in Table A.8, which reports the average posterior class probabilities (AvePPs) obtained from the logit model, all of which are considerably larger than 0.7.

**Table A.8:** Average posterior probabilities (AvePPs) by country using a logit link

| Country | AvePP | | |
|---|---|---|---|
| | $T_c$ | $T_u$ | $T_c$ & $T_u$ |
| ARG | 0.92 | 0.96 | 0.94 |
| BRA | 0.94 | 0.96 | 0.95 |
| CHL | 0.93 | 0.97 | 0.95 |
| COL | 0.93 | 0.96 | 0.95 |
| CRI | 0.92 | 0.96 | 0.94 |
| DOM | 0.93 | 0.96 | 0.94 |
| ECU | 0.92 | 0.96 | 0.94 |
| ESV | 0.92 | 0.94 | 0.93 |
| GTM | 0.92 | 0.97 | 0.94 |
| HND | 0.92 | 0.96 | 0.94 |
| MEX | 0.93 | 0.95 | 0.94 |
| NIC | 0.92 | 0.95 | 0.94 |
| PAN | 0.94 | 0.97 | 0.95 |
| PAR | 0.93 | 0.98 | 0.95 |
| PER | 0.92 | 0.96 | 0.94 |
| URU | 0.92 | 0.96 | 0.94 |
| VEN | 0.93 | 0.95 | 0.94 |

Also in line with our baseline findings, the probabilities of allocating respondents to each type are very similar throughout the continent, as shown in Figure A.12. In fact, these probabilities are statistically indistinguishable across countries.

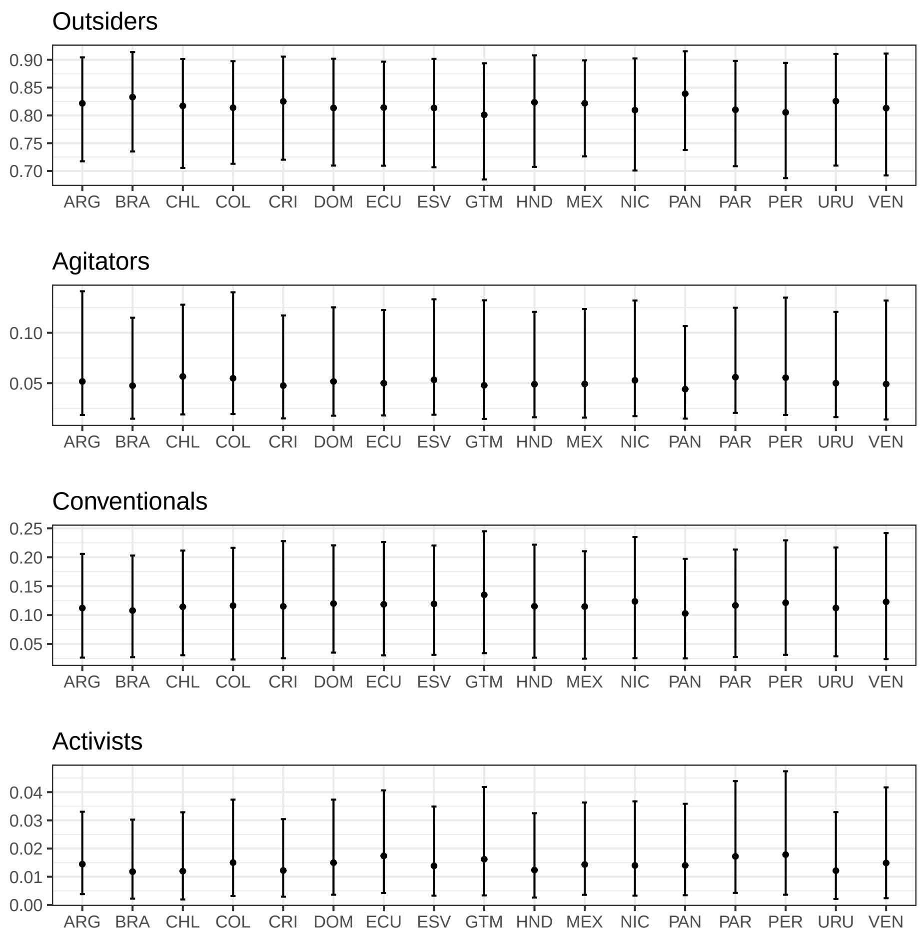


**Figure A.12: Posterior probabilities of type assignment by country for the model specifying $F(\cdot)$ as a standard logistic cdf.** Circles represent posterior means. Vertical lines give 95% credible intervals.

Finally, we examine the relationship between the probabilities of type assignment and the micro- and macro-level factors. Figure A.13 plots the "marginal effects" of individual and country-level covariates on these probabilities. The results are broadly aligned with those emerging from Figure 3 in the research note. In particular, *Crime Victimization* is among the most important determinants of type assignment, along with respondents' socio-economic characteristics. As in Figure 3 of the manuscript, none of the contextual variables has a statistically significant influence on individuals' allocation to participatory types.

Similarly, Figure A.14 shows that the model using a logit link reveals no statistically significant relationship between unobserved country characteristics and the allocation of respondents to participatory types - as was the case under our baseline specification (see Figure A.6 in Section A.3.1 above).

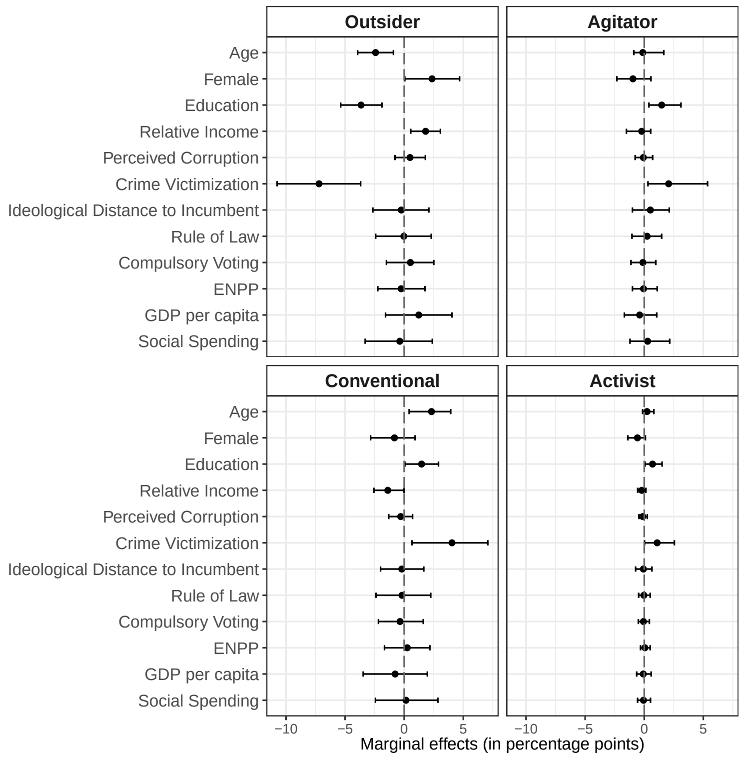


**Figure A.13: "Marginal effects" of individual and contextual variables on type assignment estimated from the model specifying $F(\cdot)$ as a standard logistic cdf.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

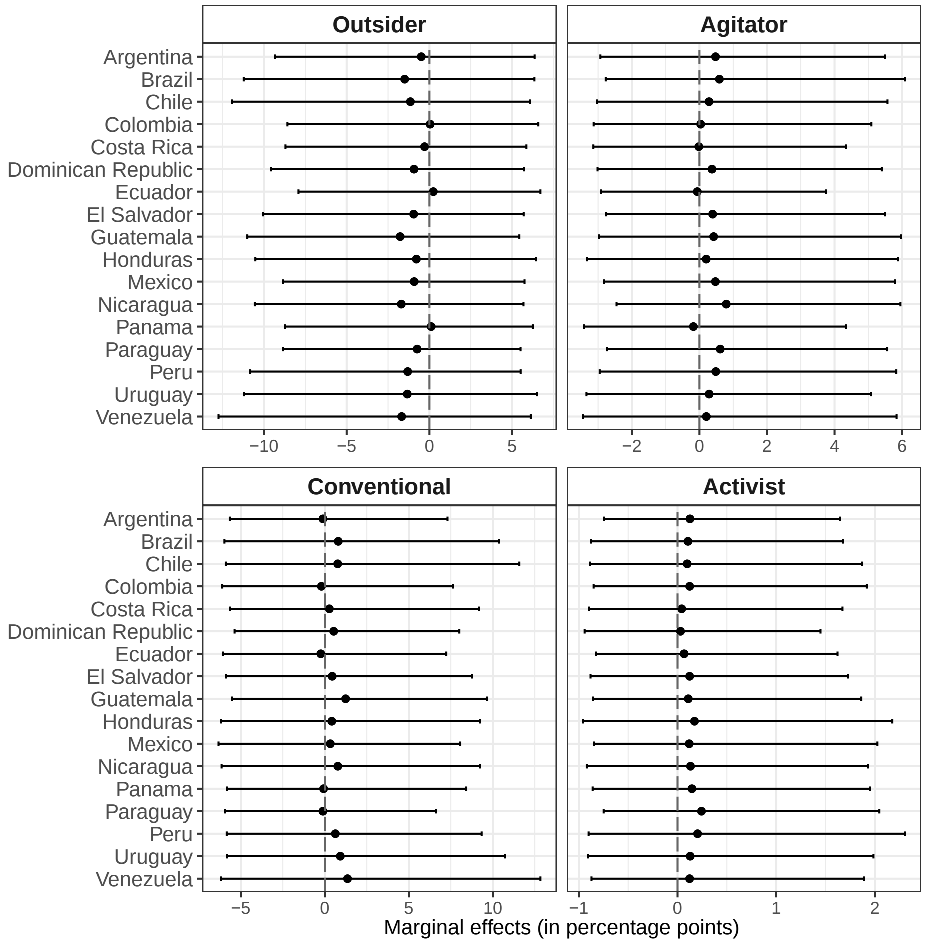


**Figure A.14: Unobserved country differences in type assignment.** The figure summarizes residual country-specific effects (captured by $\eta$) on the probabilities that individuals are allocated to the different types. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

### A.3.3 Results from specifications replacing ***Relative Income (proxy)*** with alternative income measures

As we noted in Section A.1, we replicated the analysis presented in the research note using alternatively *Income (proxy)*, *Above-average (monetary) Income*, *Continuous LAPOP Income Variable*, and the income quartile indicators instead of *Relative Income (proxy)*, as well as replacing *Relative Income (proxy)* with *Perceived Relative Deprivation*. Figures A.15-A.19 below display the expected change in the probabilities of type assignment associated with a change in the covariates – i.e., "marginal effects" – from each of these alternative specifications.

The results are broadly similar across the various specifications, and generally consistent also with those presented in Figure 3 of the research note. None of the changes in the value of the objective (monetary and consumption-based) income indicators in Figures A.16-A.18 is significantly correlated with the probabilities of type assignment. *Perceived Relative Deprivation* is also not systematically associated with the likelihood that the average respondent is allocated to any of the four participatory types, as seen in Figure A.19.

While *Income (proxy)* is significantly and negatively related to the probability of being conventional in Figure A.15, the impact of this variable on the likelihood of being allocated to the other participatory types is again statistically indistinguishable from zero.

Altogether, the estimates in Figures A.15-A.19, along with those reported in Figure 3 of the manuscript, indicate that respondents' economic situation is not a powerful predictor of their propensity to engage in conventional or unconventional forms of political participation, irrespective of the particular operationalization of this variable.

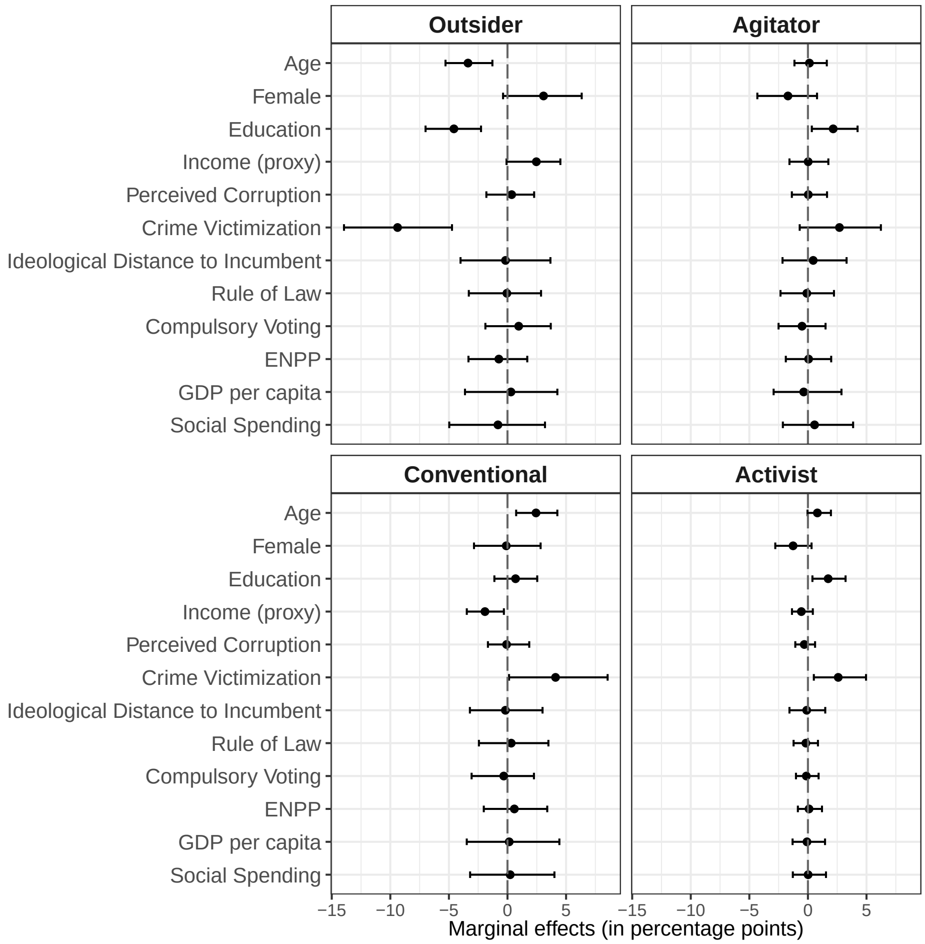


**Figure A.15: "Marginal effects" of individual and contextual variables on type assignment, using *Income (proxy)* instead of *Relative Income (proxy)* as a predictor.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

