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The Meaning of Democracy among Mass Publics

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Abstract:	In most cross-national research on democratic attitudes, there is an implicit assumption that citizens more or less share a common understanding of democracy. We contend, however, that basic views regarding the meaning of democracy vary significantly within and across national populations. Using data from the World Values Survey, we explore the structural properties of a battery of "essential" characteristics of democracy and find significant variance in how mass publics conceptualize it. First, results from utilize multi-group confirmatory factor analysis (MGCFA) indicate that only the "procedural" qualities of democracy satisfy minimally-acceptable levels of invariance. Second, latent profile analysis (LPA) reveals the number and, importantly, type of composite views of democracy vary across countries. These findings encourage caution for analyses of cross-national mass opinion about democracy; in particular, latent variable modeling using pooled survey data should pay careful attention to both data generating processes and the peculiarities of the survey response.

Department of
Political Science
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October 14, 2019

Dear Editorial Team,

We are pleased to submit our manuscript, "The Meanings of Democracy among Mass Publics" for consideration for publication at the *British Journal of Political Science*. This interdisciplinary work grapples seriously with political theory, public opinion, and political methodology. Our primary contribution involves showing that "profiles" of democratic expectations (or meanings) not only vary within countries, but across them as well. Simply put, how citizens of democracies envision democracy is particular to context. This finding may seem simple, but it has been lost in previous work. Moreover, it has significant consequences for how political scientists link democratic expectations to evaluations of it. Our findings encourage caution for analyses of cross-national mass opinion about democracy; in particular, latent variable modeling using pooled survey data should pay careful attention to both data generating processes and the peculiarities of the survey response.

Best wishes,

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The Meanings of Democracy among Mass Publics

In most cross-national research on democratic attitudes, there is an implicit assumption that citizens more or less share a common understanding of democracy. We contend, however, that basic views regarding the meaning of democracy vary significantly within *and* across national populations. Using data from the World Values Survey, we explore the structural properties of a battery of "essential" characteristics of democracy and find significant variance in how mass publics conceptualize it. First, results from utilize multi-group confirmatory factor analysis (MGCFA) indicate that only the "procedural" qualities of democracy satisfy minimally-acceptable levels of invariance. Second, latent profile analysis (LPA) reveals the number and, importantly, type of composite views of democracy vary across countries. These findings encourage caution for analyses of cross-national mass opinion about democracy; in particular, latent variable modeling using pooled survey data should pay careful attention to both data generating processes and the peculiarities of the survey response.

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Perhaps no question has animated contemporary political science more than how (if not whether) citizens understand democracy. By definition, democracy is based on some form of "consent of the governed," but the form or shape that such consent takes remains ambiguous and contested. Are "minimalist" definitions emphasizing voting, majority rule, and competitive elections adequate? What responsibility do democracies have for providing citizens with basic necessities or addressing social, economic, and political inequalities? In turn, do citizens living in democratic states connect these ideas together?

These questions are vital in the aftermath of Fukuyama's (1992) heady expectations about the sustainability of liberal democracy. No few democracies have experienced an expansion of executive authority, limitations on political opposition, and the undermining of democratic processes, institutions, and norms by partisan actors (Diamond 2008; Levitsky and Ziblatt 2018). Against this backdrop, gauging the public's understanding of democracy looms as a critical and practical concern – particularly given concern about declining public support for it (Foa and Mounk 2017).

In this manuscript, we analyze the durability of "procedural" and "substantive" definitions of democracy. Using data from the World Values Survey, we show that how citizens parse these features of democracy and the extent to which they connect them together varies significantly within *and* across national populations. First, results from utilize multi-group confirmatory factor analysis (MGCFA) indicate that only the "procedural" qualities of democracy are roughly equivalent cross-nationally, and even here they achieve metric but not scalar invariance – a finding that has consequences for pooled analyses of these items. Second, latent profile analysis (LPA) reveals that composite views of democracy's essential characteristics vary in the number of groups present within a country, which are often conceptually different from classes uncovered in other countries. Taken together, this evidence encourages caution when analyzing cross-national mass opinion about the meaning of democracy.

Attitudes about democracy in the cross-national context

Scholars of comparative politics recognize that democratic attitudes may vary across country contexts (e.g. Diamond and Plattner 2008; Ferrin and Kriesi 2016). Examining meanings of democracy in "unlikely places," Dalton, Shin, and Jou (2007) argue that a liberal understanding of democracy has been widely diffused and is strongly associated with political freedom and civil rights. When asked to define democracy in an open-ended format, individuals throughout the world – even in nondemocratic countries – define it primarily in terms of freedom. Procedural democracy (majority rule, free and fair elections) and social benefits (economic equality), in contrast, are mentioned less often (see also Carlin 2018).

Yet, other research challenges whether citizens' reflections about the nature of democracy are illuminating. Examining this literature, Bratton (2010, pg. 106) concludes that "I doubt whether global comparisons about the quality of democracy, at least as judged by citizens themselves, can be justified at all." His concern is that, while individuals might well associate democracy with political freedom at an abstract level, their understanding of political freedom may also be heavily contingent upon cultural and context. Definitions of democracy may share terms (political freedom), but not common understandings of what those terms mean.

The difference here is partly methodological. Dalton, Shin, & Jou (2007) allow respondents to define democracy in response to an open-ended prompt. While this gives survey respondents more of an opportunity to define democracy in their own words, the words used may have unique cultural meanings. Instead, Bratton (2010) argues for more specific questions and for vignettes that can "anchor" respondent understandings of democracy, a solution that improves the comparability of cross-national survey research (c.f. King et al. 2004). While Bratton is less convinced that publics share understandings of democracy, other recent research suggests that citizens reliably associate several types of features with democracy. These ideas range from the distinction between procedural and substantive characteristics (Baviskar and Malone 2004), to the incorporation of social benefits (Crow 2010), and to the production of political and social goods (Oser and Hooghe 2018).

Curiously, while there are some theoretical commonalities among this work – usually involving the notion that citizens parse the "political" outputs of democracy from "social" ones – this body of research has not sufficiently explored the psychometric properties of the survey response. First, it is not clear whether beliefs about the characteristics of democracy are invariant. For example, does the concept of *equal rights* vary systematically across country contexts, or is it more or less understood universally? This property matters with respect to trying to ascertain composite views of democracy. While past research has used parametric models to describe different "classes" or "groups" of meanings of democracy (e.g. Oser and Hooghe 2018), it has not sufficiently wrestled with whether and how the measurement properties of citizens' beliefs contribute to how respondents connect these ideas across country contexts.

In fact, these properties have significant modeling and, by extension, theoretical consequences. We propose a slightly different approach for delineating a public's composite understandings of democracy. We ought to begin by assessing whether or not individuals view a standard battery of survey questions similarly, irrespective of a respondent's country of origin. If the pattern of findings is dissimilar, then we should question whether or not methods suited to uncover latent patterns within the data can produce valid results when cross-national survey data is pooled for analysis. Our theoretical expectation is that the distinction between procedural and substantive definitions of democracy is somewhat artificial. Instead, we draw on Pennock's (1966, pg. 421) dormant conceptualization of "political goods," which encompass the goals pursued by a political system. If democracy's singular feature is an emphasis on equality – if not in *condition*, but at least in *opportunity* – then, the both legal and material goods generated by a political system involve the priorities of mass publics. Empirically, if such underlying political and social priorities vary across countries (Lipset and Rokkan 196; Wheatley 2015), then we should observe that permutations of democratic meanings vary both *within* and *across* countries.

