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ORIGINAL RESEARCH

The Meanings of Democracy among Mass Publics

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Abstract
In this paper, we illustrate that composite views about democracy vary significantly within *and* across national populations. Using World Values Survey data, we use latent class analysis to demonstrate that composite views of democracy display only modest consensus across country contexts. Although the features of procedural democracy are widely viewed as a cornerstone of democracy, their perceived importance and the way that they interact with substantive features varies considerably across and within democratic countries. These findings encourage caution when analyzing cross-national mass opinion about democracy. In particular, latent variable modeling using pooled survey data should pay careful attention to the unique permutations that democracy takes in the minds of citizens.

Keywords Democracy · Latent class analysis · Public opinion

1 Introduction

Perhaps no question has animated contemporary political science more than how (and whether) citizens understand democracy. Historically, democracy is linked to self-determination and the "consent of the governed" (Sabine 1937). Yet, the shape that such consent takes remains contested, while the word "democracy" remains intentionally ambiguous in its public use and subject to scholarly dispute (Prothro and Grigg 1960).

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One common attempt to categorize the meanings of democracy involves accounting for its production of political goods, a blend of institutional outputs, priorities, and structures (Pennock 1966; Almond et al. 2004).[1] “Minimalist” definitions emphasize voting, majority rule, and competitive elections with the consent of the governed rooted in the selection of competing elites (Schumpeter 1942; Dahl 1971). In minimal democracies, the public interest is theoretically secured by elite calculations that one set of ruling elites will some day be replaced another (Przeworski 1999). Substantive and deliberative democratic theorists, in contrast, include not just the consent of the governed but also condition what democratic processes must look like and what democratic outcomes must achieve. Democratic processes must be deliberative or participatory (Habermas 1989; Pateman 2012) and democratic outcomes must be democratizing, meaning that they should create the conditions for economic equality and provide democratic citizenries with basic economic necessities (Rawls 1971). Among the central questions of contemporary democratic theory are whether there is a tradeoff between liberty and equality and, within liberal democracies, how to create institutions that balance political equality (one person, one vote) with economic inequalities (Pateman 2012). For radical democratic theorists, such balancing is impossible, as the meaning of democracy is constantly in flux as is the tradeoff between liberty and equality (Laclau 2001; Laclau and Mouffe 2001).

If scholars differ widely in the meanings they assign to democracy and the weights they assign to democracy’s “essential” characteristics, substantial variance in how the public understands democracy should hardly be surprising. Indeed, comparative scholars have long recognized the variance in scholarly and public understandings of democracy (Almond and Verba 1963; Dahl 1971). Yet, at the same time, they have often implicitly assumed or even explicitly argued that survey responses to questions about the quality of democracy are comparable both within and across countries despite evidence to the contrary (Ariely and Davidov 2011; Oser and Hooghe 2018b; Jacobsen and Fuchs 2020). This problem is particularly pressing in the research agenda regarding support for democracy, which assumes that citizens share common underlying views about the contours of democracy across widely varying geographic, cultural, and political contexts. What does it mean, then, to say that democratic support is backsliding (Mounk 2018; Foa and Mounk 2016)? Backsliding from what?[2]

In this paper, we investigate how mass publics combine the essential characteristics of democracy to form composite understandings of what democracy means. Our purpose here is to reconsider how citizens think about democracy. Are “minimalist” definitions emphasizing voting, majority rule, and competitive elections adequate to describe how citizens think about democracy? What responsibility do democracies have for providing basic necessities or addressing social, economic, and political inequalities? Do citizens think about democracy through a maximalist lens that accounts for these features? If so, do individuals living in democratic states with different histories and institutions connect these ideas together in common ways?

Past research finds that there are effective “archetypes” that describe citizens’ impressions of and expectations for democracy with respect to how procedural and substantive dimensions of democracy are wedded together (Oser and Hooghe 2018a, b). We illustrate that composite views of democracy vary both within and, importantly, across national

[1] For example, well-known theorists like Habermas (1996) and Dahl (1989) depict democracy by its production of rights; freedoms of expression, association, assembly, movement, and so on giving democracy its functional meaning.

[2] Recent research has questioned the evidence of democratic backsliding, noting that it is is often cherry-picked and does not capture the ambiguity in the term “democracy” (Wuttke et al. 2020a, b; Zilinksy 2019).

populations. In other words, constructing a universal typology of democratic meanings is not applicable. Using latent class analysis, we show that pooling respondents across democracies produces a much different picture of both the nature and prevalence of composite views toward democracy than conducting such analysis on individual countries. These findings echo other calls for renewed care when analyzing pooled, cross-national survey data regarding multi-dimensional concepts like democracy (e.g. Cutler et al. 2013; King et al. 2004; Wuttke et al. 2020a, b). In particular, we argue that latent variable modeling of democracy's attributes using such data should pay careful attention to both data generating processes and the peculiarities of the survey response.

2 Attitudes about democracy in the cross-national context

Scholars of comparative politics recognize that democratic values are diffused widely (e.g. Diamond and Plattner 2008; Ferrín and Kriesi 2016; Ulbricht 2018). Even in "unlikely places," Dalton et al. (2007) argue that a liberal understanding of democracy is both pervasive and associated with political freedom and civil rights. In other words, citizens seem to reliably depict democracy in terms of the production of its civil and procedural outputs. Yet, other research challenges whether citizens' reflections about the nature of democracy are shared. While individuals might well associate democracy with political freedom at an abstract level, their understanding of political freedom may also be heavily contingent upon culture and context. In other words, definitions of democracy may share terms (political freedom), but not common understandings of what those terms mean, in part because institutional contexts mediate such meanings (Bratton 2010; Ulbricht 2018; Laclau and Mouffe 2001).

Vernacular differences in how citizens understand freedom notwithstanding, a second-order concern involves how individuals think more broadly about the outputs and qualities of democracy. This involves the well-known distinction between procedural or minimal definitions of democracy (e.g. Dahl 1971) and the substantive production of welfare goods associated with democracy (e.g. Schumpeter 1942). Democracies clearly vary in the extent to which they produce welfare-maximizing goods. Social democracies with robust systems of public health, labor protections, and poverty-alleviating programs look much different from liberal democracies that have internalized the neoliberal qualities of limited state intervention in the marketplace (see Held 2006 for a compilation of models of democracy). These differences frustrate cross-national analysis of democracy to the extent that measuring and comparing democracies as a unit of analysis probably warrants a multidimensional approach (e.g. Coppedge et al. 2011; Wuttke et al. 2020a, b). In other words, the permutations that democracy takes are simply too varied to try and shoehorn democracy into a single index or indicator.

The idea that democracy is multidimensional in structure has not been lost on scholars attempting to analyze how *the public* views democratic process and institutions. Scholars routinely uncover dimensionality in public opinion data toward democracy that reveals that citizens not only distinguish procedural from substantive elements (e.g. Baviskar and Malone 2004; Ferrín and Kriesi 2016; Carlin 2018), but associate the incorporation of social benefits (Crow 2010) and social goods more broadly with democracy (Oser and Hooghe 2018a, b). Although much attention has been paid to support for democracy (e.g. Claasen 2020; Merkley et al. 2019), the characteristics citizens associate with democracy convey important information about the expectations that they have for it.

One way of making sense of this survey data has been the attempt to explore whether or not—institutional design notwithstanding—citizens from different countries share broadly similar conceptualizations of what they expect from democracy. Ferrín and Kriesi (2016), for example, illustrate that, while citizens of different European democracies vary in the extent to which they place importance on certain qualities of democracy, there appears to be shared understanding of different institutional features. Oser and Hooghe (2018a, b) take a somewhat different approach and instead sort individuals into groups or "archetypes" of democracy in both Europe and the United States and find that there is a distinct set of permutations that democracy takes in the minds of citizens (see also Hooghe et al. 2017).

This latter approach reveals a curious set of findings. On the one hand, it seems reasonable to assume that citizens living in different countries would view democracy in similar ways –European and American democracies presumably share some common epistemological footings that overlap into shared views of democracy. On the other hand, even among countries that presumably produce procedural goods in common ways, this seems to gloss over the dynamic historical movements that give these democracies their nature. In that case, it seems odd that we might find a basic or universal "menu" of democratic profiles that emerge across countries, similar though they may be. Indeed, among scholars of comparative politics and political theorists, there is no single model of democracy but rather a wide range of models capturing various "essential features" of democratic governance (Held 2006). It would be surprising then if citizen understandings of democracy were not at least as varied within and across countries.

3 Our contribution

We propose two extensions of this past work, which we believe have interesting implications for the broader research agenda involving citizens' appraisals of democracy. First, in their latent class analysis of the characteristics that people associate with democracy, Oser and Hooghe (2018a, b) recode the underlying instruments used to construct their typology of democracy. This decision complicates how we interpret the raw survey response, which was bivalent and symmetrical, and presents a potential problem for model-based equivalence testing. Thus, here, we leave the data in their original form and analyze responses using a latent class model that can account for the un-transformed, polytomous responses.

Second, we extend the dataset of available countries to include a richer set of democracies. Although there is the justifiable tendency to treat western and non-western democracies as categorically different with respect to public opinion on democracy (grounded in the finding that the psychometric properties of the survey data are often distinct across these contexts; Ariely 2015), we take full advantage of the coverage of survey data provided by the World Values Survey to explore the possibility that a typology of democratic meanings is portable. Although there are both substantive and methodological tensions involved in trying to field and compare survey data across consolidated, mature democracies and emerging ones (Mattes 2008), this analysis represents a unique opportunity to situate the "transformation model" of democratic public opinion (Rose et al. 1998) within the larger ecosystem of democracies worldwide.

4 Data and measures

The data for these analyses are drawn from the "essential characteristics of democracy" battery included in the Wave 5 (2005–2009) questionnaire of the World Values Survey (WVS). These data are now over a decade old, but they still constitute the most recent, largest and diverse sample of countries that has ever fielded these questions.[3] We restrict the sample to countries that score a 6 or better on the Polity Index at the time of survey fielding; this decision was made to ensure that we included a wide range of countries that are more or less "democratic," while excluding publics that live under autocracy or anocracy. While it would be interesting to explore how persons in those countries view democracy, we nevertheless restrict our sample to countries that score the "minimum" value conventionally associated with democratic states. The sample formally includes 37 countries.

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. These items include: whether (1) government should tax the rich to subsidize poor; (2) the economy prospers; (3) citizens receive state aid for employment; (4) people choose leaders in free elections, (5) can change laws via referendums, and (7) civil rights protect people's liberties from state oppression and (8) women have the same rights as men; (9) criminals are severely punished; (9) the army takes over when government is incompetent; (10) religious authorities interpret laws. To be sure, these characteristics of democracy cover a wide array of facets of democracy. Items one through three reflect "substantive" outputs, while items four through eight embody the types of outputs that are commonly described as "procedural" goods." Although unconventional measures of support for civil or liberty goods, items nine and ten fit within this latter category because associating democracy with either feature conveys a disregard for secular pluralism and elected self-determination—both core features of functional democracy.[4]

While many of these instruments have been widely used in past studies (e.g. Norris 2011; Welzel 2011; Shin 2012; De Regt 2013; Ariely 2015), we remain agnostic at the extent to which they are invariant. It is possible that some instruments are understood differently across democratic contexts. In fact, we would expect this to be the case in a sample as diverse as the World Values Study. As Welzel and Inglehart (2016, pg. 1072) caution, however, psychometric tests involving individual-level attitudes often offer modest insight into "how prevalent these values are in a country." Because our analytical quantity of interest is in the prevalence of democratic groups derived from latent class models both within countries and the distribution of those groups across countries, we tend to be less concerned about invariance than other research that models the correlates of such beliefs.

[3] At the time of writing, the Wave 7 WVS data had not been released publicly. It may provide new, contemporaneous updates to this analysis. Wave 6, in contrast, provides more limited coverage of the "essential characteristics of democracy," which limits the countries available for our sample. Analysis of Wave 6 data are comparable to the results presented here and are available upon requests from the authors. The European Social Survey, especially Round 6, provided a robust set of questions specifically on the meanings of democracy (Ferrín and Kriesi 2014). The inclusion of countries from various regions and with different cultures and political systems, however, made the World Values Survey a better choice for this analysis.

[4] In particular, army rule is sometimes asked in a different question format as a measure of *support* for democracy (Magalhaes 2014; Miller and Davis 2020). However, because it was included in the battery—and because it represents a rejection of the liberal principles that underscore virtually any reasonable definition of democracy—we retain it for analysis here. We also include *all the available items* in the World Values Survey to address criticisms that a more limited set of items would bias the results. We have run the analysis with a more limited set of items. Those results confirm the pattern of findings presented here.

5 Results

One (blunt) way of exploring differences in how individuals think about democracy's nature across democratic contexts involves simply looking at the distribution of responses to questions in the WVS battery. Although we possess ten instruments for 37 countries, depicting that amount of information visually can be unwieldy. Thus, Fig. 1 illustrates the central tendencies (mean, mode) and variance of three of the ten characteristics of democracy for five countries. Each of the countries varies with respect to historical, institutional, and social-cultural dynamics, which hopefully renders an interesting set of contexts within which to explore similarities and differences.

Panel A reveals that, while the average importance of free elections is quite high across the five countries, some modest variation is nevertheless present in Brazil, Japan, the United Kingdom and the United States. On the matter of harsh punishment for criminals in Panel B, we see significant variance across the countries. Japan is least likely to associate punitive remedies with wrongdoing; the UK and the United States score lower on these instruments, but there is significant variance in the distribution of responses in Brazil, Sweden, the UK, and the United States. Panel C illustrates a similar pattern with respect to redistribution. Across this limited sample of countries, there is much variation in the preference for the role that taxes play in generating material equality in democracy.

The descriptive data helps illustrate that there is general consensus *and* differences on some characteristics of democracy both within and across countries. To test how citizens connect ideas about the properties of democracy into composite views about democracy, both globally and within each country, we now turn to a series of latent class analyses (LCA). We begin by building an LCA that includes all 37 countries in our sample. To estimate the models, we use poLCA in R (Linzer and Lewis 2011) The process of fitting LCA is iterative: we fit a model with k classes and then compare the fit indices of a model with $k+1$ classes. The terminal or final number of classes 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 et al. 2007), as well as the substantive implications of the terminal solution. For example, a model that appears justifiable on the grounds of the fit indices, but that produces many classes with extremely small assignment probabilities, may actually exhibit overfitting. Fitting the optimal number of classes to the data ultimately requires the researcher to balance these considerations (Oberski 2016).

In the interest of brevity, we truncate the modeling output associated with our LCA in Table 1, 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 3 and 4 in the "Appendix"). The results produce no clearly optimal number of classes, but it is possible to converge upon a defensible solution nonetheless. First, while the BIC values objectively hit their nadir at the 22-class solution, the decrease in BIC is very marginal past the 7-class solution (Column 6), where entropy dips. Although we have sufficient data to parse additional classes, these expansive solutions create extremely small, country-specific classes that contain small numbers of persons and likely reflects overfitting by the algorithm. Thus, as a secondary criterion for model selection, we avoid models that produce classes with less than a 5% probability of assignment (details on the distribution of class prevalence is available in Table 4 in the "Appendix"). This leaves us with a seven-class model, which we present in Fig. 1.

