Online Appendix

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2. Sample Characteristics
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4. Item-Level Descriptive Statistics
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6. Construct Level Descriptive Statistics and Multiple Imputation
7. Extended Latent Profile Analysis Results
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Sampling Scheme

Using ads on social media, we targeted participants on internet search engines and Facebook. When we were targeting the population, we accounted for the general German electorate socio-demographics as well as specified political interests (such as populist parties, movements, organizations, and politicians). Additionally, some of our participants were recruited from an online panel study for the general German electorate. Participants were invited to take an online survey in return for a chance to win €25. We started the data collection on the 17th of October 2017 and completed it on the 27th of December. We used the following visual to advertise our survey.

Figure 1 Visual used in Facebook ads. The text reads: “Are you interested in politics? Your opinion counts.”

Eventually, approximately 62 % of the participants landed on the online survey platform via the ad on Facebook; approximately 14 % of the participants came from the internet search engines (Bing, Yahoo, Google, and a few German domains); the remaining 24 % are recruits from the online panel study for the general German electorate. A total number of 7346 people saw our survey’s first page; the completing rate was 11.42%; we ended up with having *N*=839. We report the sample characteristics with the following plots.

Sample Characteristics

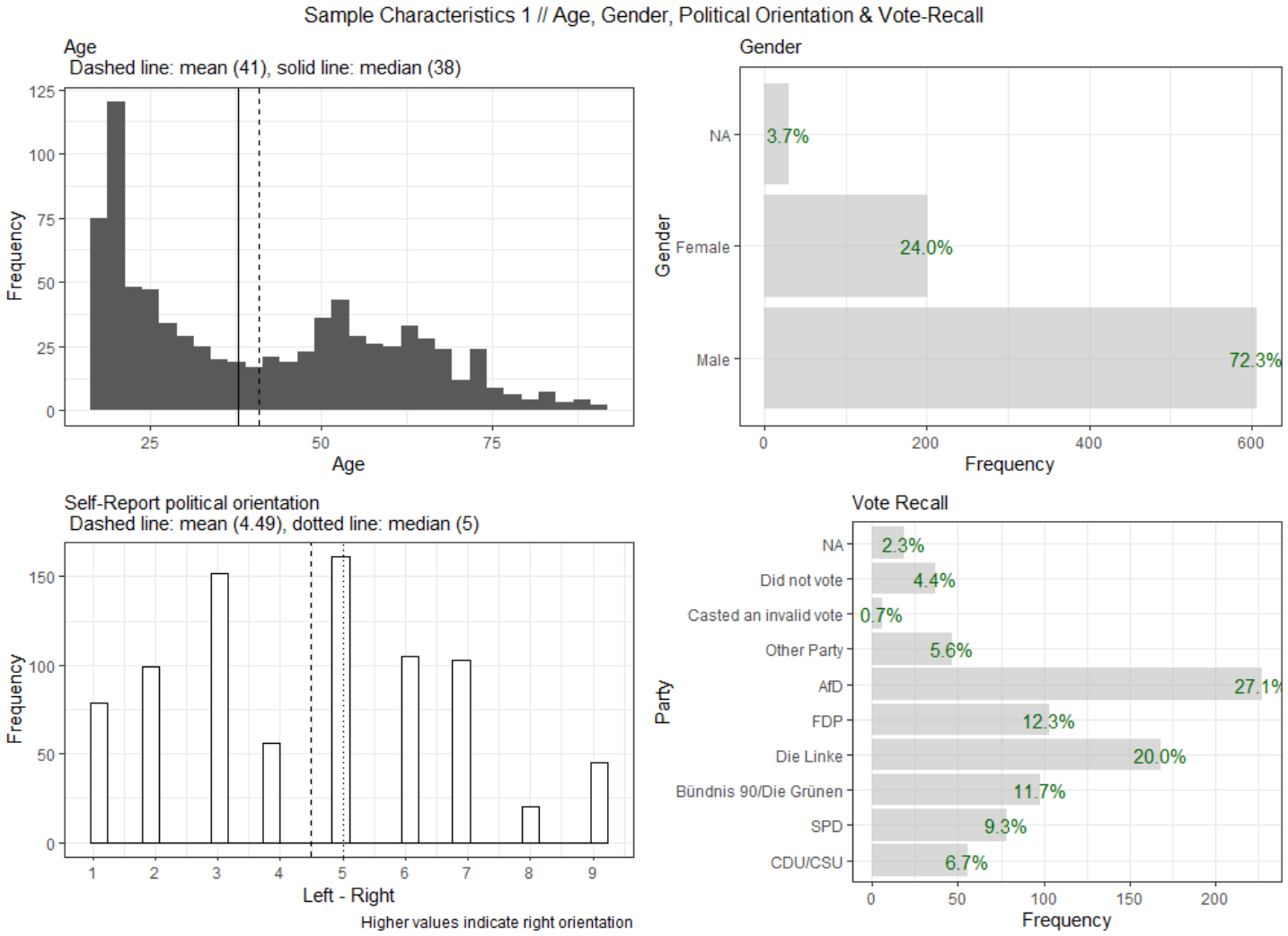


Figure 2

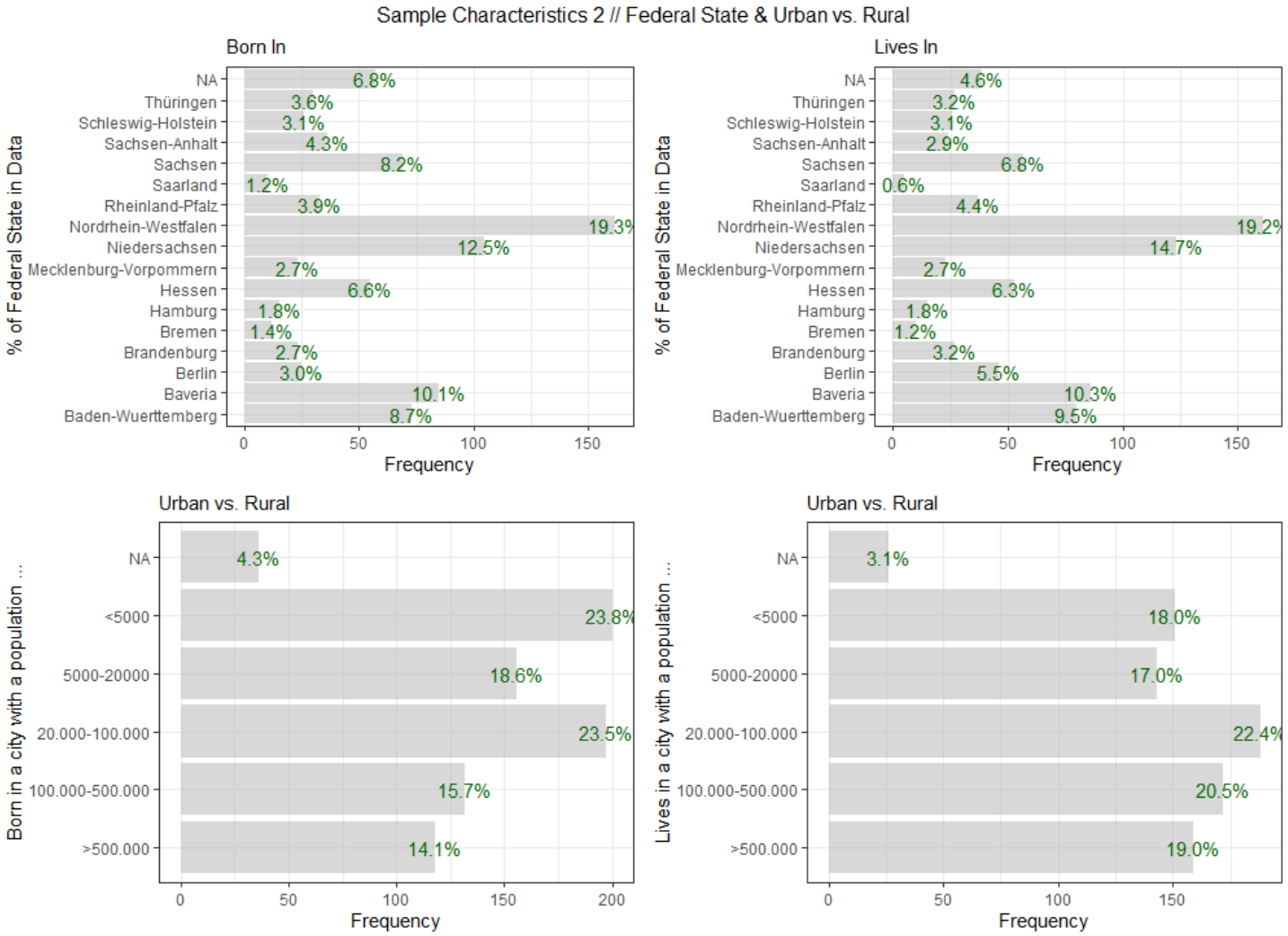

Sample Characteristics 2 // Federal State & Urban vs. Rural
Born In
Lives In
% of Federal State in Data
NA
Thüringen
Schleswig-Holstein
Sachsen-Anhalt
Sachsen
Saarland
Rheinland-Pfalz
Nordrhein-Westfalen
Niedersachsen
Mecklenburg-Vorpommern
Hessen
Hamburg
Bremen
Brandenburg
Berlin
Baveria
Baden-Wuerttemberg
6.8%
3.6%
3.1%
4.3%
8.2%
1.2%
3.9%
19.3%
12.5%
2.7%
6.6%
1.8%
1.4%
2.7%
3.0%
10.1%
8.7%
4.6%
3.2%
3.1%
2.9%
6.8%
0.6%
4.4%
19.2%
14.7%
2.7%
6.3%
1.8%
1.2%
3.2%
5.5%
10.3%
9.5%
0
50
100
150
Frequency
Urban vs. Rural
Born in a city with a population ...
Lives in a city with a population ...