Our analytic strategy

One way of assessing whether beliefs about the features of democracy are static involves multi-group confirmatory factor analysis, which analyzes whether items are equivalent or "invariant" country contexts. One of the central challenges of survey research is asking questions in way that is comparable across social, political, and cultural contexts (Ariely and Davidov 2011, Davidov, et al. 2014, Ippel, et al. 2014, Alemán and Woods 2016). Differences across contexts may reflect different understandings of the latent construct being measured (construct bias), differences in survey methods across countries (methods bias), or differences in individual items (item bias; Byrne and Watkins 2003, Davidov, et al. 2014). The larger underlying question, however, remains the same among these considerations: *Can we make meaningful comparisons of survey responses across contexts?* For our purposes, we might ask: Can we make meaningful comparisons of how mass publics understand different features of democracy cross-nationally?

Given the multiplicity of meanings assigned to democracy, questions of measurement invariance are critical to studies of democratic attitudes (Canache, et al. 2001, Ariely and Davidov 2011, Canache 2012a, Ariely 2015). Ariely and Davidov (2011), for example, have tested the cross-cultural equivalence of the "democratic-autocracy preference" scale and the "democratic performance evolution" scale across 36 countries, which convey whether respondents prefer democracy and the extent to which they perceive their governments are making good upon such promises. They found that, while the scales are roughly comparable across countries, the items are neither equivalent nor is the scale comparable across all countries. More relevant to our forthcoming analysis, Ariely (2015) ran a MGCFA and found that the procedural elements of democracy, which include some of the items we investigate here, achieve only partial metric invariance.[1]

[1] As we discuss at length below, we perform a similar test but include additional substantive measures and limit the analysis to countries scoring 6 or above because our interest is restricted only to countries that can be classified as democracies.

Tests of measurement invariance can be conceptualized along a graded continuum (Van de Schoot, Lugtig, and Hox, 2012). Configural invariance is the basic threshold for which a set of items should achieve and indicates whether a latent variable is a function of the same set of observed variables across context. If so, then this suggests that the structure behind the latent variable is the same across countries. Metric invariance indicates whether or not the factor loadings on the latent variable are the same across countries (Kim et al., 2017). Satisfying metric invariance indicates that the unit and the interval of the latent variable are roughly equivalent cross-nationally. Perhaps stated differently, metric invariance tells us whether a one unit increase on the democracy scale in one country (e.g., United States) is equivalent to a one unit increase in another country (e.g., United Kingdom, Japan, or Sweden). Thus, not only is the raw material more or less equivalent across country contexts, but the dynamics of the latent construct work similarly.

Scalar invariance evaluates the intercepts of each item across groups. Achieving scalar invariance allows comparisons of mean values across countries. Failure to satisfy scalar invariance means that countries tend to systematically give higher or lower item responses. Finally, strict invariance investigates if residual variances are consistent across groups *after satisfying the assumptions of metric and scalar invariance.* Strict invariance provides evidence that the mean differences across groups are driven by real group differences and not by error. While strict invariance is the ideal, the requirements to satisfy it are generally too difficult to meet in practice (Davidov et al., 2008; Jang et al., 2017; Meredith, 1993).

Our interest in these properties stems from our desire to understand the permutations that combinations of these attitudes might take. In other words, we want to know whether there are a core set of "profiles" that describe how individuals think about democracy and whether these groups systematically vary across countries. Put another way, we ask: Are there universal conceptualizations of democracy that involve certain combinations of features?

This task involves latent profile analysis (LPA), which uses a parametric model to place respondents into classes (or clusters) based on their response patterns.[2] In LPA, the number of classes is determined by the expectation-maximization algorithm which involves an iterative process until the model converges on a best fit for the data. This involves the notion that there should be shared variance within the clusters, and that clusters should be empirically distinct from each other (i.e. conditional response probabilities should clearly parcel respondents into a given class and not another; Olivera-Aguilar and Rikoon 2018). Within this framework, model fit is selected by triangulating several goodness of fit measures and substantive interpretability (Oberski 2016).

Within political science, such “person-centric” methods have been used to develop media use profiles in Netherlands (Bos, et al. 2016), profiles of undecided voters (“fence sitters”) in New Zealand (Greaves, et al. 2015), classes of donation-giving in the United States (Rhodes, Schaffner, and La Raja 2018), and groups of democratic participants (Oser, et al. 2013) and citizenship (Hooghe, et al. 2016). While latent class analysis (LCA), a form of finite mixture modeling that uses *categorical* rather than *continuous* variables, has been used to categorize how people think about democracy (Oser and Hooghe 2018), this past research is characterized by two serious flaws. First, it does not take into account the psychometric properties of the input items – i.e. whether responses to the instruments are invariant across countries – in order to establish whether pooling all of the data together prior to running the analysis is appropriate. Instead, the authors perform both partial and homogenous equivalence tests within the LCA framework. This decision is problematic, however, because it is related to a second questionable choice to collapse the original response scales into three-category instruments, where values 0 to 7 are coded “1,” values 8 to 9 are coded “2,” and the value 10 coded “3.” This action violates the interpretation of the raw survey response, which was bivalent and symmetrical, rending the later tests for equivalence flawed.

Instead, we pursue an “inductive approach” (Wheatley 2015) by first performing the MGCFA described above, and then analyzing the data based on whether it is justified to pool

[2] It has also been used to test measurement equivalence (Davidov, et al. 2014). If the underlying constructs are roughly equivalent, the same set of classes should emerge across countries.

the data together or analyze the countries individually. Further, rather than rely on an artificial recoding scheme, we should let the data speak for itself. Thus, a more suitable analytical technique like LPA is preferable because it adequately handles *continuous* input items, which permits us to remain agnostic about the skew inherent in democratic beliefs, which usually tend to be quite “positive.” In sum, this modeling approach should allow us to use the full range of data to determine the appropriate number of profiles that describe how mass publics conceptualize democracy and whether such composites are broadly applicable to all democracies.

Data and measures

The data for these analyses are drawn from the "essential characteristics of democracy" questions from Wave 5 (2005-2009) of the World Values Survey (WVS), which was selected due to the breadth of countries available for analysis. We limit the analysis to countries that score a 6 or better on the Polity Index. The WVS fields a standardized instrument within many countries, and the democracy questions are often surveyed in places that are classified either as autocracy or anocracy. While it would be interesting to explore how persons in those countries view democracy, we restrict our sample to countries that score the "minimum" value conventionally associated with democratic states. The sample formally includes the following 22 countries, which represent a wide range of regions, cultures, and political institutions: Argentina, Australia, Brazil, Bulgaria, Canada, Chile, Finland, France, Georgia, Hungary, Japan, Mexico, Netherlands, Norway, Poland, Romania, Serbia, Slovenia, Sweden, United Kingdom, United States, and Uruguay.[3]

The essential characteristics battery is useful for our purposes because it asks respondents to rate a wide variety of features that might ostensibly be related to or associated with democracy. Individuals are asked to read the following prompt:

> *Many things may be desirable, but not all of them are essential characteristics of democracy. Please tell me for each of the following things how essential you think it is as a characteristic of democracy. Use this scale where 1 means "not at all an essential characteristic of democracy" and 10 means it definitely is "an essential characteristic of democracy."*

While there are ten instruments in the battery, the cross-country coverage of all questions is poor. Thus, we selected the following six instruments that exhibited the most consistent cross-country coverage to examine: (1) Government taxes rich to subsidize poor; (2) Religious authorities interpret laws; (3) People choose leaders in free elections; (4) People receive state aid for employment; (5) Civil rights protect people's liberties from state oppression; (6) Women have the same rights as men.[4] These items have been widely used in the existing literature,

[3] We also did not include Trinidad and Tobago, Colombia, Cyprus, Moldova, Mali, Burkina Faso, Zambia, Taiwan, New Zealand.