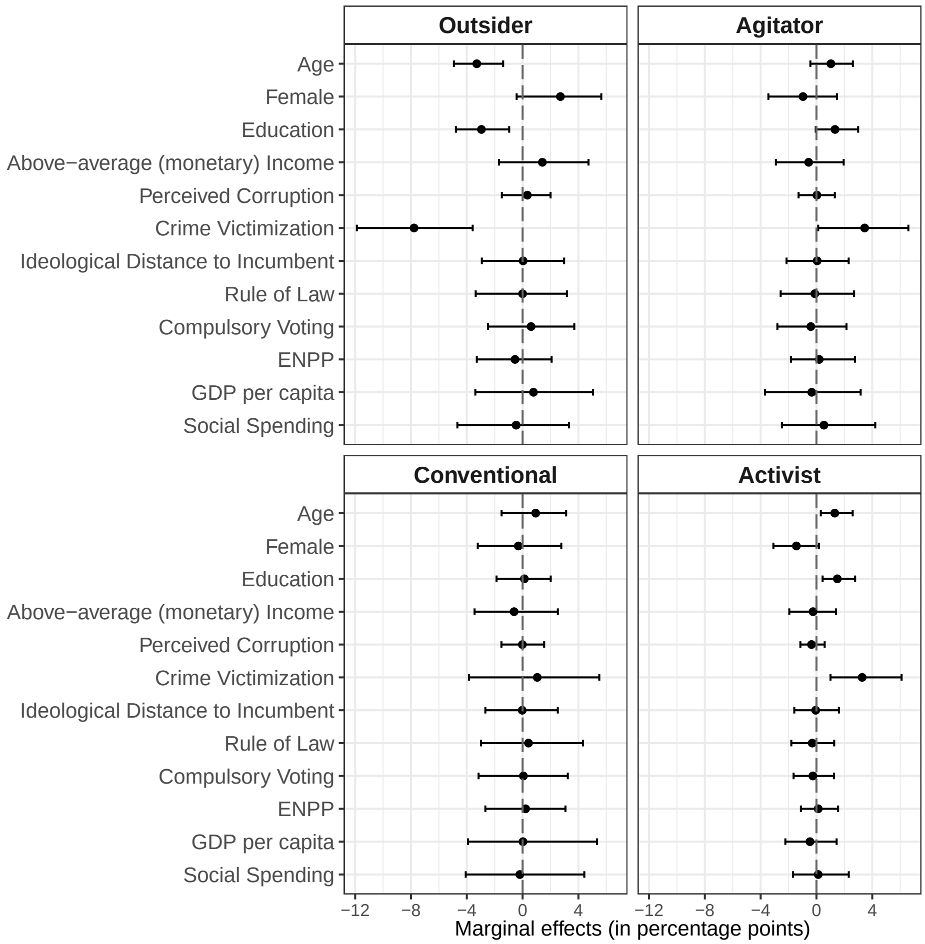


**Figure A.16: "Marginal effects" of individual and contextual variables on type assignment, using *Above-average (monetary) Income* instead of *Relative Income (proxy)* as a predictor.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

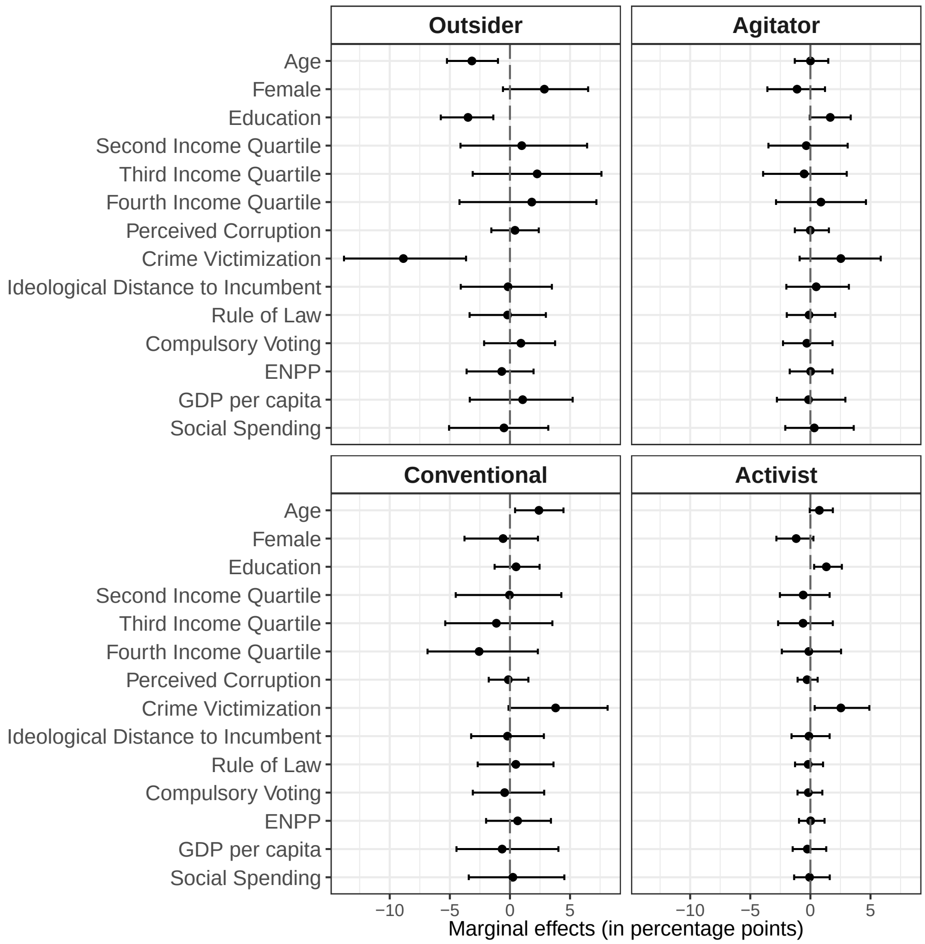


**Figure A.17: "Marginal effects" of individual and contextual variables on type assignment, using indicators for the *Second*, *Third* and *Fourth Income Quartile*s computed from the original income measure included in the 2012 AmericasBarometer survey instead of *Relative Income (proxy)* as a predictor.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

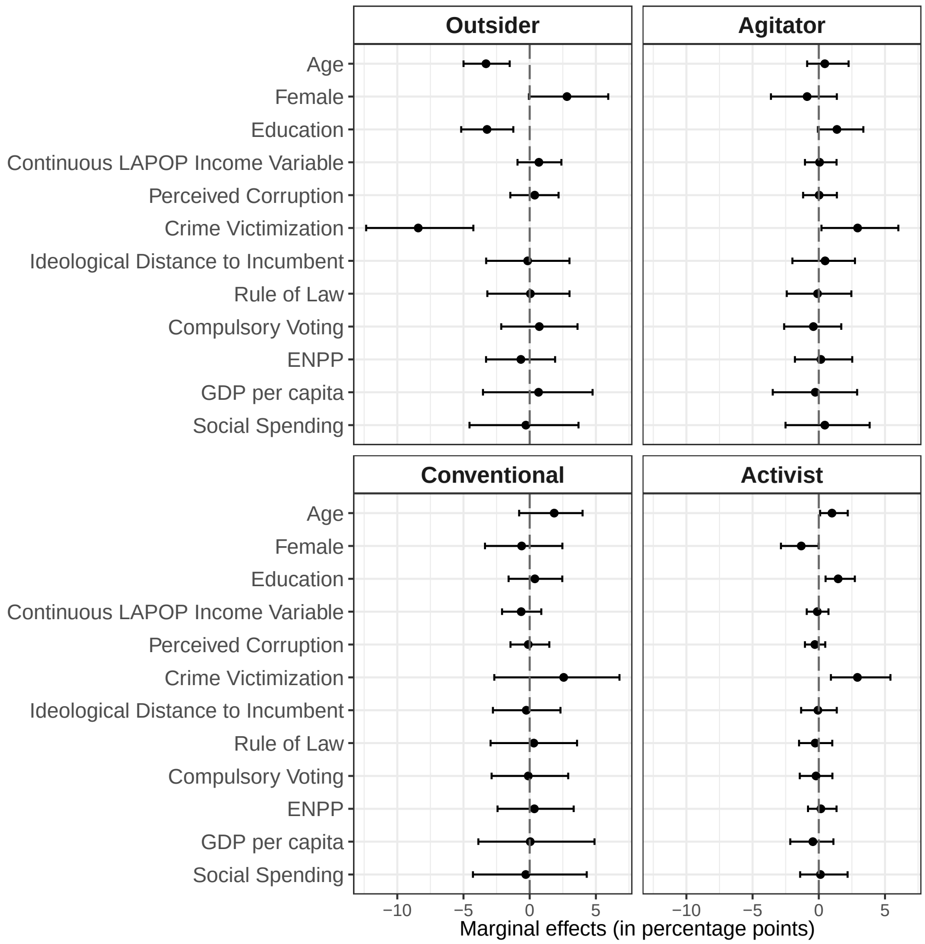


**Figure A.18: "Marginal effects" of individual and contextual variables on type assignment, using *Continuous LAPOP Income Variable* instead of *Relative Income (proxy)* as a predictor.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

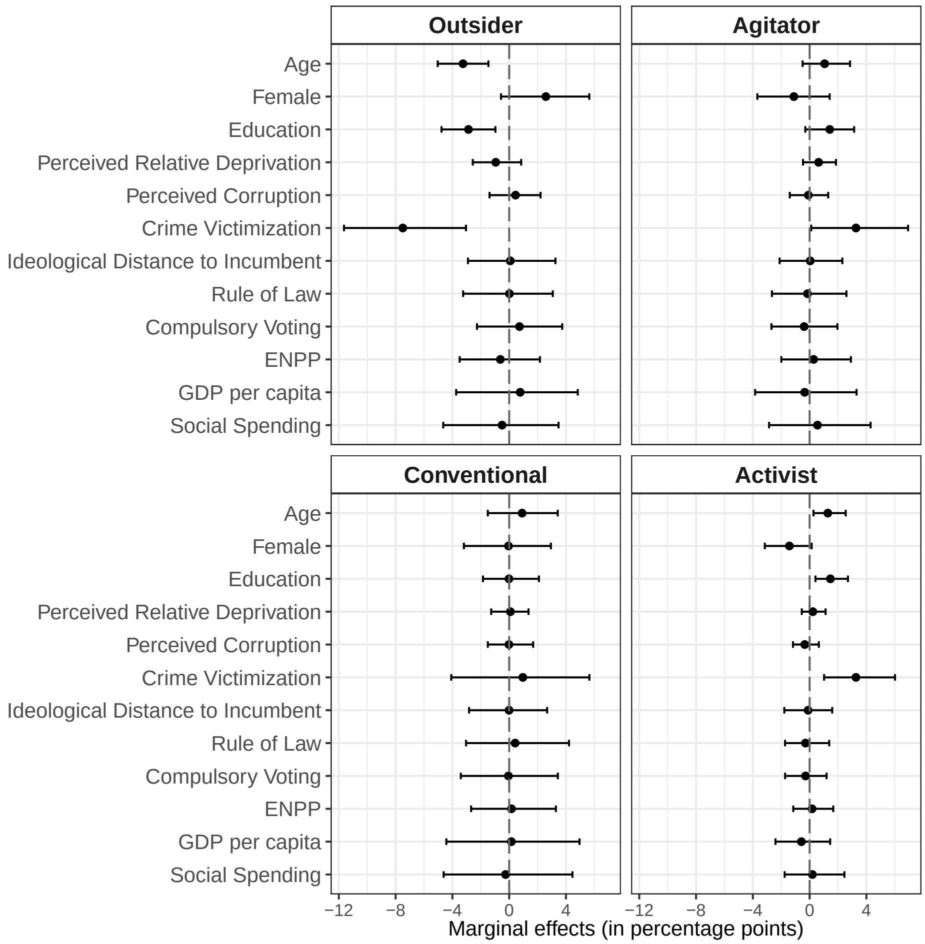


**Figure A.19: "Marginal effects" of individual and contextual variables on type assignment, using *Perceived Relative Deprivation* instead of *Relative Income (proxy)* as a predictor.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

### A.3.4 Results from a model replacing ***Ideological Distance to Incumbent*** with ***Government Support***

As we noted in Section A.1 above, *Ideological Distance to Incumbent* - which relied on data from Baker (2019) to code incumbents' ideological placement - could only be constructed for 17 Latin American countries, with a total sample size of 26,227. By contrast, *Government Support*, *Prospective Vote for Incumbent* and *Close to Incumbent Party* are all coded directly from questions included in the 2012 AmericasBarometer survey of the Latin America Public Opinion Project. This allows us to expand the geographical coverage of our analysis to 23 Latin American and Caribbean countries, and to increase the sample size (n. observations = 35,602).

Table A.9 reports the posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries, estimated from the specification replacing *Ideological Distance to Incumbent* with *Government Support*. Figure A.20 plots posterior summaries for the country-specific parameters $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$, while Figure A.21 plots the activity-specific intercepts $\alpha_{j,k}$ for each country. Despite differences in the magnitude of the estimates, the general patterns emerging from Table A.9 and Figures A.20 and A.21 are broadly consistent with those discussed in the research note and in Sections A.3.1 and A.3.2 above.

**Table A.9:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries replacing *Ideological Distance to Incumbent* with *Government Support*

| **Activity** | Dimension | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.296 | 0.320 |
| | (0.010, 0.821) | (0.011, 0.730) |
| Municipal meeting | 1.083 | 0.000 |
| | (0.094, 1.851) | (0.000, 0.000) |
| Contacting municipality | 0.926 | 1.056 |
| | (0.026, 2.455) | (0.023, 2.129) |
| Contacting local authority | 0.784 | 1.101 |
| | (0.015, 2.159) | (0.023, 2.458) |
| Contacting national authority | 0.513 | 0.947 |
| | (0.011, 1.429) | (0.077, 2.130) |
| Improvements meeting | 0.842 | 0.862 |
| | (0.029, 1.792) | (0.053, 1.887) |
| Solving community problems | 0.745 | 0.798 |
| | (0.028, 1.631) | (0.074, 1.780) |
| Party meeting | 0.600 | 0.783 |
| | (0.022, 1.366) | (0.150, 1.416) |

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Table A.9 – *Continued from previous page*

| **Activity** | Dimension | |
|---|---|---|
| | Conventional | Unconventional |
| Petitioning | 0.443 | 0.857 |
| | (0.014, 1.246) | (0.102, 1.683) |
| Sharing online | 0.204 | 0.469 |
| | (0.006, 0.678) | (0.017, 1.376) |
| Protesting | 0.254 | 0.926 |
| | (0.007, 0.815) | (0.040, 2.351) |
| Blocking | 0.000 | 0.803 |
| | (0.000, 0.000) | (0.050, 2.136) |

The table reports posterior means and 95% credible intervals (in parentheses) for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ for each activity $j$ averaged across all $k$, estimated from a specification replacing *Ideological Distance to Incumbent* with *Government Support*.

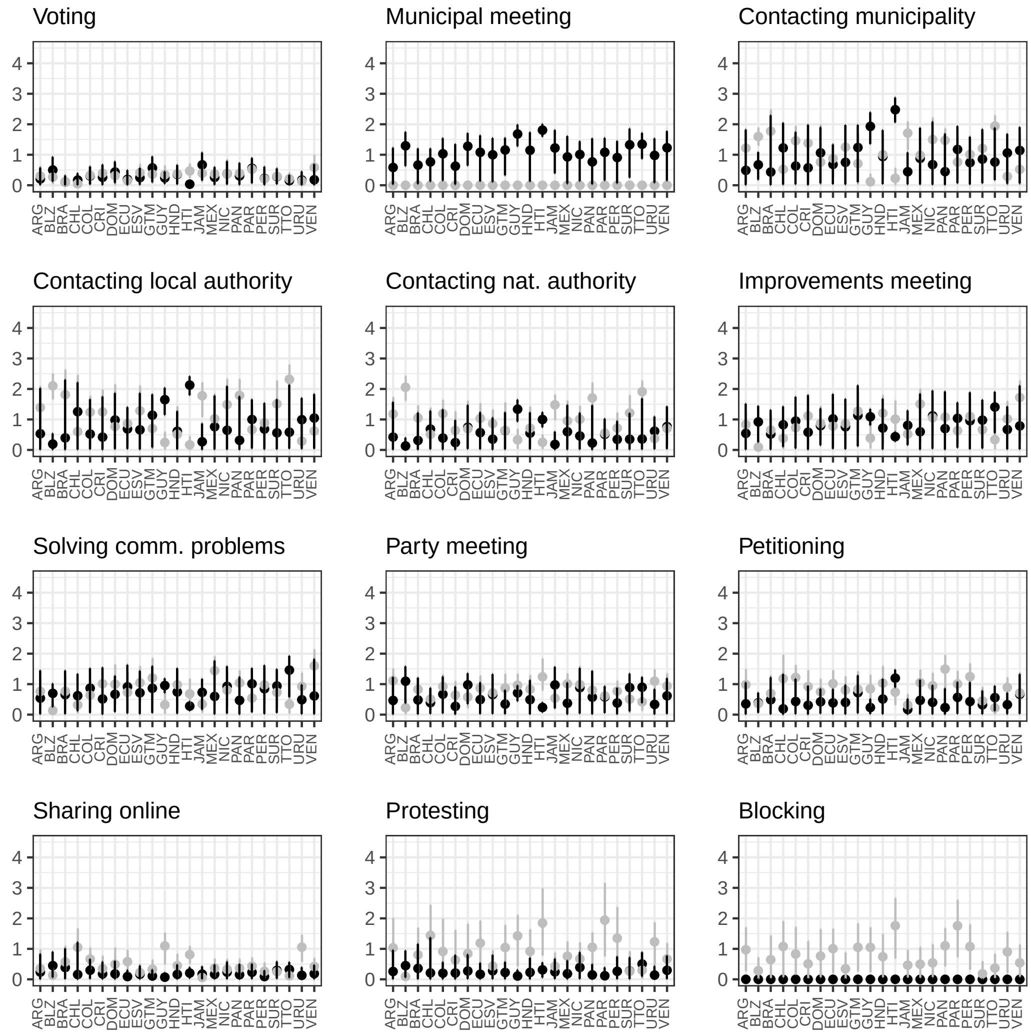


**Figure A.20: Posterior summaries for $\alpha_{c,j,k}$ (in black) and $\alpha_{u,j,k}$ (in gray) $\forall\ j$, $k$, estimated from a model replacing *Ideological Distance to Incumbent* with *Government Support.*** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals.