NA
<5000
5000-20000
20.000-100.000
100.000-500.000
>500.000
4.3%
23.8%
18.6%
23.5%
15.7%
14.1%
3.1%
18.0%
17.0%
22.4%
20.5%
19.0%
0
50
100
150
200
Frequency

Figure 3

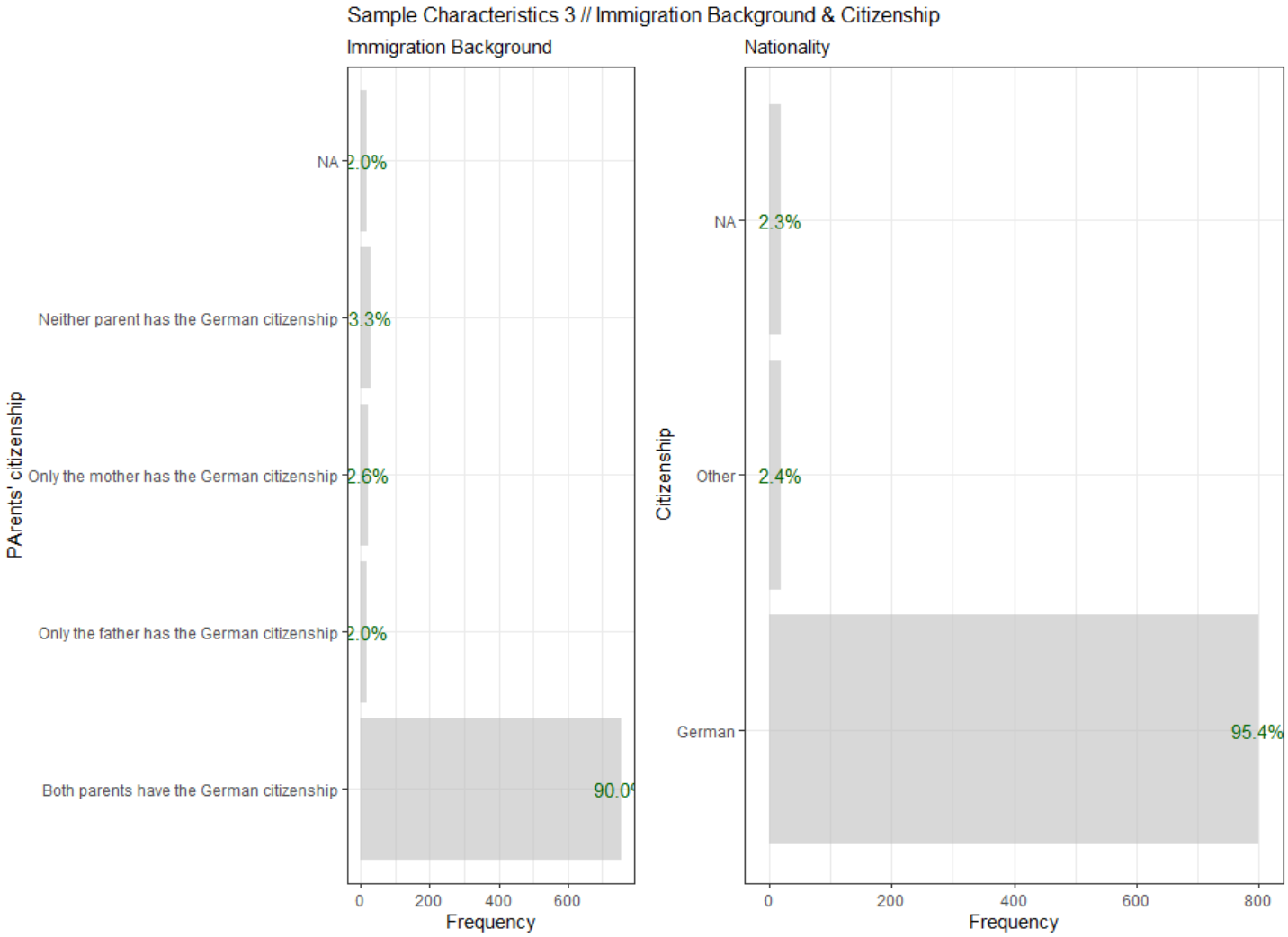

Sample Characteristics 3 // Immigration Background & Citizenship
Immigration Background
PArents' citizenship
NA
2.0%
Neither parent has the German citizenship
3.3%
Only the mother has the German citizenship
2.6%
Only the father has the German citizenship
2.0%
Both parents have the German citizenship
90.0%
0
200
400
600
Frequency
Nationality
Citizenship
NA
2.3%
Other
2.4%
German
95.4%
0
200
400
600
800
Frequency

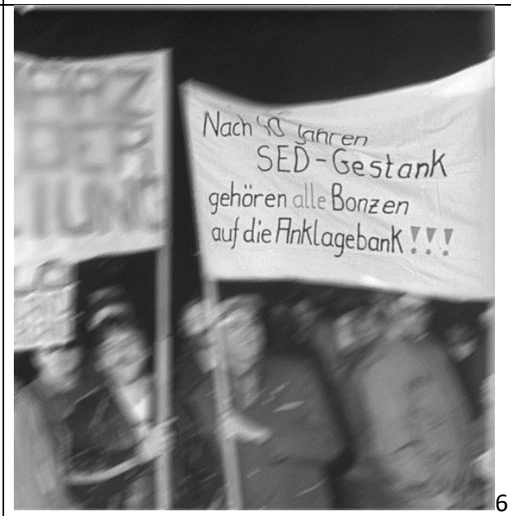
Figure 4

Experimental Procedure

After welcoming and informing the participants on the first page, we presented them the items on socio-demographics on the first page. In the second page, we measured the populist attitudes. The third page only had the vote-recall question. The fourth page included two blocks: one with items on political orientation, the other on trust. We had the authoritarianism items in the following page; the following sixth page included the national identification and collective narcissism items.

We administered the experimental treatment on the seventh-page. Here, participants in the control-group responded to the populism battery a second time after being exposed to the images displayed in the first column of the table below (Table 1); participants in the PEGIDA-condition responded to the populism battery after being exposed to the images displayed in the second column; participants in the Leipzig-condition responded to the populism battery after being exposed to the images displayed in the third column. All participants were also asked to write their comments on the demonstrating group. Participants in the experimental groups (PEGIDA & Leipzig) are specifically instructed to pay attention to the slogans in the images; the slogans were also provided as text in the instructions of the questionnaire. On this eight-page, we also asked the participants to respond to the two items that asked them whether they found the demonstration relevant and polarizing. Finally, right before the participants left the survey, we administered the final scale that measured (dis-)identification with the demonstrating group (items adopted from Becker and Tausch (2014)).

Table 1: Experimental manipulations.