[4] Specifically, the excluded items are: (1) Army takes over when government is incompetent; (2) The economy is prospering; (3) Criminals are severely punished; (4) People can change the laws in referendums.

often in a comparative context (e.g. Norris 2011, Welzel 2011, Shin 2012, De Regt 2013, Ariely 2015). Moreover, they each capture a facet of the political goods commonly associated with democracy.

Results

To illustrate the possibility that beliefs about the essential characteristics of democracy vary across countries, we begin by plotting the distribution of responses to several of the individual items that comprise our battery. Due to the large number of countries in our sample, we focus on a limited set to convey a sense of the range of responses and the differences in those responses across countries. Figure 1 and 2 present the distribution of the responses to one of the "procedural" and "welfare" items as raincloud plots for Brazil, Japan, Serbia, Sweden, the United Kingdom, and the United States. Although there is general consensus about the importance of civil rights across countries (Figure 1), there is still modest variation among responses both within and across countries. However, in the case of redistributive taxation, this variation is much more significant (Figure 2).

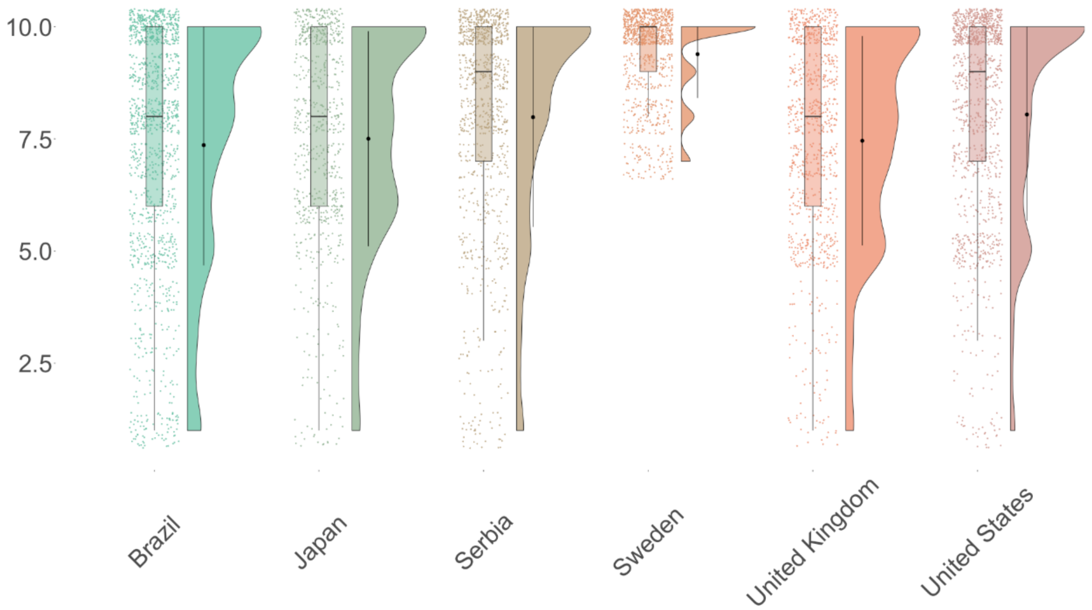

Figure 1. Distribution of the essentialness of civil rights in democracy across select countries. Figure illustrates average response (point estimate), along with histogram and a box-and-whisker plot (where horizontal line denotes median response).

Although these results suggest that mass publics interpret some of qualities of democracy differently, they are anecdotal. To test whether or not these differences are significant, we present the results of a multi-group confirmatory factor analysis (MGCFA) in Table 1. In this analytical framework, model fit is interpreted accordingly to three indices: chi-square, comparative fit index (CFI), and root mean squared error of approximation (RMSEA). Because chi-square values are sensitive to sample size and the number of groups included in the analysis (Bentler and Bonett 1980; Jang et al. 2017), we primarily rely on CFI and RMSEA. Conventionally, a CFI greater than 0.95 and an RMSEA less than 0.05 indicate acceptable model fits (Hu and Bentler 1999). Within the MGCFA framework, however, previous research advocates for a more liberal RMSEA cutoff <=0.10 based on simulation results showing that the number of groups affects the RMSEA cutoff (Rutkowski and Svetina 2014).

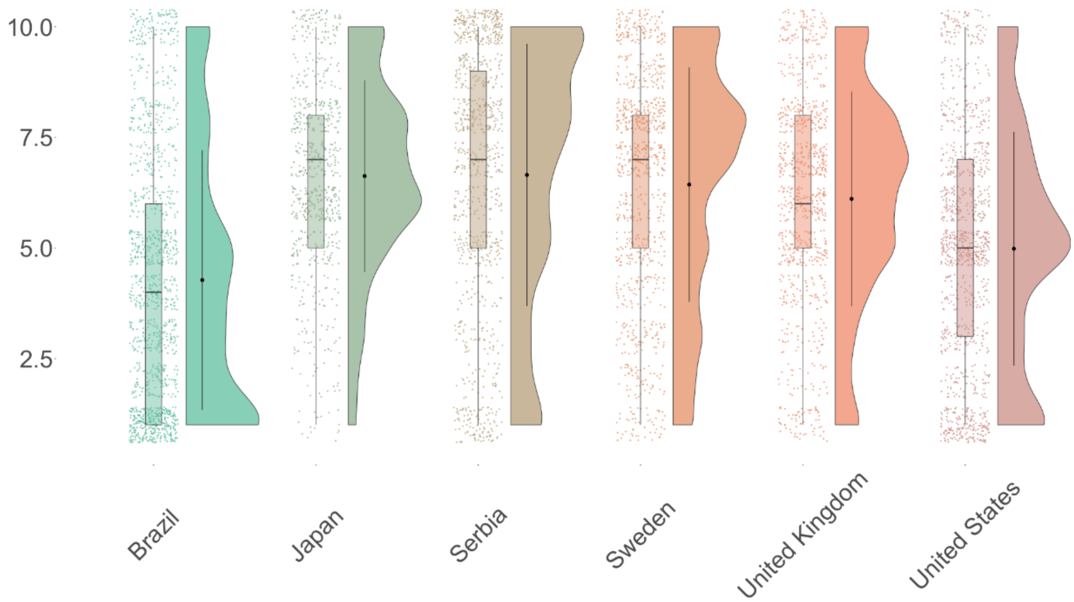

Figure 2. Distribution of the essentialness of taxing rich to subsidize poor in democracy across select countries. Figure illustrates average response (point estimate), along with histogram and a box-and-whisker plot (where horizontal line denotes median response).

Exploring the latent properties of the essential characteristics of democracy

We first conducted an MGCFA using the *lavaan* package in R with all six of the essential characteristics of democracy across the full sample. This logic assumes that all of the items tap into a single, latent construct. This analysis resulted in a poorly-fitted model. Alternatively, we divided countries into western democracies (e.g. Australia, Canada, Finland, France, Netherlands, Norway, Sweden, United Kingdom, and the United States) and not. Because western democracies may draw from some common lineage (e.g. classical liberalism), it may be that the essential characteristics of democracy have similar meanings among these countries, but not others. Again, model fit is poor for both metric and scalar invariance across the split samples.

As a third possibility, we focused the analysis on the four essential characteristics of democracy that best capture a procedural understanding of democracy (per Ariely 2015), leaving out the variables that perhaps reflected more substantive qualities. Focusing specifically on these procedural variables, we find that the models fit reasonably well when it comes to achieving metric invariance for both western countries and the rest of the world. Neither model, however, achieves the higher thresholds of scalar invariance.