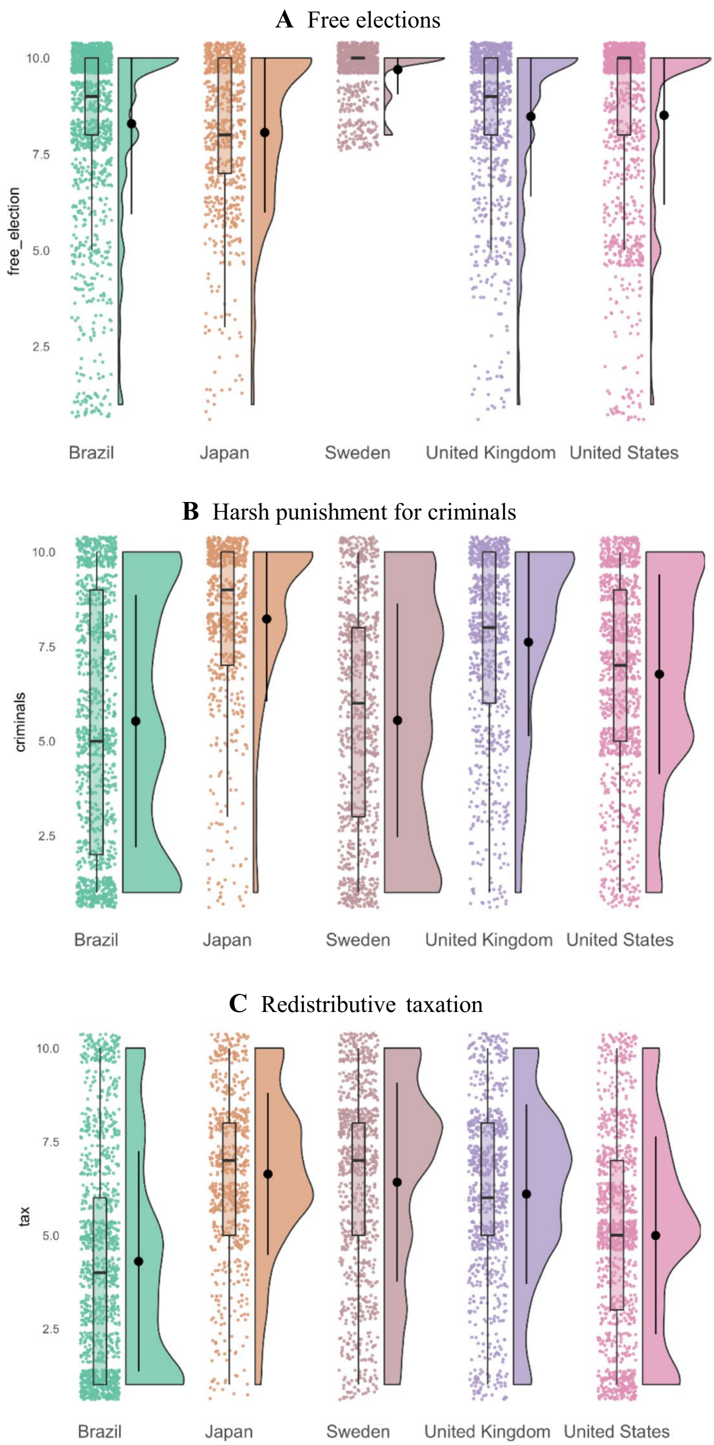

Fig. 1 Distribution of responses to free elections, gender equality, and redistributive taxation across selected democracies

Table 1 LCA output for class solutions ranging up to eight classes

# of Classes	Log-likelihood	Residual DF	BIC	Total change in BIC from baseline	Change in BIC from previous model	Change in change	LR	Entropy
(A) *LCA output estimates associated with one- to eight-class solutions*								
1	−771,758.63	40,330	1,544,471.90				735,351.17	–
2	−717,794.15	40,239	1,437,508.19	−6.93%	−7.44%		627,422.22	0.87
3	−700,677.57	40,148	1,404,240.26	−9.08%	−2.37%	−68.16%	593,189.05	0.85
4	−692,588.25	40,057	1,389,026.86	−10.06%	−1.10%	−53.77%	577,010.40	0.83
5	−686,629.11	39,966	1,378,073.83	−10.77%	−0.79%	−27.43%	565,092.13	0.83
6	−682,259.50	39,875	1,370,299.86	−11.28%	−0.57%	−28.62%	556,352.91	0.81
7	*−678,534.10*	*39,784*	*1,363,814.30*	*−11.70%*	*−0.48%*	*−16.18%*	*548,902.11*	*0.80*
8	−675,486.95	39,693	1,358,685.25	−12.03%	−0.38%	−20.62%	542,807.81	0.80

# of Classes	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
(B) *Prevalence of classes across full sample*								
1	2%	–	–	–	–	–	–	–
2	49%	51%	–	–	–	–	–	–
3	42%	39%	20%	–	–	–	–	–
4	25%	23%	15%	37%	–	–	–	–
5	25%	6%	22%	13%	34%	–	–	–
6	20%	21%	6%	25%	19%	9%	–	–
7	*18%*	*19%*	*16%*	*6%*	*14%*	*20%*	*8%*	–
8	12%	19%	18%	9%	2%	18%	5%	16%

Seven class solution (italics) balances both BIC-related criteria (Panel A) and class prevalence (Panel B). In particular, efficiency gains and class prevalence becomes remarkably thin in solutions past seven classes. Full output estimates, including aBIC and aAIC, is available in the "Appendix", which includes class solutions all the way through 25-classes

Interpreting the results of the model is eased by visually inspecting the estimated value associated with each input item across the groups. We begin with one important observation: there are roughly three "shapes" to the classes. Class 2 comprises about 16% of all respondents and pairs relatively high values of procedural support (free elections, civil rights, referendums, general equality) with *very* low levels of support for religious authorities interpreting the law and the army taking over under conditions of instability. This is distinct from the "apathetic" or "indifferent" persons that comprise classes 3 and 7. Persons belonging to these groups—about 14% of all respondents—give relatively low rankings to all of the qualities of democracy; none of the ten items assigned a value higher than 6.0. Class 7 is more negative in its evaluation of democracy's qualities, but both classes exhibit the same rough pattern of responses.

In contrast to these two patterns, Classes 1, 4, 5, and 6 exhibit high levels of support for both procedural and substantive outputs. Class 4 comprises almost 20% of respondents and assigns substantive outputs like redistributive taxation, economic prosperity, and state aid the highest levels of essentiality across the sample. Curiously, while it contains high levels of support for free elections and civil rights, it *also* exhibits high levels of punitiveness with respect to punishing criminals. Classes 1 and 5 are very similar, exhibit only modest intercept differences on substantive outputs, while Class 6 is more moderate across both dimensions.

To the extent the general *pattern* of these responses illustrates a common view of democracy, nearly 70 percent of respondents belong to one of these four groups. However, while members of these groups all concur generally about the importance of free elections, referendums, civil rights, and gender equality and seem to reject army rule, mean group values on these input items do vary in meaningful ways. For example, there is almost a three-point difference in the essentialness of civil rights between Classes 4 and 5. This finding is lost, however, on models that pool this data together as if the essential characteristics of democracy are more or less "invariant" across country contexts. Thus, while the most common vision of democracy across democracies involves connecting both economic and welfare goods together, we do see some of the classic tensions involving the distinction between social and liberal democracy present here.[5]

Although a 7-class solution emerges as the most reasonable, "best-fitting" depiction of how respondents connect certain facets of democracy together, it is not clear whether this set of classes spontaneously emerges within each country or whether each country possesses a more limited range of classes. Past research using European Social Survey (ESS) data conveys that a single, uniform model explains how respondents view democracy (Oser and Hooghe 2018a). In other words, a pooled model, like the one presented in Fig. 2 fully captures composite democratic beliefs within each country, and we would expect to find evidence of all seven classes within every country included in the sample. That earlier analysis involved only European countries and a different set of data, so it is possible that a more diverse sample of democracy would not produce such results although, even eyeballing the descriptive data in Fig. 1, it would seem unlikely that Sweden and the UK would contain the same number, much less type of classes of democracy.

[5] With substantial amounts of data, LCA will pull out fine-grain distinctions that may have little substantive utility. While Classes 1 and 4 are similar, one to two-point differences are substantively significant when the modal response is one of support. Seven classes may risk cutting the data too thin, but we feel that these distinctions are nonetheless warranted given the efficiency gains in the Bayesian Information Criterion.

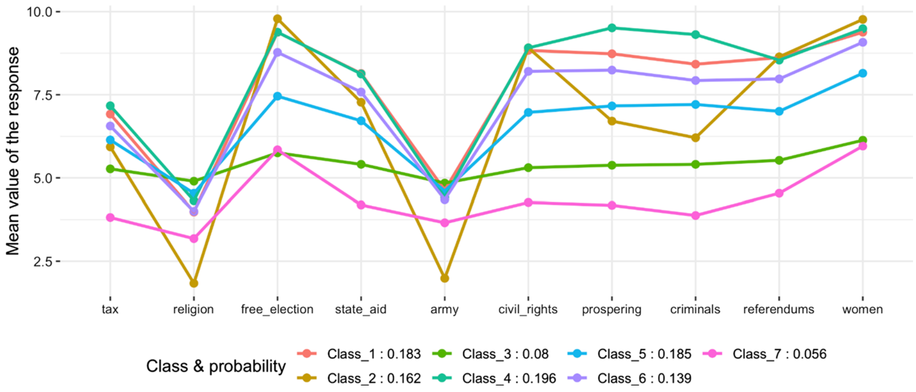

Fig. 2 Latent Class Analysis pooling respondents across all countries. Input items are arrayed on the x-axis; y-axis corresponds to the predicted mean value of input item for members of a given class. Prevalence or the probability of a respondent being assigned to a given class is presented alongside class in legend. Full modeling output associated with the modeling procedure is available in the "Appendix A"

Table 2 Number of unique classes emerging from best-fitting solution to the latent class analysis in the respective country

2 Classes	3 Classes		4 Classes	5 Classes	6 Classes
Argentina	Australia	Netherlands	Cyprus	Mexico	Thailand
India	Brazil	Norway	Indonesia	South Africa	
Sweden	Bulgaria	Peru	Mali		
Trinidad	Canada	Poland	Turkey		
	Chile	Romania	United States		
	Finland	Russia	Uruguay		
	France	Slovenia			
	Georgia	Spain			
	Ghana	Switzerland			
	Hungary]	Taiwan			
	Indonesia	Ukraine			
	Japan	United Kingdom			
	Moldova				

Full modeling output for these outcomes is available in "Appendix B"

To test the prevalence and distribution of classes within each country, we proceed by fitting LCA models across each individual country in our sample. This approach naturally generates an enormous number of estimates. In lieu of presenting iterative BIC values in tabular form or visually via elbow-plots for each country here in the main text, we simply report the number of classes that best fit the countries in the sample (model output is available in "Appendix B"). Table 2 reveals that, while the three-class model most frequently describes the distribution of classes within a given country, almost 30% of the sample produces two, four, or five classes of democratic visions.

These results indicate that the universal model of democratic beliefs presented in Fig. 2—which illustrates that a full seven classes sufficiently describes the variation in composite views of democracy—does not fit the individual country models. However, comparing the counts of classes across countries does little to inform how these composite views of democracy vary substantively within and across geographic contexts. To

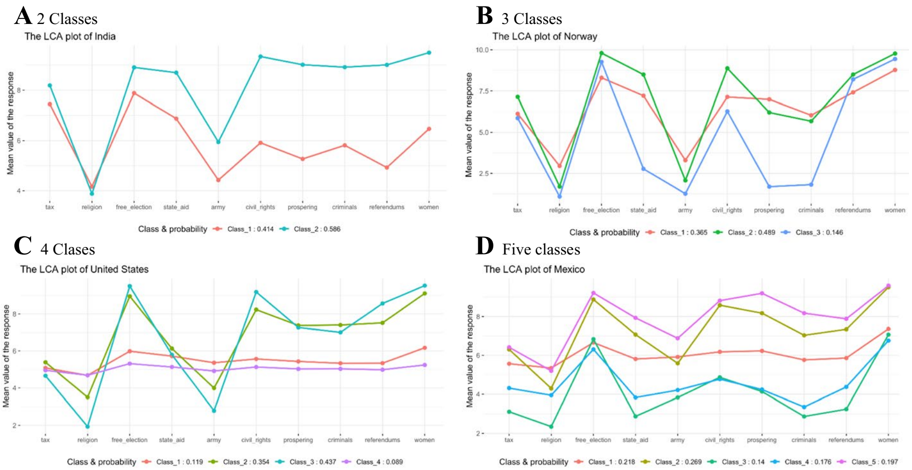

Fig. 3 Class plots of composite views of democracy for selected countries. Classes in each panel are calculated using iterative modeling process for respective country. Full output modeling for this process for the full sample of 37 countries is available in "Appendices B and C"

investigate the distribution of the *types* of classes that encompass mass views of democracy at the country level, we again proceed using a visual portrayal of the mean values associated with the input items across classes.

Each panel of Fig. 3 illustrates such plots for India, Norway, the United States, and Mexico. The plots for every individual country are presented in "Appendix C". These plots produce a number of observations. First, each panel contains a country that has a different number of classes. India produces two classes, while Mexico produces five. Second, the substantive nature of the classes also vary across each country. In India, there are two very distinct views of democracy—one that associates democracy with both procedural and substantive goods *and* one that is quite indifferent to these qualities. In Norway, there are three classes that are all modestly distinct from each other. In contrast, in the United States and Mexico, there are four and five classes respectively, some of which are fairly similar to the other. On balance, however, the seven-class solution that best fit the pooled data in no way fits the class solution in any of the individual countries. The lack of a distinct pattern, then, implies that the efficacy of a pooled view of democracy across the world is low.

While this finding is not necessarily unexpected, perhaps we effectively "stack-the-deck" by analyzing too many diverse and disparate democracies. To investigate whether or not this is the case, we pivot next to a series of four panels in Fig. 4 that illustrates the best-fitting class solutions for several European democracies—which presumably might exhibit greater commonality with respect to how citizens define democracy. Again, it is not clear that composite views of democracy are portable even across these western democracies. Sweden produces only two classes of democracy in Panel B, and these are unlike the classes present in Spain. The United Kingdom produces three classes, but two of the three are very similar and not substantively similar to those present in Norway. Even with their common epistemological heritage, we find that mass publics view democracy in textured ways, although it is relevant to note that support for procedural goods is nearly uniformly high within these countries. To the extent that elections and civil liberties are cornerstone features of democracy, the citizens of these countries seem to recognize that democracy

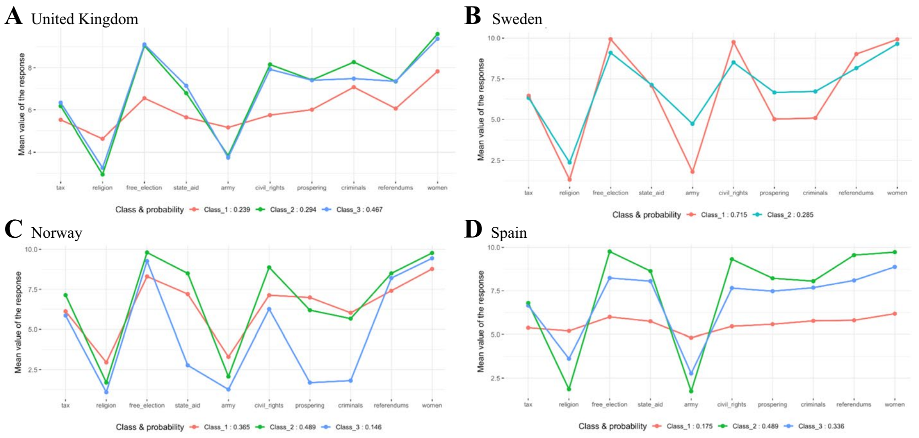

Fig. 4 Class plots of composite views of democracy for selected European countries. Classes in each panel are calculated using iterative modeling process for respective country. Full output modeling for this process for the full sample of 37 countries is available in "Appendices B and C"

involves these features, albeit to varying degrees. However, differences do exist when we wed citizens' beliefs about the procedural and substantive elements of democracy together. In some countries this produces several classes of democracy, in others only two. But under no circumstances do we ever find evidence of a standardized menu of democratic concepts that fits all countries equally. Simply put the distribution of beliefs about democracy is largely peculiar to the individual country context.

6 Discussion and conclusion

The extent to which public understandings of democracy are directly comparable cross-nationally is important for benchmarking how we approach analyzing public opinion toward democracy. In reassessing past work on democratic typologies (e.g. Oser and Hooghe's 2018b), our latent class analysis indicates that there is neither a single, shared understanding of democracy across countries nor, for that matter, a set of shared understandings, per se. Pooling all respondents from the 37 countries together, we found that a 7-class solution best fit the data. Substantively, this finding might be odd—how would 10 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. Notably, 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 classes vary in modest, but important ways—an observation that is not readily apparent if the values on the input items are truncated or arbitrarily recoded (as in past research). In turn, because the data are sufficiently large, subtle, but theoretically interesting differences manifest using a semi-supervised machine learning approach like LCA.

Overall, our analysis confirms recent research calling for greater sensitivity to measurement of multi-dimensional and multi-layered concepts, such as public understandings of democracy, cross-nationally (Ariely and Davidov 2011; Cutler et al. 2013; King et al. 2004; Wuttke et al. 2020c). Put simply, the meanings of democracy vary across and within countries, raising fundamental questions about what it means when scholars say that democratic support is eroding. Eroding from what? The answer to this question clearly depends on where one begins. For most scholars, this begins with an academic definition of democracy, despite the plethora of scholarly definitions noted earlier, and waning support is gauged from this pre-defined yardstick. The public may, however, have a very different idea of what democracy is supposed to entail, how its processes are supposed to work, and what outcomes it is supposed to produce. What appears as declining support may instead reflect declining support for democracy as currently practiced within a particular context. Despite measurable differences in public understandings of democracy, the vast majority of respondents across countries are "pro-democracy." The differences that emerge reflect different values respondents place on specific characteristics, e.g., free and fair elections, free speech, and economic equality. In the United States, 79 percent of respondents were assigned to two classes of democratic understanding that displayed strong support for the essential characteristics of democracy, but differed in the relative value of specific features. Approximately 21 percent, in contrast, belonged to classes of democracy that are better described as indifferent. We would not, however, describe them as "anti-democracy." This is comparable to the United Kingdom where 76 percent of respondents were assigned to pro-democracy classes while 24 percent were less supportive of democracy's essential characteristics. In Sweden, the two classes that emerge are very much pro-democracy. The classes we have developed here help us better understand where the public begins, and should subsequently enrich, rather than undermine, subsequent analyses of democratic support.