	Control Group	Experimental Treatment 1 (PEGIDA demonstration)	Experimental Treatment 2 (Leipzig demonstration)
People-Centric Slogan	 1	 3	 5
Anti-Establishment Slogan	 2	 4	 6

1 Autor: Rufus46, CC BY-SA 3.0, https://commons.wikimedia.org/wiki/File:Ostermarsch_M%C3%BCnchen_2005.jpg
2 Autor: blu-news.org, CC BY-SA 2.0, https://commons.wikimedia.org/wiki/File:Rucksack_und_Friede_(12269701676).jpg
3 Autor: Metropolico.org, CC BY-SA 2.0, https://commons.wikimedia.org/wiki/File:PEGIDA_Demonstration_Dresden_2015-03-23_16903273726_2e40a0b844_o.jpg
4 Autor: Kalispera Dell, CC BY 3.0, https://commons.wikimedia.org/wiki/File:PEGIDA_Demo_DRESDEN_25_Jan_2015_116139763.jpg "Politicians live in a different reality"
5 Autor: Thomas Lehmann, CC-BY-SA 3.0, https://commons.wikimedia.org/wiki/File:Bundesarchiv_Bild_183-1989-1104-008,_Berlin,_Plakate_auf_Kundgebung_am_Alexanderplatz.jpg
6 Autor: Wolfgang Kluge, CC-BY-SA 3.0, https://commons.wikimedia.org/wiki/File:Bundesarchiv_Bild_183-1990-0129-029,_Leipzig,_Montagsdemonstration.jpg "All big-wigs need to go to trial"

Item-Level Descriptive Statistics

Table 2

People-centrism

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
Politicians should always listen closely to the problems of the people	PC1_pre	2.15 %	6.38	1.12	-2.6	8	7	1-7	0.04
Politicians don't have to spend time among ordinary people to do a good job (R)	PC2_pre	1.91 %	5.76	1.74	-1.36	0.78	7	1-7	0.06
The will of the people should be the highest principle in this country's politics	PC3_pre	2.03 %	5.83	1.52	-1.43	1.49	6	1-7	0.05

Table 3

Anti-Elitism

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
The government is pretty much run by a few big interests looking out for themselves	AE1_pre	2.15 %	5.2	1.79	-0.83	-0.34	6	1-7	0.06
Government officials use their power to try to improve people's lives (R)	AE2_pre	2.26 %	4.63	1.67	-0.04	-1.12	5	1-7	0.06
Quite a few of the people running the government are crooked	AE3_pre	2.50 %	4.48	1.95	-0.29	-1.11	5	1-7	0.07

Table 4

Manichean View of Politics

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
You can tell if a person is good or bad if you know their politics	MW1_pre	2.15 %	3.01	1.76	0.38	-0.89	3	1-7	0.06
The people I disagree with politically are not evil (R)	MW2_pre	2.38 %	2.6	1.65	0.94	0.14	2	1-7	0.06
The people I disagree with politically are just misinformed	MW3_pre	2.15 %	3.77	1.71	-0.02	-0.75	4	1-7	0.06

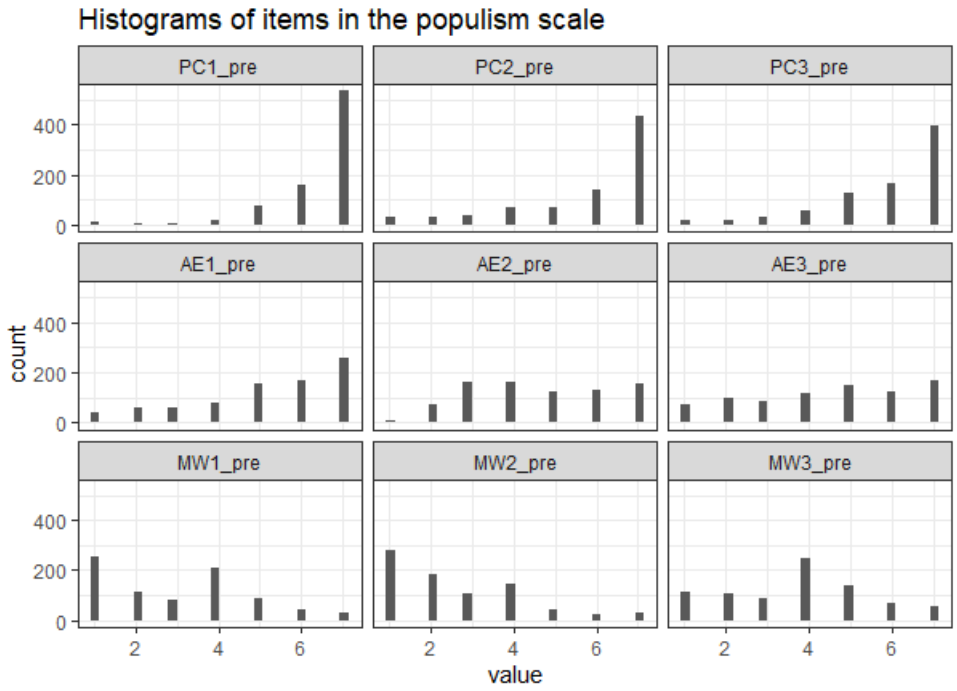


Figure 5

Table 5

Right-Wing Authoritarianism

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
We should be grateful for leaders, that tell us exactly what we shall do and how.	auth01sub1	1.79 %	1.91	0.93	0.71	-0.25	2	1-5	0.03
The age in which discipline and obedience for authority are some of the most important virtues should be over (R).	auth02sub2R	2.26 %	2.57	1.23	0.31	-0.89	3	1-5	0.04
Our society for once has to crack down harder on criminals.	auth03agg1	1.91 %	3.71	1.23	-0.58	-0.74	4	1-5	0.04
It is important to also protect the rights of criminals (R).	auth04agg2R	2.15 %	2.8	1.32	0.22	-1.08	3	1-5	0.05
This country would flourish if young people paid more attention to traditions and values.	auth05con1	2.03 %	3.09	1.25	-0.1	-0.96	3	1-5	0.04
Our country needs people who oppose traditions and try out different ideas (R).	auth05con2R	1.91 %	2.66	1.21	0.29	-0.75	3	1-5	0.04

Table 6

Collective Narcissism

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
Germany deserves special treatment.	cn2	2.38 %	2.63	1.73	0.77	-0.28	2	1-7	0.06
I will never be satisfied until Germany gets all it deserves.	cn3	2.50 %	2.93	1.9	0.54	-0.87	3	1-7	0.07
It really makes me angry when others criticize Germany.	cn5	2.50 %	2.9	1.77	0.57	-0.65	3	1-7	0.06
If other countries listened to Germany more, the world would be a much better place.	cn6	2.38 %	3.24	1.73	0.23	-0.83	4	1-7	0.06
Not many people seem to fully understand the importance of Germany.	cn8	2.50 %	3.59	1.86	0.1	-1	4	1-7	0.07

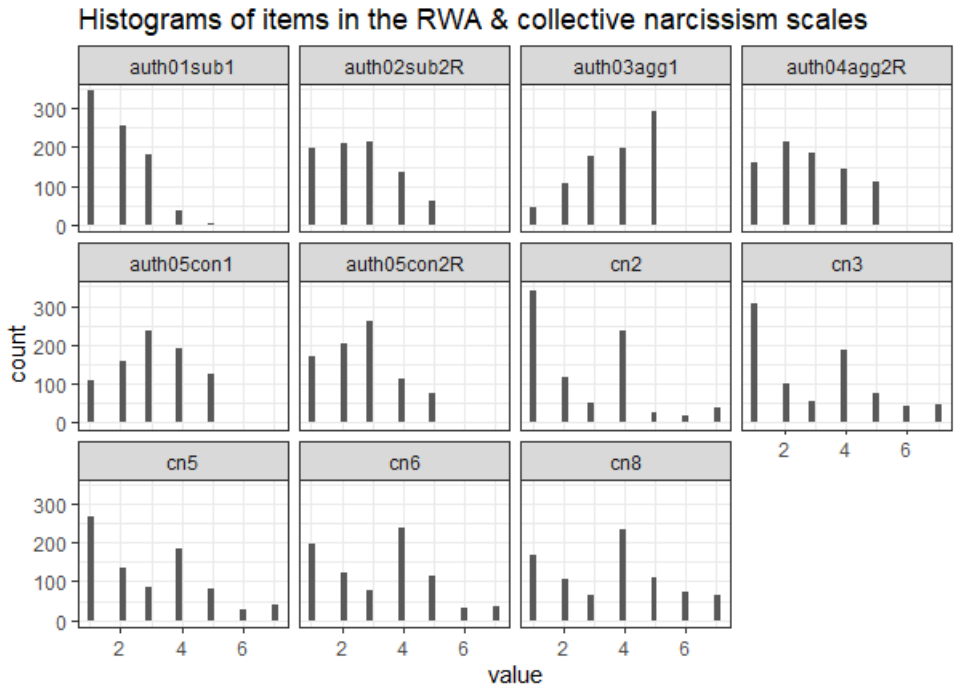


Figure 6

Table 7

National Identity: Centrality

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
I often think about the fact that I am German.	nice01	2.98 %	2.64	1.25	0.25	-0.97	3	1-5	0.04
The fact that I am German is an important part of my identity.	nice02	2.62 %	3.26	1.34	-0.35	-1.07	4	1-5	0.05
Being German is an important part of how I see myself.	nice03	2.62 %	2.69	1.32	0.22	-1.09	3	1-5	0.05