So practically speaking, what does this mean? Recall that achieving metric invariance means that the intervals on the latent construct are roughly equal across groups (here, countries). In other words, when a set of items achieve metric invariance, we can say that moving across the values of the scale means approximately the same “thing” among the groups in the sample. We do find modest evidence that a subset of the essential characteristics of democracy seem to vary systematically across countries, but the failure to reach scalar invariance implies that caution is warranted with respect to interpreting mean levels of support using composite indices of these items. Put another way, it is unlikely that the range of the latent construct is interpretable consistently across the countries. In our view, these results suggest that it is improbable that a common number of composite views of democracy would exist across countries. It may be interesting to pool the sample together to assess the gross number of democratic profiles, but it is unlikely that those visions of democracy exist within every country.

	Invariance	Western countries	Rest of world
All six variables in essential characteristics battery: 1) Subsidize poor 2) Religious authorities 3) Free elections 4) State aid 5) Civil liberties 6) Women's rights	Metric	x^2 = 2291.20 df = 121 CFI = 0.77 RMSEA = 0.13	x^2 = 2506.50 df = 177 CFI = 0.81 RMSEA = 0.12
	Scalar	x^2 = 4058.80 df = 161 CFI = 0.59 RMSEA = 0.15	x^2 = 5532.20 df = 237 CFI = 0.58 RMSEA = 0.15
Procedural variables only: 1) Free elections 2) Civil liberties 3) Women's rights 4) Religious authorities	Metric	x^2 = 390.25 df = 42 CFI = 0.95 RMSEA = 0.08	x^2 = 258.00 df = 62 CFI = 0.97 RMSEA = 0.06
	Scalar	x^2 = 1158.38 df = 66 CFI = 0.83 RMSEA = 0.12	x^2 = 1095.62 df = 98 CFI = 0.81 RMSEA = 0.12

Table 1. Tests of invariance using full and partial set of items from the essential characteristics of democracy battery. Df = Degrees of freedom; CFI = Comparative fit index; RMSEA = Root mean squared error of approximation.

Building cross-national profiles of democratic beliefs

To assess how citizens connect ideas about the properties of democracy into composite visions of it, we now turn to a series of latent profile analyses (LPAs). We begin by building an LPA that includes all 22 countries within the sample. The process of fitting LPA is iterative: we fit a model with *k* classes or "profiles" and then compare the fit indices of a model with *k*+1 profiles. The terminal or final number of profiles is chosen by consulting different fit qualities. Traditionally, the solution with the lowest Bayesian Information Criterion (BIC) determines acceptable model fit (i.e. the optimal number of groups that describes the data); however, the adjusted Akaike information criterion (cAIC) and model entropy are also important features to consider (Nylund, Asparouhov, and Muthen 2007), as well as the substantive implications of the terminal solution. Namely, a model that appears justifiable on the grounds of the fit indices, but that produce many profiles with extremely small assignment probabilities, may actually exhibit overfitting.

Fitting the optimal number of profiles to the data ultimately requires the user to balance these considerations (Oberski, 2016). In the interest of brevity, we truncate the modeling output associated with our LPA in Table 2, such that it reports fit statistics associated only with those models near the "threshold" for appropriate class enunciation (the full modeling output is available in Tables A1 and A2 in the appendix). The results produce no single optimal number of profiles, but it is possible to converge upon a defensible solution nonetheless. First, while the BIC values objectively hit their nadir at the 11-profile solution, the decrease in BIC is marginal past the 9-profile solution. Second, this finding is corroborated by the fact that the adjusted AIC values indicate that the 9-profile solution is appropriate. Finally, entropy suffers as the number of profiles expands beyond 9 profiles. Although we do not present profile assignment probabilities here, the number of non-informative classes produced by profiles beyond the 10-profile threshold grows (i.e. profiles with less than a 5% probability of assignment). In those expanded solutions, over-fitting is a legitimate concern.

# Profiles	BIC	% change in BIC	ABIC	cAIC	Entropy
8	450782.2	-0.19%	449387.0	451221.2	0.716
9	450490.1	-0.06%	448920.2	450984.1	0.682
10	450447.7	-0.01%	448703.0	450996.7	0.665
11	450305.3	-0.03%	448385.9	450909.3	0.676
12	450312.8	0.00%	448218.6	450971.8	0.651
13	450314.5	0.00%	448045.4	451028.5	0.678

Table 2: Estimates of Model Fit. Notes: Estimates for solutions comprising 1 through 7 profiles omitted. These estimates and additional fit information is available in the appendix. Shaded cells associated with the optimal solution.

We settle on a nine-profile solution, which is illustrated in Figure 3. Interpreting the results of the model is eased by visually inspecting the estimated value associated with each input item across the groups. The nature of these profiles varies significantly. Consider Profile 1, in which respondents score roughly "neutral" values across the range of input items. The probability of assignment to this class is small, but it constitutes and interesting group insofar as these are respondents who effectively expressed no meaningful associations with democracy across the entire batter of responses. This group differs from Profile 8, which registers negative values on taxation and religion, and much lower-than-average scores on civil rights.

Profiles 3 and 9 exhibit similar patterns across the input items, but the scores are significantly lower in Profile 3. This group rejects taxation and state aid to the poor as essential to democracy; likewise their beliefs about civil rights are considerably less positive than Profile 9. Although the two groups seem somewhat “conservative” with respect to connecting redistributive economic interventions to democracy, Profile 9 still places an extraordinary high value on civil liberties.

The rest of the profiles exhibit extremely similar movement across the input items, varying only with respect to how essential the individual items are to democracy. Profile 2 scores convey taxation, state aid, and civil liberties are essential to democracy. Meanwhile, Profile 8 exhibits much lower values across each of these categories. Thus, although the permutations of essential characteristics of democracy are not wildly divergent, the extent to which items are considered essential varies. In some sense, we observe differing levels of support for social democracy, as well as for democracy that is more muted in its protections of civil liberties. But the common element in these latter profiles involves the notion that, where social goods are considered essential, so, too, are civil liberty or political goods. The most common vision of democracy across these countries involves connecting both economic and welfare goods together.