In some ways, this tells us what we already know. People think about democracy differently in the United States than in the United Kingdom, India, or Norway. We know this well, and yet in survey research we often implicitly assume these differences away or explicitly argue that there is a shared understanding of what democracy means over time and across space. The research presented in this article bridges this divide, providing quantitative classifications of the meaning of democracy while simultaneously taking seriously the unique context of each individual country. Differences in democratic meaning are observed here in two ways: The number of classes of identifiable classes (or meanings) that emerge within a specific country and the contours those classes take across countries. Countries with a three-class solution are not necessarily comparable in terms of the shape and the distribution of those classes. What does this mean for future research? We would posit that the differences across country are not just noise, but are instead the result of systematic variations in institutional design (number of parties, presidential versus parliamentary political systems, parallelism within media systems), political culture (individual versus collective), and contemporary economic and social forces (current economic conditions, the presence of right-wing populist movements). The task of modeling these differences is beyond the scope of the current analysis and the task of future research. We would note, however, that taking seriously what democracy means cross-nationally requires addressing the differences in understanding both in the terms of the number and the distribution of those differences.

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 are important as a guide to future work involving support for democracy. Research on the democratic deficit, for example, suggests that the disconnect between what citizens want and what democracy produces is problematic (e.g. Norris 2011). This typology might be useful for contextualizing what, specifically, mass publics demand from democracy. More fundamentally, the forces that generate competing visions of democracy are not well understood. What institutional characteristics shape the number of classes of democratic meanings that are present with a system? In turn, how does a country's social-cultural or economic milieu shape the expectations that citizens have for democracy? These are important questions to answer, and, as we have shown here, answering them requires careful attention to data generating processes and the peculiarities of the survey response.

Acknowledgement We should acknowledge one important limitation, however. Understandings of democracy might not only reflect differences across individuals and countries, they may also reflect differences across data sets. Using the European Social Survey or any other World Barometer data might yield a different set of patterns. This, in our view, only underscores our broader point. How mass publics combine democratic features into a composite understanding of democracy is tenuous and context dependent.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Availability of Data World Values Survey (http://www.worldvaluessurvey.org/WVSContents.jsp).

Code Availability poLCA (https://cran.r-project.org/web/packages/poLCA/poLCA.pdf).

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

See Tables 3 and 4.

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

See Tables 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40 and 41.

Table 3 Fit statistics for pooled Latent class analysis of democratic meanings

Model	Log-likelihood	resid_df	BIC	Total change in BIC from baseline	Change in BIC from previous model	Change in change	ABIC	cAIC	Likelihood-ratio	Entropy
1	−771,758.63	40,330	1,544,471.90				1,544,185.88	1,544,561.90	735,351.17	–
2	−717,794.15	40,239	1,437,508.19	−6.93%	−7.44%		1,436,932.97	1,437,689.19	627,422.22	0.87
3	−700,677.57	40,148	1,404,240.26	−9.08%	−2.37%	−68.16%	1,403,375.85	1,404,512.26	593,189.05	0.85
4	−692,588.25	40,057	1,389,026.86	−10.06%	−1.10%	−53.77%	1,387,873.25	1,389,389.86	577,010.40	0.83
5	−686,629.11	39,966	1,378,073.83	−10.77%	−0.79%	−27.43%	1,376,631.02	1,378,527.83	565,092.13	0.83
6	−682,259.50	39,875	1,370,299.86	−11.28%	−0.57%	−28.62%	1,368,567.84	1,370,844.86	556,352.91	0.81
7	*−678,534.10*	*39,784*	*1,363,814.30*	*−11.70%*	*−0.48%*	*−16.18%*	*1,361,793.09*	*1,364,450.30*	*548,902.11*	*0.80*
8	−675,486.95	39,693	1,358,685.25	−12.03%	−0.38%	−20.62%	1,356,374.84	1,359,412.25	542,807.81	0.80
9	−672,744.68	39,602	1,354,165.95	−12.32%	−0.33%	−11.59%	1,351,566.34	1,354,983.95	537,323.27	0.80
10	−671,302.55	39,511	1,352,246.94	−12.45%	−0.14%	−57.48%	1,349,358.13	1,353,155.94	534,439.02	0.79
11	−669,869.61	39,420	1,350,346.31	−12.57%	−0.14%	−0.82%	1,347,168.30	1,351,346.31	531,573.14	0.79
12	−668,582.36	39,329	1,348,737.05	−12.67%	−0.12%	−15.23%	1,345,269.85	1,349,828.05	528,998.64	0.78
13	−667,438.65	39,238	1,347,414.87	−12.76%	−0.10%	−17.76%	1,343,658.47	1,348,596.87	526,711.22	0.79
14	−666,445.00	39,147	1,346,392.81	−12.83%	−0.08%	−22.64%	1,342,347.21	1,347,665.81	524,723.91	0.76
15	−665,582.63	39,056	1,345,633.32	−12.87%	−0.06%	−25.65%	1,341,298.52	1,346,997.32	522,999.17	0.75
16	−664,688.93	38,965	1,344,811.16	−12.93%	−0.06%	8.32%	1,340,187.16	1,346,266.16	521,211.76	0.75
17	−664,043.05	38,874	1,344,484.64	−12.95%	−0.02%	−60.28%	1,339,571.44	1,346,030.64	519,920.00	0.73
18	−663,411.08	38,783	1,344,185.95	−12.97%	−0.02%	−8.50%	1,338,983.55	1,345,822.95	518,656.07	0.73
19	−662,855.79	38,692	1,344,040.62	−12.98%	−0.01%	−51.34%	1,338,549.03	1,345,768.62	517,545.49	0.81
20	−662,298.44	38,601	1,343,891.16	−12.99%	−0.01%	2.85%	1,338,110.37	1,345,710.16	516,430.79	0.75
21	−661,793.90	38,510	1,343,847.32	−12.99%	0.00%	−70.67%	1,337,777.33	1,345,757.32	515,421.70	0.76
22	−661,278.00	38,419	1,343,780.76	−12.99%	0.00%	51.81%	1,337,421.57	1,345,781.76	514,389.90	0.75
23	−660,832.34	38,328	1,343,854.70	−12.99%	0.01%	−211.08%	1,337,206.31	1,345,946.70	513,498.60	0.72
24	−660,416.00	38,237	1,343,987.26	−12.98%	0.01%	79.28%	1,337,049.68	1,346,170.26	512,665.92	0.75

Table 3 (continued)

Model	Log-likelihood	resid_df	BIC	Total change in BIC from baseline	Change in BIC from previous model	Change in change	ABIC	cAIC	Likelihood-ratio	Entropy
25	−660,051.99	38,146	1,344,224.48	−12.97%	0.02%	78.91%	1,336,997.69	1,346,498.48	511,937.89	0.77

Italics profile indicates "best-fitting" solution on the basis of convergent criteria involving BIC, cAIC, and entropy

Table 4 Profile assignment probabilities

Number of classes	Class																								
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	2%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
2	49%	51%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
3	42%	39%	20%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
4	25%	23%	15%	37%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
5	25%	6%	22%	13%	34%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
6	20%	21%	6%	25%	19%	9%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
7	*18%*	*19%*	*16%*	*6%*	*14%*	*20%*	*8%*	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
8	12%	19%	18%	9%	2%	18%	5%	16%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
9	17%	18%	8%	9%	2%	18%	6%	5%	17%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
10	1%	18%	6%	8%	4%	5%	17%	8%	17%	17%	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
11	15%	4%	8%	4%	10%	1%	16%	6%	6%	15%	15%	–	–	–	–	–	–	–	–	–	–	–	–	–	–
12	10%	4%	4%	15%	16%	4%	10%	11%	6%	5%	1%	15%	–	–	–	–	–	–	–	–	–	–	–	–	–
13	5%	11%	5%	6%	13%	10%	5%	4%	15%	3%	15%	9%	1%	–	–	–	–	–	–	–	–	–	–	–	–
14	5%	6%	15%	3%	3%	4%	15%	11%	1%	4%	9%	3%	12%	10%	–	–	–	–	–	–	–	–	–	–	–
15	4%	1%	11%	4%	4%	12%	9%	10%	4%	3%	3%	7%	6%	9%	14%	–	–	–	–	–	–	–	–	–	–
16	3%	3%	9%	4%	12%	3%	3%	13%	8%	4%	1%	2%	7%	6%	9%	13%	–	–	–	–	–	–	–	–	–
17	3%	4%	8%	3%	4%	3%	3%	7%	2%	12%	7%	1%	8%	12%	9%	13%	2%	–	–	–	–	–	–	–	–
18	1%	3%	11%	2%	12%	7%	6%	4%	3%	8%	13%	7%	4%	3%	3%	2%	9%	1%	–	–	–	–	–	–	–
19	13%	2%	3%	4%	4%	1%	6%	11%	2%	3%	8%	3%	6%	5%	9%	7%	3%	10%	1%	–	–	–	–	–	–
20	2%	10%	6%	2%	3%	3%	8%	6%	7%	3%	4%	3%	1%	4%	2%	1%	12%	7%	8%	8%	–	–	–	–	–
21	1%	1%	7%	3%	10%	12%	8%	6%	3%	6%	1%	2%	7%	5%	6%	4%	8%	2%	2%	3%	5%	–	–	–	–
22	3%	5%	2%	7%	1%	3%	9%	5%	4%	1%	4%	8%	2%	2%	7%	4%	3%	8%	11%	7%	3%	2%	–	–	–
23	5%	4%	5%	2%	3%	1%	2%	8%	1%	3%	4%	1%	7%	2%	4%	8%	7%	7%	2%	3%	6%	11%	5%	–	–
24	5%	7%	3%	1%	2%	5%	2%	11%	5%	4%	4%	1%	7%	3%	3%	9%	1%	2%	4%	1%	6%	6%	1%	8%	–

Table 4 (continued)

Number of classes	Class																								
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
25	1%	1%	1%	4%	2%	3%	3%	6%	3%	5%	6%	7%	1%	5%	5%	4%	2%	9%	2%	5%	6%	7%	3%	8%	1%

Italics cells indicate profile for which the probability of assignment is less than 5%

Table 5 Latent class model estimates for Argentina

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−10,364.72	595	21,317.09	21,031.32	21,407.09	12,461.13	–	1	–	–	–	–
Model 2	*−9311.35*	*504*	*19,804.52*	*19,229.82*	*19,985.52*	*10,354.38*	*0.92*	*0.36*	*0.64*	–	–	–
Model 3	−9039.32	413	19,854.63	18,991	20,126.63	9810.32	0.88	0.46	0.33	0.21	–	–
Model 4	−8850.68	322	20,071.53	18,918.96	20,434.53	9433.04	0.82	0.21	0.28	0.29	0.22	–
Model 5	−8717.49	231	20,399.33	18,957.82	20,853.33	9166.66	0.76	0.11	0.19	0.3	0.16	0.24

Italic row indicates best-fitting model. Data drawn from World Values Survey

Table 6 Latent class model estimates for Australia

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−23,692.71	1235.00	48,032.45	47,746.56	48,122.45	28,540.82	–	1.00	–	–	–	–
Model 2	−22,312.04	1144.00	45,925.33	45,350.37	46,106.33	25,779.49	0.87	0.41	0.59	–	–	–
Model 3	*−21,867.69*	*1053.00*	*45,690.84*	*44,826.82*	*45,962.84*	*24,890.78*	*0.84*	*0.16*	*0.52*	*0.31*	–	–
Model 4	−21,546.94	962.00	45,703.55	44,550.46	46,066.55	24,249.28	0.83	0.19	0.16	0.24	0.41	–
Model 5	−21,364.42	871.00	45,992.71	44,550.56	46,446.71	23,884.23	0.82	0.40	0.08	0.19	0.22	0.11

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 7 Latent class model estimates for Brazil

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−24,749.32	1174.00	50,141.42	49,855.54	50,231.42	31,738.84	–	1.00	–	–	–	–
Model 2	−22,900.87	1083.00	47,094.45	46,519.51	47,275.45	28,041.94	0.89	0.43	0.57	–	–	–
Model 3	*−22,466.90*	*992.00*	*46,876.43*	*46,012.43*	*47,148.43*	*27,173.99*	*0.85*	*0.35*	*0.34*	*0.32*	–	–
Model 4	−22,204.48	901.00	47,001.52	45,848.46	47,364.52	26,649.16	0.83	0.30	0.12	0.22	0.36	–
Model 5	−21,963.93	810.00	47,170.35	45,728.23	47,624.35	26,168.07	0.86	0.26	0.22	0.10	0.27	0.16

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 8 Latent class model estimates for Bulgaria

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−12,594.26	578.00	25,773.90	25,488.14	25,863.90	16,784.51	–	1.00	–	–	–	–
Model 2	−11,551.83	487.00	24,280.94	23,706.25	24,461.94	14,699.66	0.90	0.47	0.53	–	–	–
Model 3	*−10,967.09*	*396.00*	*23,703.35*	*22,839.73*	*23,975.35*	*13,530.18*	*0.93*	*0.42*	*0.41*	*0.17*	–	–
Model 4	−10,683.61	305.00	23,728.27	22,575.72	24,091.27	12,963.21	0.90	0.15	0.41	0.35	0.10	–
Model 5	−10,513.09	214.00	23,979.13	22,537.65	24,433.13	12,622.18	0.80	0.32	0.10	0.14	0.06	0.39

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 9 Latent class model estimates for Canada

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−32,879.99	1642.00	66,431.11	66,145.19	66,521.11	40,022.37	–	1.00	–	–	–	–
Model 2	−31,244.06	1551.00	63,837.84	63,262.82	64,018.84	36,750.51	0.83	0.52	0.49	–	–	–
Model 3	*−30,683.04*	*1460.00*	*63,394.40*	*62,530.28*	*63,666.40*	*35,628.48*	*0.80*	*0.29*	*0.29*	*0.42*	–	–
Model 4	−30,435.95	1369.00	63,578.81	62,425.59	63,941.81	35,134.30	0.78	0.28	0.30	0.20	0.23	–
Model 5	−30,211.65	1278.00	63,808.79	62,366.48	64,262.79	34,685.69	0.79	0.18	0.15	0.22	0.32	0.14

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 10 Latent class model estimates for Chile

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 14,651.34	679.00	29,900.75	29,614.96	29,990.75	19,345.73	–	1.00	–	–	–	–
Model 2	– 13,496.09	588.00	28,194.94	27,620.19	28,375.94	17,035.23	0.90	0.48	0.53	–	–	–
Model 3	*– 13,028.45*	*497.00*	*27,864.36*	*27,000.64*	*28,136.36*	*16,099.94*	*0.92*	*0.20*	*0.45*	*0.35*	–	–
Model 4	– 12,831.24	406.00	28,074.64	26,921.95	28,437.64	15,705.52	0.88	0.16	0.30	0.33	0.21	–
Model 5	– 12,646.12	315.00	28,309.10	26,867.45	28,763.10	15,335.28	0.87	0.21	0.16	0.18	0.17	0.28

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 11 Latent class model estimates for Cyprus

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 18,061.69	944.00	36,748.10	36,462.24	36,838.10	22,749.52	–	1.00	–	–	–	–
Model 2	– 16,574.24	853.00	34,404.84	33,829.96	34,585.84	19,774.61	0.88	0.42	0.58	–	–	–
Model 3	– 15,717.72	762.00	33,323.44	32,459.54	33,595.44	18,061.57	0.87	0.41	0.43	0.16	–	–
Model 4	*– 15,324.28*	*671.00*	*33,168.20*	*32,015.27*	*33,531.20*	*17,274.68*	*0.89*	*0.43*	*0.07*	*0.11*	*0.40*	–
Model 5	– 15,063.69	580.00	33,278.68	31,836.72	33,732.68	16,753.50	0.91	0.12	0.05	0.21	0.34	0.29

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 12 Latent class model estimates for Finland

