Appendix: The Ontological Core of Political Radicalism. Exploring the role of Antagonist, Dogmatic, and Populist Beliefs in Structuring Radical Ideologies

This Appendix provides additional information and robustness checks for the analyses carried out in the manuscript. All the materials that are required to replicate the figures and the tables present in the text (custom-programmed R functions, R scripts, and Mplus scripts) are accessible through the author's public GitHub profile. The data used for the paper can be requested and used according to the terms of use defined by the ISPO, the data provider.

We used R version 4.2.1 (R Core Team, 2022) and the following R packages: bookdown v. 0.28 (Xie, 2016, 2022), data.table v. 1.14.8 (Dowle & Srinivasan, 2023), fastDummies v. 1.6.3 (Kaplan, 2020), flextable v. 0.7.3 (Gohel, 2022), ggrepel v. 0.9.1 (Slowikowski, 2021), ggstatsplot v. 0.9.4 (Patil, 2021), glue v. 1.6.2 (Hester & Bryan, 2022), gt v. 0.8.0 (Iannone et al., 2022), gtsummary v. 1.6.1 (Sjoberg et al., 2021), here v. 1.0.1 (Müller, 2020), knitr v. 1.44 (Xie, 2014, 2015, 2023), labelled v. 2.9.1 (Larmarange, 2022), latex2exp v. 0.9.4 (Meschiari, 2022), lavaan v. 0.6.15 (Rosseel, 2012), ltm v. 1.2.0 (Rizopoulos, 2006), MplusAutomation v. 1.1.0 (Hallquist & Wiley, 2018), nnet v. 7.3.17 (Venables & Ripley, 2002), officer v. 0.6.2 (Gohel, 2023), patchwork v. 1.1.1 (Pedersen, 2020), performance v. 0.10.2 (Lüdecke et al., 2021), reshape2 v. 1.4.4 (Wickham, 2007), rmarkdown v. 2.25 (Allaire et al., 2023; Xie et al., 2018, 2020), semoutput v. 1.0.2 (Tsukahara, 2023), sjlabelled v. 1.2.0 (Lüdecke, 2022), survey v. 4.1.1 (Lumley, 2004, 2010, 2020), tidyLPA v. 1.1.0 (Rosenberg et al., 2018), tidyverse v. 2.0.0 (Wickham et al., 2019).

LP-CFA MODEL

Model specification

LP-CFA model belongs to the broader class of Finite Mixture Models (FMM). In this paper, the LP-CFA model is similar to the model proposed by Magidson & Vermunt (2001) and referred to as FMM-1. In the FMM framework, this model corresponds to the EEI (equal volume, equal shape [and undefined orientation]) model (Scrucca et al., 2016). In the literature on FMM, the employed modelling approach is described as hybrid modelling with a non-parametric factor distribution due to the absence of within-in class variability of the latent factors (Hancock & Samuelsen, 2007).

The model is specified with a diagonal within-class covariance matrix with latent factor variances set to zero and loadings and intercepts equality across classes. This ensures that the different factors are being measured the same way across all the estimated classes. The main difference between the used LP-CFA model and a FMM-1 model is that the item intercepts across the different classes are held to 0. This allows to estimate a latent mean for each class and has the additional advantage that, since all the variables are centered and standardized, the estimated latent means can be interpreted as the standard deviation from the average of the sample on that specific latent factor (in this case, the proposed ontological components of radical beliefs).

This approach has four clear advantages compared to traditional methods that employ mean comparison and presuppose observed subgroups to be homogeneous. First, unlike traditional factor analysis, the LP-CFA does not assume that individuals belong to a single homogeneous population. Rather, it classifies individuals into different latent classes while taking into account the heterogeneity of the estimated latent factors. Second, it simultaneously assesses the reliability and validity of the estimated latent variables and the unobserved similarities between individuals on such constructs. This provides a more precise classification of individuals into different ideological profiles. Third, the used LP-CFA does not impose normality on the factor distribution, an important advantage when studying radical belief systems where the probability density functions are usually log-normal. Lastly, LP-CFA models can be employed to assess the relationship between a set of background variables and the extracted profiles while taking into account the potential classification error (Asparouhov & Muth'en, 2014). This improves the reliability of the estimates and provides more accurate insights on which specific sub-groups of respondents are more likely to subscribe to certain ideological profiles.