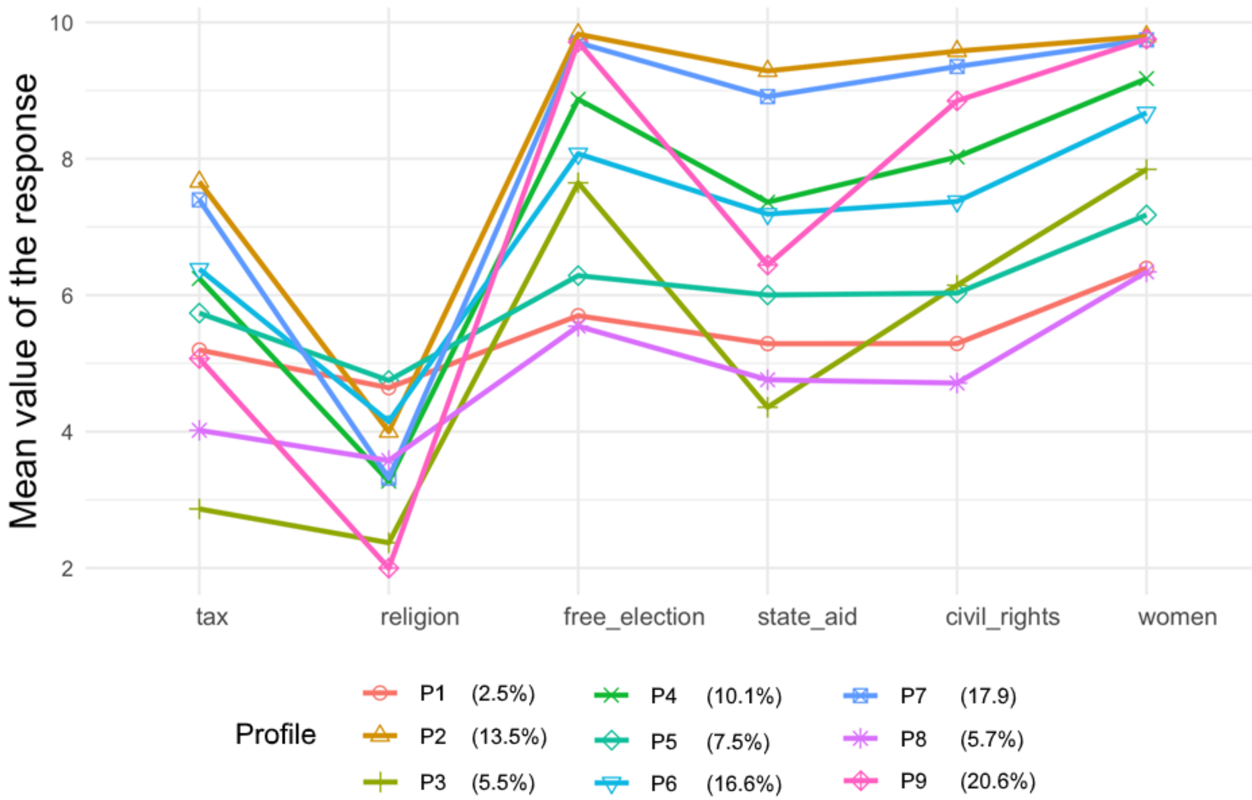

Figure 3: Latent Profile Analysis using pooled sample of respondents across all countries. Input items are arrayed on the x-axis; y-axis corresponds to the predicted mean value of input item for members of a given profile. Percentages in parenteses convey probability of assignment to given profile; all estimats should sum to 100%. Full modeling output associated with the modeling procedure is available in the Appendix.

Although a 9-profile solution emerges as the best-fitting depiction of how respondents connect certain facets of democracy together, it is not clear whether this set of profiles spontaneously emerges within each country or whether each country possesses a more limited range of profiles. Put another way, we know little about the distribution of profiles that emerge within each country. Past research using European Social Survey (ESS) data conveys that a single, uniform model explains how respondents view democracy (Oser and Hooghe 2018). As we outlined above, this finding involves a transformation of the input item responses into arbitrary intervals. Yet, this research is also limited for two additional reasons: 1) it is unclear that these findings would describe democratic profiles *outside* of Europe, and 2) the authors do not provide descriptive tests for whether the same five classes actually manifest across their sample of countries.

In light of the analysis supplied in the previous section, we proceed by fitting LPA models across each individual country in our sample. This approach naturally generates an enormous amount of estimates. In lieu of presenting iterative BIC values – in tabular form or visually via elbow-plots – for each country, we simply report the number of profiles uncovered across the countries in the sample. As Table 3 indicates, a 3-profile model emerges for most countries, with several notable exceptions. For example, Sweden, Argentina, Japan, Poland, and Romania each yield a 2-class solution. In addition, the model produces a 4-class solution for Serbia.

Given the past literature regarding how democracy is conceptualized, we might expect a limited set of profiles to emerge across each country. The distinction between "procedural" and "substantive" manifestations of democracy, for example, more or less parses whether respondents support the welfare state. However, it is possible that the substantive meanings of the classes that manifest in each country vary, and we would do well to explore the nature of the profiles individually. Again, we proceed using a visual portrayal of the mean values associated with the input items across classes. Each panel of Figure 3 illustrates such profile plots for the group of six countries we presented in the first set of analyses.

2-profile solution	3-profile solution	4-profile solution
Argentina	Australia	Serbia
Japan	Brazil	
Poland	Bulgaria	
Romania	Canada	
Sweden	Chile	
	Finland	
	France	
	Georgia	
	Hungary	
	Mexico	
	Netherlands	
	Norway	
	Slovenia	
	United Kingdom	
	United States	
	Uruguay	

Table 3. Number of unique profiles emerging from best-fitting solution to the latent profile analysis in the respective country. Full modeling output is available in the Appendix.

These profile plots produce a number of observations. First, the profiles that emerge within a country rarely conform to those that manifest in the other countries. For example, the three classes that emerge in the United States look very different from the three classes that emerge in the United Kingdom or Brazil. The mean values across the input items manifest in permutations that vary markedly across the countries. To the extent that these countries all have different historical and cultural legacies of self-rule, this makes some sense.

Yet, these results also warrant an interesting caveat. In some countries, the classes that emerge as distinct appear to have only minor differences among members of competing profiles. In Sweden, for example, the two classes are only barely distinguishable with the largest difference appearing on issues related to civil liberties. Similarly, in the United Kingdom differences between the two classes noted by the red and green line appear marginal. In some places, public understandings of democracy are almost monolithic – which runs counter to the evidence produced by earlier analyses of European (Oser and Hooghe 2018) and United States data (Davis, Gaddie, and Goidel 2019).

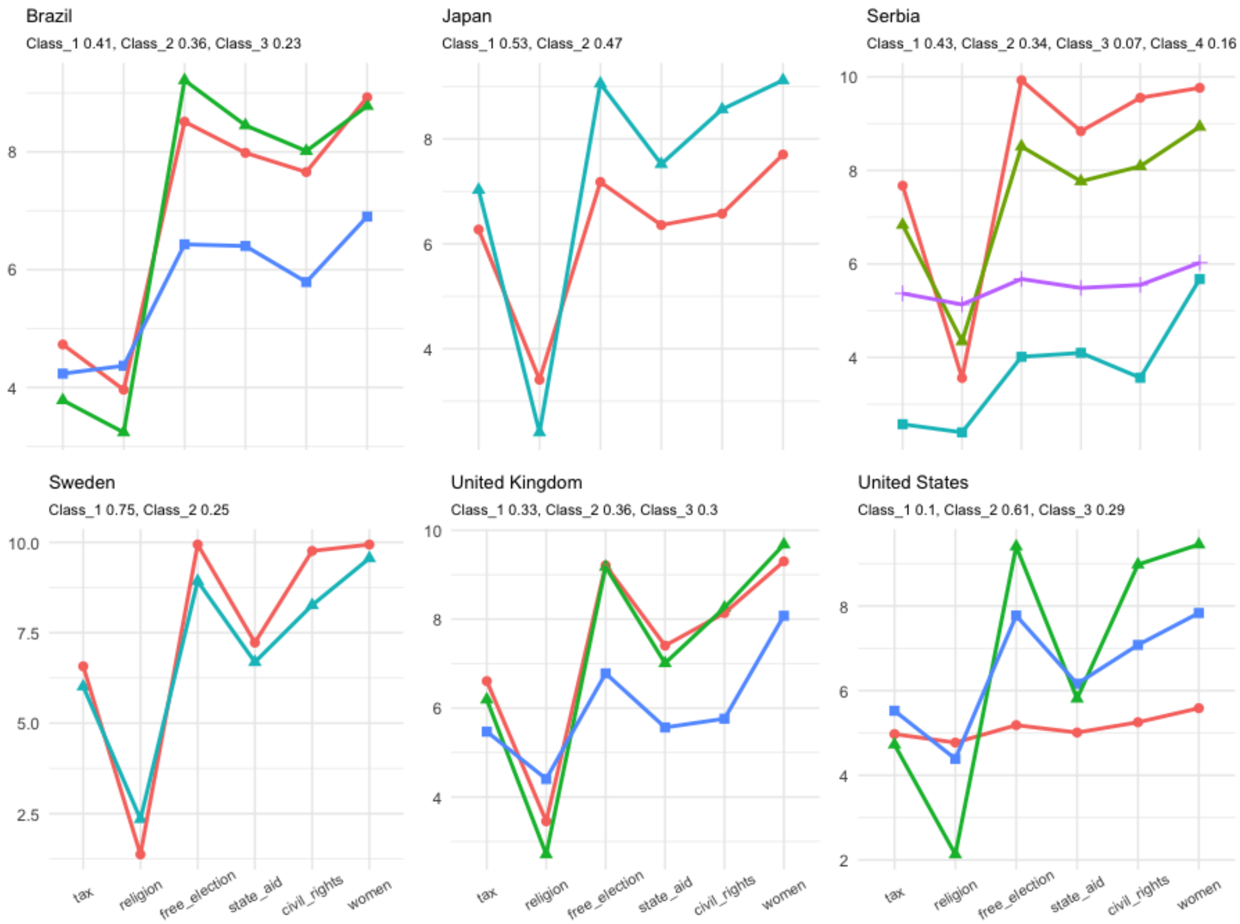

Figure 4: Profile plots of composite views of democracy for selected countries. Profiles in each panel are calculated using iterative modeling process for respective country. Terminal solution to the latent profile analysis is determined using BIC. Full modeling output for these countries, as well as visual profile plots for remaining countries is available in the Appendix.