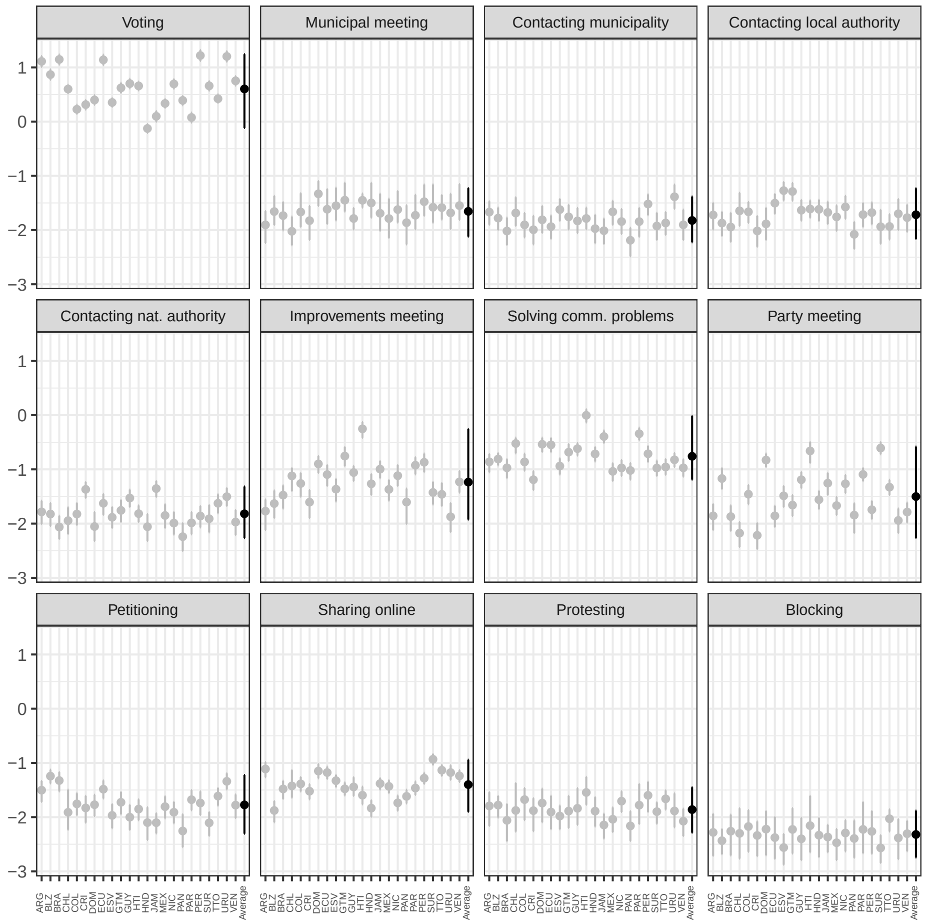


**Figure A.21: Posterior summaries for $\alpha_{j,k}$ $\forall$ $j$, $k$, from the model replacing *Ideological Distance to Incumbent* with *Government Support*.** Circles represent point estimates (posterior means), and vertical lines give the 95% credible intervals. Country-specific estimates for each activity are displayed in gray; activity-specific means averaged across countries are displayed in black.

Figure A.22 replicates the information displayed in Figure 1 of the research note and Figure A.10 in Section A.3.2 of this Online Appendix. The probabilities of type assignment - averaged across all countries - are very similar to those reported in Figure 1 of the research note, despite the fact that this alternative specification covers six additional countries. The average posterior membership probability is highest for the outlier type (0.64), followed by the conventional (0.18) and agitator (0.13) types. As in our benchmark specification, Latin Americans are least likely to belong to the activist type (0.06).

The lower panel of the figure shows that, also in this expanded sample, the classes are well separated - i.e., the average posterior probabilities of type assignment are significantly different.

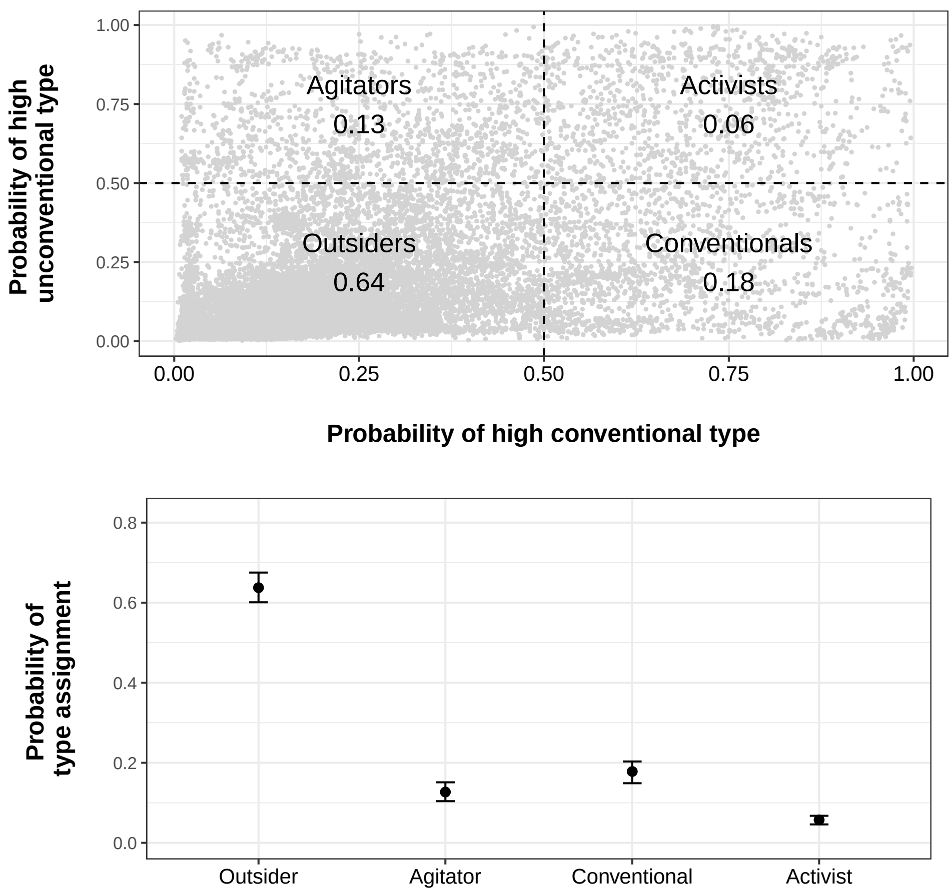


**Figure A.22: Posterior probabilities of type assignment averaged across 23 Latin American and Caribbean countries, estimated from a model replacing *Ideological Distance to Incumbent* with *Government Support*.** The upper panel depicts the relationship between the probability of being assigned a high conventional and high unconventional type. Circles represent survey respondents. The lower panel reports posterior means (dots) and 95% credible intervals for the probabilities of type assignment, averaged across countries.

Furthermore, as seen in Figure A.23, the posterior probabilities of assignment to each participatory type are extremely similar across countries – as was the case for our baseline specification and its variant using a logistic link.

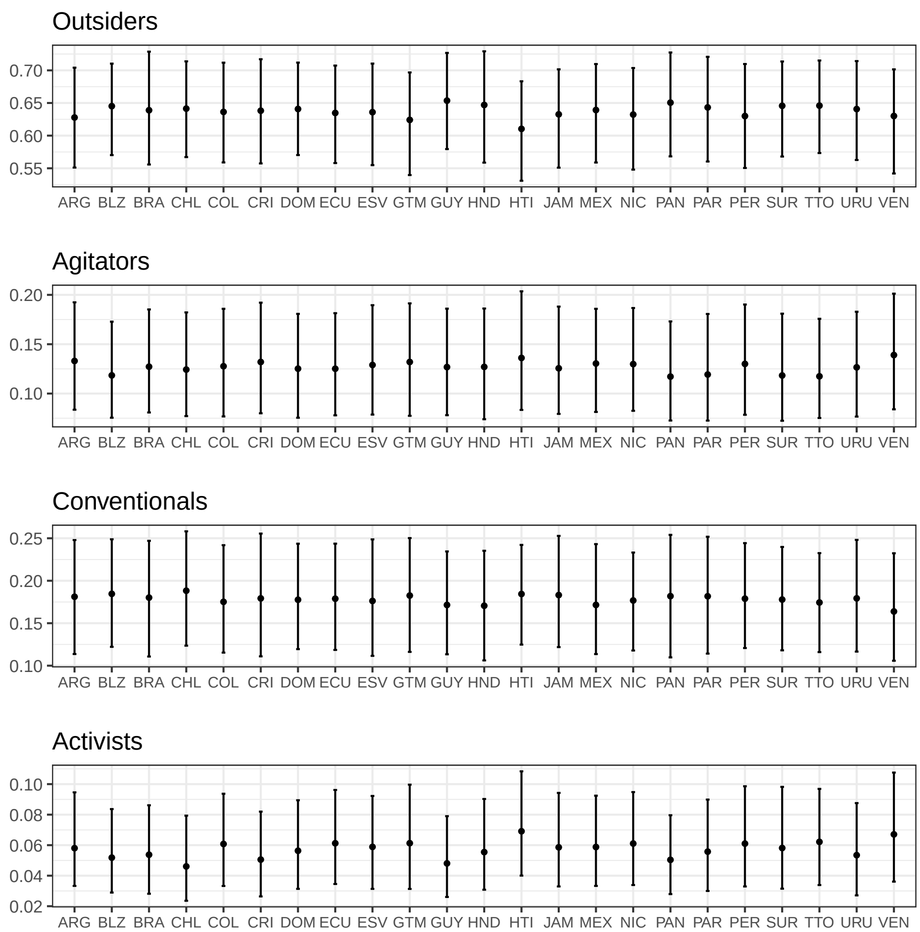


**Figure A.23: Posterior probabilities of type assignment by country, for the model replacing *Ideological Distance to Incumbent* with *Government Support.*** Circles represent posterior means. Vertical lines give 95% credible intervals.

In fact, there are no statistically significant differences in the probabilities of type assignment between the 23 Latin American and Caribbean countries included in this expanded sample.

In sum, our measurement approach is not particularly sensitive to the specific operationalization of respondents' ideological preferences and, more importantly, is robust to the inclusion of a larger number of Latin American and Caribbean countries. In other words, the general findings reported in the research note are not due to the exclusion of Belize, Guyana, Haiti, Jamaica, Suriname and Trinidad and Tobago from our main sample.

Finally, Figure A.24 plots the expected change in the probabilities of type assignment associated with a change in the covariates estimated from this alternative model. The relationships between individual and contextual variables and the probabilities of type assignment are generally aligned with those emerging from previous specifications. The main differences pertain precisely to the "marginal effects" of *Government Support* and *Ideological Distance to Incumbent*.

For the average respondent, each increase in *Government Support* - measured on a 5-point scale - is associated with a 1.41 percentage point drop in the probability of becoming an outsider. By contrast, we noted in the discussion of the results reported in Figure 3 of the research note that increases in the left-right distance between respondents and incumbents did not have a systematic impact on individuals' propensity to participate in political activities. The same conclusion held for the model using a logit link (Figure A.13 in Section A.3.2).

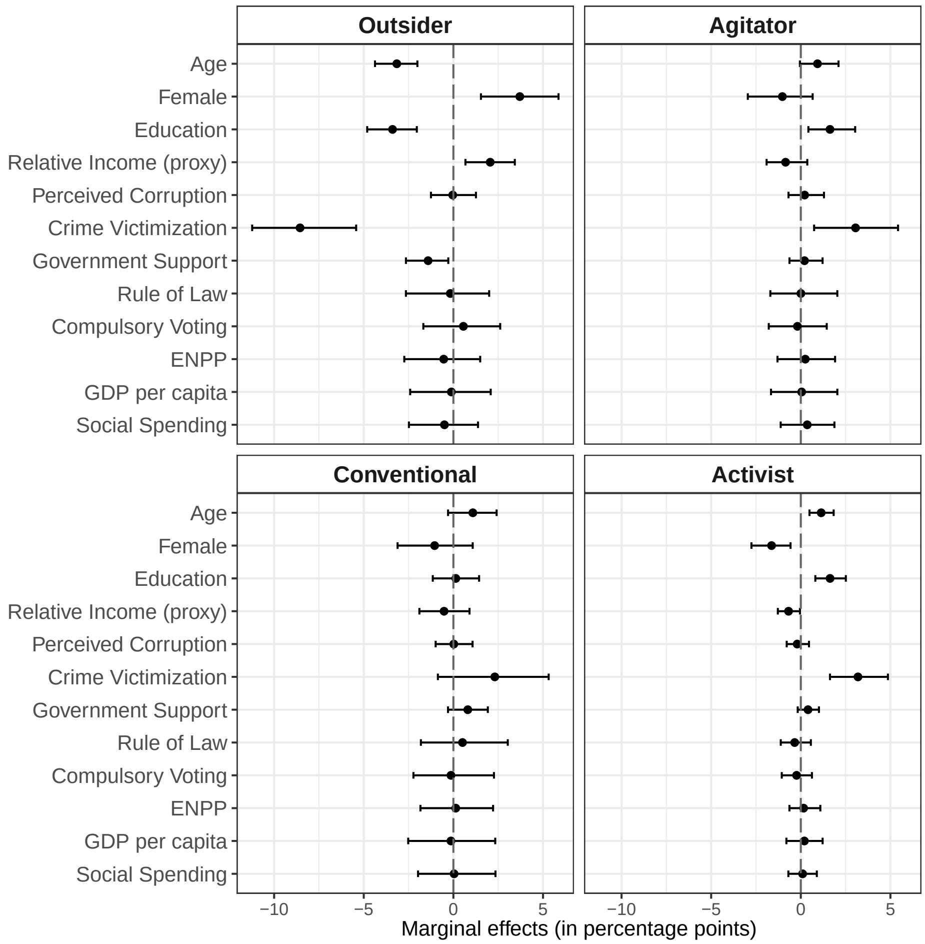


**Figure A.24: "Marginal effects" of individual and contextual variables on type assignment, estimated from the model replacing *Ideological Distance to Incumbent* with *Government Support.*** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

It is worth emphasizing that the sign and direction of the estimated "marginal effects" of *Government Support* remain essentially unchanged if the alternative specification is fitted to the original 17-country sample - i.e., excluding Belize (BLZ), Guyana (GUY), Haiti (HTI), Jamaica (JAM), Suriname (SUR) and Trinidad and Tobago (TTO). That is, the difference between the estimates for *Government Support* and *Ideological Distance to Incumbent* reflects the fact that these two variables are in all likelihood gauging somewhat different concepts, and is not a product of the inclusion of additional countries in the analysis. Even acknowledging the limitations imposed by the available data on respondents' ideological leanings, this is a reassuring finding regarding the generalizability of our conclusions throughout Latin America.