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 17,474.04	858.00	35,564.96	35,279.13	35,654.96	21,998.19	–	1.00	–	–	–	–
Model 2	– 16,571.71	767.00	34,384.06	33,809.21	34,565.06	20,193.53	0.84	0.53	0.47	–	–	–
Model 3	*– 16,171.38*	*676.00*	*34,207.14*	*33,343.28*	*34,479.14*	*19,392.87*	*0.82*	*0.47*	*0.12*	*0.41*	–	–
Model 4	– 15,970.14	585.00	34,428.42	33,275.55	34,791.42	18,990.40	0.84	0.37	0.42	0.10	0.11	–
Model 5	– 15,822.54	494.00	34,756.95	33,315.07	35,210.95	18,695.19	0.82	0.32	0.12	0.13	0.38	0.05

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 13 Latent class model estimates for France

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 18,578.08	857.00	37,772.97	37,487.13	37,862.97	24,310.94	–	1.00	–	–	–	–
Model 2	– 17,444.10	766.00	36,128.65	35,553.80	36,309.65	22,042.97	0.88	0.48	0.52	–	–	–
Model 3	*– 17,020.90*	*675.00*	*35,905.89*	*35,042.04*	*36,177.89*	*21,196.57*	*0.86*	*0.34*	*0.35*	*0.31*	–	–
Model 4	– 16,735.21	584.00	35,958.16	34,805.29	36,321.16	20,625.18	0.87	0.32	0.33	0.23	0.13	–
Model 5	– 16,543.82	493.00	36,199.03	34,757.15	36,653.03	20,242.40	0.87	0.30	0.10	0.33	0.13	0.14

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 14 Latent class model estimates for Georgia

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 15,679.01	882.00	31,977.16	31,691.32	32,067.16	18,753.73	–	1.00	–	–	–	–
Model 2	– 14,034.86	791.00	29,314.89	28,740.04	29,495.89	15,465.44	0.93	0.37	0.63	–	–	–
Model 3	*– 13,463.85*	*700.00*	*28,798.89*	*27,935.02*	*29,070.89*	*14,323.41*	*0.91*	*0.37*	*0.14*	*0.49*	–	–
Model 4	– 13,179.11	609.00	28,855.43	27,702.54	29,218.43	13,753.93	0.95	0.38	0.13	0.23	0.27	–
Model 5	– 12,980.97	518.00	29,085.16	27,643.26	29,539.16	13,357.64	NaN	0.09	0.21	0.17	0.15	0.38

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 15 Latent class model estimates for Ghana

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−25,253.35	1248.00	51,147.34	50,864.63	51,236.34	31,691.73	–	1.00	–	–	–	–
Model 2	−23,918.44	1158.00	49,125.36	48,556.75	49,304.36	29,021.91	0.83	0.42	0.58	–	–	–
Model 3	*−23,420.30*	*1068.00*	*48,776.90*	*47,922.41*	*49,045.90*	*28,025.62*	*0.83*	*0.43*	*0.26*	*0.31*	–	–
Model 4	−23,176.54	978.00	48,937.23	47,796.85	49,296.23	27,538.12	0.85	0.27	0.43	0.20	0.11	–
Model 5	−22,964.75	888.00	49,161.48	47,735.20	49,610.48	27,114.53	0.80	0.05	0.19	0.26	0.36	0.14

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 16 Latent class model estimates for Hungary

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 15,674.76	794.00	31,960.13	31,674.31	32,050.13	19,684.55	–	1.00	–	–	–	–
Model 2	– 14,377.84	703.00	29,983.66	29,408.84	30,164.66	17,090.69	0.89	0.57	0.44	–	–	–
Model 3	*– 13,772.25*	*612.00*	*29,389.87*	*28,526.05*	*29,661.87*	*15,879.51*	*0.93*	*0.42*	*0.48*	*0.11*	–	–
Model 4	– 13,493.12	521.00	29,449.01	28,296.19	29,812.01	15,321.27	0.95	0.09	0.22	0.33	0.35	–
Model 5	– 13,321.61	430.00	29,723.37	28,281.56	30,177.37	14,978.25	1.00	0.32	0.23	0.08	0.32	0.05

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 17 Latent class model estimates for India

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−9119.07	938.00	18,862.32	18,576.47	18,952.32	6667.62	–	1.00	–	–	–	–
Model 2	*−8491.49*	*847.00*	*18,238.28*	*17,663.41*	*18,419.28*	*5412.46*	*0.75*	*0.59*	*0.41*	–	–	–
Model 3	−8259.65	756.00	18,405.73	17,541.82	18,677.73	4948.79	0.78	0.37	0.09	0.54	–	–
Model 4	−8060.26	665.00	18,638.06	17,485.13	19,001.06	4550.00	0.81	0.50	0.06	0.05	0.39	–
Model 5	−7916.71	574.00	18,982.07	17,540.11	19,436.07	4262.89	0.81	0.05	0.21	0.23	0.45	0.06

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 18 Latent class model estimates for Indonesia

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−27,951.91	1450.00	56,564.38	56,278.47	56,654.38	34,502.36	–	1.00	–	–	–	–
Model 2	−25,463.78	1359.00	52,256.01	51,681.02	52,437.01	29,526.09	0.91	0.45	0.55	–	–	–
Model 3	−24,843.85	1268.00	51,684.06	50,819.98	51,956.06	28,286.24	0.90	0.41	0.45	0.14	–	–
Model 4	*−24,468.54*	*1177.00*	*51,601.34*	*50,448.17*	*51,964.34*	*27,535.62*	*0.87*	*0.35*	*0.09*	*0.21*	*0.35*	–
Model 5	−24,211.21	1086.00	51,754.57	50,312.32	52,208.57	27,020.96	0.79	0.33	0.10	0.05	0.32	0.20

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 19 Latent class model estimates for Japan

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 12,695.86	612.00	25,981.57	25,695.81	26,071.57	16,323.24	–	1.00	–	–	–	–
Model 2	– 11,759.24	521.00	24,704.74	24,130.03	24,885.74	14,450.00	0.90	0.49	0.51	–	–	–
Model 3	*– 11,452.37*	*430.00*	*24,687.42*	*23,823.76*	*24,959.42*	*13,836.27*	*0.87*	*0.41*	*0.19*	*0.40*	–	–
Model 4	– 11,242.89	339.00	24,864.85	23,712.25	25,227.85	13,417.29	0.83	0.12	0.20	0.36	0.32	–
Model 5	– 11,079.75	248.00	25,134.98	23,693.43	25,588.98	13,091.01	0.86	0.35	0.17	0.13	0.04	0.30

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 20 Latent class model estimates for Mali

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 19,669.27	992.00	39,967.34	39,681.48	40,057.34	25,785.01	–	1.00	–	–	–	–
Model 2	– 17,200.73	901.00	35,666.03	35,091.14	35,847.03	20,847.93	0.94	0.54	0.46	–	–	–
Model 3	– 16,569.66	810.00	35,039.67	34,175.74	35,311.67	19,585.79	0.90	0.24	0.33	0.43	–	–
Model 4	*– 16,190.45*	*719.00*	*34,917.01*	*33,764.05*	*35,280.01*	*18,827.36*	*0.89*	*0.23*	*0.20*	*0.43*	*0.15*	–
Model 5	– 15,874.75	628.00	34,921.41	33,479.41	35,375.41	18,195.97	0.91	0.10	0.25	0.41	0.14	0.11

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 21 Latent class model estimates for Mexico

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−26,570.01	1215.00	53,785.67	53,499.78	53,875.67	35,128.19	–	1.00	–	–	–	–
Model 2	−23,845.16	1124.00	48,988.81	48,413.86	49,169.81	29,678.50	0.94	0.39	0.61	–	–	–
Model 3	−23,141.00	1033.00	48,233.31	47,369.30	48,505.31	28,270.17	0.91	0.32	0.37	0.31	–	–
Model 4	−22,661.12	942.00	47,926.39	46,773.31	48,289.39	27,310.42	0.93	0.30	0.24	0.19	0.27	–
Model 5	*−22,333.73*	*851.00*	*47,924.43*	*46,482.29*	*48,378.43*	*26,655.63*	*0.91*	*0.21*	*0.18*	*0.20*	*0.14*	*0.27*

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 22 Latent class model estimates for Moldova

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 17,121.67	789.00	34,853.44	34,567.62	34,943.44	22,609.10	–	1.00	–	–	–	–
Model 2	– 16,165.03	698.00	33,557.03	32,982.21	33,738.03	20,695.82	0.86	0.55	0.45	–	–	–
Model 3	*– 15,678.09*	*607.00*	*33,200.00*	*32,336.19*	*33,472.00*	*19,721.93*	*0.87*	*0.20*	*0.45*	*0.35*	–	–
Model 4	– 15,482.47	516.00	33,425.63	32,272.82	33,788.63	19,330.69	0.89	0.45	0.10	0.26	0.20	–
Model 5	– 15,285.18	425.00	33,647.92	32,206.12	34,101.92	18,936.11	0.88	0.24	0.15	0.10	0.41	0.10

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 23 Latent class model estimates for Netherlands

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 16,817.01	826.00	34,247.83	33,962.00	34,337.83	21,231.08	–	1.00	–	–	–	–
Model 2	– 15,575.87	735.00	32,386.16	31,811.33	32,567.16	18,748.79	0.90	0.51	0.49	–	–	–
Model 3	*– 15,228.72*	*644.00*	*32,312.48*	*31,448.64*	*32,584.48*	*18,054.48*	*0.86*	*0.43*	*0.29*	*0.28*	–	–
Model 4	– 15,021.18	553.00	32,518.03	31,365.19	32,881.03	17,639.41	0.85	0.24	0.41	0.29	0.07	–
Model 5	– 14,852.64	462.00	32,801.57	31,359.72	33,255.57	17,302.33	0.84	0.20	0.13	0.32	0.24	0.11

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 24 Latent class model estimates for Norway

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 17,307.70	894.00	35,235.65	34,949.80	35,325.65	21,097.04	–	1.00	–	–	–	–
Model 2	– 16,567.27	803.00	34,381.92	33,807.06	34,562.92	19,616.18	0.81	0.34	0.66	–	–	–
Model 3	*– 16,117.21*	*712.00*	*34,108.94*	*33,245.07*	*34,380.94*	*18,716.06*	*0.82*	*0.15*	*0.49*	*0.37*	–	–
Model 4	– 15,841.85	621.00	34,185.36	33,032.47	34,548.36	18,165.34	0.84	0.35	0.08	0.44	0.13	–
Model 5	– 15,618.84	530.00	34,366.48	32,924.56	34,820.48	17,719.32	0.75	0.34	0.14	0.32	0.08	0.13

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 25 Latent class model estimates for Peru

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−23,608.57	1128.00	47,856.59	47,570.71	47,946.59	30,238.32	–	1.00	–	–	–	–
Model 2	−21,814.08	1037.00	44,914.16	44,339.23	45,095.16	26,649.34	0.89	0.52	0.48	–	–	–
Model 3	*−21,256.46*	*946.00*	*44,445.46*	*43,581.48*	*44,717.46*	*25,534.09*	*0.86*	*0.43*	*0.27*	*0.30*	–	–
Model 4	−20,958.70	855.00	44,496.51	43,343.47	44,859.51	24,938.59	0.88	0.10	0.29	0.22	0.39	–
Model 5	−20,684.75	764.00	44,595.16	43,153.07	45,049.16	24,390.69	0.86	0.09	0.10	0.35	0.26	0.20

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 26 Latent class model estimates for Poland

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 14,054.84	687.00	28,708.68	28,422.88	28,798.68	17,998.89	–	1.00	–	–	–	–
Model 2	– 12,988.09	596.00	27,180.82	26,606.05	27,361.82	15,865.38	0.90	0.43	0.57	–	–	–
Model 3	*– 12,606.98*	*505.00*	*27,024.23*	*26,160.50*	*27,296.23*	*15,103.15*	*0.90*	*0.17*	*0.46*	*0.37*	–	–
Model 4	– 12,388.50	414.00	27,192.92	26,040.22	27,555.92	14,666.19	0.88	0.19	0.10	0.39	0.32	–
Model 5	– 12,234.07	323.00	27,489.71	26,048.05	27,943.71	14,357.35	0.86	0.22	0.24	0.24	0.11	0.20

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 27 Latent class model estimates for Romania

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 19,285.35	1250.00	39,218.74	38,932.85	39,308.74	20,679.23	–	1.00	–	–	–	–
Model 2	– 17,756.30	1159.00	36,815.88	36,240.92	36,996.88	17,621.13	0.88	0.32	0.68	–	–	–
Model 3	*– 17,309.79*	*1068.00*	*36,578.10*	*35,714.08*	*36,850.10*	*16,728.11*	*0.84*	*0.33*	*0.58*	*0.10*	–	–
Model 4	– 17,061.88	977.00	36,737.52	35,584.43	37,100.52	16,232.30	0.77	0.22	0.31	0.37	0.09	–
Model 5	– 16,851.05	886.00	36,971.09	35,528.93	37,425.09	15,810.63	0.82	0.33	0.08	0.37	0.04	0.18

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 28 Latent class model estimates for Russia

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 22,081.31	1397.00	44,820.02	44,534.12	44,910.02	24,581.95	–	1.00	–	–	–	–
Model 2	– 20,250.03	1306.00	41,822.18	41,247.19	42,003.18	20,919.39	0.88	0.67	0.33	–	–	–
Model 3	*– 19,788.91*	*1215.00*	*41,564.64*	*40,700.57*	*41,836.64*	*19,997.14*	*0.86*	*0.15*	*0.28*	*0.58*	–	–
Model 4	– 19,521.56	1124.00	41,694.65	40,541.51	42,057.65	19,462.44	0.85	0.11	0.26	0.06	0.57	–
Model 5	– 19,362.36	1033.00	42,040.97	40,598.74	42,494.97	19,144.05	0.82	0.35	0.11	0.06	0.16	0.33

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 29 Latent class model estimates for Slovenia

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 14,435.79	702.00	29,472.29	29,186.49	29,562.29	18,445.86	–	1.00	–	–	–	–
Model 2	– 13,445.73	611.00	28,099.55	27,524.78	28,280.55	16,465.73	0.87	0.49	0.52	–	–	–
Model 3	*– 13,068.64*	*520.00*	*27,952.76*	*27,089.02*	*28,224.76*	*15,711.56*	*0.86*	*0.24*	*0.40*	*0.36*	–	–
Model 4	– 12,875.42	429.00	28,173.70	27,020.98	28,536.70	15,325.11	0.88	0.21	0.41	0.13	0.25	–
Model 5	– 12,683.87	338.00	28,398.00	26,956.30	28,852.00	14,942.02	0.88	0.14	0.22	0.09	0.25	0.30

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 30 Latent class model estimates for South Africa

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−48,308.23	2307.00	97,316.84	97,030.89	97,406.84	60,059.77	–	1.00	–	–	–	–
Model 2	−45,304.74	2216.00	92,018.01	91,442.93	92,199.01	54,052.78	0.87	0.51	0.49	–	–	–
Model 3	−44,008.18	2125.00	90,133.05	89,268.85	90,405.05	51,459.66	0.86	0.30	0.30	0.40	–	–
Model 4	*−43,433.11*	*2034.00*	*89,691.08*	*88,537.75*	*90,054.08*	*50,309.53*	*0.86*	*0.12*	*0.40*	*0.28*	*0.20*	–
Model 5	−43,068.97	1943.00	89,670.95	88,228.49	90,124.95	49,581.24	0.85	0.15	0.12	0.20	0.18	0.36

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 31 Latent class model estimates for Spain

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 17,304.71	889.00	35,229.20	34,943.36	35,319.20	21,866.26	–	1.00	–	–	–	–
Model 2	– 15,480.15	798.00	32,206.76	31,631.90	32,387.76	18,217.14	0.93	0.55	0.45	–	–	–
Model 3	*– 14,767.75*	*707.00*	*31,408.63*	*30,544.75*	*31,680.63*	*16,792.34*	*0.91*	*0.18*	*0.49*	*0.34*	–	–
Model 4	– 14,486.62	616.00	31,473.06	30,320.17	31,836.06	16,230.10	0.90	0.16	0.07	0.32	0.44	–
Model 5	– 14,261.73	525.00	31,649.94	30,208.03	32,103.94	15,780.31	0.87	0.24	0.24	0.17	0.29	0.06

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 32 Latent class model estimates for Sweden