On the one hand, these findings constitute compelling evidence that there is no “universal” template that explains how mass publics conceptualize democracy. The same profiles do not appear in each country. However, the patterns do bear some resemblance, and we should be careful not to overstate the uniqueness of these different perspectives. While additional profiles are statistically identified, in some cases they may be substantively similar. Connecting this to the findings on measurement invariance presented above, the differences may have less to do with the relationships across variables and more to do with the tendency within some countries to rate items more (or less) essential. The pattern of findings in Sweden and Japan, for example, look similar, but gaps between the two groups are much larger on questions relating to free elections, state aid for the unemployed, civil liberties, and women's rights.

Finally, in countries with three classes a common element seems to describe the emergence of the third profile. This group is often less supportive of democracy across a range of issues. In Serbia, the only country with four classes, the two additional classes are less supportive of democracy. Meanwhile, the third profile in the United States is virtually indifferent regarding the essential characteristics that describe democracy.

Discussion and conclusion

Scholars have devoted considerable energy to understanding how mass publics think about democracy (e.g. Baviskar and Malone 2004; Dalton, Shin, and Jou 2007; Diamond and Plattner 2008; Ferrin and Kriesi 2016; Carlin 2018). Although past research has also explored compound views of democracy (Oser and Hooghe 2017, 2018), our contribution to this important agenda has been to carefully analyze the extent to which the component characteristics of democracy are psychometrically similar cross-nationally, which has natural consequences for how these properties are linked together into composite visions of democracy. This exercise is not just methodological doodling. In fact, it raises a critical substantive question: To what extent are public understandings of democracy directly comparable cross-nationally?

Our analysis of the measurement equivalence of the essential characteristics of democracy is more or less consistent with Ariely's (2015) conclusion that procedural items achieve the requirements of partial metric invariance. They do not, however, meet the more rigorous standards for scalar invariance. Practically speaking, this means that drawing conclusions from comparisons of mean values on these items is not advisable. Further, given the poor model fit produced by analyzing all six items together, it is clear that the procedural and substantive understandings of democracy are conceptually distinct.

It is perhaps unsurprising, then, that the latent profile analysis indicates that there is neither a single, shared understanding of democracy across countries nor, for that matter, a set of shared understandings. Pooling all respondents from the 22 countries together, we found that a nineclass solution best fit the data. Substantively, this finding might be curious – how would six items combine together to form so many permutations of democratic meanings? Looking at the individual countries' profile plots sheds some light on this result. In most of the countries included in the analysis, a three class solution provides the best fit to the data. In a small subset set of countries, a two class solution provides a better fit to the data. Notably, however, the patterns across countries are similar, though not identical: robust support for civil rights and welfare goods in one class, and a second class where such support is usually lower. While a common set of patterns may exist with respect to the way the data fit together, the "intercepts" or the average values of the input items across many of these profiles vary in modest, but important ways. In turn, because the data are sufficiently large, subtle, but theoretically interesting differences manifest.

A typology is ultimately an abstraction of reality. In theory, such models ought to help us make sense of the world around us in concrete ways. These findings suggest that scholars ought to pay closer attention to how people think about democracy within a particular context before making sweeping conclusions about the nature of democratic beliefs or, perhaps, support for democracy cross-nationally (e.g. Foa and Mounk 2017). While we find that democratic expectations in one country may approximate those in another, other differences, which might be grounded in party systems, competition, or the distribution of political ideology, presumably affect how democratic outputs are rationalized. Understanding what sustains these composite visions of democracy and how they affect regime support lies at the heart of building resilient democratic theory. In our view, more attention should be paid to the important differences in composite views of democracy and, for example, what implications these beliefs have for regime support. Such a task, however, requires careful attention to data generating processes and the peculiarities of the survey response.

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Supporting materials for:

The Meanings of Democracy among Mass Publics

Table of contents

Appendix A: Model output for pooled Latent Profile Analysis of all 22 countries

Table A1. Fit statistics for pooled latent profile analysis of democratic meanings

Profiles	Log-likelihood	Residual DF	BIC	% change in BIC	ABIC	cAIC	likelihood-ratio	Entropy
1	-248925.77	22770	498393.5	---	498221.9	498447.5	117443.3	---
2	-233802.32	22715	468698.5	-5.96%	468352.1	468807.5	87196.35	0.815
3	-229534.02	22660	460713.9	-1.70%	460192.7	460877.9	78659.74	0.772
4	-227273.18	22605	456744.2	-0.86%	456048.2	456963.2	74138.07	0.751
5	-225807.12	22550	454364.0	-0.52%	453493.2	454638	71205.95	0.752
6	-224729.17	22495	452760.1	-0.35%	451714.5	453089.1	69050.05	0.729
7	-223903.04	22440	451659.7	-0.24%	450439.4	452043.7	67397.78	0.717
8	-223188.27	22385	450782.2	-0.19%	449387.0	451221.2	65968.24	0.716
9	-222766.24	22330	450490.1	-0.06%	448920.2	450984.1	65124.20	0.682
10	-222469.08	22275	450447.7	-0.01%	448703.0	450996.7	64529.88	0.665
11	-222121.93	22220	450305.3	-0.03%	448385.9	450909.3	63835.56	0.676
12	-221849.70	22165	450312.8	0.00%	448218.6	450971.8	63291.10	0.651
13	-221574.56	22110	450314.5	0.00%	448045.4	451028.5	62740.82	0.678

Note: Highlighted profile indicates “best-fitting” solution on the basis of convergent criteria involving BIC, cAIC, and entropy.

Table A2. Profile assignment probabilities

Solution size	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	Profile 7	Profile 8	Profile 9	Profile 10	Profile 11	Profile 12	Profile 13
1	1.000	-	-	-	-	-	-	-	-	-	-	-	-
2	0.450	0.550	-	-	-	-	-	-	-	-	-	-	-
3	0.469	0.360	0.171	-	-	-	-	-	-	-	-	-	-
4	0.182	0.152	0.394	0.273	-	-	-	-	-	-	-	-	-
5	0.062	0.383	0.255	0.130	0.171	-	-	-	-	-	-	-	-
6	0.139	0.086	0.060	0.164	0.188	0.362	-	-	-	-	-	-	-
7	0.138	0.176	0.060	0.073	0.143	0.339	0.070	-	-	-	-	-	-
8	0.026	0.139	0.340	0.061	0.124	0.075	0.070	0.166	-	-	-	-	-
9	0.075	0.207	0.101	0.025	0.178	0.166	0.055	0.057	0.135	-	-	-	-
10	0.145	0.051	0.073	0.017	0.199	0.156	0.152	0.073	0.093	0.041	-	-	-
11	0.067	0.137	0.047	0.069	0.159	0.084	0.022	0.135	0.032	0.194	0.053	-	-
12	0.086	0.016	0.151	0.063	0.039	0.204	0.130	0.031	0.015	0.124	0.070	0.071	-
13	0.015	0.061	0.016	0.102	0.068	0.029	0.099	0.137	0.037	0.070	0.074	0.089	0.203

Notes: Shaded cells indicate profile for which the probability of assignment is less than 5%.