The estimated "marginal effects" for the other individual and contextual variables tend to coincide between the two models: socio-demographic characteristics and crime victimization remain the most important individual-level determinants of type allocation. As in the analyses summarized in Figure 3 of the research note and Figure A.13 above, none of the contextual factors has a systematic influence on the probabilities of type allocation.

Also in line with our baseline and logistic specifications, all the country-specific residual effects (captured by $\eta$) are statistically indistinguishable from zero (Figure A.25 below).

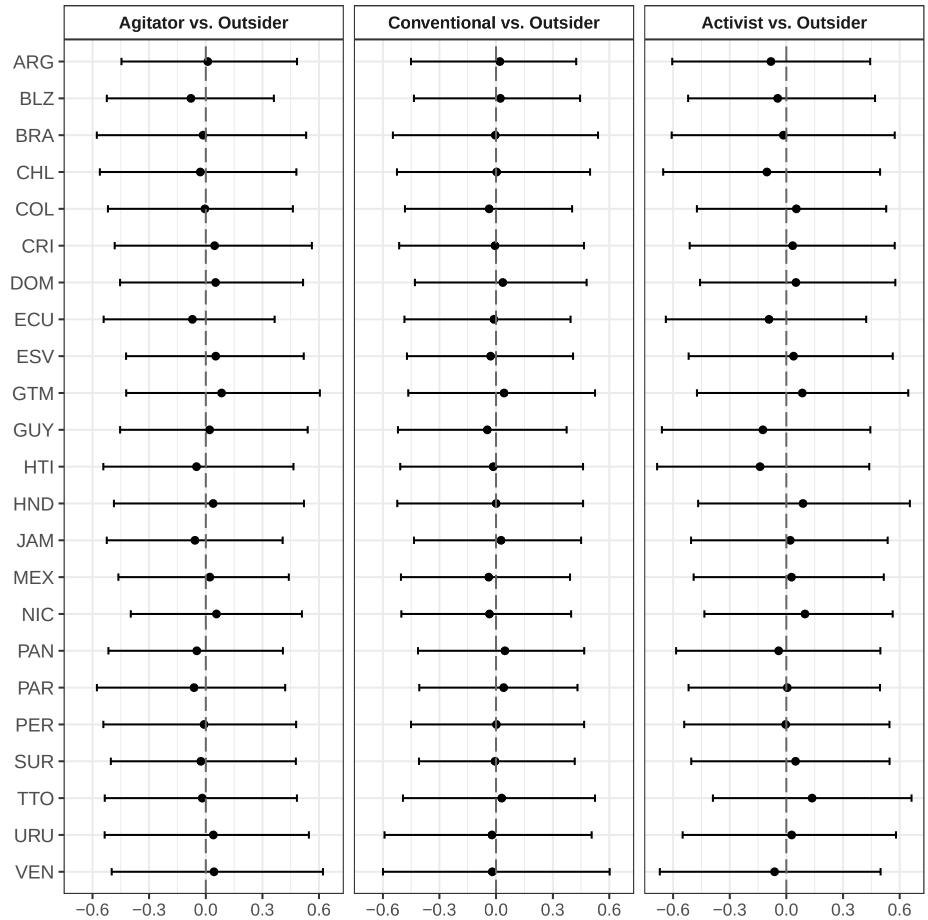


**Figure A.25: Unobserved country differences in type assignment estimated from a model replacing *Ideological Distance to Incumbent* with *Government Support.*** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

The same patterns hold when replacing *Ideological Distance to Incumbent* with *Prospective Vote for Incumbent* or *Close to Incumbent Party*. Just for illustration purposes, Figures A.26-A.28 replicate Figures A.22-A.23 using these alternative measures of respondents' ideological preferences in lieu of *Ideological Distance to Incumbent*.

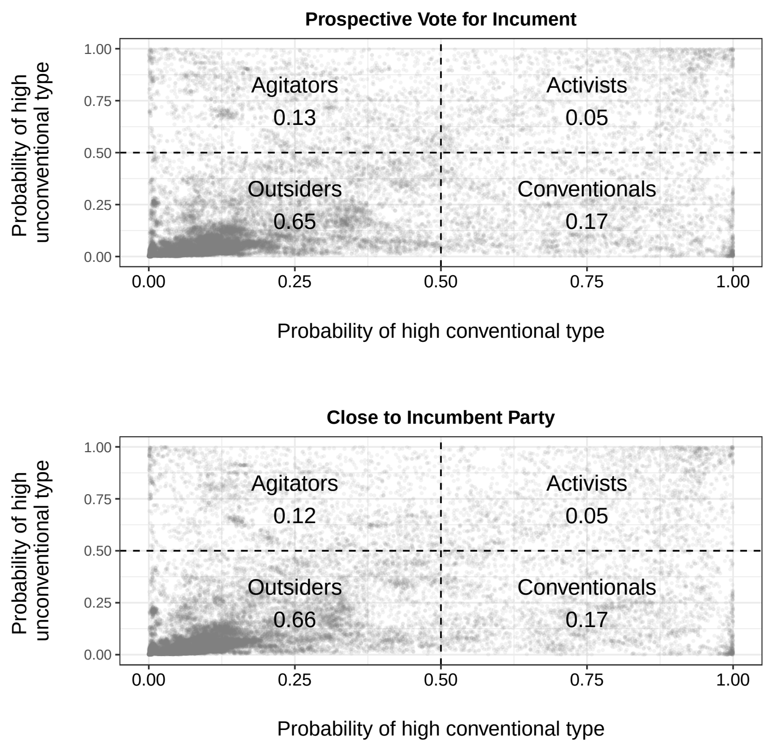


**Figure A.26: Relationship between the probability of being assigned a high conventional and high unconventional type, using additional measures of respondents' ideological preferences.** The upper panel reports estimates from a model replacing *Ideological Distance to Incumbent* with *Prospective Vote for Incumbent*. The lower panel reports estimates from a model using *Close to Incumbent Party* as a measure of ideological preferences instead. Circles represent survey respondents.

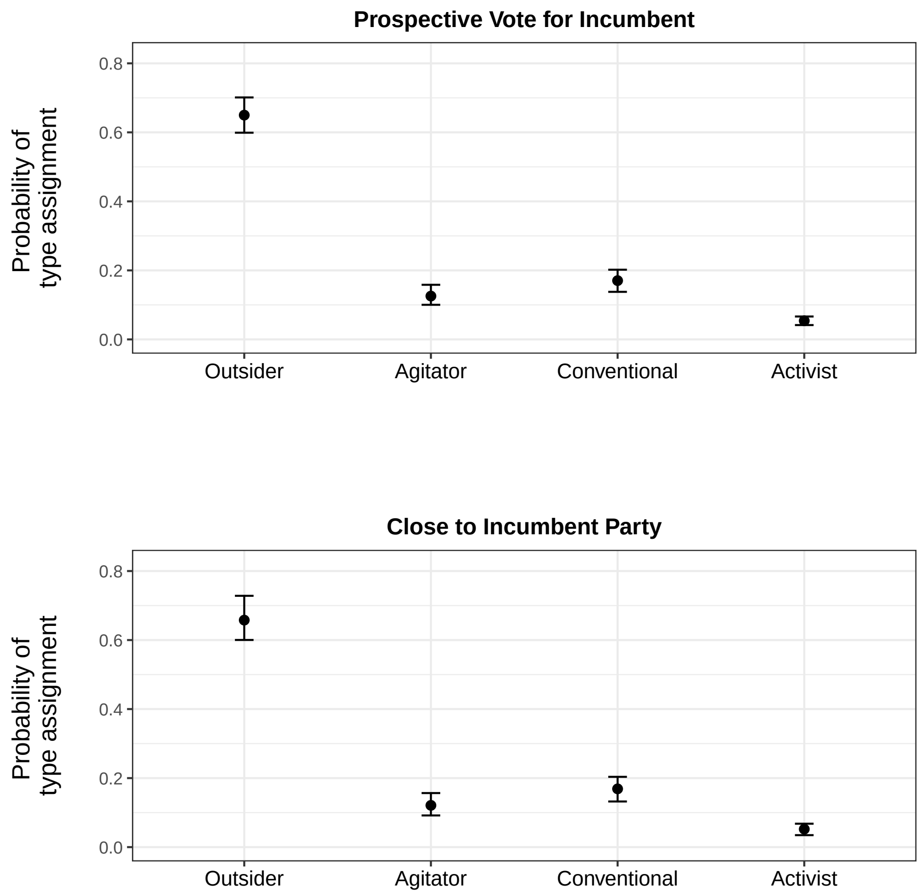


**Figure A.27: Posterior summaries for the probabilities of type assignment averaged across countries, using additional measures of respondents' ideological preferences.** The upper panel reports estimates from a model replacing *Ideological Distance to Incumbent* with *Prospective Vote for Incumbent*. The lower panel reports estimates from a model using *Close to Incumbent Party* as a measure of ideological preferences instead.

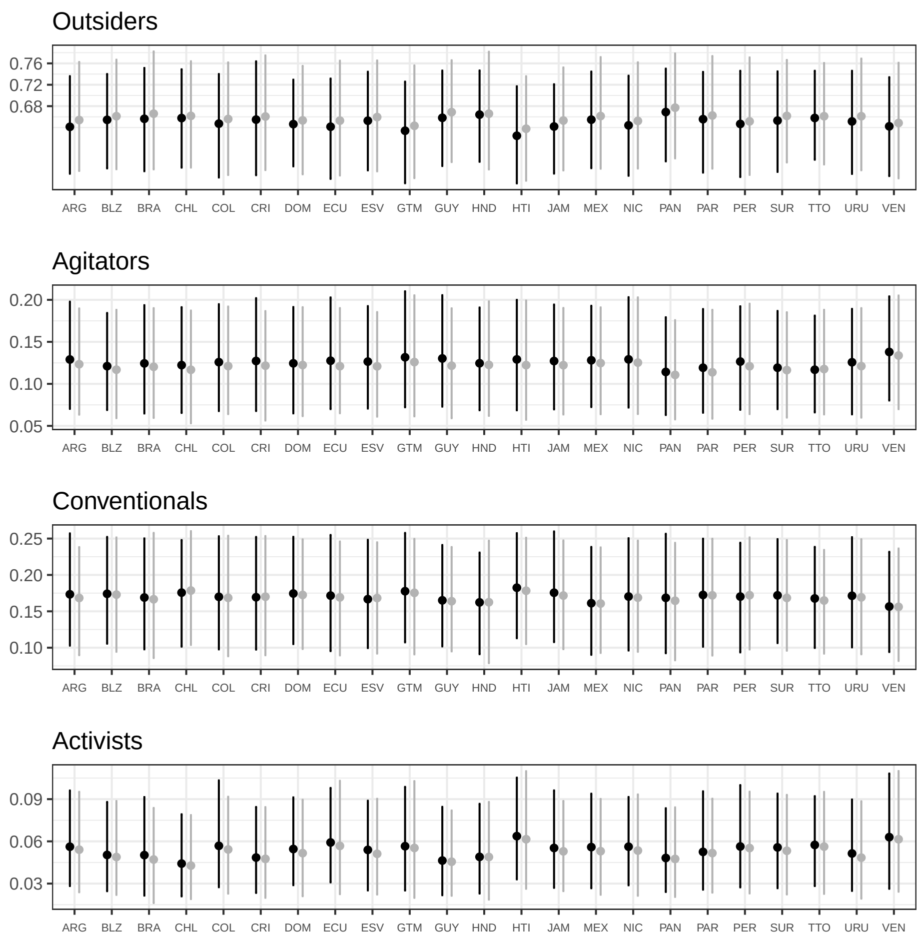


**Figure A.28: Posterior probabilities of type assignment by country, using additional measures of respondents' ideological preferences.** Estimates from a model replacing *Ideological Distance to Incumbent* with *Prospective Vote for Incumbent* (*Close to Incumbent Party*) are displayed in black (gray). Circles represent point estimates (posterior means); vertical lines give 95% credible intervals.

### A.3.5 Results for the period 2010-2018

To assess whether the basic patterns reported in the research note hold beyond 2012, we fitted our baseline model to data from all the AmericasBarometer surveys fielded between 2010 and 2018 (i.e., 2010, 2012, 2014, 2016 and 2018). As we mentioned in Section A.1, only a subset of the questions about participation in political activities considered in our main analysis were included in every one of these surveys. Specifically, the outcome variables for the model covering this extended period are:

1. Voting in the last general election (*Voting*);
2. Attending municipal meetings (*Municipal meeting*);
3. Attending meetings of a committee of improvements (*Improvements meeting*);
4. Attending meetings of a political party (*Party meeting*);
5. Participating in peaceful protests (*Protesting*);

The dependent and explanatory variables were only available throughout this period for 7 Latin American countries: Dominican Republic, El Salvador, Honduras, Mexico, Nicaragua, Paraguay, and Peru. This is the longest and most up-to date temporal analysis that can be conducted using AmericasBarometer surveys. The sample sizes are reported in Table A.10.

**Table A.10:** Sample sizes for the analysis covering 2010-2018

| Country | Abbreviation | Wave | | | | | Total |
|---|---|---|---|---|---|---|---|
| | | 2010 | 2012 | 2014 | 2016 | 2018 | |
| Dominican Republic | DOM | 1,498 | 1,512 | 1,520 | 1,518 | 1,516 | 7,564 |
| El Salvador | ESV | 1,550 | 1,497 | 1,512 | 1,551 | 1,511 | 7,621 |
| Honduras | HND | 1,596 | 1,728 | 1,561 | 1,560 | 1,560 | 8,005 |
| Mexico | MEX | 1562 | 1,560 | 1,535 | 1,563 | 1,580 | 7,800 |
| Nicaragua | NIC | 1,540 | 1,686 | 1,546 | 1,560 | 1,547 | 7,879 |
| Paraguay | PAR | 1,501 | 1,510 | 1,503 | 1,528 | 1,515 | 7,557 |
| Peru | PER | 1,500 | 1,500 | 1,500 | 2,647 | 1,521 | 8,668 |
| Observations | | 10,747 | 10,993 | 10,677 | 11,927 | 10,750 | 55,094 |

Tables A.11-A.15 report posterior means and 95% credible intervals (in parentheses) for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$, averaged across countries, for each of these survey waves estimated independently.[10] For identification purposes, the parameters $\alpha_{c,\text{Municipal meeting},k}$ and $\alpha_{u,\text{Protesting},k}$ are set to zero $\forall k$ in every year.

Two main conclusions emerge from these tables. First, while the point estimates vary somewhat between years, there are no statistically significant differences in the parameters capturing the strength of the association between each political activity and participatory dimension over 2010-2018 period. That is, the 95% posterior credible intervals for the cross-country

[10]We also estimated a model pooling the data from the 2010-2018 waves, but allowing the random effects of the model to vary by country and year. The basic patterns are analogous to those reported in this section.

averages of $\alpha_{c,j,k}$ overlap across 2010, 2012, 2014, 2016 and 2018 $\forall\ j$, and the same is true for $\alpha_{u,j,k}$ $\forall\ j$.[11]

Second, for most activities, the posterior distributions of $\alpha_c$ and $\alpha_u$ are also statistically indistinguishable across survey waves.[12] In other words, the majority of the activities cannot be simply classified as either conventional or unconventional. Instead, as we noted in the discussion of our benchmark results, participation in these activities reflects respondents' propensities to engage in both conventional and unconventional forms of political activism.

[11]In fact, despite the differences in the number of outcome variables and the countries under study, the posterior distributions of the cross-country averages of $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ are also statistically indistinguishable from those obtained from our baseline model.

[12]The only activities for which these distributions are significantly different are those used as anchors, i.e., *Municipal meeting* and *Protesting*.