Table 8

National Identity: Solidarity

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
I feel a bond with Germans.	niso01	2.74 %	3.66	1.1	-0.85	0.18	4	1-5	0.04
I feel solidarity with Germans.	niso02	2.98 %	3.68	1.02	-0.81	0.35	4	1-5	0.04
I feel committed to Germans.	niso03	2.74 %	3.14	1.3	-0.23	-1.05	3	1-5	0.05

Table 9

National Identity: Satisfaction

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
I am glad to be German.	nisa01	2.62 %	3.69	1.09	-0.71	0.08	4	1-5	0.04
It is pleasant to be German.	nisa02	2.86 %	3.7	1.05	-0.79	0.27	4	1-5	0.04
Being German gives me a good feeling.	nisa03	3.10 %	3.39	1.15	-0.42	-0.47	3	1-5	0.04

Table 10

National Identity: Self-Stereotyping

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
I have a lot in common with the average German person.	niss01	2.74 %	3.19	1.08	-0.28	-0.6	3	1-5	0.04
I am similar to the average German person.	niss02	2.86 %	3.09	1.09	-0.22	-0.7	3	1-5	0.04
I am a typical German.	niss03	2.86 %	3.03	1.11	-0.16	-0.73	3	1-5	0.04

Table 11

National Identity: In-Group Homogeneity

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
German people have a lot in common with each other.	niho01	2.74 %	3.4	0.94	-0.54	-0.12	4	1-5	0.03
German people are very similar to each other.	niho02	2.86 %	2.84	1.04	-0.02	-0.66	3	1-5	0.04
German share a lot of the same characteristics.	niho03	2.74 %	3.13	1.03	-0.3	-0.6	3	1-5	0.04

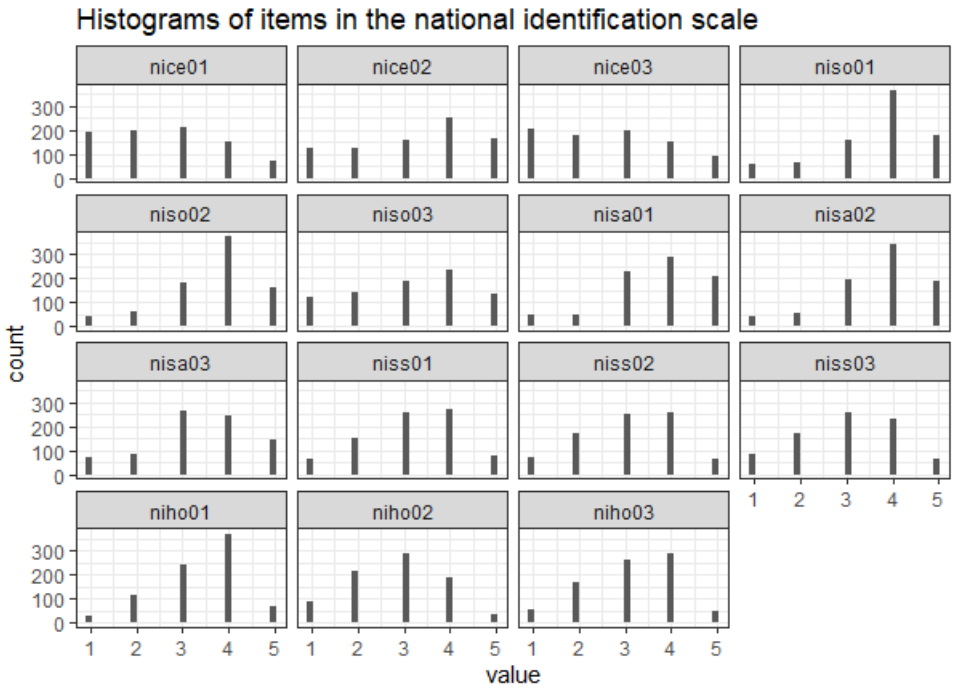


Figure 7

Table 12

Outcome variables by experimental condition: control group

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
When you think of the concerns of the demonstrators in [experimental manipulation], how relevant do you think the issues they raised are? Not relevant at all, Not very relevant, Partly relevant, Somewhat relevant, Very relevant [1-5; higher scores indicate finding the issues raised relevant].	sl_rel	5.41 %	3.69	1.07	-0.45	-0.48	4	1-5	0.06
When you think of the .[experimental manipulation] demonstrations and their consequences, do you believe that these demonstrations have brought the German population together or pushed it apart? The [experimental manipulation] demonstration … brought together … neither … pushed apart [1-7; higher scores indicate finding the demonstrations polarizing].	sl_pol	5.41 %	3.70	1.12	-0.28	1.45	4	1-7	0.06

Table 13

Outcome variables by experimental condition: PEGIDA condition

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
When you think of the concerns of the demonstrators in [experimental manipulation], how relevant do you think the issues they raised are?	sl_rel	4.03 %	3.31	1.24	-0.19	-1.01	3	1-5	0.08
When you think of the .[experimental manipulation] demonstrations and their consequences, do you believe that these demonstrations have brought the German population together or pushed it apart?	sl_pol	4.4 %	4.93	1.76	-0.41	-0.66	5	1-7	0.11

Table 14

Outcome variables by experimental condition: LEIPZIG condition

Item Wording	*Variable Name*	*Missing*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
When you think of the concerns of the demonstrators in [experimental manipulation], how relevant do you think the issues they raised are?	sl_rel	5.56 %	4.32	0.83	-1.25	1.8	5	1-5	0.05
When you think of the .[experimental manipulation] demonstrations and their consequences, do you believe that these demonstrations have brought the German population together or pushed it apart?	sl_pol	5.56 %	2.65	1.47	0.68	0.0	2	1-7	0.10

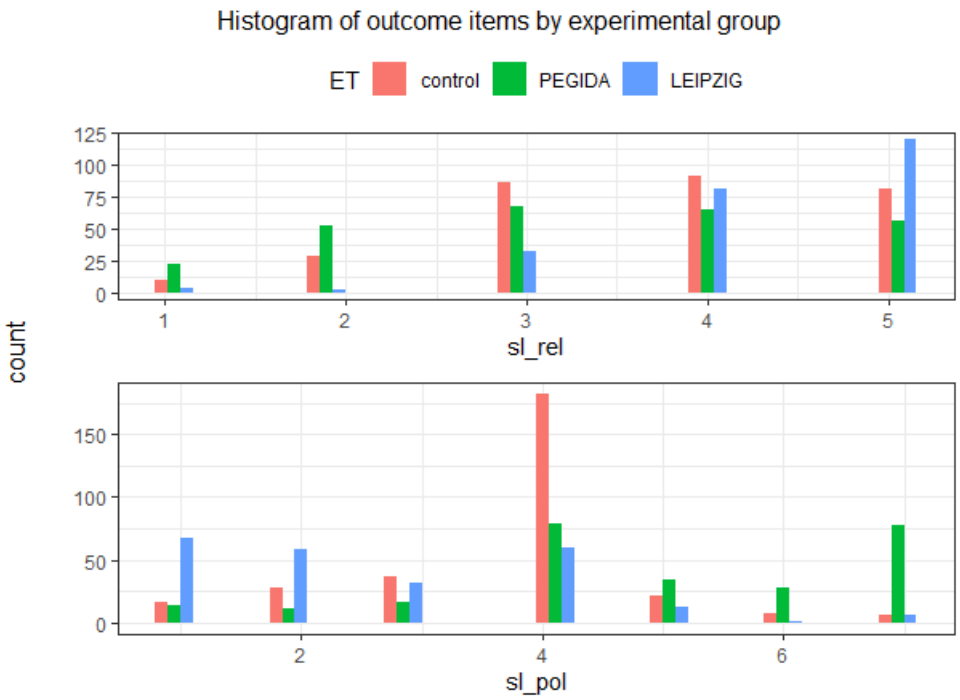


Figure 8

Psychometric Quality and Measurement Models

We assessed the psychometric qualities of the scales by utilizing a graded response model from the item response theory (IRT) framework. This assessment method is an extension of the two-parameter logistic model to ordinal responses (Baker, 2017). In other words, we treat every response option (ranging from strongly disagree to strongly agree) as ordered categories. Here, we report information on the individual items as well as the scale itself. While item information curves (ICC) and category characteristic curves (CCC) provide evidence about the items, test information & standard error (I &SE) and test characteristic curve (TCC) provide evidence about the scale itself.