The model is fitted using a multi-stage optimization process that combines expectation–maximization (EM) and maximum likelihood (ML) estimation with robust standard errors. Since LP-CFA models (like any other mixture model) are known to converge on local, rather than global solutions, random draws and perturbations are used in the estimation procedure (Asparouhov & Muthen, 2019). To ensure that the best log-likelihood is replicated at least 10 times and, thus, the maximization function has reached a global, rather than a local, maxima, we adjust upward the number of the initial stage starts in the EM step (500 random starts with 15 iterations) and in the final likelihood step of the ML estimation (125 random stars with 500 iterations) (Ferguson et al., 2020) Results on model fit and convergence can be found in the Mplus .out files on the author's public GitHub profile.

Profile enumeration and robustness

The procedure for determining the optimal number of latent profiles has been performed following the recommendations in Muth'en (2003), Nylund-Gibson & Choi (2018), and Schmidt et al. (2021). The results of the VLMR test suggest that a 4-class solution would be sufficient to describe our data in a parsimonious manner. Log-likelihood-based fit indices (e.g., BIC), however, continue improving for each additional extracted class, suggesting that a larger number of profiles provides additional explanatory power. However, it is known that, with large sample sizes, the continuous improvement in log-likelihood-based fit indices can lead to an overestimation of the number of classes needed to accurately describe the data (Weller et al., 2020). In these cases, an elbow plot and the corresponding drop in BIC between the k – 1 class model and a k class model (ΔBIC) can be used to assess the best-fitting model (Nylund-Gibson & Choi, 2018). The plot suggests that the biggest decrease in log-based measures for any model with more than 4 classes is between the 5- and 6-class solution with small gains in log-likelihood after the 6-class solution.