**Table A.11:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries

Wave: 2010

| Activity | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.488 | 0.329 |
| | (0.039, 0.974) | (0.015, 0.858) |
| Municipal meeting | 1.073 | 0.00 |
| | (0.073, 1.882) | (0.00, 0.00) |
| Improvements meeting | 1.083 | 0.490 |
| | (0.050, 1.877) | (0.010, 1.516) |
| Party meeting | 0.974 | 0.551 |
| | (0.032, 1.917) | (0.015, 1.736) |
| Protesting | 0.000 | 0.450 |
| | (0.000, 0.000) | (0.016, 1.202) |

**Table A.12:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries

Wave: 2012

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.437 | 0.418 |
| | (0.020, 1.072) | (0.016, 1.220) |
| Municipal meeting | 0.856 | 0.00 |
| | (0.031, 1.728) | (0.00, 0.00) |
| Improvements meeting | 0.874 | 0.757 |
| | (0.020, 1.954) | (0.016, 1.837) |
| Party meeting | 0.799 | 0.712 |
| | (0.013, 1.905) | (0.014, 2.034) |
| Protesting | 0.000 | 0.539 |
| | (0.000, 0.000) | (0.017, 1.373) |

**Table A.13:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries

Wave: 2014

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.656 | 0.276 |
| | (0.072, 1.430) | (0.010, 0.963) |
| Municipal meeting | 1.055 | 0.00 |
| | (0.149, 1.619) | (0.00, 0.00) |
| Improvements meeting | 1.241 | 0.293 |
| | (0.122, 2.079) | (0.008, 1.194) |
| Party meeting | 1.099 | 0.328 |
| | (0.069, 1.935) | (0.008, 1.356) |
| Protesting | 0.000 | 0.287 |
| | (0.000, 0.000) | (0.009, 0.920) |

**Table A.14:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries

Wave: 2016

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.640 | 0.427 |
| | (0.127, 1.126) | (0.022, 1.128) |
| Municipal meeting | 1.375 | 0.00 |
| | (0.455, 2.222) | (0.00, 0.00) |
| Improvements meeting | 1.433 | 0.612 |
| | (0.369, 2.153) | (0.017, 1.583) |
| Party meeting | 1.172 | 0.670 |
| | (0.230, 1.849) | (0.022, 1.661) |
| Protesting | 0.000 | 0.763 |
| | (0.000, 0.000) | (0.028, 1.934) |

**Table A.15:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries

Wave: 2018

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.612 | 0.383 |
| | (0.047, 1.207) | (0.016, 1.084) |
| Municipal meeting | 1.152 | 0.00 |
| | (0.081, 1.813) | (0.00, 0.00) |
| Improvements meeting | 1.265 | 0.569 |
| | (0.065, 2.116) | (0.015, 1.628) |
| Party meeting | 1.062 | 0.768 |
| | (0.038, 2.090) | (0.024, 1.924) |
| Protesting | 0.000 | 0.781 |
| | (0.000, 0.000) | (0.024, 2.145) |

Next, for each survey wave, Figure A.29 plots the posterior probabilities of type assignment averaged across respondents from the seven countries included in this analysis. While the average type-specific probabilities exhibit some temporal fluctuations, they are statistically indistinguishable across survey waves.

The main patterns emerging from Figure 1 in the research note continue to hold throughout the 2010–2018 period. Latin Americans are always significantly more likely to be classified as outsiders than to be assigned to any of the other three classes. That is, in any given year, the average respondent is more likely to stay away from politics than to engage in either conventional or unconventional forms of participation. At the other extreme, the average survey participant is always least likely to be assigned to the activist type.

The country-specific probabilities of type assignment are also aligned with the results from our main specification. Figures A.30-A.34 plot the posterior probabilities of assignment to the four participatory types for each country and survey wave. As was the case for Figure 2 of the research note, these probabilities are statistically indistinguishable across countries for any given year.

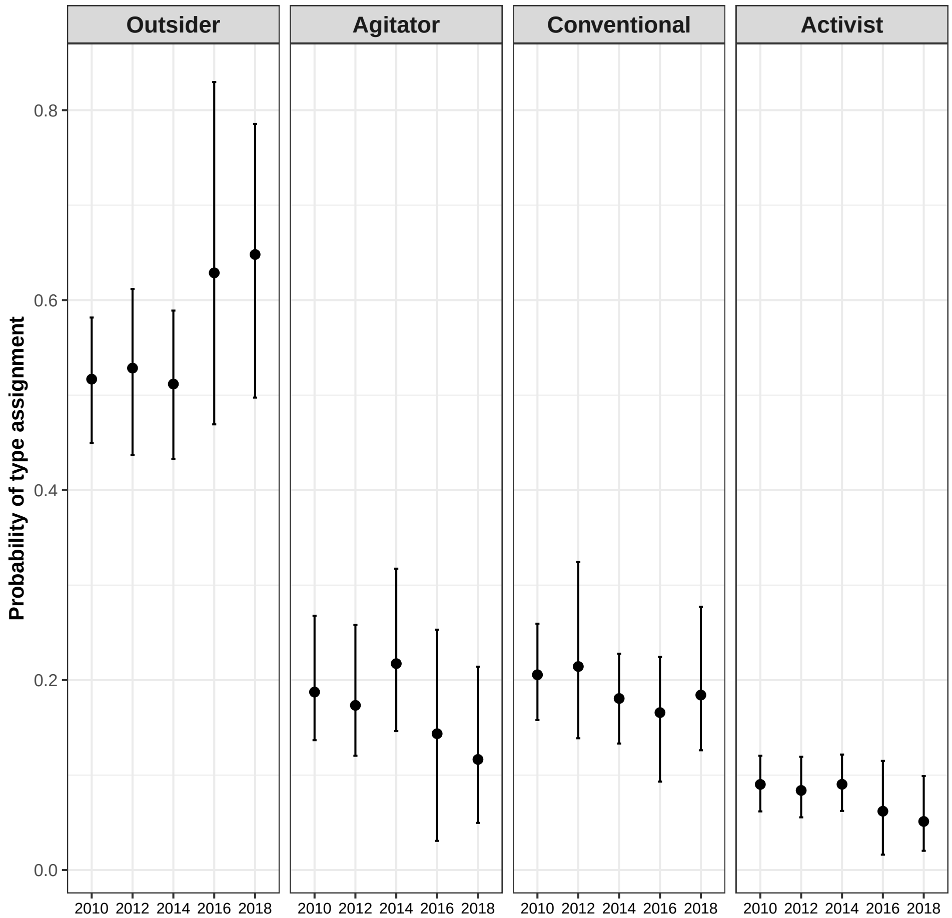


**Figure A.29: Posterior probabilities of type assignment for each survey wave, averaged across the 7 countries included in the sample.** Circles represent point estimates (posterior means across respondents from all the countries in any given year); vertical lines give the 95% credible intervals.

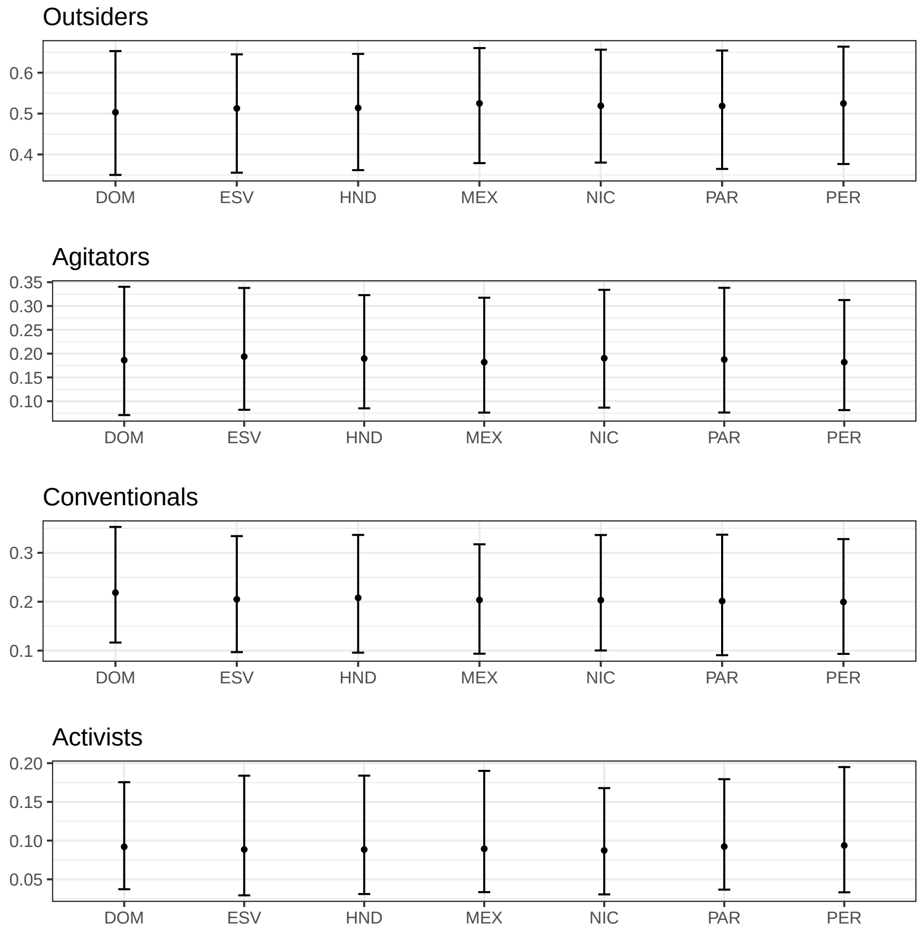


**Figure A.30: Probabilities of type assignment, by country, estimated from the 2010 AmericasBarometer survey.** Circles represent posterior means. Vertical lines give 95% credible intervals.

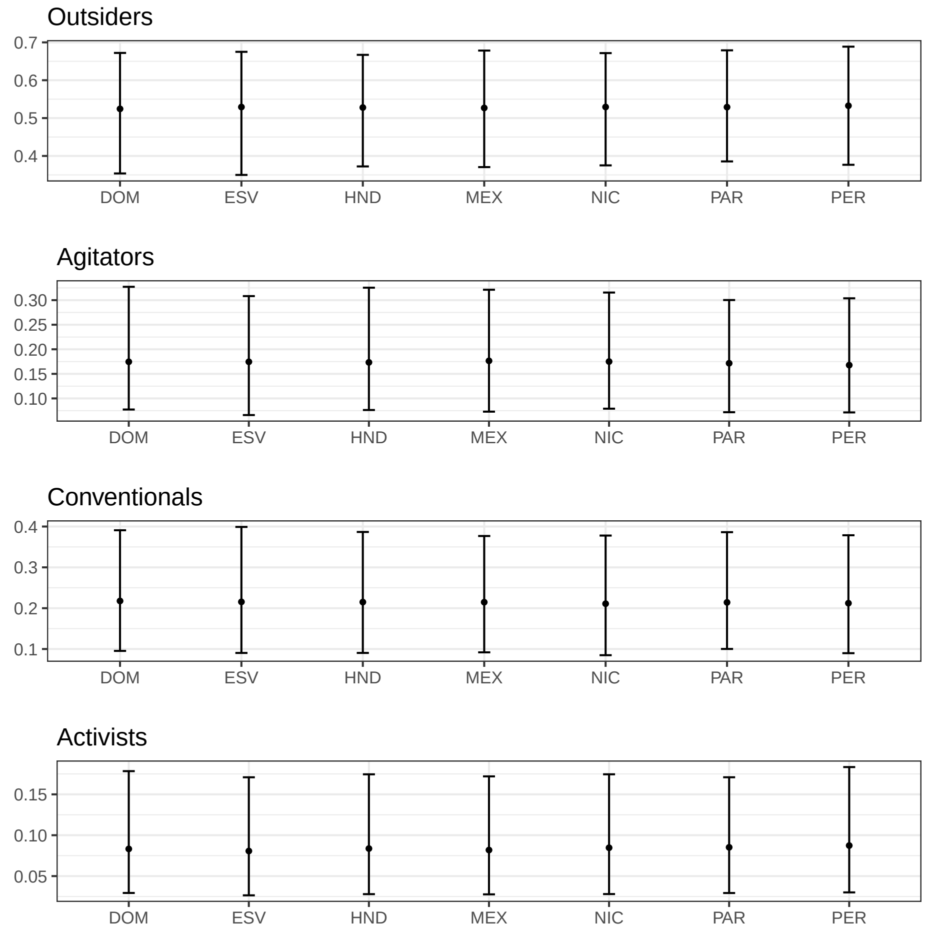


**Figure A.31: Probabilities of type assignment, by country, estimated from the 2012 AmericasBarometer survey.** Circles represent posterior means. Vertical lines give 95% credible intervals.

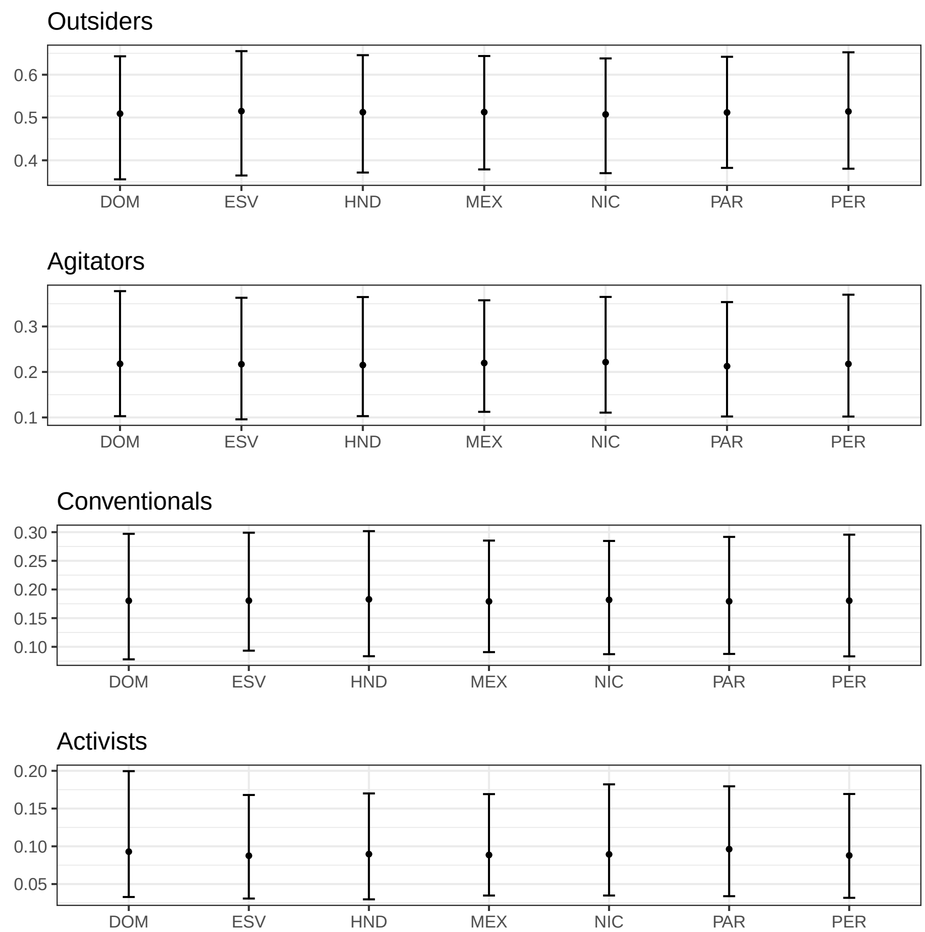


**Figure A.32: Probabilities of type assignment, by country, estimated from the 2014 AmericasBarometer survey.** Circles represent posterior means. Vertical lines give 95% credible intervals.