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 12,982.07	850.00	26,538.66	26,271.89	26,622.66	13,421.52	–	1.00	–	–	–	–
Model 2	*– 12,392.42*	*765.00*	*25,940.72*	*25,403.99*	*26,109.72*	*12,242.22*	*0.79*	*0.29*	*0.72*	–	–	–
Model 3	– 12,117.09	680.00	25,971.41	25,164.72	26,225.41	11,691.55	0.78	0.51	0.22	0.28	–	–
Model 4	– 11,956.85	595.00	26,232.28	25,155.64	26,571.28	11,371.07	0.81	0.20	0.25	0.40	0.15	–
Model 5	– 11,841.74	510.00	26,583.41	25,236.82	27,007.41	11,140.84	0.79	0.18	0.32	0.17	0.09	0.23

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 33 Latent class model estimates for Switzerland

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−17,407.96	993.00	35,444.79	35,158.93	35,534.79	19,979.35	–	1.00	–	–	–	–
Model 2	−16,333.22	902.00	33,931.17	33,356.28	34,112.17	17,829.87	0.86	0.38	0.62	–	–	–
Model 3	*−15,976.89*	*811.00*	*33,854.37*	*32,990.44*	*34,126.37*	*17,117.22*	*0.84*	*0.35*	*0.58*	*0.08*	–	–
Model 4	−15,736.80	720.00	34,010.05	32,857.09	34,373.05	16,637.03	0.80	0.05	0.40	0.23	0.32	–
Model 5	−15,580.33	629.00	34,332.98	32,890.98	34,786.98	16,324.10	0.76	0.42	0.13	0.15	0.05	0.25

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 34 Latent class model estimates for Taiwan

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−20,705.59	1099.00	42,048.45	41,762.58	42,138.45	24,840.98	–	1.00	–	–	–	–
Model 2	−18,986.35	1008.00	39,254.33	38,679.40	39,435.33	21,402.50	0.91	0.49	0.51	–	–	–
Model 3	*−18,528.26*	*917.00*	*38,982.51*	*38,118.54*	*39,254.51*	*20,486.32*	*0.90*	*0.12*	*0.51*	*0.38*	–	–
Model 4	−18,288.32	826.00	39,147.00	37,993.97	39,510.00	20,006.45	0.88	0.49	0.13	0.28	0.10	–
Model 5	−18,088.61	735.00	39,391.94	37,949.87	39,845.94	19,607.03	0.85	0.21	0.15	0.09	0.22	0.33

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 35 Latent class model estimates for Thailand

								Class prevalence				
Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class1	Class2	Class3	Class4	Class5
Model 1	−31,613.61	1408.00	63,885.28	63,599.38	63,975.28	41,739.07	–	1.00	–	–	–	–
model 2	−28,891.30	1317.00	59,106.05	58,531.06	59,287.05	36,294.45	0.93	0.35	0.65	–	–	–
Model 3	−27,713.14	1226.00	57,415.11	56,551.04	57,687.11	33,938.13	0.92	0.28	0.56	0.17	–	–
Model 4	−27,070.33	1135.00	56,794.87	55,641.72	57,157.87	32,652.51	0.91	0.28	0.13	0.35	0.25	–
Model 5	*−26,634.79*	*1044.00*	*56,589.17*	*55,146.94*	*57,043.17*	*31,781.43*	*0.94*	*0.11*	*0.26*	*0.26*	*0.23*	*0.15*

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 36 Latent class model estimates for Trinidad

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 17,181.54	825.00	34,976.77	34,690.95	35,066.77	22,114.25	–	1.00	–	–	–	–
Model 2	*– 15,974.25*	*734.00*	*33,182.73*	*32,607.90*	*33,363.73*	*19,699.68*	*0.90*	*0.59*	*0.41*	–	–	–
Model 3	– 15,689.23	643.00	33,233.20	32,369.36	33,505.20	19,129.63	0.86	0.28	0.28	0.43	–	–
Model 4	– 15,480.64	552.00	33,436.55	32,283.71	33,799.55	18,712.45	0.85	0.27	0.26	0.19	0.28	–
Model 5	– 15,339.90	461.00	33,775.60	32,333.75	34,229.60	18,430.98	0.81	0.11	0.23	0.13	0.28	0.26

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 37 Latent class model estimates for Turkey

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 21,575.87	1109.00	43,789.76	43,503.89	43,879.76	27,144.56	–	1.00	–	–	–	–
Model 2	– 19,265.26	1018.00	39,813.67	39,238.74	39,994.67	22,523.34	0.94	0.52	0.48	–	–	–
Model 3	– 18,589.80	927.00	39,107.88	38,243.91	39,379.88	21,172.44	0.90	0.11	0.42	0.47	–	–
Model 4	*– 18,254.37*	*836.00*	*39,082.14*	*37,929.11*	*39,445.14*	*20,501.57*	*0.88*	*0.29*	*0.10*	*0.36*	*0.25*	–
Model 5	– 18,032.99	745.00	39,284.49	37,842.41	39,738.49	20,058.81	0.86	0.19	0.30	0.08	0.29	0.13

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 38 Latent class model estimates for Ukraine

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	− 13,200.33	587.00	26,987.24	26,701.48	27,077.24	17,772.25	–	1.00	–	–	–	–
Model 2	− 12,060.85	496.00	25,301.39	24,726.70	25,482.39	15,493.29	0.95	0.65	0.35	–	–	–
Model 3	*− 11,604.61*	*405.00*	*24,982.03*	*24,118.40*	*25,254.03*	*14,580.83*	*0.92*	*0.30*	*0.29*	*0.41*	–	–
Model 4	− 11,414.08	314.00	25,194.07	24,041.50	25,557.07	14,199.75	0.89	0.28	0.13	0.31	0.27	–
Model 5	− 11,252.15	223.00	25,463.33	24,021.83	25,917.33	13,875.91	0.91	0.25	0.18	0.24	0.25	0.09

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 39 Latent class model estimates for United Kingdom

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−16,852.34	773.00	34,313.13	34,027.31	34,403.13	22,041.76	–	1.00	–	–	–	–
Model 2	−16,040.71	682.00	33,305.05	32,730.24	33,486.05	20,418.48	0.85	0.49	0.51	–	–	–
Model 3	*−15,701.93*	*591.00*	*33,242.69*	*32,378.89*	*33,514.69*	*19,740.93*	*0.82*	*0.24*	*0.47*	*0.29*	–	–
Model 4	−15,522.27	500.00	33,498.57	32,345.77	33,861.57	19,381.60	0.78	0.19	0.26	0.22	0.33	–
Model 5	−15,364.84	409.00	33,798.91	32,357.13	34,252.91	19,066.75	0.79	0.30	0.17	0.28	0.11	0.14

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 40 Latent class model estimates for United States

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	−22,251.18	1081.00	45,138.27	44,852.40	45,228.27	28,510.75	–	1.00	–	–	–	–
Model 2	−20,661.22	990.00	42,601.31	42,026.39	42,782.31	25,330.83	0.91	0.30	0.70	–	–	–
Model 3	−19,825.01	899.00	41,571.87	40,707.90	41,843.87	23,658.41	0.90	0.36	0.49	0.15	–	–
Model 4	*−19,421.16*	*808.00*	*41,407.14*	*40,254.12*	*41,770.14*	*22,850.71*	*0.89*	*0.12*	*0.44*	*0.09*	*0.35*	–
Model 5	−19,122.85	717.00	41,453.49	40,011.43	41,907.49	22,254.10	0.95	0.07	0.11	0.43	0.05	0.33

Italics row indicates best-fitting model. Data drawn from World Values Survey

Table 41 Latent class model estimates for Uruguay

Model	Log-likelihood	Resid. DF	BIC	ABIC	cAIC	LR	Entropy	Class prevalence				
								Class1	Class2	Class3	Class4	Class5
Model 1	– 16,396.56	810.00	33,405.33	33,119.51	33,495.33	20,840.10	–	1.00	–	–	–	–
Model 2	– 14,947.32	719.00	31,125.87	30,551.04	31,306.87	17,941.62	0.93	0.60	0.40	–	–	–
Model 3	– 14,369.89	628.00	30,590.04	29,726.21	30,862.04	16,786.77	0.92	0.43	0.41	0.16	–	–
Model 4	*– 14,057.29*	*537.00*	*30,583.84*	*29,431.02*	*30,946.84*	*16,161.56*	*0.90*	*0.39*	*0.22*	*0.22*	*0.17*	–
Model 5	– 13,820.33	446.00	30,728.95	29,287.12	31,182.95	15,687.64	0.96	0.21	0.32	0.11	0.20	0.16

Italics row indicates best-fitting model. Data drawn from World Values Survey

Appendix C: Country-specific class plots

See Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40 and 41.

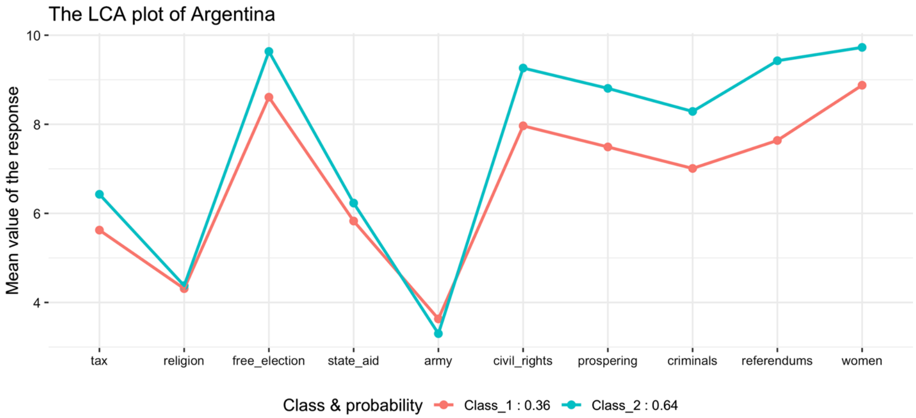

Fig. 5 Mean input values across classes for Argentina. *Notes*: Class solution corresponds to output estimates in Appendix Table 5

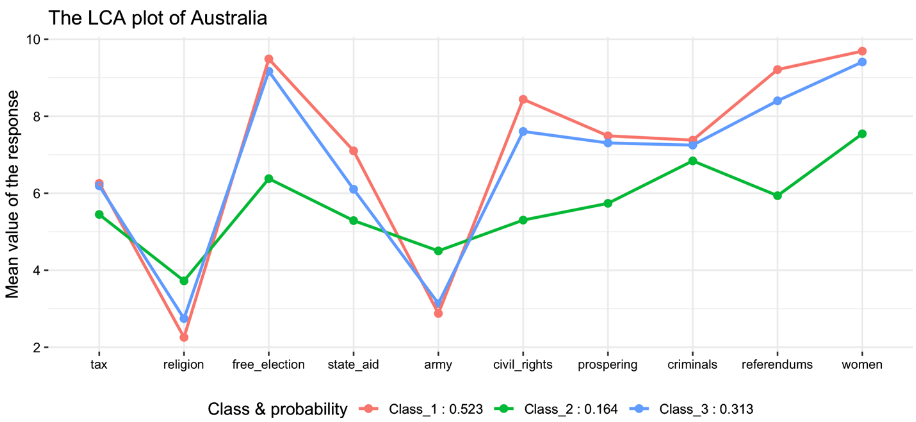

Fig. 6 Mean input values across classes for Australia. *Notes*: Class solution corresponds to output estimates in Appendix Table 6

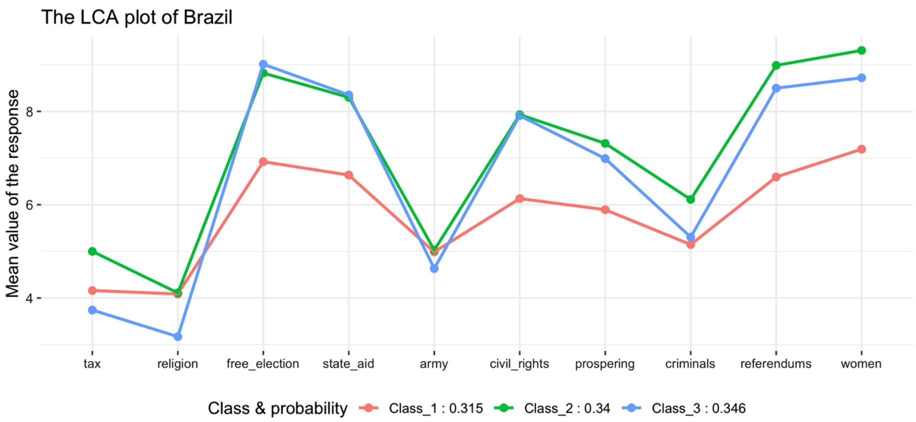

Fig. 7 Mean input values across classes for Brazil. *Notes*: Class solution corresponds to output estimates in Appendix Table 7

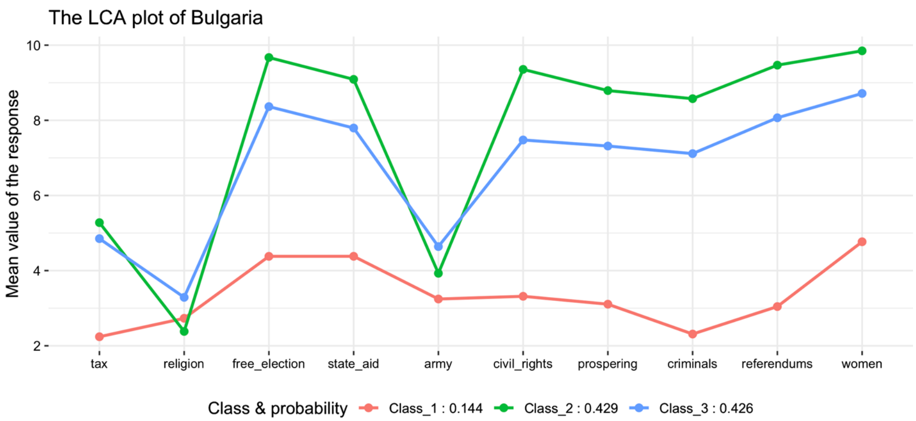

Fig. 8 Mean input values across classes for Bulgaria. *Notes*: Class solution corresponds to output estimates in Appendix Table 8

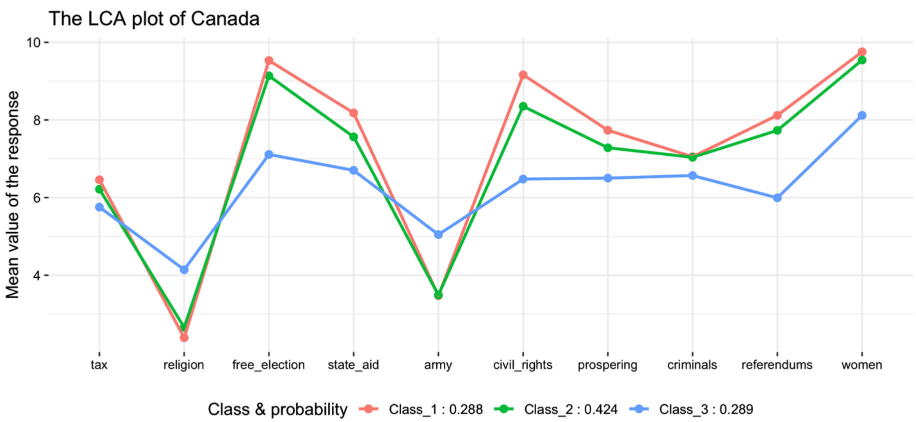

Fig. 9 Mean input values across classes for Canada. *Notes*: Class solution corresponds to output estimates in Appendix Table 9

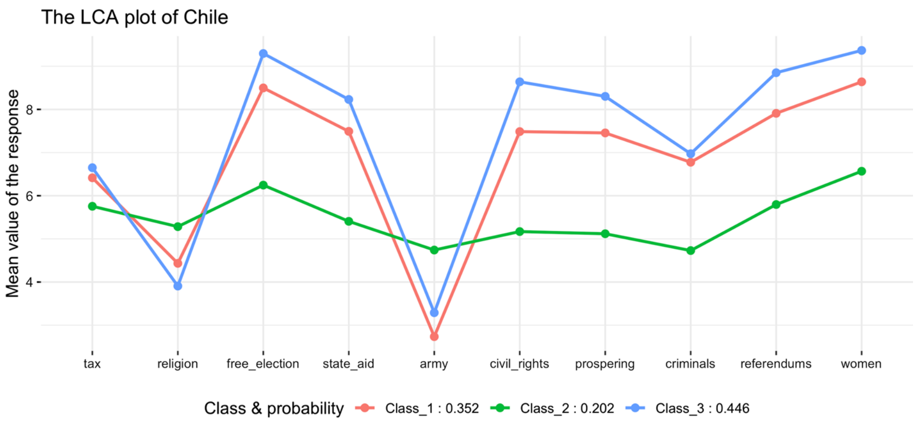

Fig. 10 Mean input values across classes for Chile. *Notes*: Class solution corresponds to output estimates in Appendix Table 10