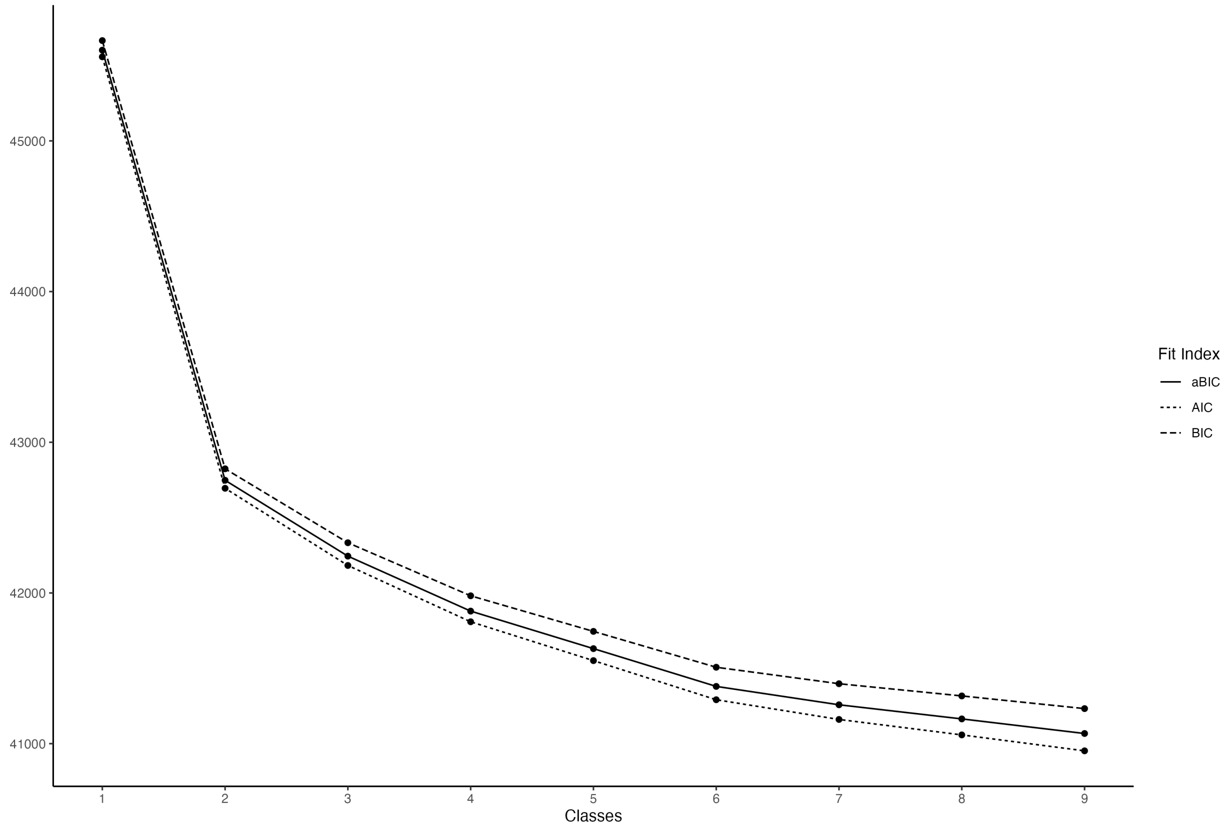

Figure 1: Scree plot for aBIC, AIC, BIC

We also rely on substantive considerations to assess the differences in the extracted profiles between the various class solutions (Schmidt et al., 2021). In order to do so, we plotted every class solution with more than 4 classes such that we could assess whether the extracted ideological profiles were meaningfully different from each other. In this case, we do not label the extracted classes so that the enumeration corresponds to the order in which the LP-CFA model extracts the various profiles. Figure 2 reveals that the 6-class model is the most adequate model: it extracts ideological profiles that are meaningfully different from each other without over- or under-fitting the data. The 7-class model does not present meaningful differences with the selected 6-class solution. It adds a 7th profile with similar means to Profile 1 extracted in the 6-class model. On the opposite, the results from the 5-class solution suggest that the model is under-extracting the number of classes with the absence of a class that scores high on antagonistic beliefs but has below-average levels of dogmatic and populist beliefs. In addition, the selected 6-class solution shows the highest entropy for any model with more than 4 classes and presents a sufficiently large number of individuals in the smallest class ($n = 110$).