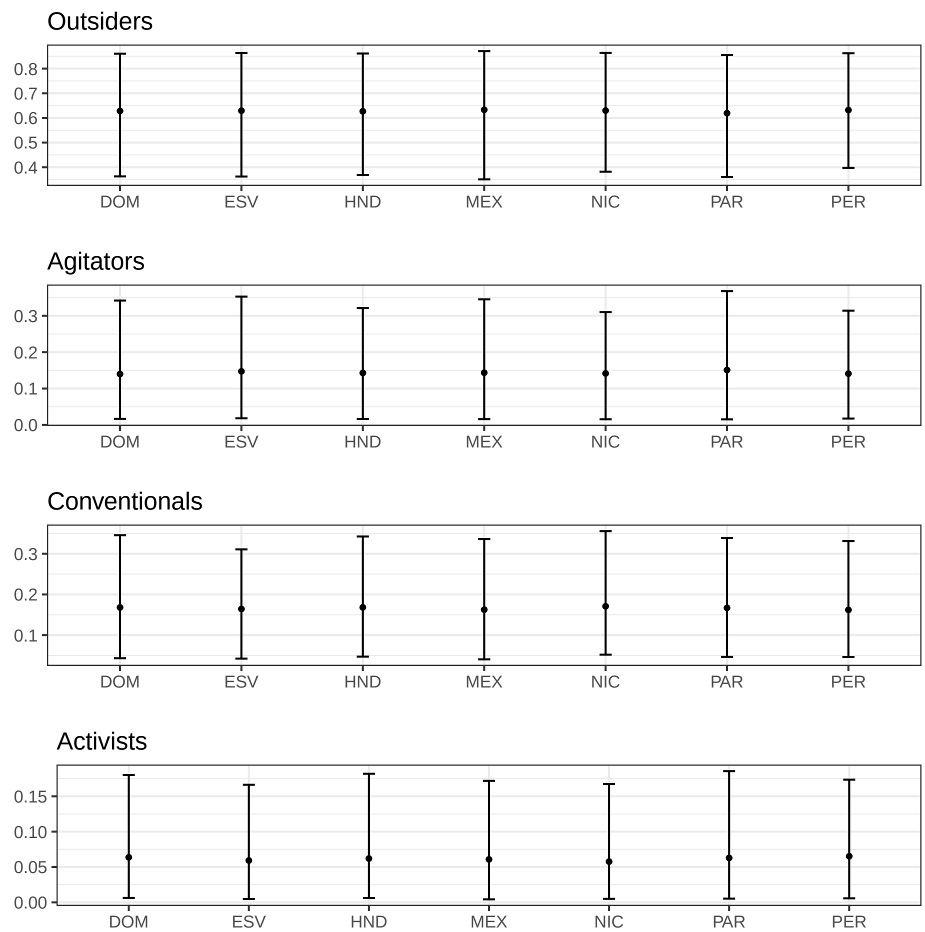


**Figure A.33: Probabilities of type assignment, by country, estimated from the 2016 AmericasBarometer survey.** Circles represent posterior means. Vertical lines give 95% credible intervals.

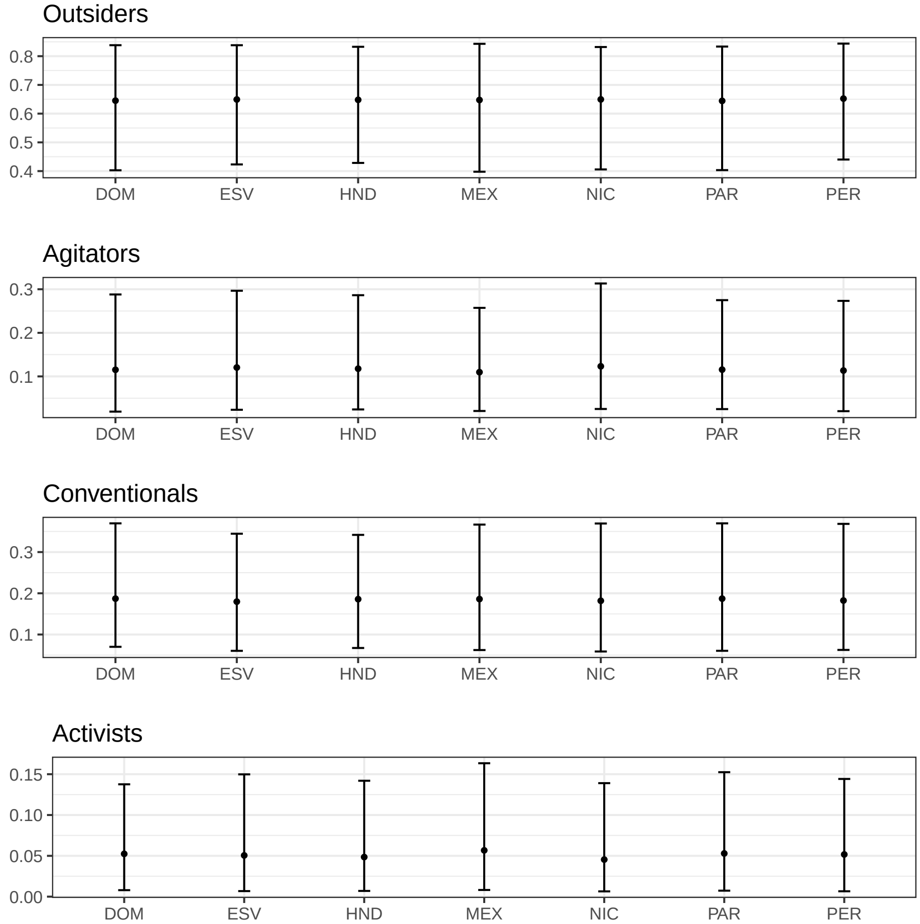


**Figure A.34: Probabilities of type assignment, by country, estimated from the 2018 AmericasBarometer survey.** Circles represent posterior means. Vertical lines give 95% credible intervals.

Figures A.35–A.39, in turn, plot the expected change in the probabilities of type assignment associated with a change in the covariates, estimated from each of the AmericasBarometer survey waves. Given the smaller sample sizes used in these exercises, it is not surprising that most of the parameters are very imprecisely estimated.

Nonetheless, throughout the whole period covered, and in line with the results reported in Figure 3 of the research note, older respondents are significantly less likely to be classified as outsiders than younger individuals. Also in consonance with the results of our baseline model, none of the country-level variables has a direct impact on individuals' probabilities of type allocation in Figures A.35–A.39.

Additionally, and also in line with our benchmark specification, none of the country-specific residual effects (captured by $\eta$ in our model) is significantly different from zero (Figures A.40–A.44).

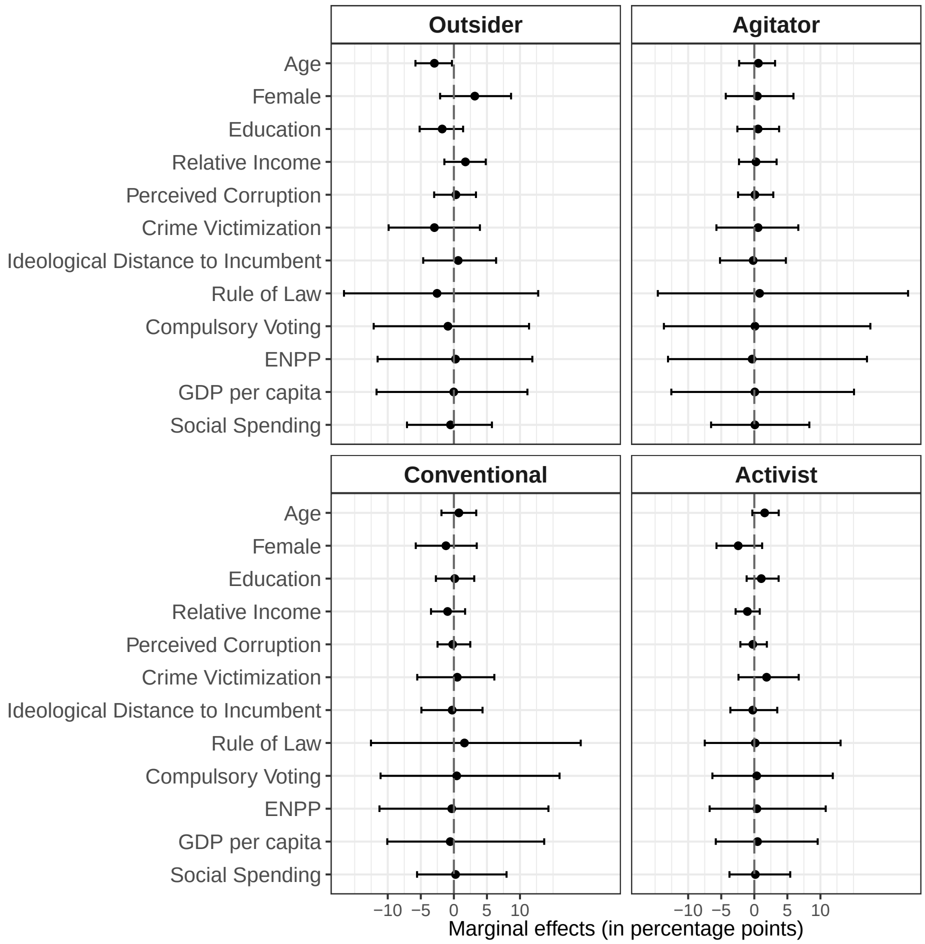


**Figure A.35: "Marginal effect" of individual and contextual variables on type assignment, estimated from the 2010 AmericasBarometer survey.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

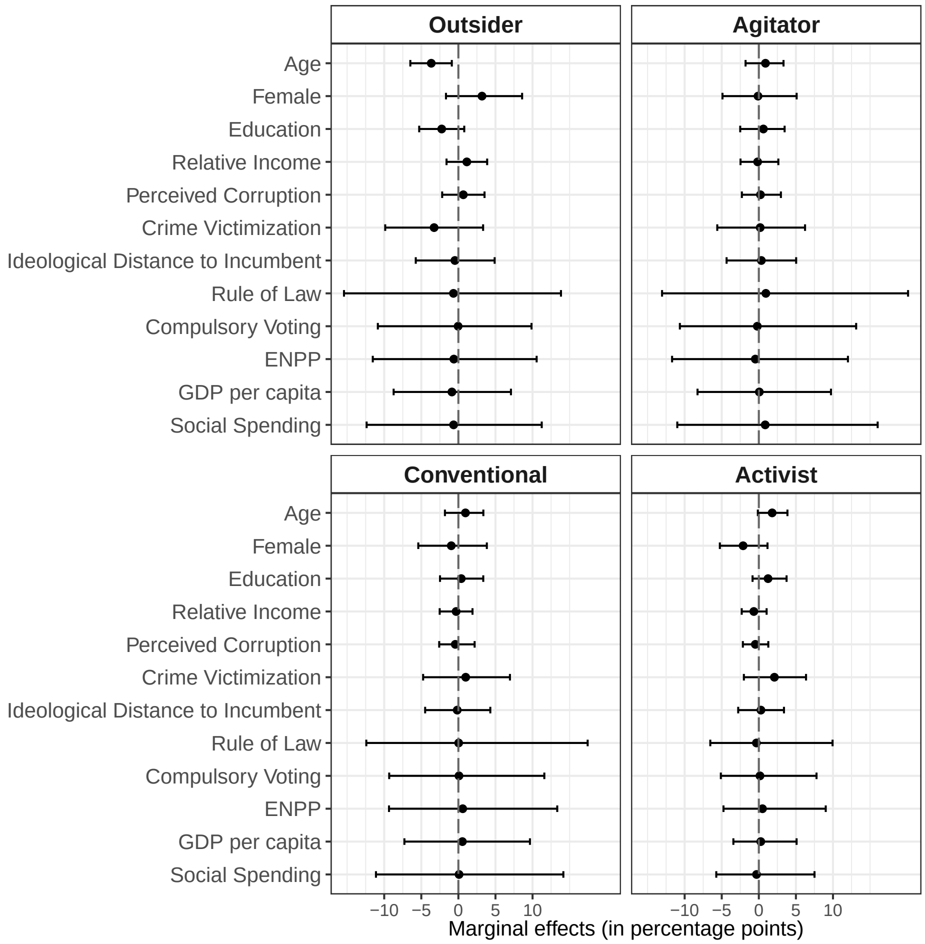


**Figure A.36: "Marginal effect" of individual and contextual variables on type assignment, estimated from the 2012 AmericasBarometer survey.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

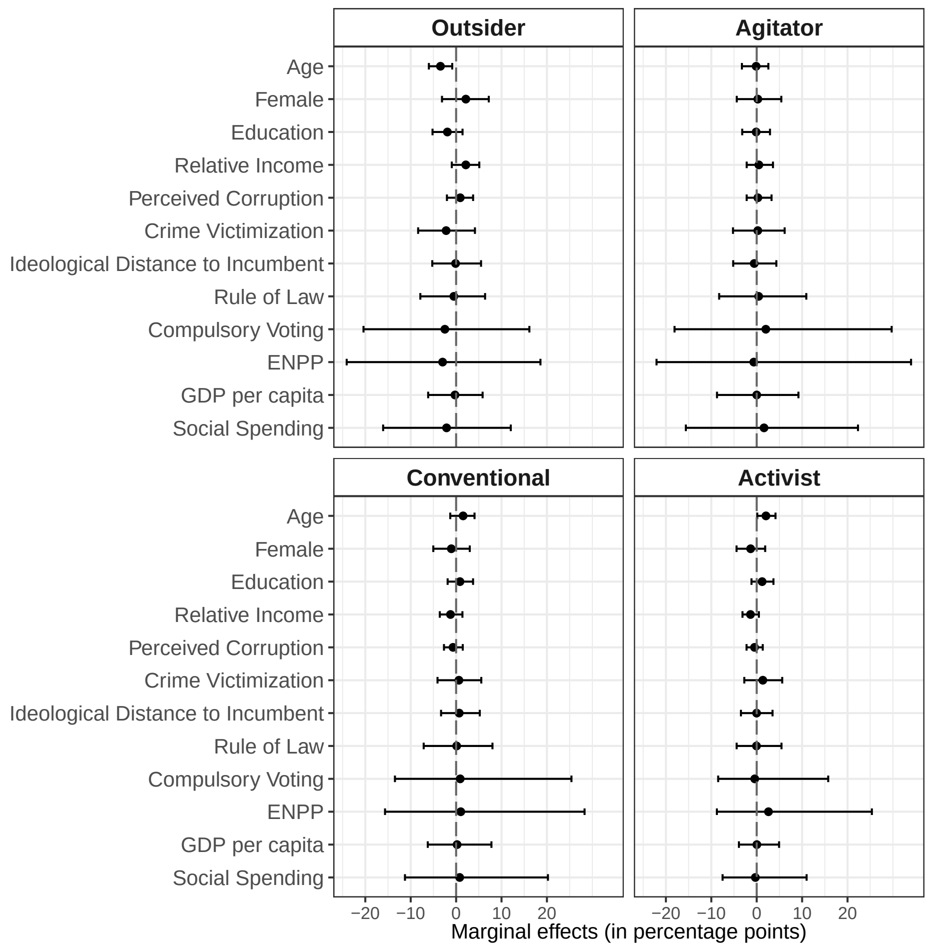


**Figure A.37: "Marginal effect" of individual and contextual variables on type assignment, estimated from the 2014 AmericasBarometer survey.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