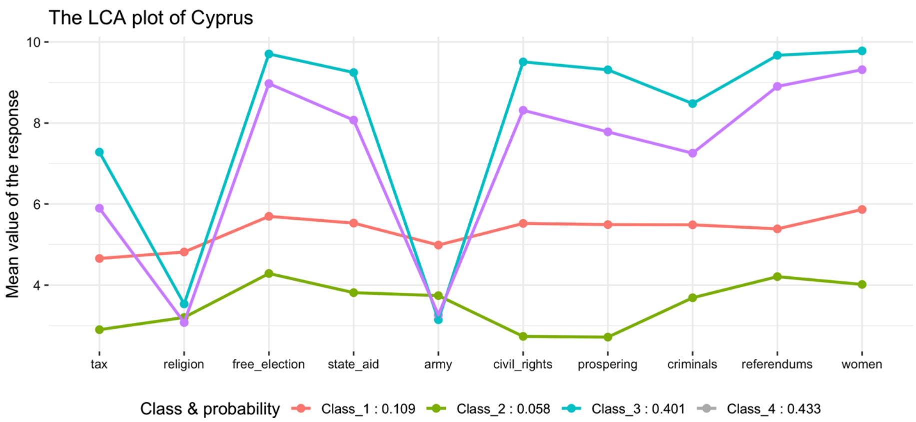

Fig. 11 Mean input values across classes for Cyprus. *Notes*: Class solution corresponds to output estimates in Appendix Table 11

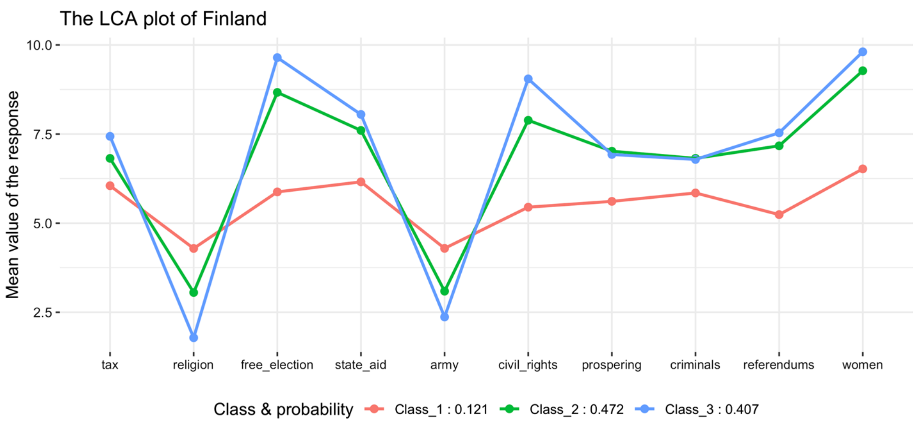

Fig. 12 Mean input values across classes for Finland. *Notes*: Class solution corresponds to output estimates in Appendix Table 12

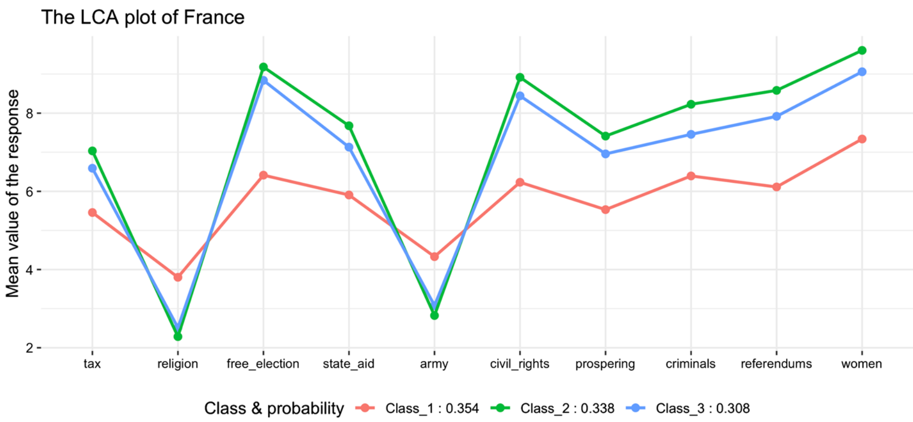

Fig. 13 Mean input values across classes for France. *Notes*: Class solution corresponds to output estimates in Appendix Table 13

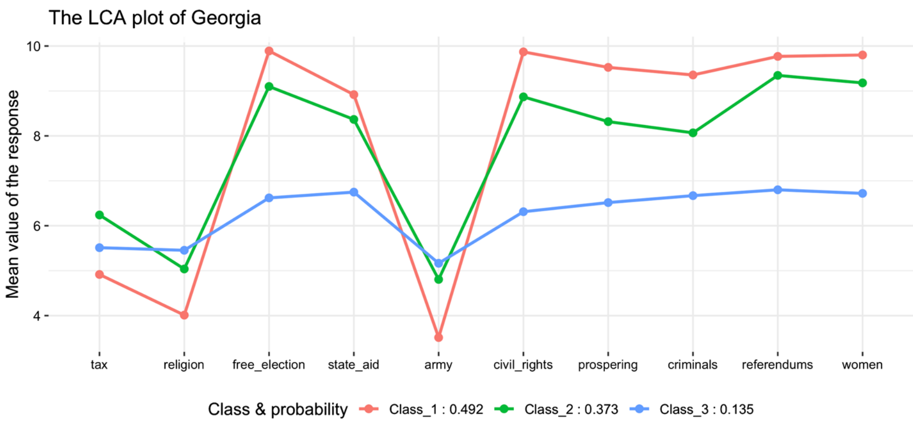

Fig. 14 Mean input values across classes for Georgia. *Notes*: Class solution corresponds to output estimates in Appendix Table 14

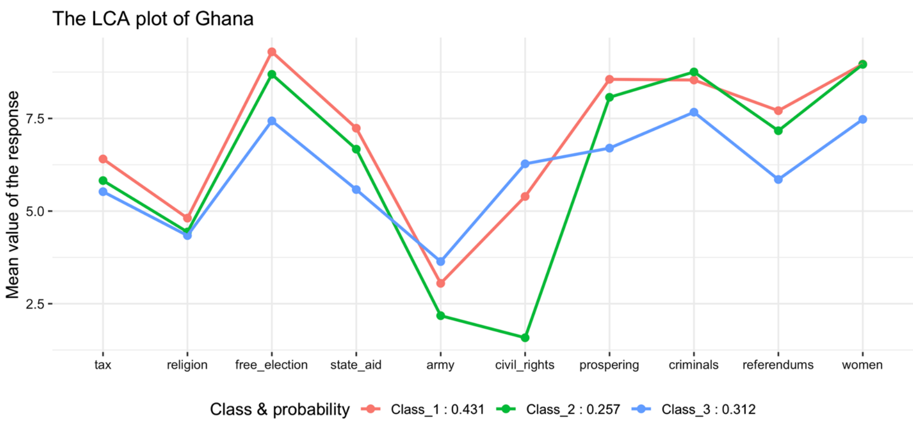

Fig. 15 Mean input values across classes for Ghana. *Notes*: Class solution corresponds to output estimates in Appendix Table 15

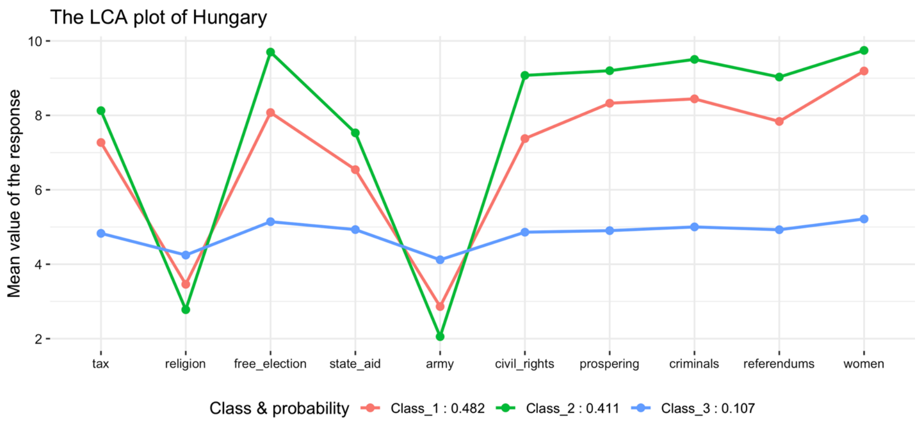

Fig. 16 Mean input values across classes for Hungary. *Notes*: Class solution corresponds to output estimates in Appendix Table 16

Fig. 17 Mean input values across classes for India. *Notes*: Class solution corresponds to output estimates in Appendix Table 17

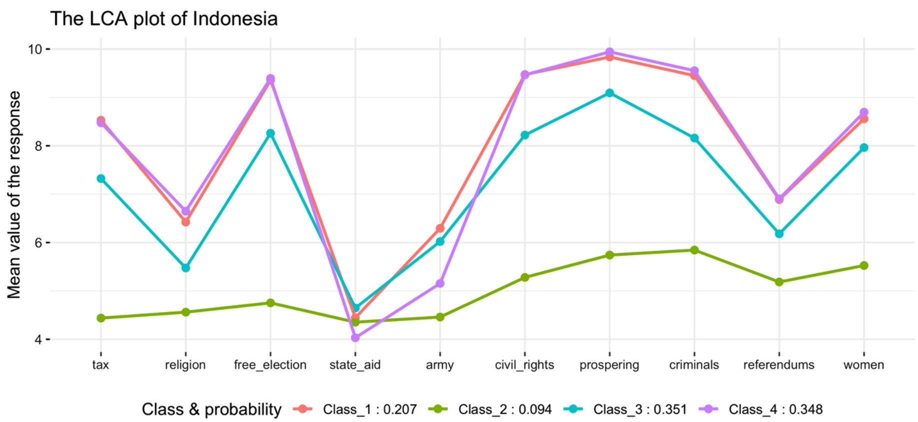

Fig. 18 Mean input values across classes for Indonesia. *Notes*: Class solution corresponds to output estimates in Appendix Table 18

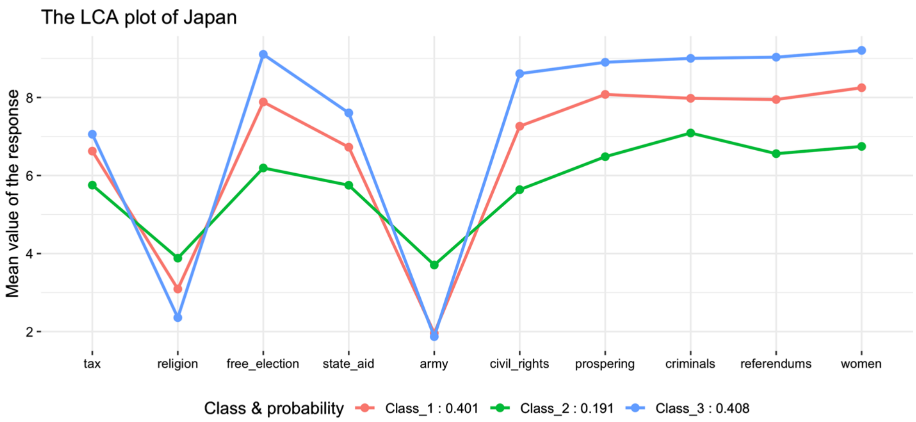

Fig. 19 Mean input values across classes for Japan. *Notes*: Class solution corresponds to output estimates in Appendix Table 19

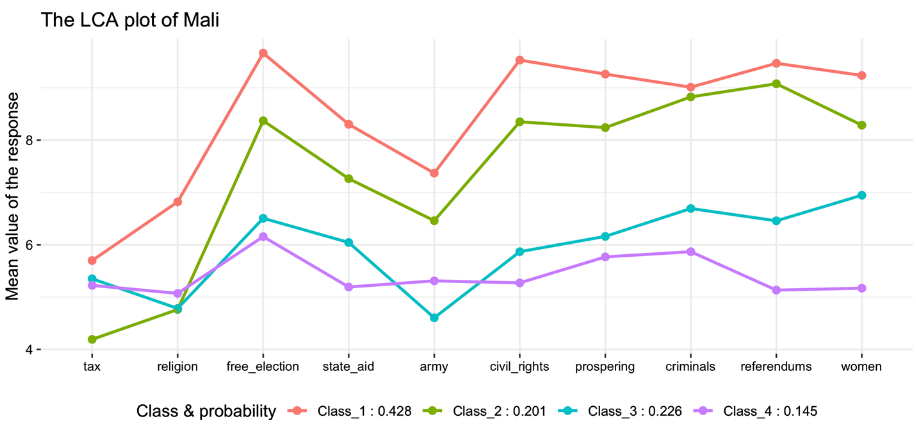

Fig. 20 Mean input values across classes for Mali. *Notes*: Class solution corresponds to output estimates in Appendix Table 20

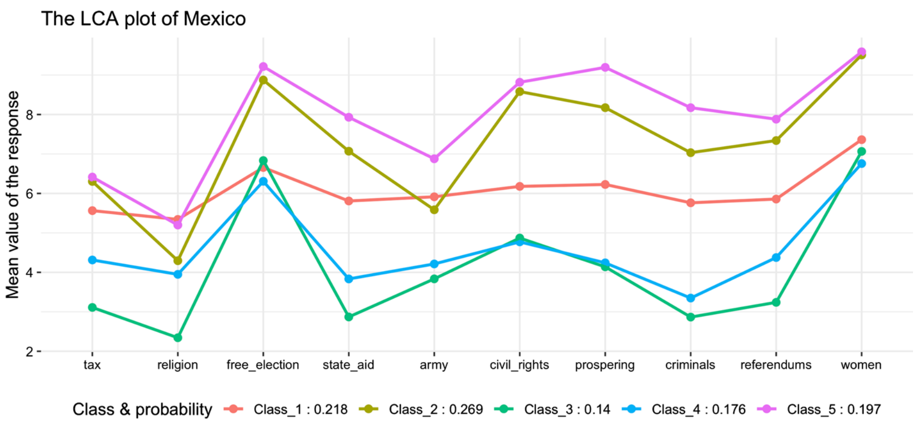

Fig. 21 Mean input values across classes for Mexico. *Notes*: Class solution corresponds to output estimates in Appendix Table 21

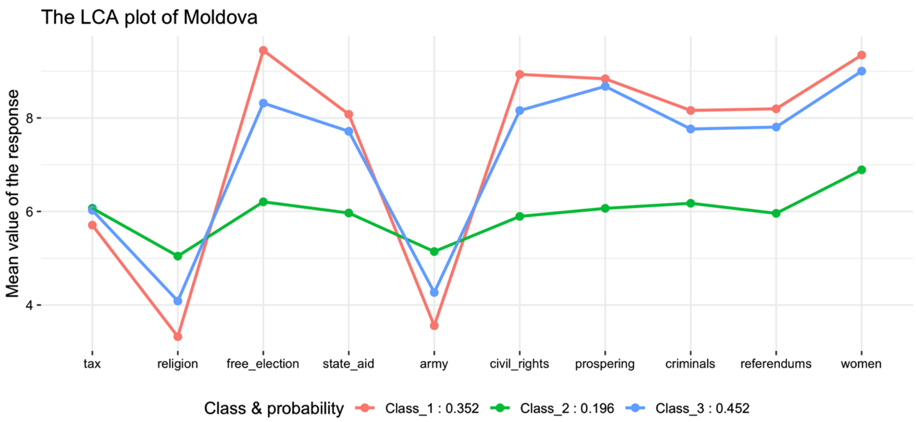

Fig. 22 Mean input values across classes for Moldova. *Notes*: Class solution corresponds to output estimates in Appendix Table 22

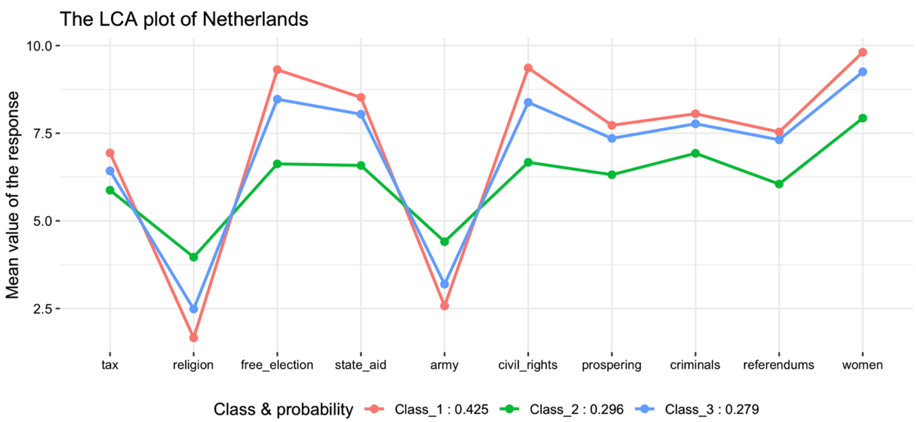

Fig. 23 Mean input values across classes for Netherlands. *Notes*: Class solution corresponds to output estimates in Appendix Table 23