In a nutshell, IRT is particularly beneficial for a rigorous examination of the internal consistency in the measurement instrument. IRT is also useful for constructing parsimonious measurement instruments. We simply use this method to eliminate the bad items in the

measurement models. A brief explanation and elaboration about the estimation are discussed in the relevant section for the first construct. After the first construct, the same heuristics on the IRT results and interpretation are relevant for all the other constructs.

Following the psychometric assessment, we construct the measurement models with confirmatory factor analysis (CFA), utilizing robust maximum likelihood estimation; following the suggestion by Graham (2003), we accounted for the missing data with the full information maximum likelihood (FIML). After fitting the measurement models, we compute the factor scores from the CFAs and use them in further analyses. We avoided taking the mean of the items in the scales simply because CFAs make it clear that the latent construct does not have the exact same influence on the items. Therefore the mean of items would bias the true score on the latent continuum. For further discussions on this empirical choice, see Linden and Hambleton (1997); Mair (2018), DiStefano, Zhu, and Mîndrilă (2009) and McNeish and Wolf (2019).

We relied on the Empirical Bayes Modal approach to compute the factor scores. We acknowledge the limitation of factor scores' uncertainty (Devlieger, Mayer, & Rosseel, 2016; Devlieger & Rosseel, 2017; Estabrook & Neale, 2013; Grice, 2001). The main problem stems from the infinite number of solutions that satisfy the equations used to estimate factor scores. Although we do not have the most elegant solution to this limitation, one buffer strategy we adopt is normalizing the factor scores, so they range between 0-1. We applied this strategy to all the constructs we used. The free & open-ware package we use, lavaan (Rosseel, 2012), tends to overestimate the correlations across latent constructs in the CFAs. Although this might influence our subsequent analyses, we have a few safety nets we can list. 1) All the scales we utilize here have been validated in earlier studies, so we know how they are supposed to behave with the factor correlations and none of the results diverged from the previous findings (***See*** Silva et al.

(2018), Castanho Silva, Jungkunz, Helbling, and Littvay (fortcoming/online-first), Aichholzer and Zeglovits (2015), Zavala, Cichocka, Eidelson, and Jayawickreme (2009)). 2) We either construct the latent trait models as higher-order construct CFAs (i.e., national identification scale) or use a single factor model (i.e., RWA and collective narcissism). So we buffer the bias of overestimated correlations across latent constructs.

Item Response Theory Models

Populism Scale -- Silva et al. (2018)

Tables 15, 16 & 17 below display the coefficients from the graded response model estimation. The alpha (α) can be interpreted as a proxy of the item's ability to discriminate individuals with different levels on the latent continuum. Higher values of α would indicate that the item's capacity to differentiate individuals on this latent construct is higher. Beta (β) values are referred to as the category thresholds; they indicate the differences in cumulative probabilities of choosing a particular response category compared to the probability of choosing another category. Coefficients ranging from the negative to the positive indicate that the item is capable of capturing negative as well as the positive poles of the latent continuum. In other words, we see the accuracy range of the measurement instrument and its capacity to capture the trait at each level of the latent construct.

Table 15

Variable Name	Discrimination	Category Thresholds					
	α	β_1	β_2	β_3	β_4	β_5	β_6
PC1_pre	2.52	-2.684	-2.439	-2.312	-1.947	-1.276	-0.501
PC2_pre	1.11	-3.307	-2.635	-2.154	-1.493	-1.007	-0.162
PC3_pre	1.95	-2.661	-2.203	-1.787	-1.332	-0.643	0.051

Table 16

Variable Name	Discrimination	Category Thresholds					
	α	β_1	β_2	β_3	β_4	β_5	β_6
AE1_pre	3.548	-1.839	-1.325	-0.993	-0.65	-0.095	0.514
AE2_pre	2.325	-2.75	-1.582	-0.641	-0.02	0.447	1.081
AE3_pre	2.927	-1.549	-0.948	-0.579	-0.145	0.394	0.95

Table 17

Variable Name	Discrimination	Category Thresholds					
	α	β_1	β_2	β_3	β_4	β_5	β_6
MW1_pre	3.548	-1.839	-1.325	-0.993	-0.65	-0.095	0.514
MW2_pre	2.325	-2.75	-1.582	-0.641	-0.02	0.447	1.081
MW3_pre	2.927	-1.549	-0.948	-0.579	-0.145	0.394	0.95

These values are displayed on the individual plots in Figures 9,10 & 11. Looking at the IIC, a visual heuristic would indicate that the first item (PC1_pre) provides the most information to measure the latent trait. While the x-axis is the latent trait continuum, the y-axis displays the information (related to the concept of reliability) of the survey-item; that is how accurate it would be to estimate the latent trait from this item. The higher, more peaked and narrower curves are more informative. That means they provide more information about the latent trait and have more ability to discriminate individuals on the latent trait.

On the CCC plot, the y-axis of the plot is the probability of endorsing one of the response categories. For example, the orderly fashion of the curves in the anti-elitism scale indicates that the more anti-elitist an individual is, the more probable that this individual will endorse a higher category.

The test information and standard error plot indicate that measurement error for the overall scale approaches the minimum within the -4 to 4 range complementing the information coming from the individual items (all items can capture negative as well as the positive side of the trait). An s shape curve is desirable for the test characteristic curve, which is the sum of item

characteristic curves representing the expected score on the instrument. Here, the overall scale is not perfect but acceptable. After here, all the heuristics mentioned below apply to all the other IRT results below.