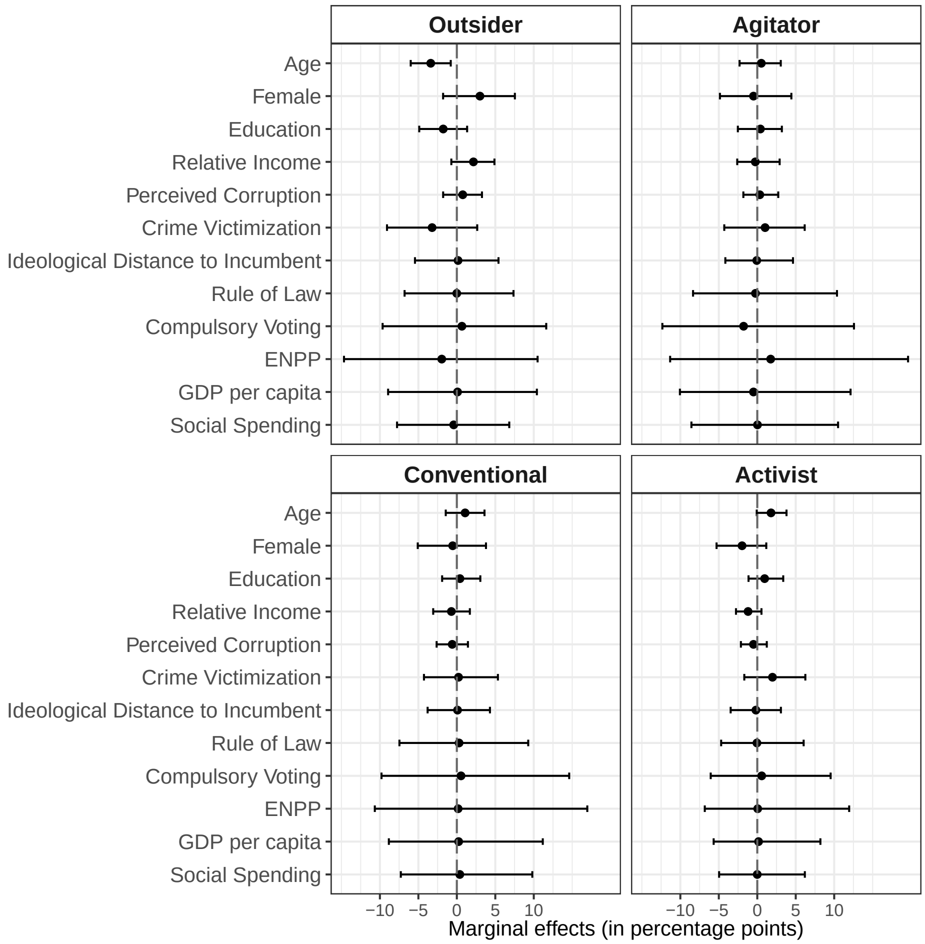


**Figure A.38: "Marginal effect" of individual and contextual variables on type assignment, estimated from the 2016 AmericasBarometer survey.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

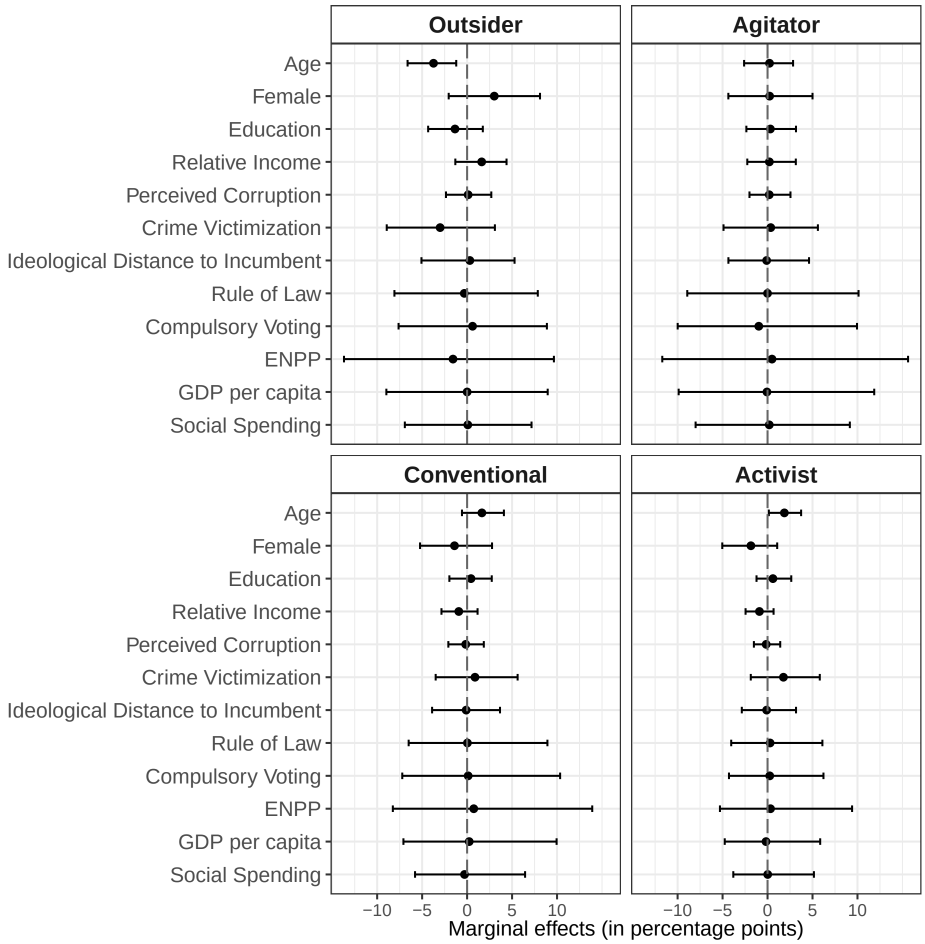


**Figure A.39: "Marginal effect" of individual and contextual variables on type assignment, estimated from the 2018 AmericasBarometer survey.** Circles represent the expected change in the probability of assignment to each type associated with a (unit) change in the covariates, in percentage points. Horizontal lines give 95% credible intervals.

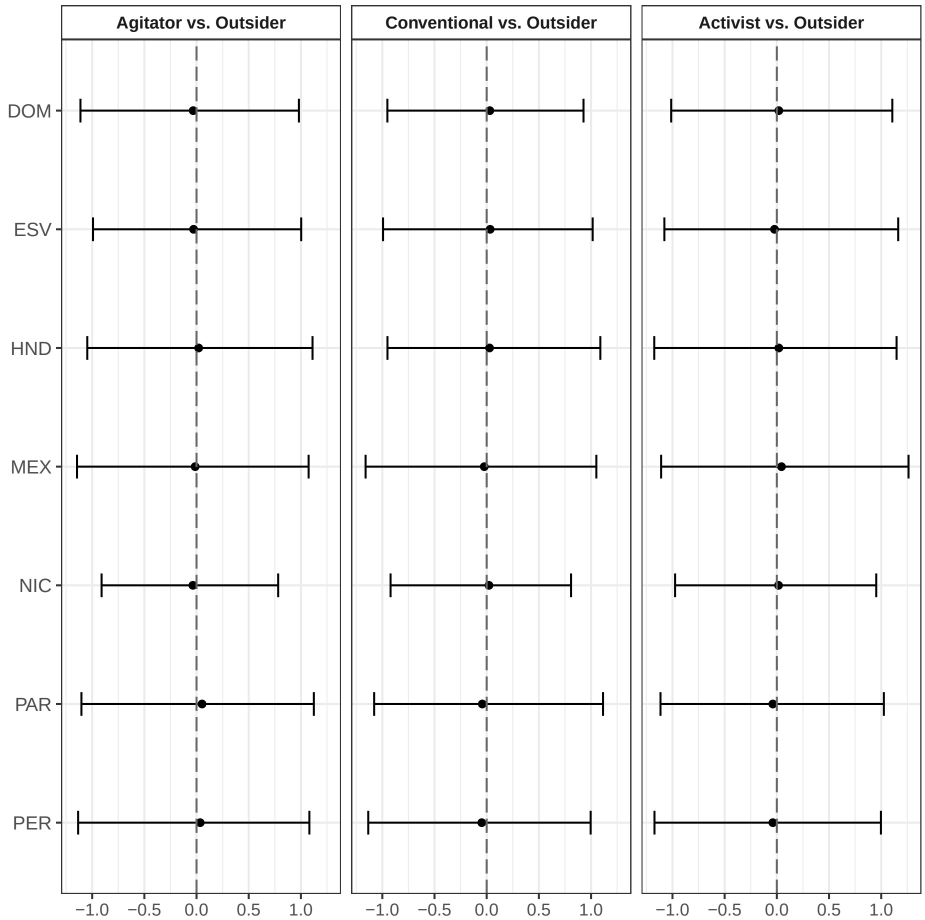


**Figure A.40: Unobserved country differences in type assignment, estimated from the 2010 AmericasBarometer survey.** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

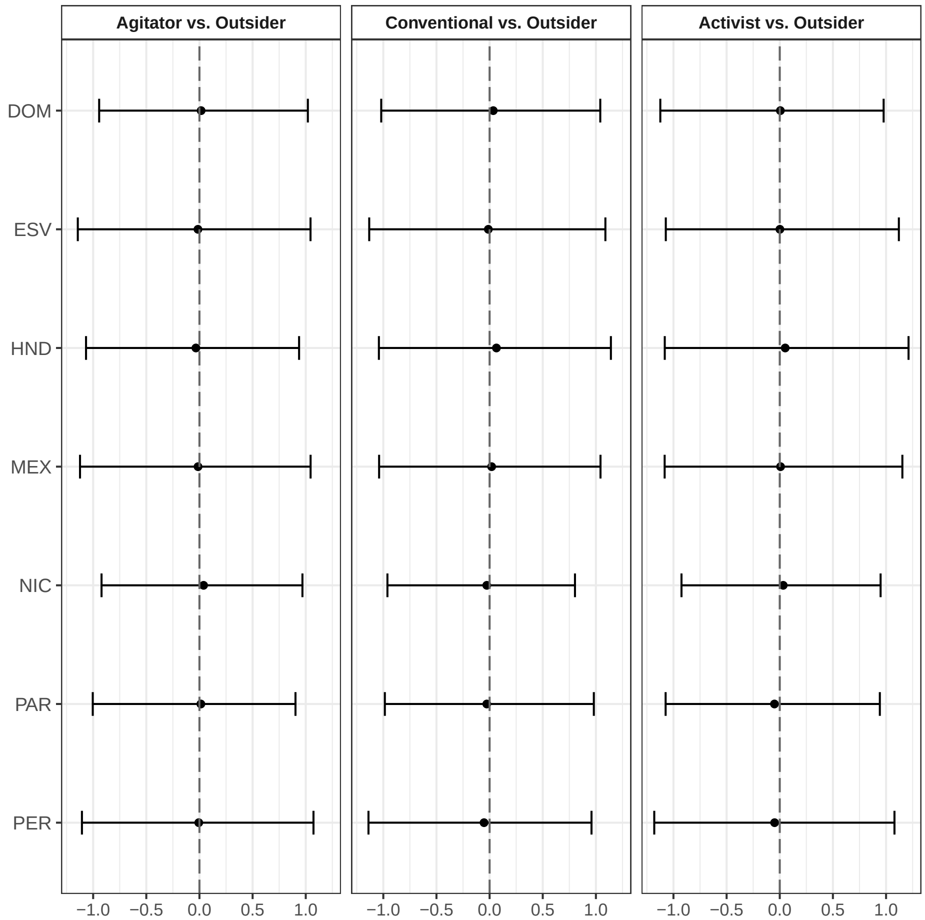


**Figure A.41: Unobserved country differences in type assignment, estimated from the 2012 AmericasBarometer survey.** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

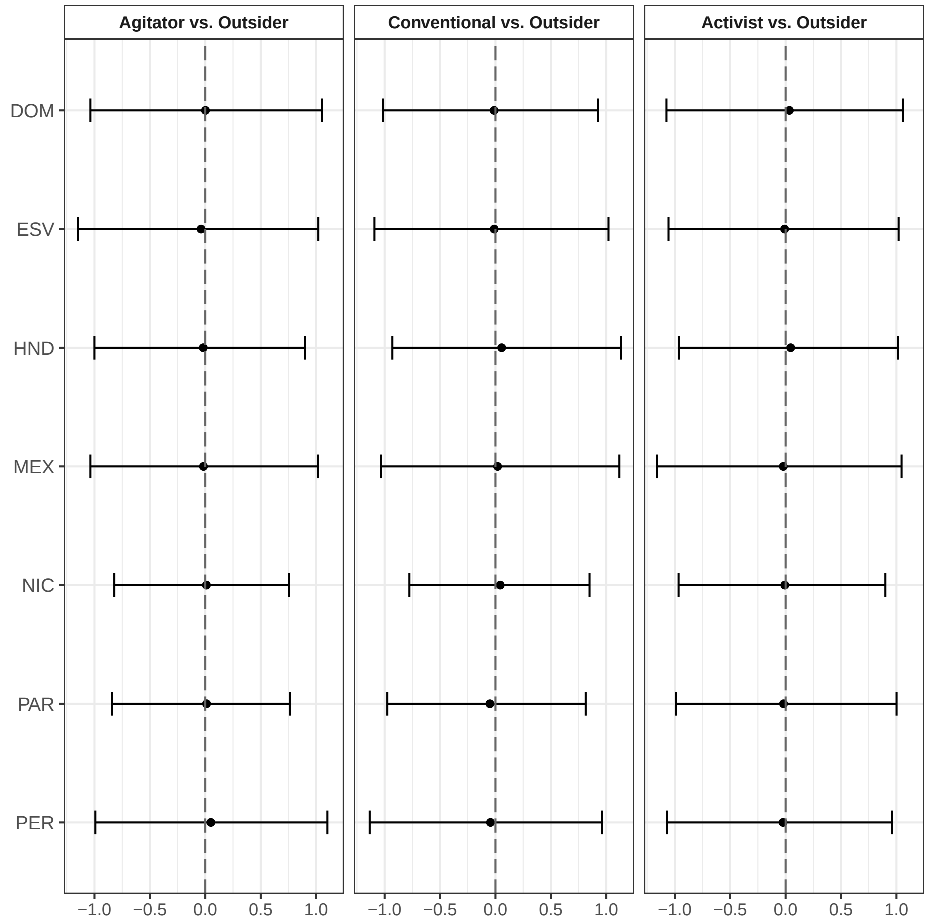


**Figure A.42: Unobserved country differences in type assignment, estimated from the 2014 AmericasBarometer survey.** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

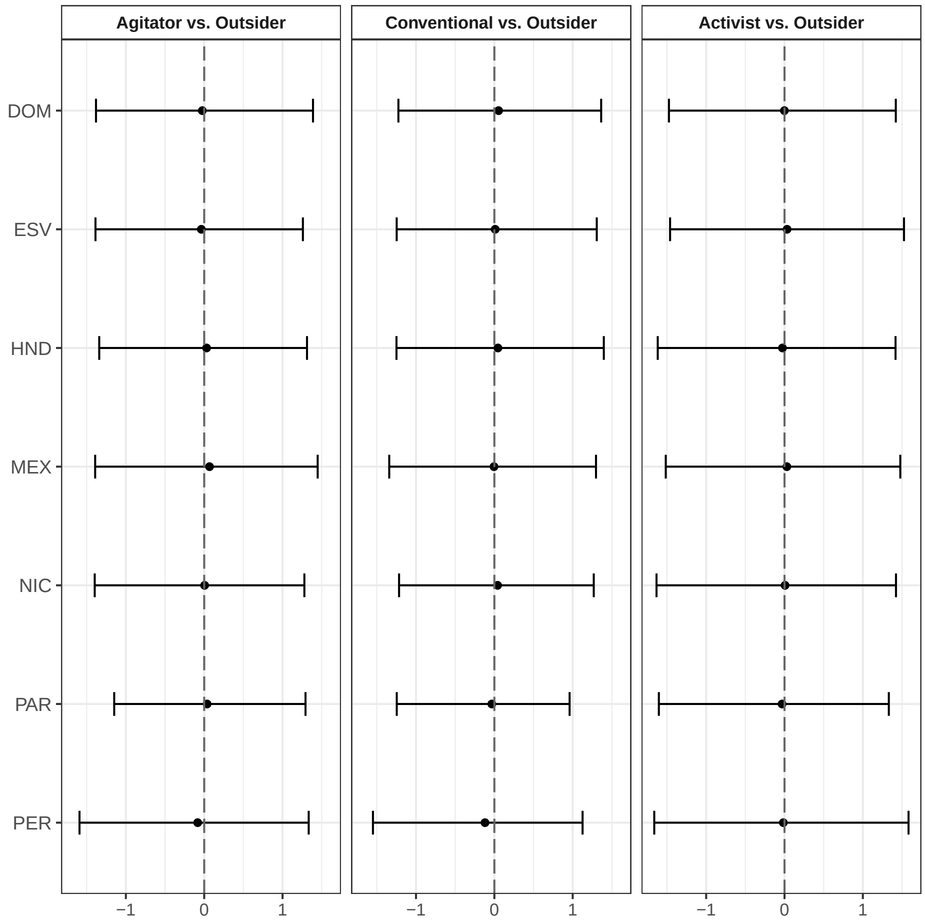


**Figure A.43: Unobserved country differences in type assignment, estimated from the 2016 AmericasBarometer survey.** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