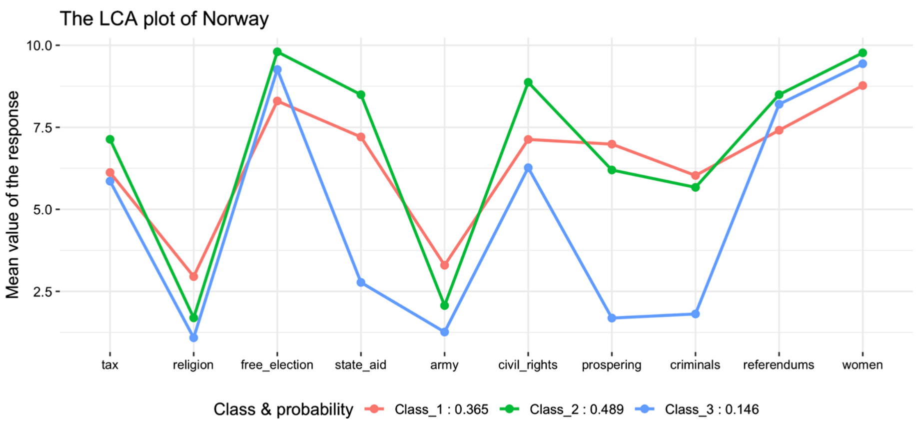

Fig. 24 Mean input values across classes for Norway. *Notes*: Class solution corresponds to output estimates in Appendix Table 24

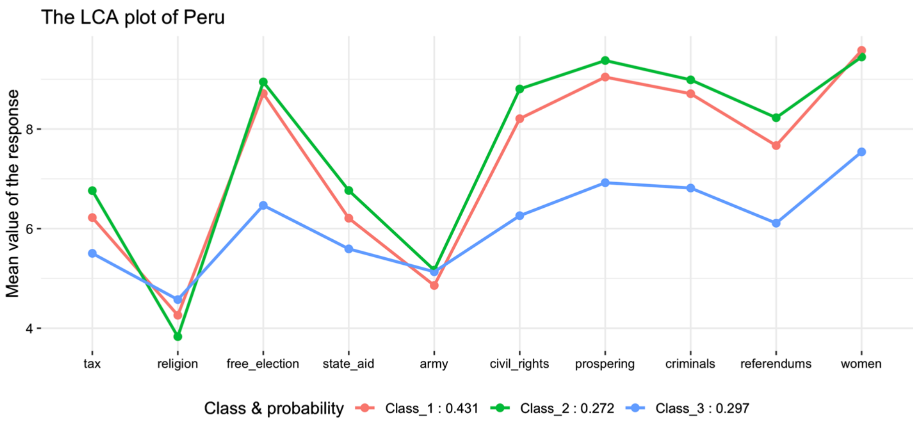

Fig. 25 Mean input values across classes for Peru. *Notes*: Class solution corresponds to output estimates in Appendix Table 25

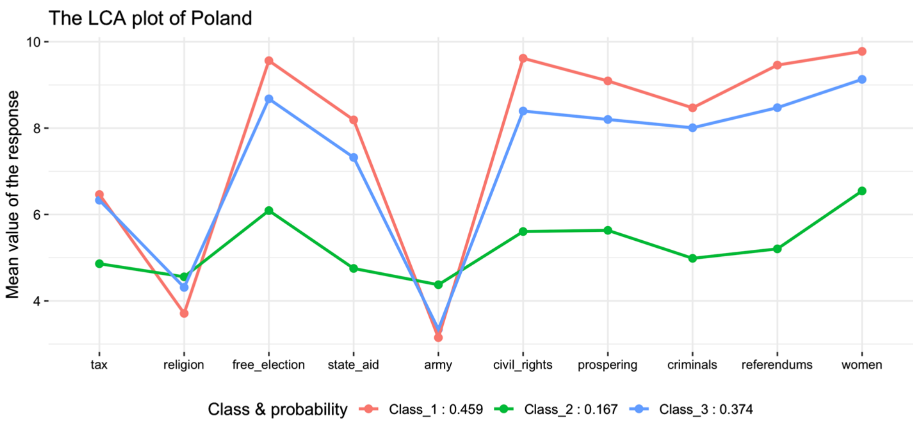

Fig. 26 Mean input values across classes for Poland. *Notes*: Class solution corresponds to output estimates in Appendix Table 26

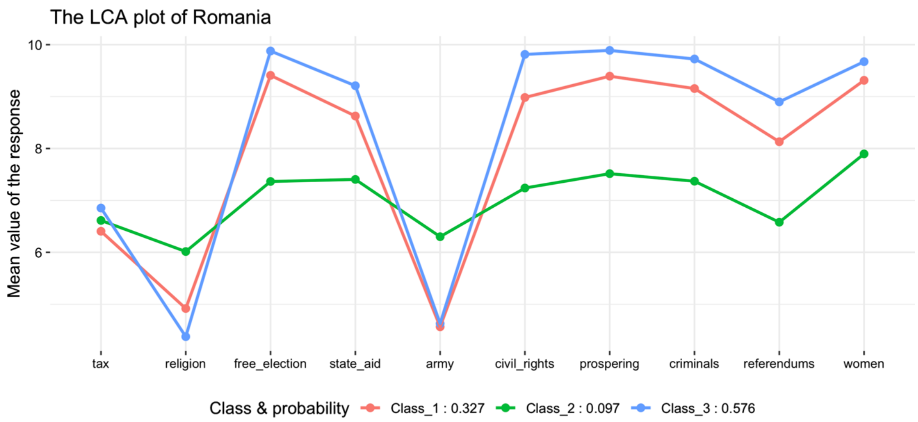

Fig. 27 Mean input values across classes for Romania. *Notes*: Class solution corresponds to output estimates in Appendix Table 27

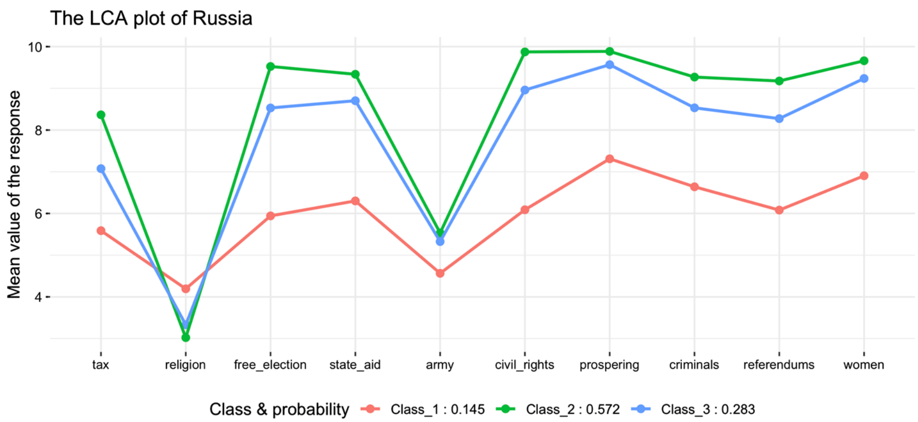

Fig. 28 Mean input values across classes for Russia. *Notes*: Class solution corresponds to output estimates in Appendix Table 28

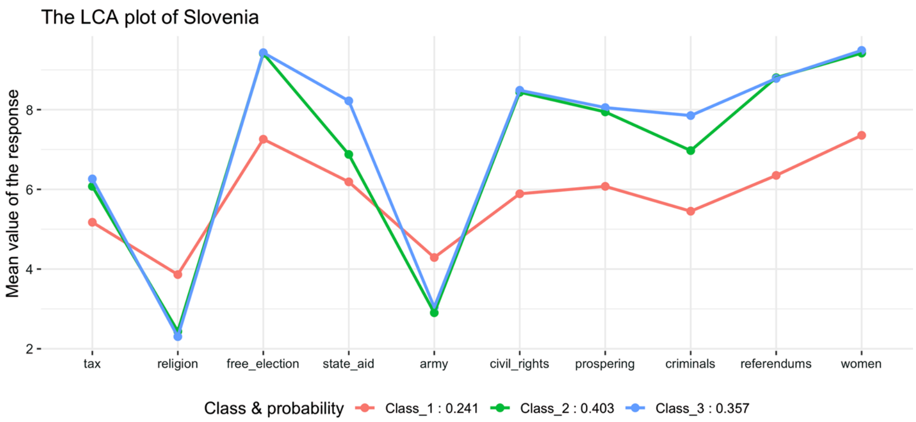

Fig. 29 Mean input values across classes for Slovenia. *Notes*: Class solution corresponds to output estimates in Appendix Table 29

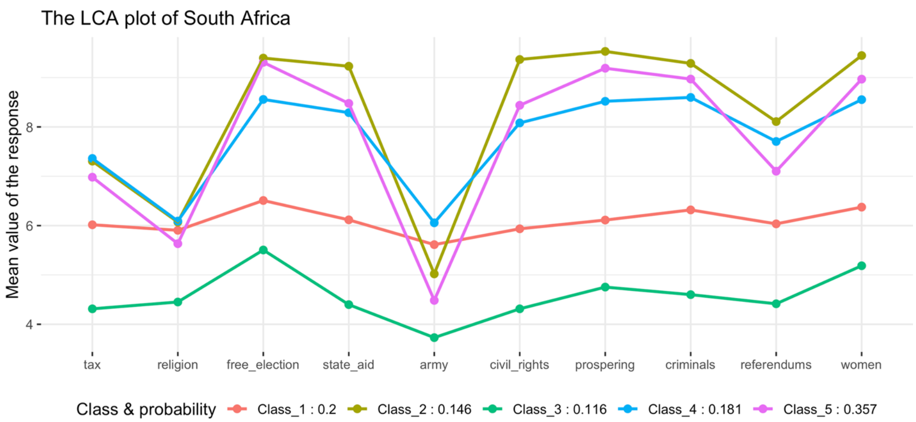

Fig. 30 Mean input values across classes for South Africa. *Notes*: Class solution corresponds to output estimates in Appendix Table 30

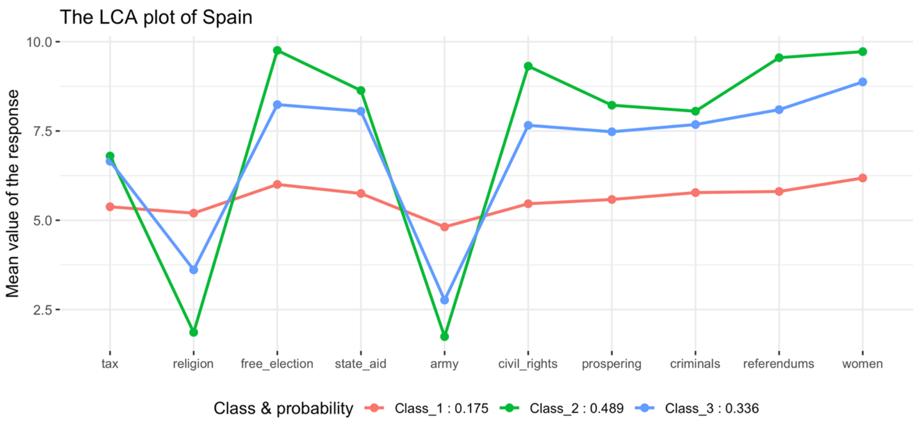

Fig. 31 Mean input values across classes for Spain. *Notes*: Class solution corresponds to output estimates in Appendix Table 31

Fig. 32 Mean input values across classes for Sweden. *Notes*: Class solution corresponds to output estimates in Appendix Table 32

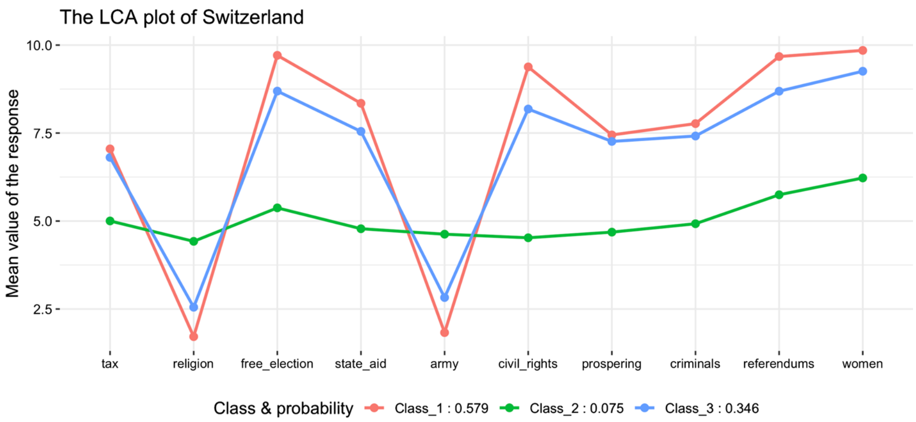

Fig. 33 Mean input values across classes for Switzerland. *Notes*: Class solution corresponds to output estimates in Appendix Table 33

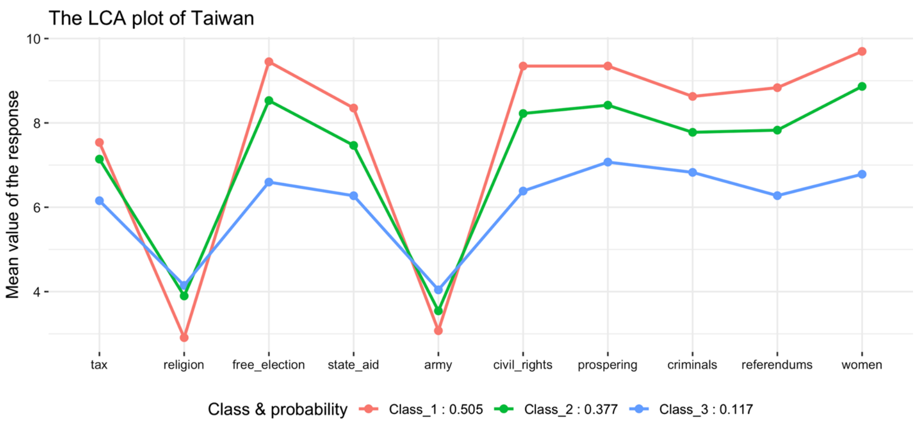

Fig. 34 Mean input values across classes for Taiwan. *Notes*: Class solution corresponds to output estimates in Appendix Table 34

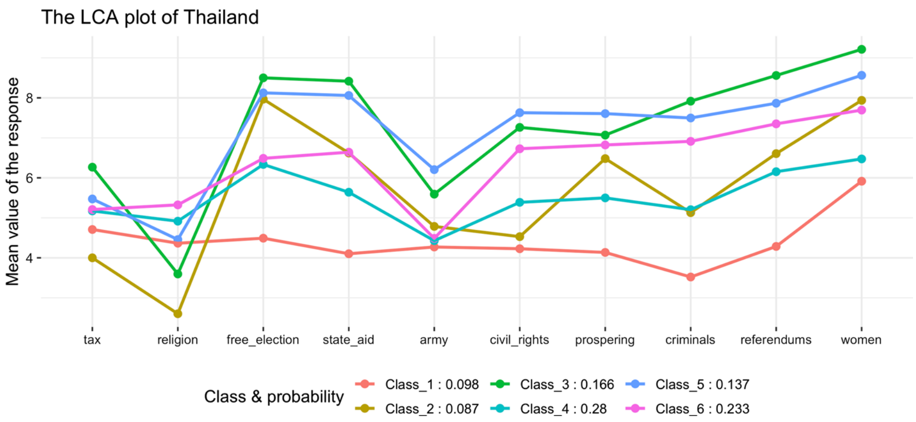

Fig. 35 Mean input values across classes for Thailand. *Notes*: Class solution corresponds to output estimates in Appendix Table 35