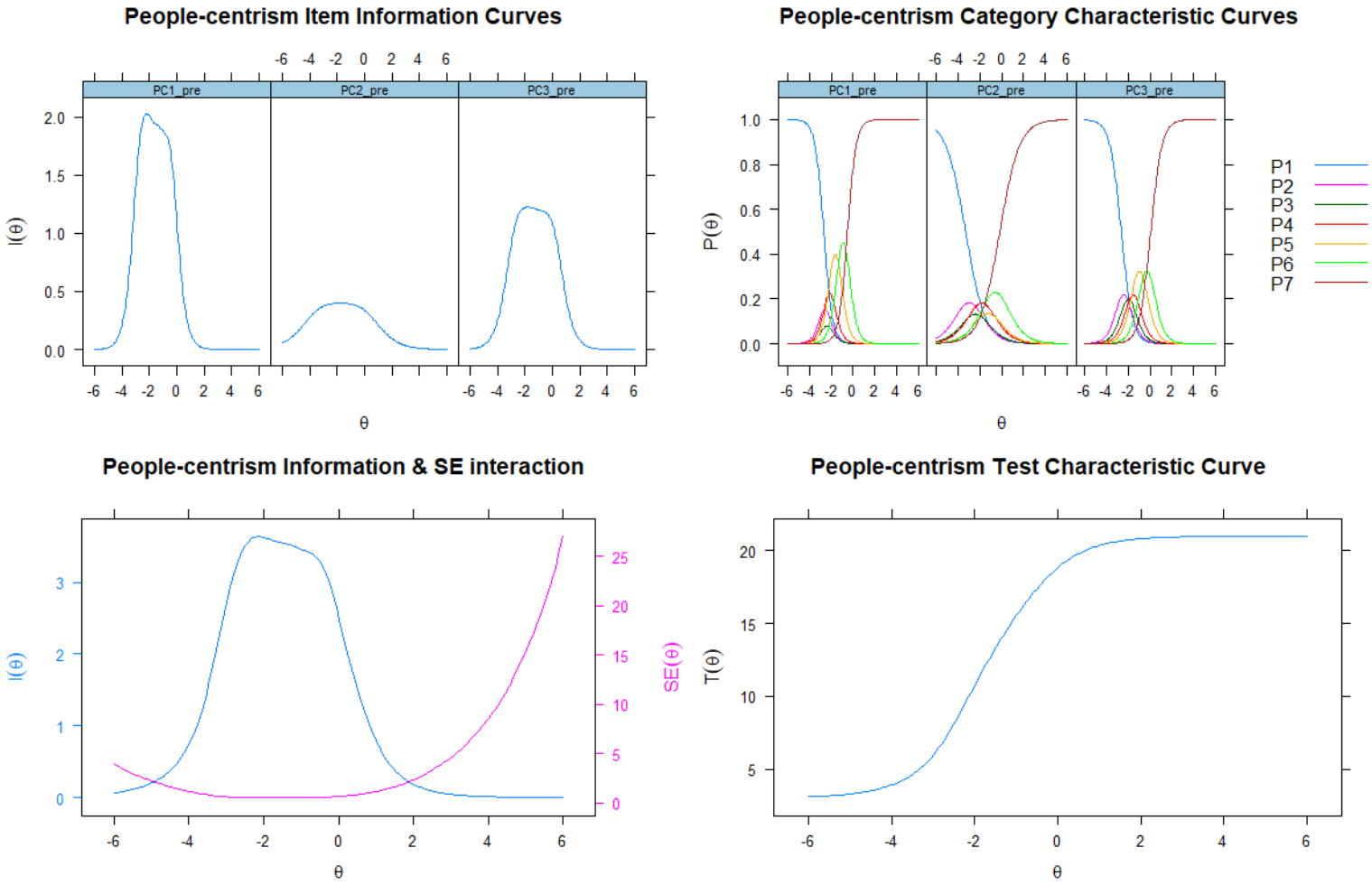


Figure 9 Results from the IRT Graded Response Model

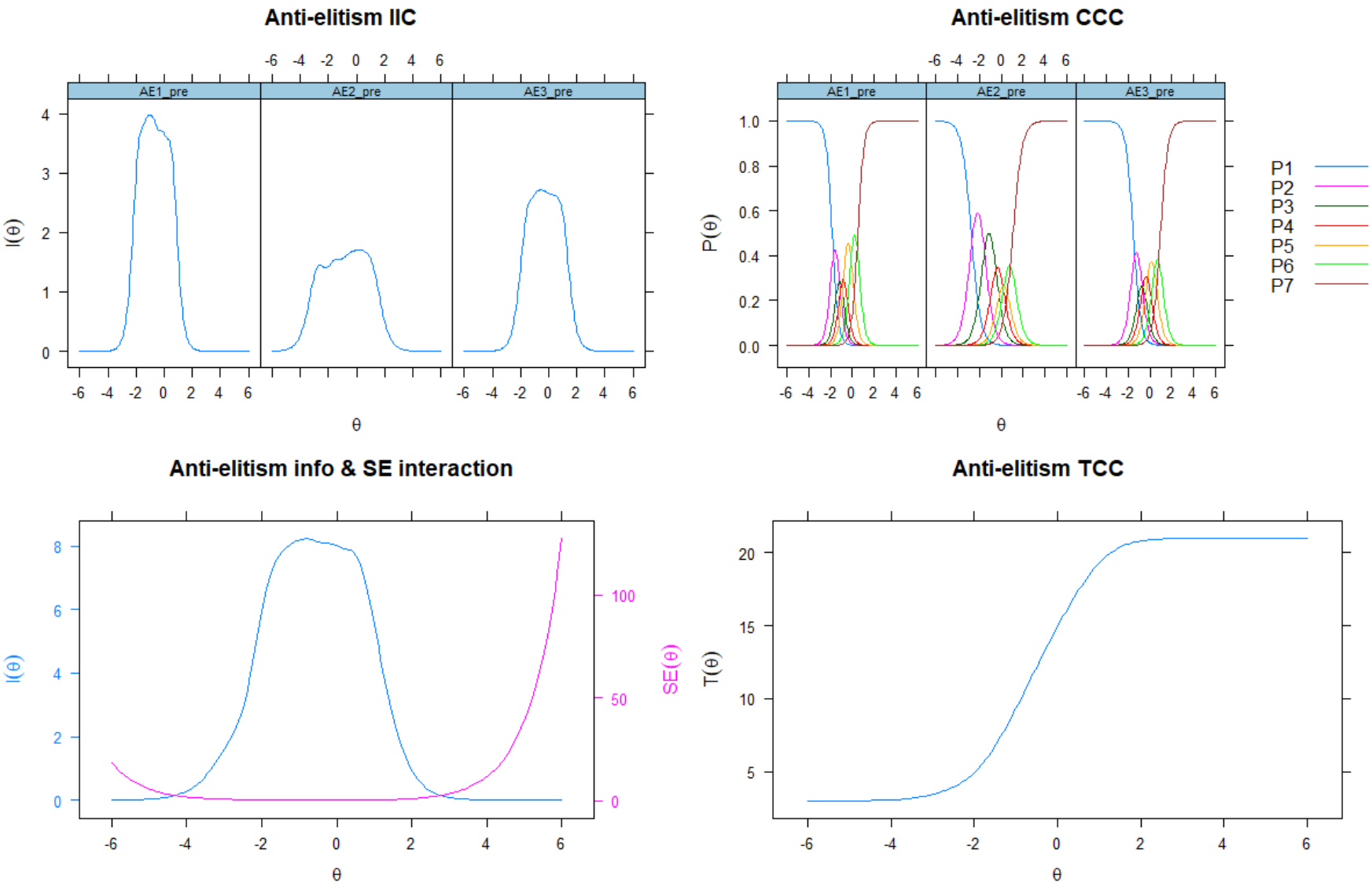


Figure 10 Results from the IRT Graded Response Model

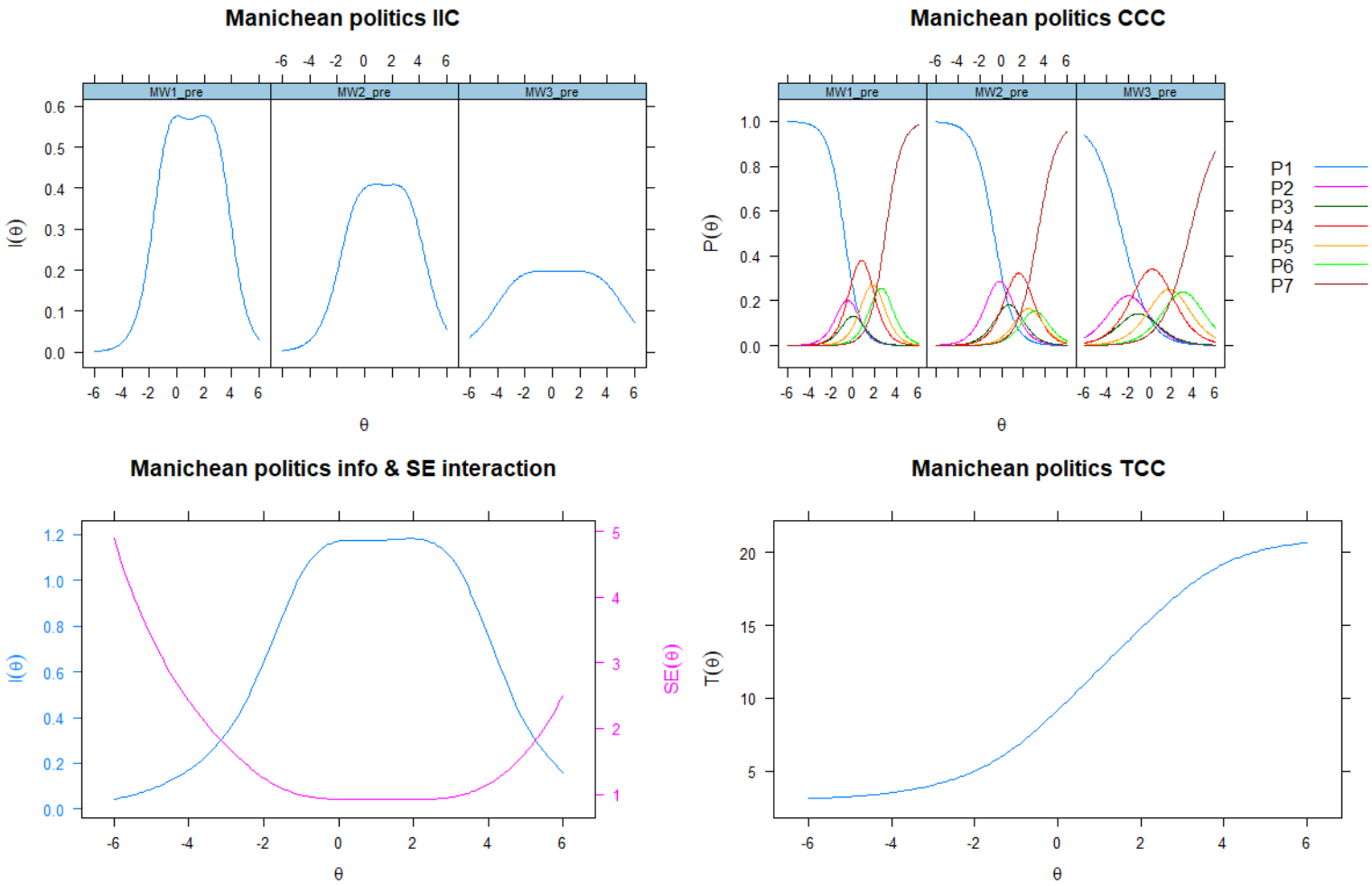


Figure 11 Results from the IRT Graded Response Model

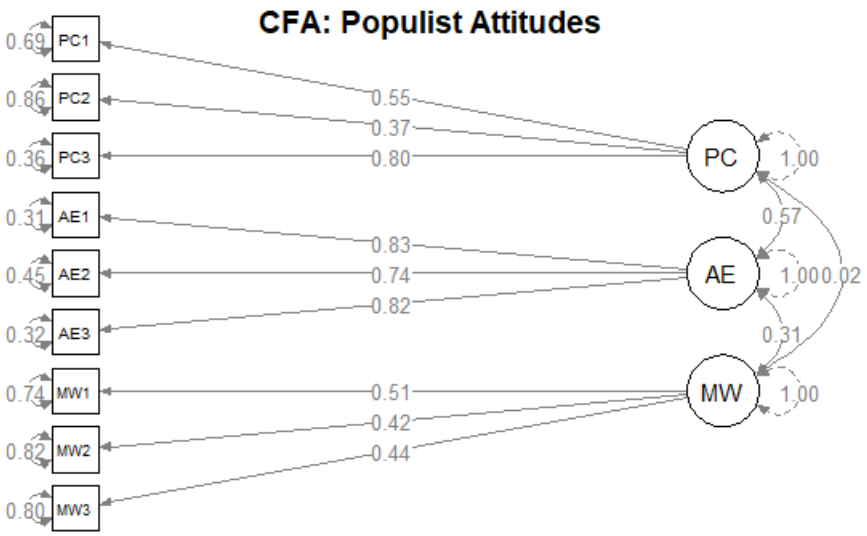


Figure 12

# of missingness patterns	9
Robust χ2 (df):	48.788***(24)
Scaling correction factor for the Yuan-Bentler correction	1.166
Robust CFI:	0.982
Robust TLI:	0.973
Robust RMSEA (P-value) 90 % CI:	0.038 (0.966) 0.023 0.054
SRMR:	0.034
McDonald's omega (ω) $_{total}$	0.76
ω $_{People\text{-}Centrism}$	0.60
ω $_{Anti\text{-}Elitism}$	0.84
ω $_{Manichean\ view\ of\ politics}$	0.45

All paths are significant at p < 0.001 level, except the correlation between MW & PC is not significant.
χ2 (df) = chi-square & degrees of freedom (good fit indicated by p>0.05); **CFI** = Comparative Fit Index (closer to 1 is better, good fit indicated by >.95); **TLI** = Tucker-Lewis Index (closer to 1 is better, good fit indicated by >.95); **RMSEA** = Root Mean Square Error of Approximation (good fit indicated by RMSEA < 0.06 & P-value > 0.05); **SRMR** = Standardized Root Mean Square Residual (good fit indicated by SRMR < 0.05) (Hu & Bentler, 1999; Kline, 2016). McDonald's (1999) omega (ω) is known to be a better indicator for the reliability of multi-dimensional CFAs with *N*>1000 (Crutzen & Peters, 2015; Revelle & Zinbarg, 2009; Rodriguez, Reise, & Haviland, 2016). While higher ω correspond to higher reliability, ω_{total} gives the reliability estimate of the overall variance in the data that is due to a general factor as well as the specific factors (Revelle & Condon, 2018). See McNeish (2018) for a review of drawbacks of Cronbach's alpha (α) and its alternatives including the ω.