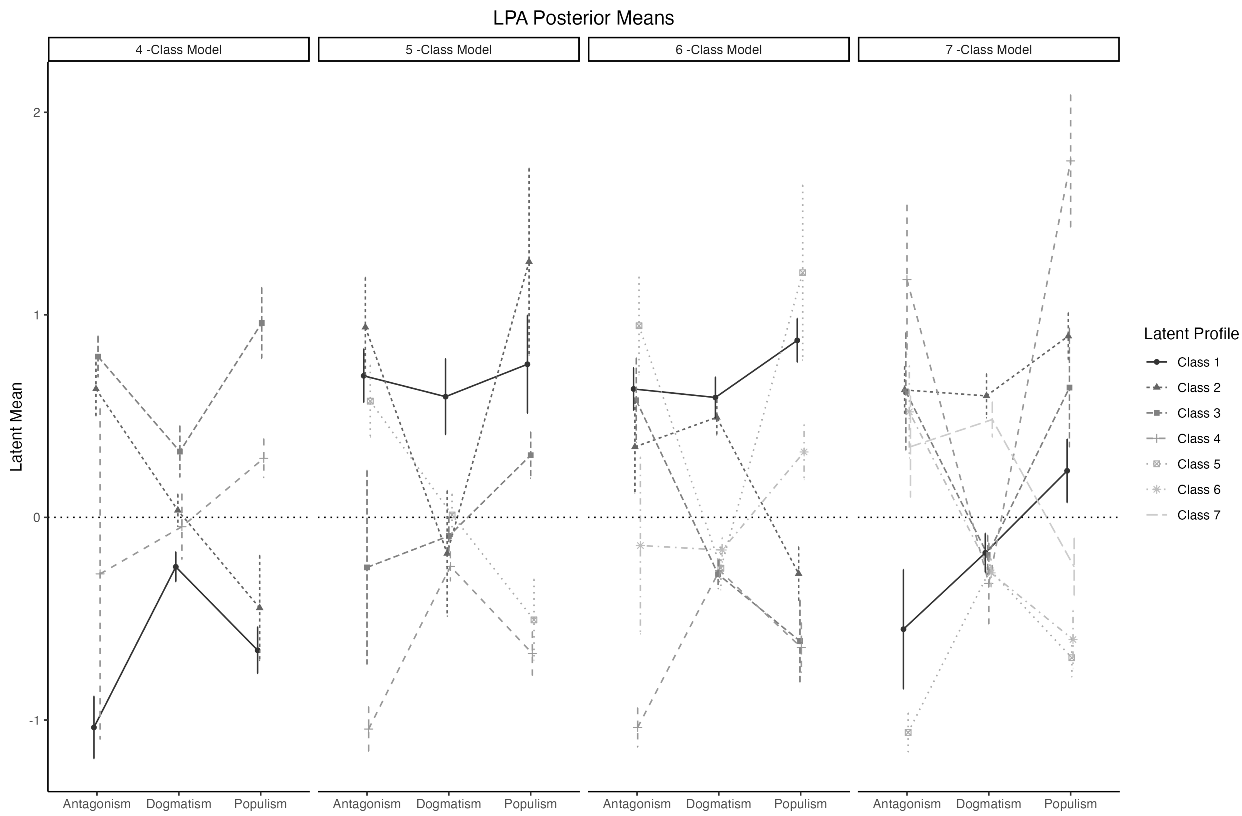

Figure 2: Latent Profile Plots for models with more than 3 classes

MULTINOMIAL REGRESSION RESULTS PREDICTING VOTE CHOICE USING CLASS ASSIGNMENT

The table reports the results of the model depicted in Figure 2 in the manuscript. The comparison column reports the p-value for the test of equality between the coefficients in the Populist Right and Populist Left columns calculated using the Delta method. As commonly done, the effects reported in the manuscript are always computed on the scale of the linear predictor (Lenth et al., 2021). This is because the transformation of the logit coefficients to odds ratio changes the standard deviation required to compute the significance of the regression coefficients.

	DV: Populist Right (Ref: Mainstream)		DV: Populist Left (Ref: Mainstream)	
	Logit	p-value	Logit	p-value
Intercept	0.44 (0.88)	0.62	1.37 (0.99)	0.17
Radical (Ref: Pro-system)	0.86 (0.34)	0.01	0.35 (0.40)	0.38
Non-dogmatic Radical (Ref: Pro-system)	1.06 (0.42)	0.01	1.18 (0.43)	0.01
Non-populist Radical (Ref: Pro-system)	-0.55 (0.42)	0.19	-0.17 (0.48)	0.72
Pluralist Antagonist (Ref: Pro-system)	-0.33 (0.43)	0.45	-0.28 (0.46)	0.54
Disaffected moderate (Ref: Pro-system)	0.62 (0.31)	0.04	0.86 (0.32)	0.01
Female (Ref: Male)	0.18 (0.21)	0.39	-0.38 (0.23)	0.10
Age	-0.20 (0.07)	0.00	-0.17 (0.07)	0.02
Education	-0.21 (0.05)	0.00	0.01 (0.06)	0.92
Non-belgian (Ref: Belgian)	-0.30 (0.32)	0.36	0.15 (0.30)	0.61
PSC: Low Middle (Ref: Working Class)	0.11 (0.26)	0.66	-0.65 (0.28)	0.02
PSC: Higher Middle/Upper (Ref: Working Class)	-0.47 (0.31)	0.13	-1.07 (0.34)	0.00
Political interest	-0.12 (0.12)	0.33	0.20 (0.13)	0.13
Institutional Trust	-0.82 (0.19)	0.00	-0.55 (0.22)	0.01
L-R self-placement	0.44 (0.05)	0.00	-0.20 (0.05)	0.00
Christian (Ref: None)	-0.49 (0.22)	0.03	-0.60 (0.27)	0.02
Free-thinker (Ref: None)	-0.85 (0.42)	0.04	-0.12 (0.35)	0.73
Other religions (Ref: None)	-0.97 (0.51)	0.06	-0.25 (0.42)	0.55