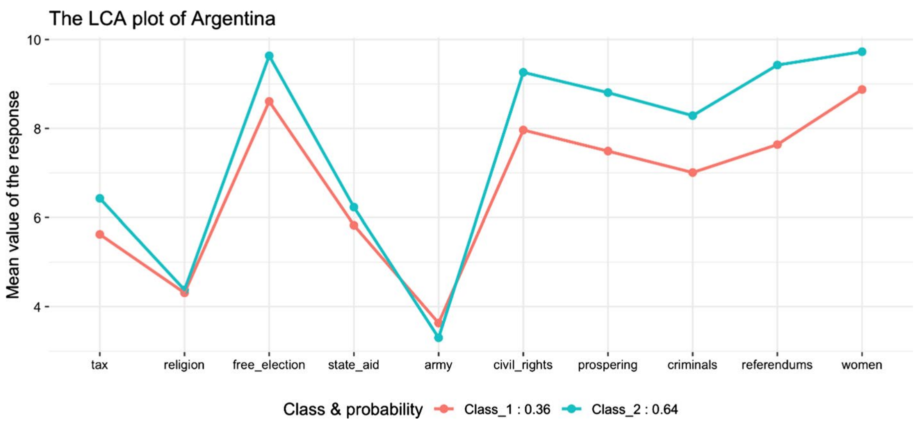

Fig. 36 Mean input values across classes for Trinidad and Tobago. *Notes*: Class solution corresponds to output estimates in Appendix Table 36

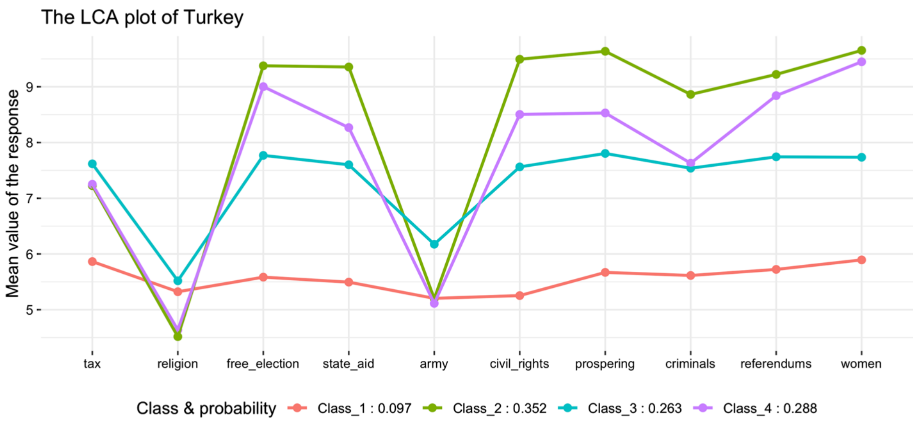

Fig. 37 Mean input values across classes for Turkey. *Notes*: Class solution corresponds to output estimates in Appendix Table 37

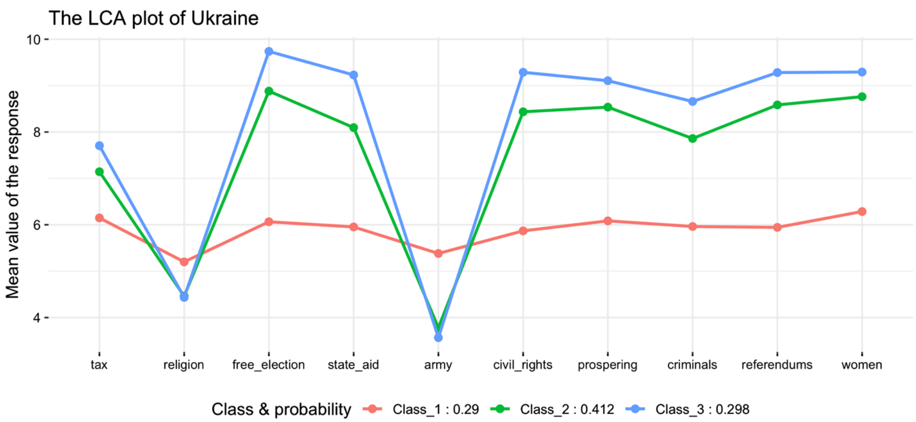

Fig. 38 Mean input values across classes for Ukraine. *Notes*: Class solution corresponds to output estimates in Appendix Table 38

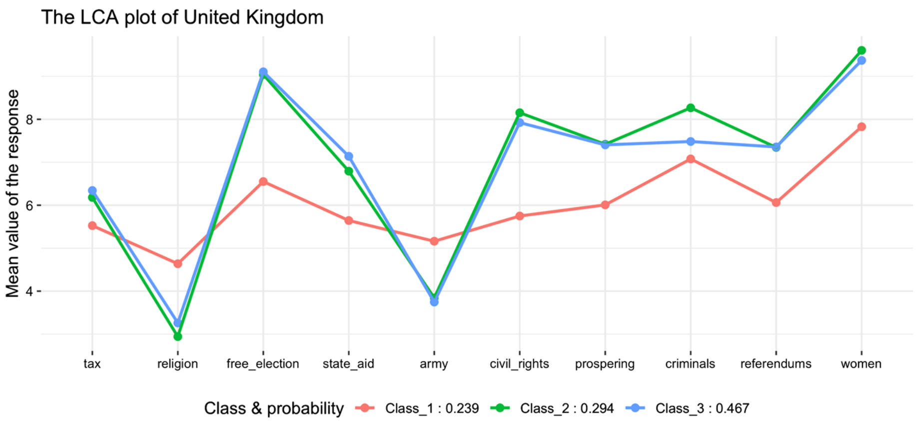

Fig. 39 Mean input values across classes for United Kingdom. *Notes*: Class solution corresponds to output estimates in Appendix Table 38

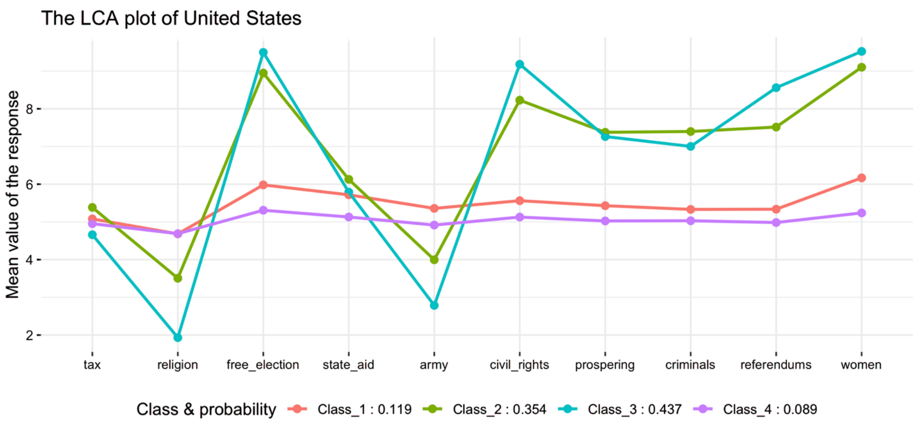

Fig. 40 Mean input values across classes for United States. *Notes*: Class solution corresponds to output estimates in Appendix Table 39

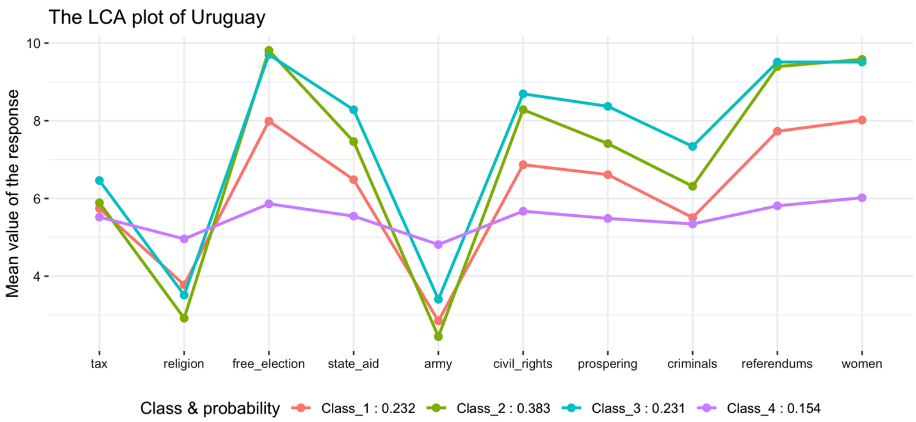

Fig. 41 Mean input values across classes for Uruguay. *Notes*: Class solution corresponds to output estimates in Appendix Table 40

References

Almond, G., Powell, G. B., Dalton, R. J., & Strom, K. J. (2004). *Comparative politics today: A theoretical framework* (5th ed.). New York: Pearson Longman.

Almond, G. A., & Verba, S. (1963). *The civic culture: Political attitudes and democracy in five nations*. Princeton, NJ: Princeton University Press.

Ariely, G. (2015). Democracy-assessment in cross-national surveys: A critical examination of how people evaluate their regime. *Social Indicators Research, 121,* 621–635.

Ariely, G., & Davidov, E. (2011). Can we rate public support for democracy in a comparable way? Cross-national equivalence of democratic attitudes in the world value survey. *Social Indicators Research, 104,* 271–286.

Baviskar, S., & Malone, M. F. (2004). What democracy means to citizens- and why it matters. *European Review of Latin American and Caribbean Studies, 76,* 3–23.

Bratton, M. (2010). The meanings of democracy: Anchoring the "D-Word" in Africa. *Journal of Democracy, 21*(4), 106–113.

Carlin, R. E. (2018). Sorting out support for democracy: A Q-method study. *Political Psychology, 39*(2), 399–422.

Claasen, C. (2020). In the mood for democracy? Democratic support as thermostatic opinion. *American Political Science Review, 114*(1), 36–53.

Coppedge, M., Gerrin, J., Altman, D., Bernhard, M., Fish, S., Hicken, A., et al. (2011). Conceptualizing and measuring democracy: A new approach. *Perspectives on Politics, 9*(2), 247–267.

Crow, D. (2010). The party's over: Citizen conceptions of democracy and political dissatisfaction in Mexico. *Comparative Politics, 43*(1), 41–61.

Cutler, F., Nuesser, A., & Nyblade, B. (2013). Evaluating the quality of democracy with individual level models of satisfaction: Or, a complete model of satisfaction with democracy. In *ECPR, general conference sciences Po. Bordeaux* (pp. 4–7).

Dahl, R. A. (1971). *Polyarchy; participation and opposition*. New Haven: Yale University Press.

Dahl, R. (1989). *Democracy and its critics*. New Haven: Yale University Press.

Dalton, R. J., Sin, T., & Jou, W. (2007). Understanding democracy: Data from unlikely places. *Journal of Democracy, 18*(4), 142–156.

De Regt, S. (2013). Arabs want democracy, but what kind? *Advances in Applied Sociology, 3*(1), 37–46.

Diamond, L. J., & Plattner, M. F. (2008). *How people view democracy, A journal of democracy book*. Baltimore: Johns Hopkins University Press.

Ferrín, M., & Kriesi, H. (2014). Europeans' understandings and evaluations of democracy: Topline results from round 6 of the European social survey. *ESS Topline Results Series, (4)*. Available online at: https://www.europeansocialsurvey.org/docs/findings/ESS6_toplines_issue_4_understandings_and_evaluations_of_democracy.pdf.

Ferrín, M., & Kriesi, H. (2016). *How Europeans view and evaluate democracy*. Oxford: Oxford University Press.

Foa, R. S., & Mounk, Y. (2016). The democratic disconnect. *Journal of Democracy, 27,* 5–17.

Habermas, J. (1989). *The Structural Transformation of the Public Sphere*. Trans. Thomas Burger. Cambridge: MIT Press.

Habermas, J. (1996). *Between facts and norms*. Cambridge, MA: MIT Press.

Held, D. (2006). *Models of democracy*. Stanford, CA: Stanford University Press.

Hooghe, M., Marien, S., & Oser, J. (2017). Great expectations: The effect of democratic ideals on political trust in European democracies. *Contemporary Politics, 23*(2), 214–230.

Jacobsen, J., & Fuchs, L.M. (2020). *Can we compare conceptions of democracy in cross-linguistic and cross-national research? Evidence from a random sample of refugees in Germany. Social indicators research* (2020).

King, G., Murray, C. J., Salomon, J. A., & Tandon, A. (2004). Enhancing the validity and cross-cultural comparability of measurement in survey research. *American Political Science Review, 98*(1), 191–207.

Laclau, E. (2001). Democracy and the question of power. *Constellations, 8*(1), 3–14.

Laclau, E., & Mouffe, C. (2001). *Hegemony and socialist strategy: Towards a radical democratic politics* (2nd ed.). London: Verso.

Linzer, D. A., & Lewis, J. B. (2011). Polca: An R package for polytomous variable latent class analysis. *Journal of Statistical Software, 42*(1), 1–29.

Magalhães, P. C. (2014). Government effectiveness and support for democracy. *European Journal of Political Research, 53*(1), 77–97.

Mattes, R. (2008). Public opinion research in new democracies: Are the processes different? In W. Donsbach, & M. Traugott (Eds.), *Sage handbook of public opinion research* (pp. 113–116). London: Sage Publications.

Merkley, E., Cutler, F., Quirk, P., & Nyblade, B. (2019). Having their say: Authority, voice, and satisfaction with democracy. *Journal of Politics, 81*(3), 848–861.

Miller, S. V., & Davis, N. T. (2020). The effect of white social prejudice on support for American democracy. *The Journal of Race, Ethnicity, and Politics*. https://doi.org/10.1017/rep.2019.55.

Mounk, Y. (2018). *The people versus democracy: Why our freedom is in danger and how to save it*. Cambridge: Harvard University Press.

Norris, P. (2011). *Democratic deficit: Critical citizens revisited*. New York: Cambridge University Press.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535–569.

Oberski, D. L. (2016). Mixture models: Latent profile and latent class analysis. In J. Robertson & M. Kaptein (Eds.), *Modern statistical methods for HCI* (pp. 275–287). Switzerland: Springer International Publishing.

Oser, J., & Hooghe, M. (2018a). Democratic ideals and levels of political participation: The role of political and social conceptualisations of democracy. *The British Journal of Politics and International Relations, 20,* 711–730.

Oser, J., & Hooghe, M. (2018b). Give me your tired, your poor? Support for social citizenship rights in the United States and Europe. *Sociological Perspectives, 61,* 14–38.

Pateman, C. (2012). Participatory democracy revisited. *Perspectives on Politics, 10*(1), 7–19. https://doi.org/10.1017/S1537592711004877.

Pennock, J. R. (1966). Political development, political systems, and political goods. *World Politics, 18*(3), 415–434.

Prothro, J. W., & Grigg, C. M. (1960). Fundamental principles of democracy. *The Journal of Politics, 22*(2), 276–294.

Przeworski, A. (1999). Minimalist conception of democracy: A defense. In I. Shapiro & C. Hacker-Cordon (Eds.), *Democracy's value*. New York: Cambridge University Press.

Rawls, J. (1971). *A theory of justice*. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.

Rose, R., Mishler, W., & Haerpfer, C. (1998). *Democracy and its alternatives: Understanding post communist societies*. Baltimore: John Hopkins University Press.

Sabine, G. H. (1937). *A history of political theory*. New York: Holt, Rinehart and Winston Inc.

Schumpeter, J. A. (1942). *Capitalism, socialism, and democracy*. New York: Harper & Brothers.

Shin, D. (2012). *Is democracy emerging as a universal value? A contrarian perspective* (No. 68). Asia Barometer Survey Working Paper.

Ulbricht, T. (2018). Perceptions and coneceptions of democracy: Applying thick conecepts of democracy to reassess desires for democracy. *Comparative Political Studies, 51*(11), 1387–1440.

Welzel, C. (2011). The asian values thesis revisited: Evidence from the world values surveys. *Japanese Journal of Political Science, 12,* 1–31.

Welzel, C., & Inglehart, R. C. (2016). Misconceptions of measurement equivalence: Time for a paradigm shift. *Comparative Political Studies, 49*(8), 1068–1094.

Wuttke, A., Gavras, K., & Schoen, H. (2020a). Have Europeans grown tired of democracy? New evidence from eighteen consolidated democracies, 1981–2018. *British Journal of Political Science*. https://doi.org/10.1017/S0007123420000149.

Wuttke, A., Gavras, K., & Schoen, H. (2020b). Leader of the free world or pioneer in democracy's decline? Examining the democratic deconsolidation hypothesis on the mass level in East and West Germany. *Research & Politics*. https://doi.org/10.1177/2053168019900822.

Wuttke, A., Schmipf, C., & Schoen, H. (2020c). When the whole is greater than the sum of its parts: On the conceptualization and measurement of populist attitudes and other multidimensional constructs. *American Political Science Review, 114*(2), 356–374.

Zilinsky, J. (2019). Democratic deconsolidation revisited: Young Europeans are not dissatisfied with democracy. Research & Politics.

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