Right-Wing Authoritarianism Scale – Aichholzer and Zeglovits (2015)

The scale taps into three dimensions (authoritarian submission, authoritarian aggression, conventionalism) with each dimension influencing two items (one positively worded, the other negatively worded). A second-order construct right-wing authoritarianism (RWA) influenced the three latent dimensions. Since fitting three IRT models to under-identified models with two items, we fitted the IRT model positing a uni-factor construct that represents the second-order RWA. Judging from the item information curves (IIC), the first item (auth01sub1) has extremely bad psychometric properties; it fails to provide any information (discrimination function). This is most likely due to the item wording (involving being grateful to a leader for saying what to do), and the particular German national context, where the population is extremely cautious and sensitive about a political leader as the memory of the World War 2 and the Holocaust is kept salient.

Table 18

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
auth01sub1	0.049	-6.629	20.244	60.281	100.454
auth02sub2R	1.785	-0.98	0.005	0.99	2.006
auth03agg1	2.236	-2.028	-1.171	-0.345	0.47
auth04agg2R	1.571	-1.307	-0.204	0.688	1.616
auth05con1	2.853	-1.332	-0.545	0.352	1.197
auth05con2	2.523	-1.022	-0.157	0.893	1.596

We decided to drop the single worst item and fit a uni-factor measurement model. All remaining indicators yield acceptable psychometric qualities. Although, the shape of the sigmoid function is not perfect, the slope we see on the TCC plot also indicate that there is enough accumulate information to distinguish individuals on the negative and positive side of the latent

trait. Additionally, the goodness of fit statistics of the measurement model with five items indicate a good fit.