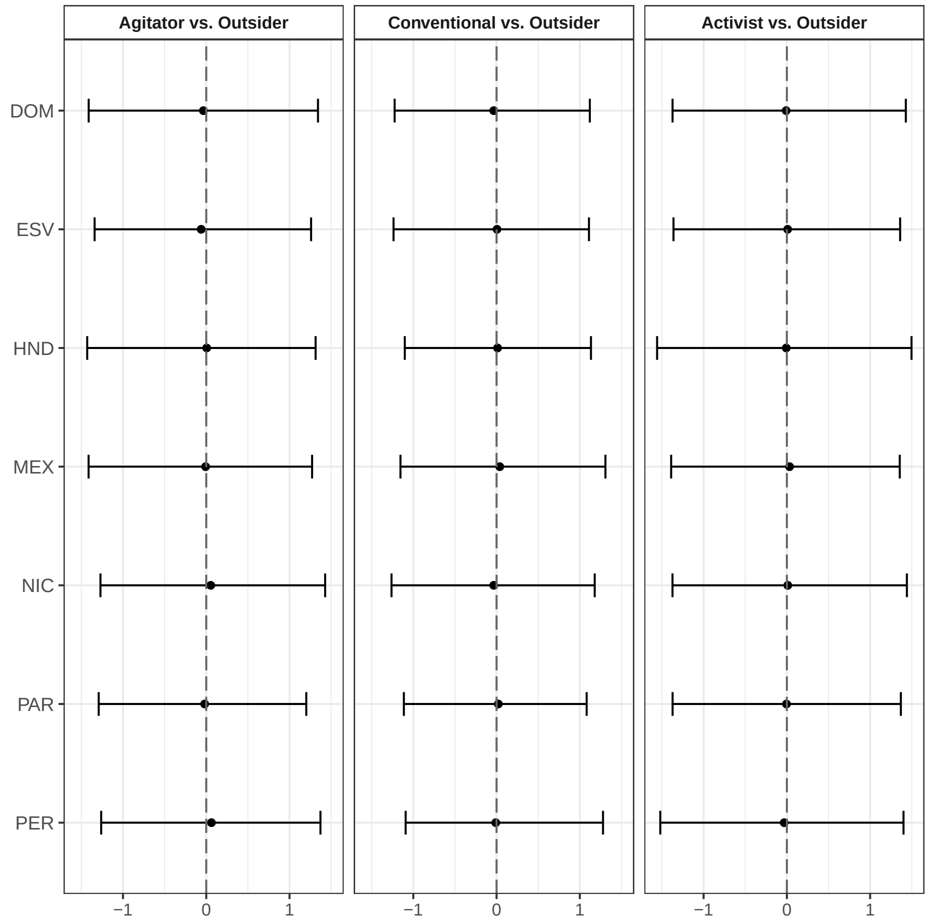


**Figure A.44: Unobserved country differences in type assignment, estimated from the 2018 AmericasBarometer survey.** The figure plots posterior summaries for residual country-specific effects in log-odds units, with the outsider category as baseline. Circles represent point estimates (posterior means). Horizontal lines give 95% credible intervals.

### A.3.6 Results from a factor-analytic model

All the specifications reported in the "Results" section of the research note and in Sections A.3.1 – A.3.5 above assume that $T_{c,i,k}$ and $T_{u,i,k}$ take discrete values. Here we summarize the main measurement results obtained from a latent trait model specifying $T_{c,i,k}$ and $T_{u,i,k}$ as continuous variables. That is, rather than modelling $T_{c,i,k}$ and $T_{u,i,k}$ as categorical latent variables taking values 1 (*low*) or 2 (*high*), we define *Normal* (0,1) prior distributions for each of these variables.[13] As a result, this specification imposes no restrictions on the number of participatory types.

As shown in Figure A.45, survey respondents estimated to have systematically higher values of the conventional/unconventional continuous latent traits are precisely those more likely to be assigned high conventional/unconventional types under our benchmark latent class model. Likewise, Figures A.46 and A.47 show that individuals estimated to score highly on the conventional/unconventional participatory dimensions of our latent class model were assigned larger values of the conventional/unconventional latent traits. This suggests that the latent class model behaved as if the algorithm was able to detect a natural cutoff along underlying participatory patterns, splitting the data in a non-arbitrary and data-driven manner. These results therefore provide empirical validation for the theoretically-derived groupings proposed by Alvarez, Levin and Núñez (2017).

[13]Latent trait analysis is similar to factor analysis. The main difference is that the outcome variables in factor analysis must be continuous, while latent trait models allow for categorical observed indicators - like the dependent variables in our model of political participation (e.g., Dunson, 2003, 2007).

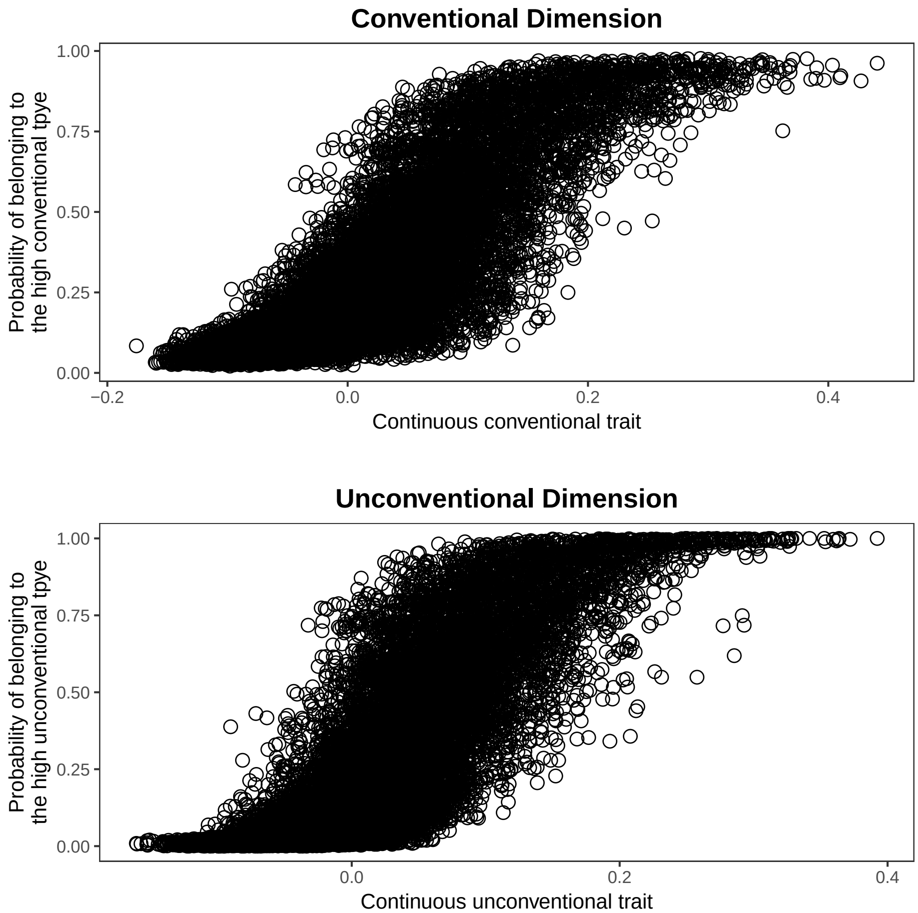


**Figure A.45: Comparison between discrete and continuous dimensions of political participation.** The figure depicts the relationship between the estimated values of the conventional (upper panel) and unconventional (lower panel) continuous latent traits (horizontal axis), and the average probability that each respondent was assigned a high conventional and unconventional type under our baseline latent class model (vertical axis). Both the latent class and the latent trait models were fitted to data from the 2012 AmericasBarometer survey of the Latin America Public Opinion Project; similar patterns hold for other survey waves as well.

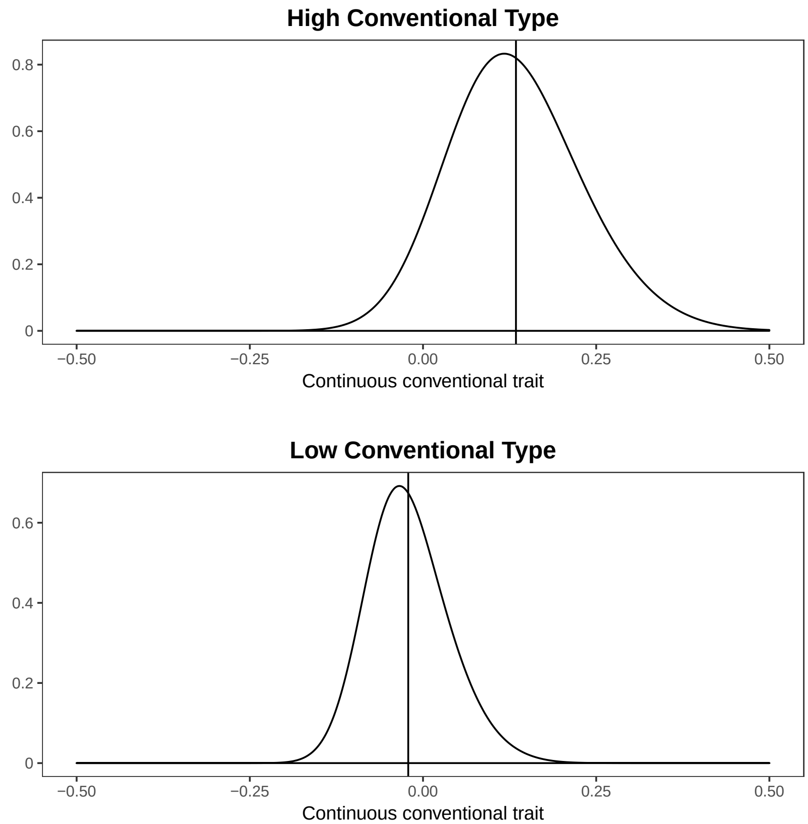


**Figure A.46: Distribution of the conventional latent trait among respondents whose maximum posterior probability is $P(T_{c,i,k} = 2)$ (upper panel) and $P(T_{c,i,k} = 1)$ (lower panel) under our latent class model.** The plot depicts the distribution of the conventional latent trait for individuals whose mean posterior probabilities of belonging to the high (upper panel) and low (lower panel) conventional type exceed 0.5 under our latent class model. Vertical lines indicate the average value of the conventional latent trait calculated among individuals whose maximum posterior probability on the discrete conventional dimension of political participation is $P(T_{c,i,k} = 2)$ (upper panel) and $P(T_{c,i,k} = 1)$ (lower panel). Both the latent class and the latent trait models were fitted to data from the 2012 AmericasBarometer survey of the Latin America Public Opinion Project; similar patterns hold for other survey waves as well.

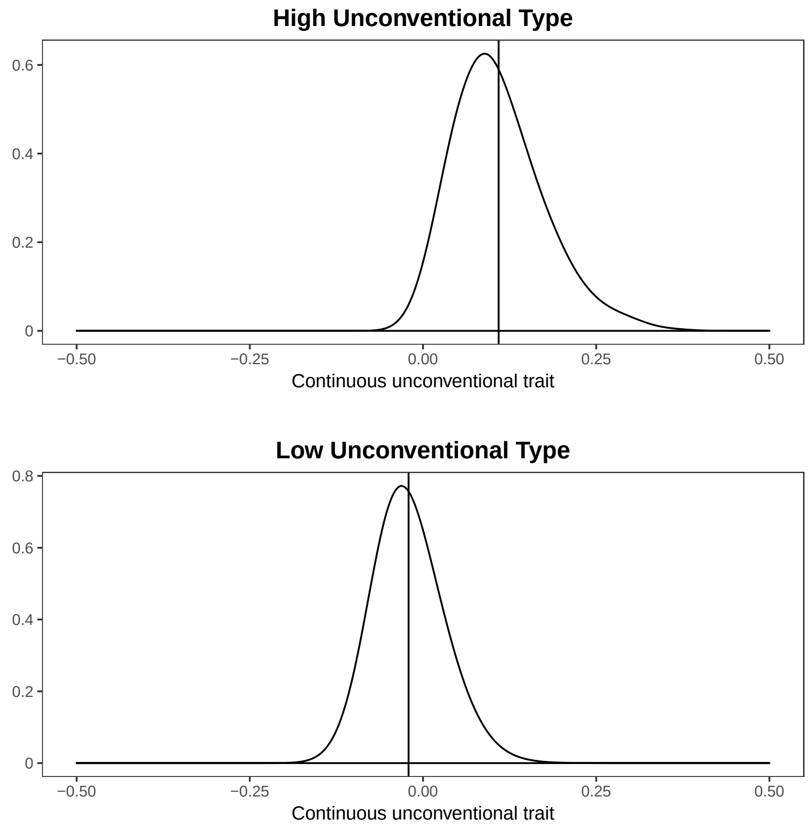


**Figure A.47: Distribution of the unconventional latent trait among respondents whose maximum posterior probability is $P(T_{u,i,k} = 2)$ (upper panel) and $P(T_{u,i,k} = 1)$ (lower panel) under our latent class model.** The plot depicts the distribution of the unconventional latent trait for individuals whose mean posterior probabilities of belonging to the high (upper panel) and low (lower panel) unconventional type exceed 0.5 under our latent class model. Vertical lines indicate the average value of the unconventional latent trait among individuals whose maximum posterior probability on the discrete unconventional dimension of political participation is $P(T_{u,i,k} = 2)$ (upper panel) and $P(T_{u,i,k} = 1)$ (lower panel). Both the latent class and the latent trait models were fitted to data from the 2012 AmericasBarometer survey of the Latin America Public Opinion Project; similar patterns hold for other survey waves as well.

Table A.16, in turn, reports posterior summaries for the cross-national averages of $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ estimated from the latent trait model. While the estimates are different from those reported in Figure 3 of the research note (due to the different model specifications), the relationship between activities and participatory dimensions are aligned with those emerging from our latent class model assuming discrete values for $T_{c,i,k}$ and $T_{u,i,k}$.

**Table A.16:** Posterior summaries for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ averaged across countries obtained from the latent trait model

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Voting | 0.018<br>(0.001, 0.057) | 0.017<br>(0.000, 0.056) |
| Municipal meeting | 0.029<br>(0.001, 0.077) | 0.000<br>(0.000, 0.000) |
| Contacting municipality | 0.023<br>(0.001, 0.068) | 0.020<br>(0.001, 0.064) |
| Contacting local authority | 0.022<br>(0.001, 0.067) | 0.020<br>(0.001, 0.064) |
| Contacting national authority | 0.021<br>(0.001, 0.064) | 0.020<br>(0.001, 0.062) |
| Improvements meeting | 0.022<br>(0.001, 0.069) | 0.021<br>(0.001, 0.064) |

*Continued on next page*

Table A.16 – *Continued from previous page*

| **Activity** | **Dimension** | |
|---|---|---|
| | Conventional | Unconventional |
| Solving community problems | 0.022 | 0.020 |
| | (0.001, 0.068) | (0.001, 0.064) |
| Party meeting | 0.021 | 0.020 |
| | (0.001, 0.065) | (0.001, 0.063) |
| Petitioning | 0.021 | 0.021 |
| | (0.001, 0.066) | (0.001, 0.064) |
| Sharing online | 0.019 | 0.019 |
| | (0.001, 0.061) | (0.001, 0.060) |
| Protesting | 0.020 | 0.020 |
| | (0.001, 0.062) | (0.001, 0.063) |
| Blocking | 0.000 | 0.026 |
| | (0.000, 0.000) | (0.001, 0.072) |

The table reports posterior means and 95% credible intervals (in parentheses) for $\alpha_{c,j,k}$ and $\alpha_{u,j,k}$ for each activity $j$ averaged across all $k$, estimated from the latent trait model treating $T_{c,i,k}$ and $T_{u,i,k}$ as continuous variables.

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