INSTRUMENTS

Table 1: Items used to in the LP-CFA model

Item Ref.	Label	Question
q76_1	Antagonism	Only radical change can solve our societal problems (1. Completely disagree – 5. Completely Agree)
q76_2	Antagonism	Not only the government, but the entire system should be replaced (1. Completely disagree – 5. Completely Agree)
q77_1	Dogmatism	There's a clear line between good and evil (1. Completely disagree – 5. Completely Agree)
q77_2	Dogmatism	There's only one way to handle most things (1. Completely disagree – 5. Completely Agree)
q77_3	Dogmatism	People who disagree with me are usually wrong (1. Completely disagree – 5. Completely Agree)
q67_1	Populism	People and not the politicians should take decisions (1. Completely disagree – 5. Completely Agree)
q67_2	Populism	People would be better represented by ordinary citizens (1. Completely disagree – 5. Completely Agree)
q67_3	Populism	Power should be returned to the people (1. Completely disagree – 5. Completely Agree)
q67_4	Populism	Better if politicians just followed the will of the people (1. Completely disagree – 5. Completely Agree)
q67_5	Populism	Ordinary people know better than politicians (1. Completely disagree – 5. Completely Agree)

Table 2: 3-step predictors, and control variables

Item Ref.	Label	Question
age6	Age	Respondent's age (Recoded in 6 categories, continuous)
q13	Education	Respondent's highest level of education (1. None – 10. University)
q2	Gender	Respondent's assigned sex at birth (1. Man, 2. Woman)

Item Ref.	Label	Question
q18, q19	Race	Respondent's family ethnic background (Recoded as Belgian, Non-Belgian)
region	Place of residence	Respondent's place of residence (1. French-speaking Belgium, 2. Flanders)
q18	Social class	Respondent's self-perceived social class (recoded as Working class, Low Middle class, and Higher Middle/Upper class)
q21	Religious denom.	Self-identified religious denomination (recoded as None, Catholic, Free-thinker, Other Religions)
q36	Pol. interest (index)	Interest in Politics (reversed, 1. No Interest – 5. Very Interested)
q37_1	Pol. interest (index)	Discuss politics with friends (reversed, 1. (Almost) always – 5. Never)
q37_2	Pol. interest (index)	Follows politics in media (reversed, 1. (Almost) always – 5. Never)
q66_1	Trust (index)	Trust in the legal system (1. Very little confidence – 5. A great lot of confidence)
q66_2	Trust (index)	Trust in the national police (1. Very little confidence – 5. A great lot of confidence)
q66_3	Trust (index)	Trust in the press (1. Very little confidence – 5. A great lot of confidence)
q66_4	Trust (index)	Trust in political parties (1. Very little confidence – 5. A great lot of confidence)
q66_5	Trust (index)	Trust in parliament (1. Very little confidence – 5. A great lot of confidence)
q66_6	Trust (index)	Trust in the king (1. Very little confidence – 5. A great lot of confidence)
q66_7	Trust (index)	Trust in the government (1. Very little confidence – 5. A great lot of confidence)