Appendix B: Model output for Latent Profile Analyses of individual countries

Table B1. Latent profile model estimates for Argentina

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-6865.71	708	14089.76	13918.29	14143.76	5399.673	-	1.000	-	-	-	-
2	-6307.48	653	13338.28	12992.16	13447.28	4283.213	0.833	0.596	0.404	-	-	-
3	-6166.54	598	13421.37	12900.6	13585.37	4001.329	0.813	0.202	0.299	0.499	-	-
4	-6064.56	543	13582.39	12886.97	13801.39	3797.363	0.768	0.274	0.247	0.273	0.206	-
5	-5979.77	488	13777.79	12907.72	14051.79	3627.794	0.687	0.094	0.228	0.156	0.304	0.217

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B2. Latent profile model estimates for Australia

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-13793.7	1282	27976.08	27804.55	28030.08	9968.347	-	1.000	-	-	-	-
2	-13073	1227	26930.59	26584.35	27039.59	8527.003	0.791	0.426	0.574	-	-	-
3	-12832.3	1172	26845	26324.04	27009	8045.547	0.740	0.202	0.398	0.399	-	-
4	-12674.3	1117	26924.91	26229.24	27143.91	7729.6	0.747	0.155	0.155	0.369	0.321	-
5	-12575	1062	27122.08	26251.71	27396.08	7530.916	0.679	0.228	0.155	0.290	0.199	0.128

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B3. Latent profile model estimates for Brazil

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-14986.4	1266	30360.9	30189.36	30414.9	12459.1	-	1.000	-	-	-	-
2	-13938.4	1211	28659.95	28313.7	28768.95	10362.96	0.845	0.412	0.588	-	-	-
3	-13731.6	1156	28641.65	28120.69	28805.65	9949.461	0.778	0.413	0.360	0.227	-	-
4	-13585.5	1101	28744.57	28048.91	28963.57	9657.193	0.719	0.160	0.261	0.238	0.342	-
5	-13448.8	1046	28866.46	27996.09	29140.46	9383.88	0.707	0.262	0.141	0.264	0.207	0.126

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B4. Latent profile model estimates for Bulgaria

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-7967.34	678	16290.86	16119.39	16344.86	7179.206	-	1.000	-	-	-	-
2	-7356.54	623	15432.03	15085.92	15541.03	5957.608	0.859	0.490	0.510	-	-	-
3	-7071.69	568	15225.09	14704.34	15389.09	5387.908	0.850	0.184	0.382	0.434	-	-
4	-6920.07	513	15284.61	14589.22	15503.61	5084.661	0.836	0.101	0.436	0.100	0.363	-
5	-6825.99	458	15459.23	14589.19	15733.23	4896.509	0.755	0.422	0.066	0.066	0.365	0.081

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B5. Latent profile model estimates for Canada

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-19669.5	1801	39745.41	39573.85	39799.41	13261.09	-	1.000	-	-	-	-
2	-18716.7	1746	38253.78	37907.49	38362.78	11355.55	0.784	0.484	0.516	-	-	-
3	-18432.5	1691	38099.19	37578.17	38263.19	10787.06	0.744	0.324	0.258	0.418	-	-
4	-18292.3	1636	38232.72	37536.96	38451.72	10506.67	0.738	0.241	0.394	0.306	0.059	-
5	-18186.1	1581	38434.31	37563.82	38708.31	10294.35	0.651	0.043	0.287	0.404	0.225	0.042

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B6. Latent profile model estimates for Chile

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9153.15	754	18667.8	18496.32	18721.8	8354.759	-	1.000	-	-	-	-
2	-8505.94	699	17741.58	17395.44	17850.58	7060.334	0.855	0.469	0.531	-	-	-
3	-8269.64	644	17637.19	17116.4	17801.19	6587.747	0.860	0.434	0.398	0.168	-	-
4	-8163.33	589	17792.77	17097.32	18011.77	6375.124	0.862	0.372	0.162	0.383	0.083	-
5	-8067.12	534	17968.55	17098.44	18242.55	6182.702	0.766	0.211	0.232	0.164	0.324	0.068

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B7. Latent profile model estimates for Finland

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9947.44	912	20266.03	20094.52	20320.03	7444.133	-	1.000	-	-	-	-
2	-9332.8	857	19414.78	19068.6	19523.78	6214.861	0.807	0.441	0.559	-	-	-
3	-9091.74	802	19310.67	18789.81	19474.67	5732.727	0.803	0.121	0.455	0.424	-	-
4	-8993.67	747	19492.56	18797.02	19711.56	5536.592	0.762	0.366	0.213	0.055	0.367	-
5	-8905.71	692	19694.66	18824.44	19968.66	5360.667	0.811	0.350	0.244	0.157	0.192	0.058

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B8. Latent profile model estimates for France

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-10890.8	902	22152.27	21980.77	22206.27	9333.929	-	1.000	-	-	-	-
2	-10252.5	847	21252.95	20906.77	21361.95	8057.157	0.831	0.536	0.464	-	-	-
3	-10020	792	21165.52	20644.66	21329.52	7592.271	0.800	0.285	0.356	0.360	-	-
4	-9877.05	737	21257.04	20561.5	21476.04	7306.344	0.808	0.249	0.287	0.127	0.336	-
5	-9775.91	682	21432.21	20562	21706.21	7104.067	0.766	0.338	0.312	0.065	0.096	0.190

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B9. Latent profile model estimates for Georgia

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-10422.8	1017	21222.28	21050.76	21276.28	7902.522	-	1	-	-	-	-
2	-9486.91	962	19734.23	19388.03	19843.23	6030.779	0.908	0.316	0.684	-	-	-
3	-9240.13	907	19624.38	19103.49	19788.38	5537.225	0.833	0.257	0.002	0.543	-	-
4	-9117.49	852	19762.8	19067.22	19981.8	5291.949	0.76	0.146	0.214	0.380	0.260	-
5	-9032.86	797	19977.23	19106.95	20251.23	5122.677	0.74	0.316	0.149	0.083	0.234	0.218

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B10. Latent profile model estimates for Hungary

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9916.13	855	20200.12	20028.62	20254.12	8255.824	-	1.000	-	-	-	-
2	-9274.24	800	19291.03	18944.86	19400.03	6972.058	0.850	0.510	0.490	-	-	-
3	-9010.7	745	19138.63	18617.79	19302.63	6444.979	0.811	0.132	0.423	0.445	-	-
4	-8904.08	690	19300.06	18604.55	19519.06	6231.732	0.730	0.095	0.207	0.283	0.416	-
5	-8810.27	635	19487.13	18616.95	19761.13	6044.121	0.817	0.208	0.361	0.037	0.089	0.305

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B11. Latent profile model estimates for Japan

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-8275.12	672	16905.96	16734.5	16959.96	7331.354	-	1.000	-	-	-	-
2	-7779.36	617	16276.76	15930.65	16385.76	6339.833	0.828	0.467	0.533	-	-	-
3	-7616.2	562	16312.76	15792.01	16476.76	6013.516	0.811	0.423	0.200	0.377	-	-
4	-7509.21	507	16461.1	15765.71	16680.1	5799.545	0.774	0.194	0.328	0.073	0.404	-
5	-7430.27	452	16665.54	15795.5	16939.54	5641.666	0.777	0.194	0.062	0.174	0.256	0.314