Item Ref.	Label	Question
q66_8	Trust (index)	Trust in the trade unions (1. Very little confidence – 5. A great lot of confidence)
q66_9	Trust (index)	Trust in science (1. Very little confidence – 5. A great lot of confidence)
q64	Powerlessness	Some people feel disregarded or abandoned by politics. (1. Never – 5. Always)
q24	Radical vote	Vote choice in the 2019 federal elections (recoded as Mainstream, Radical Left, Radical Right)

DESCRIPTIVES

Variable	N	N = 1,406
Age (age6)	1,403	
Mean (SD)		4.08 (1.66)
Median (IQR)		4.00 (3.00, 6.00)
Range		1.00 - 6.00
Education (q13)	1,406	
Mean (SD)		7.26 (2.44)
Median (IQR)		8.00 (6.00, 9.00)
Range		1.00 - 10.00
Left-Right Orientation (q57)	1,366	
Mean (SD)		5.02 (2.20)
Median (IQR)		5.00 (4.00, 7.00)
Range		0.00 - 10.00
Antagonism (q76_1)	1,386	
Mean (SD)		3.18 (1.01)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00
Antagonism (q76_2)	1,386	
Mean (SD)		3.34 (1.04)
Median (IQR)		4.00 (3.00, 4.00)
Range		1.00 - 5.00
Dogmatism (q77_1)	1,388	
Mean (SD)		3.05 (0.97)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00
Dogmatism (q77_2)	1,397	
Mean (SD)		2.51 (0.99)

Variable	N	N = 1,406
Median (IQR)		2.00 (2.00, 3.00)
Range		1.00 - 5.00
Dogmatism (q77_3)	1,403	
Mean (SD)		2.10 (0.83)
Median (IQR)		2.00 (2.00, 2.00)
Range		1.00 - 5.00
Populism (q67_1)	1,400	
Mean (SD)		2.96 (1.04)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00
Populism (q67_2)	1,400	
Mean (SD)		3.00 (0.99)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00
Populism (q67_3)	1,397	
Mean (SD)		2.63 (0.99)
Median (IQR)		2.00 (2.00, 3.00)
Range		1.00 - 5.00
Populism (q67_4)	1,394	
Mean (SD)		2.87 (1.01)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00
Populism (q67_5)	1,399	
Mean (SD)		2.51 (0.96)
Median (IQR)		2.00 (2.00, 3.00)
Range		1.00 - 5.00

Variable	N	N = 1,406
Sex at birth (q2)	1,406	
Man		775 / 1,406 (55%)
Woman		631 / 1,406 (45%)
Political Interest (q36, q37_1, q37_2)	1,394	
Mean (SD)		3.04 (0.93)
Median (IQR)		3.00 (2.33, 3.67)
Range		1.00 - 5.00
Place of Residence (region)	1,406	
Flanders		880 / 1,406 (63%)
Wallonia		526 / 1,406 (37%)
Ethnic background (q18, q19)	1,405	
Belgian		1,183 / 1,405 (84%)
Other		222 / 1,405 (16%)
Religious Denomination (q21)	1,400	
None		393 / 1,400 (28%)
Christian		784 / 1,400 (56%)
Free-thinker		127 / 1,400 (9.1%)
Others		96 / 1,400 (6.9%)
Radical Vote Choice (q24)	1,406	
Mainstream		1,187 / 1,406 (84%)
Populist Left		97 / 1,406 (6.9%)
Populist Right		122 / 1,406 (8.7%)
Institutional Trust (q66_x)	1,339	
Mean (SD)		2.99 (0.56)
Median (IQR)		3.00 (2.56, 3.33)
Range		1.22 - 5.00

Variable	N	N = 1,406
Powerlessness (q64)	1,385	
Mean (SD)		2.91 (1.04)
Median (IQR)		3.00 (2.00, 4.00)
Range		1.00 - 5.00

[1]n / N (%)

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