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B12. Latent profile model estimates for Mexico

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-16117.3	1306	32624.23	32452.7	32678.23	14551.67	-	1.000	-	-	-	-
2	-14588.3	1251	29963.08	29616.83	30072.08	11493.68	0.900	0.415	0.585	-	-	-
3	-14278.4	1196	29740.04	29219.08	29904.04	10873.8	0.831	0.372	0.249	0.379	-	-
4	-14094.9	1141	29769.86	29074.18	29988.86	10506.78	0.802	0.303	0.134	0.209	0.354	-
5	-13947.5	1086	29872.06	29001.68	30146.06	10212.14	0.799	0.292	0.128	0.156	0.217	0.207

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B13. Latent profile model estimates for Netherlands

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9946.89	905	20264.54	20093.04	20318.54	7928.024	-	1.000	-	-	-	-
2	-9143.78	850	19035.93	18689.75	19144.93	6321.797	0.868	0.496	0.504	-	-	-
3	-8930.6	795	18987.21	18466.35	19151.21	5895.449	0.817	0.238	0.446	0.316	-	-
4	-8800.51	740	19104.64	18409.1	19323.64	5635.254	0.824	0.425	0.261	0.058	0.256	-
5	-8703.65	685	19288.55	18418.34	19562.55	5441.541	0.783	0.190	0.088	0.060	0.416	0.246

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B14. Latent profile model estimates for Norway

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9634.08	938	19640.75	19469.25	19694.75	6704.547	-	1.000	-	-	-	-
2	-9189.79	883	19131.65	18785.47	19240.65	5815.966	0.781	0.602	0.398	-	-	-
3	-8992.91	828	19117.38	18596.51	19281.38	5422.206	0.790	0.101	0.560	0.339	-	-
4	-8848.67	773	19208.38	18512.82	19427.38	5133.717	0.784	0.294	0.077	0.092	0.538	-
5	-8769.75	718	19430.02	18559.78	19704.02	4975.876	0.770	0.408	0.289	0.091	0.135	0.078

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B15. Latent profile model estimates for Poland

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9002.67	776	18368.29	18196.81	18422.29	7558.253	-	1.000	-	-	-	-
2	-8470.07	721	17672.77	17326.63	17781.77	6493.054	0.824	0.433	0.567	-	-	-
3	-8299.22	666	17700.76	17179.95	17864.76	6151.363	0.842	0.387	0.085	0.528	-	-
4	-8181.04	611	17834.07	17138.6	18053.07	5914.994	0.792	0.378	0.249	0.290	0.084	-
5	-8099.4	556	18040.48	17170.35	18314.48	5751.725	0.768	0.335	0.073	0.099	0.212	0.280

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B16. Latent profile model estimates for Romania

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-12698.5	1387	25789.74	25618.2	25843.74	8102.204	-	1.000	-	-	-	-
2	-11879.7	1332	24552.21	24205.96	24661.21	6464.654	0.801	0.315	0.685	-	-	-
3	-11679.7	1277	24552.23	24031.26	24716.23	6064.653	0.768	0.292	0.097	0.611	-	-
4	-11507.3	1222	24607.32	23911.63	24826.32	5719.718	0.786	0.033	0.247	0.362	0.357	-
5	-11384.4	1167	24761.71	23891.3	25035.71	5474.088	0.783	0.102	0.389	0.324	0.151	0.034

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B17. Latent profile model estimates for Serbia

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-11236.3	944	22845.44	22673.94	22899.44	10172.26	-	1.000	-	-	-	-
2	-10292.7	889	21338.06	20991.87	21447.06	8285.063	0.896	0.473	0.527	-	-	-
3	-9914.81	834	20962.17	20441.3	21126.17	7529.351	0.894	0.361	0.469	0.169	-	-
4	-9644.67	779	20801.7	20106.15	21020.7	6989.068	0.888	0.157	0.433	0.072	0.338	-
5	-9510.04	724	20912.26	20042.02	21186.26	6719.812	0.856	0.441	0.325	0.105	0.092	0.037

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B18. Latent profile model estimates for Slovenia

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-8873.45	784	18110.37	17938.88	18164.37	7279.068	-	1.000	-	-	-	-
2	-8327.79	729	17389.27	17043.12	17498.27	6187.76	0.818	0.478	0.522	-	-	-
3	-8142.22	674	17388.33	16867.52	17552.33	5816.617	0.811	0.308	0.222	0.470	-	-
4	-8027.82	619	17529.73	16834.26	17748.73	5587.816	0.808	0.192	0.129	0.466	0.213	-
5	-7930.95	564	17706.21	16836.07	17980.21	5394.084	0.620	0.187	0.102	0.194	0.131	0.386

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B19. Latent profile model estimates for Sweden

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-7095.18	916	14520.18	14367.73	14568.18	3323.887	-	1.000	-	-	-	-
2	-6750.81	867	14168.11	13860.04	14265.11	2635.129	0.766	0.751	0.249	-	-	-
3	-6596.4	818	14195.99	13732.29	14341.99	2326.326	0.776	0.219	0.557	0.224	-	-
4	-6531.31	769	14402.48	13783.17	14597.48	2196.139	0.735	0.228	0.412	0.176	0.185	-
5	-6478.01	720	14632.56	13857.62	14876.56	2089.537	0.765	0.150	0.498	0.064	0.203	0.085

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B20. Latent profile model estimates for United Kingdom

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion)				
								Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-10253.2	857	20874.31	20702.81	20928.31	8470.419	-	1.000	-	-	-	-
2	-9773.18	802	20289.15	19942.98	20398.15	7510.458	0.762	0.511	0.489	-	-	-
3	-9567.73	747	20253.04	19732.2	20417.04	7099.553	0.759	0.363	0.304	0.334	-	-
4	-9448.75	692	20389.88	19694.37	20608.88	6861.591	0.720	0.210	0.333	0.311	0.146	-
5	-9378.14	637	20623.47	19753.28	20897.47	6720.378	0.700	0.266	0.188	0.140	0.265	0.142

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B21. Latent profile model estimates for United States

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-12782.8	1128	25947.56	25776.03	26001.56	10573.43	-	1.000	-	-	-	-
2	-11835.9	1073	24442.93	24096.71	24551.93	8679.686	0.867	0.323	0.677	-	-	-
3	-11447.5	1018	24055.34	23534.42	24219.34	7902.974	0.887	0.290	0.607	0.103	-	-
4	-11275.6	963	24100.59	23404.97	24319.59	7559.1	0.764	0.099	0.250	0.249	0.402	-
5	-11109.3	908	24157.18	23286.86	24431.18	7226.566	0.712	0.087	0.243	0.490	0.130	0.049

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.

Table B22. Latent profile model estimates for Uruguay

# of profiles	log-likelihood	Degrees of Freedom	BIC	ABIC	cAIC	LR	Entropy	Assignment probability (proportion) Profile 1	Profile 2	Profile 3	Profile 4	Profile 5
1	-9783.78	854	19935.36	19763.86	19989.36	8236.768	-	1.000	-	-	-	-
2	-9011.86	799	18766.15	18419.98	18875.15	6692.943	0.856	0.385	0.615	-	-	-
3	-8726.68	744	18570.4	18049.56	18734.4	6122.574	0.826	0.171	0.358	0.471	-	-
4	-8590.26	689	18672.18	17976.67	18891.18	5849.738	0.815	0.171	0.161	0.415	0.254	-
5	-8482.8	634	18831.88	17961.7	19105.88	5634.817	0.812	0.240	0.092	0.157	0.174	0.337

Notes: Shaded row indicates best-fitting model. Data drawn from World Values Survey.