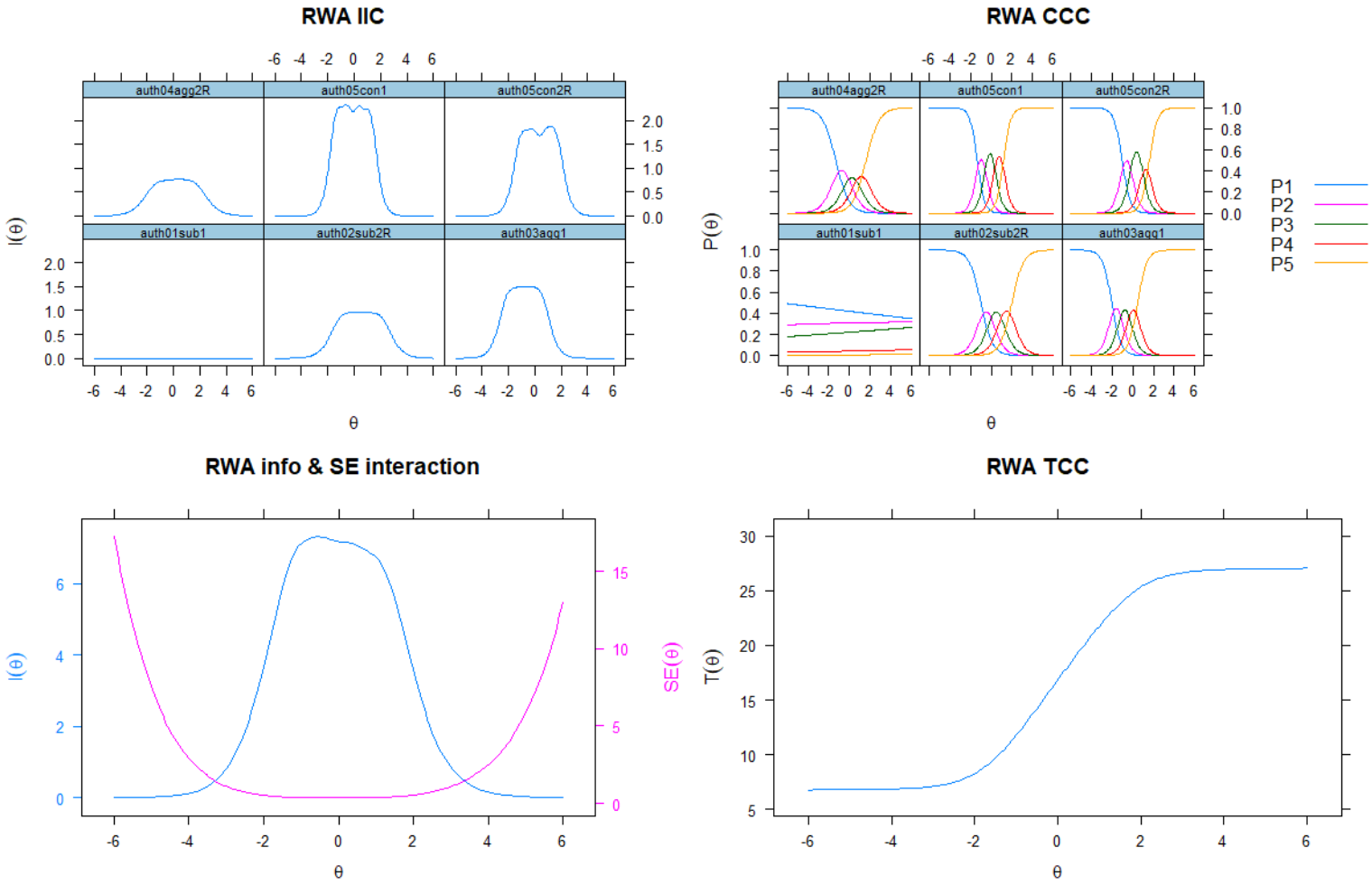


Figure 13 Results from the IRT Graded Response Model

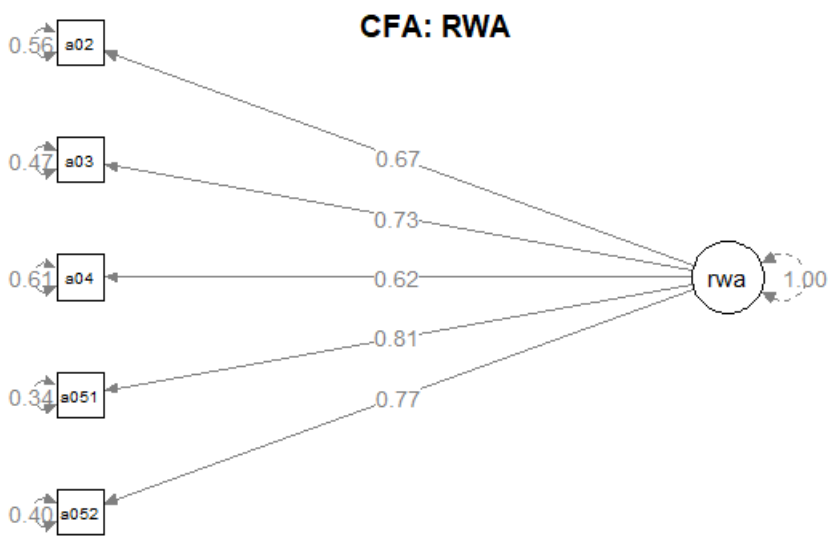


Figure 14

# of missingness patterns	4
Robust χ2 (df):	27.315***(5)
Scaling correction factor for the Yuan-Bentler correction	1.265
Robust CFI:	0.982
Robust TLI:	0.964
Robust RMSEA (P-value) 90 % CI:	0.083 (0.045) 0.054 0.114
SRMR:	0.23
McDonald's omega (ω) $_{total}$	0.84
ω $_{RWA}$	0.84
All paths are significant at p < 0.001 level.	

Collective Narcissism Scale – Zavala et al. (2009)

All indicators yield acceptable psychometric qualities. The goodness of fit statistics of the measurement model indicate a good fit.

Table 19

Variable Name	Discrimination	Category Thresholds					
	α	β_1	β_2	β_3	β_4	β_5	β_6
cn2	2.671	-0.265	0.14	0.325	1.506	1.773	2.054
cn3	3.819	-0.332	0.009	0.205	0.894	1.332	1.744
cn5	2.57	-0.524	-0.002	0.313	1.082	1.654	2.022
cn6	1.438	-1.069	-0.414	-0.046	1.144	2.123	2.672
cn8	2.039	-1.038	-0.492	-0.226	0.683	1.239	1.868

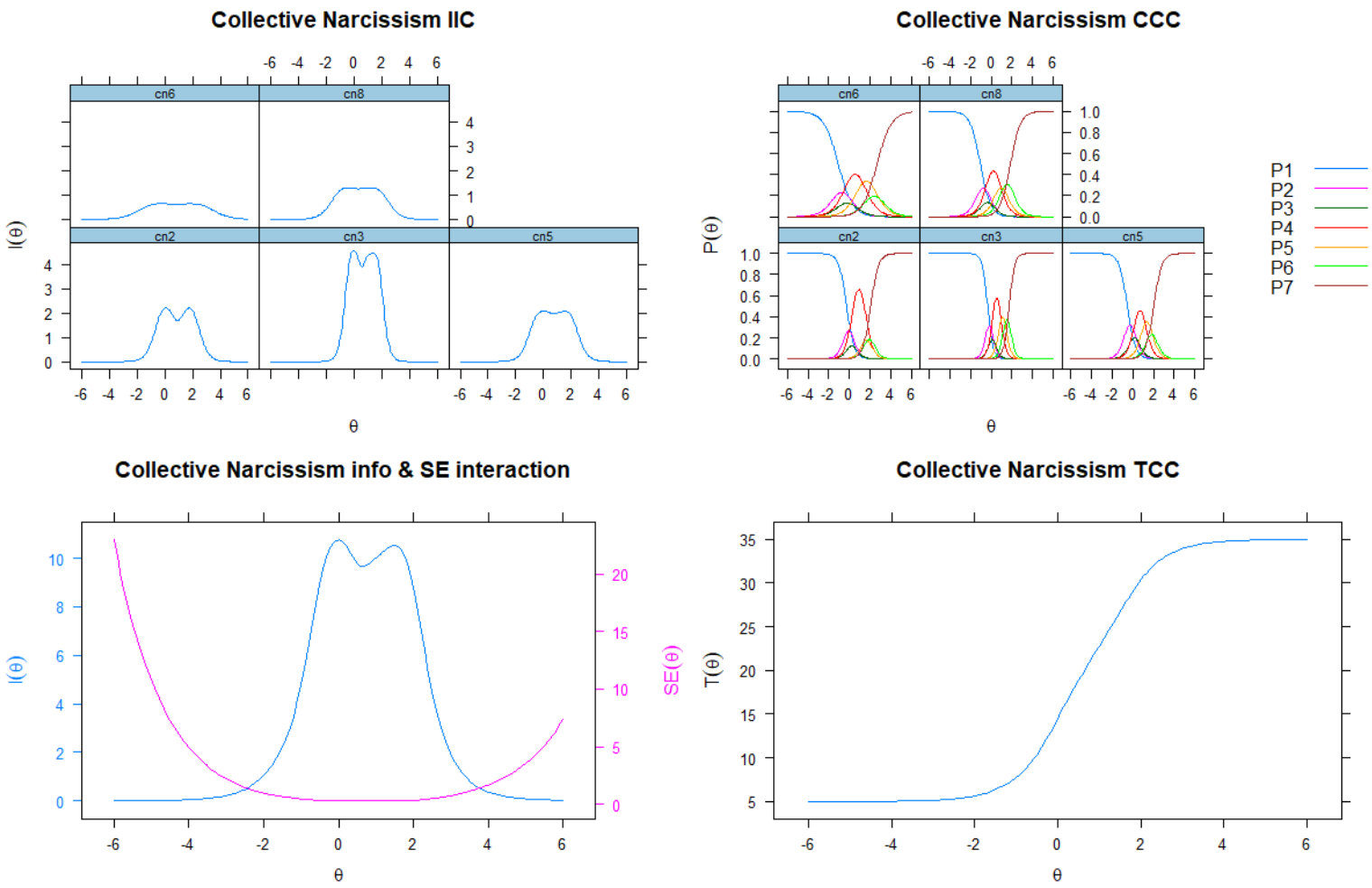


Figure 15 Results from the IRT Graded Response Model

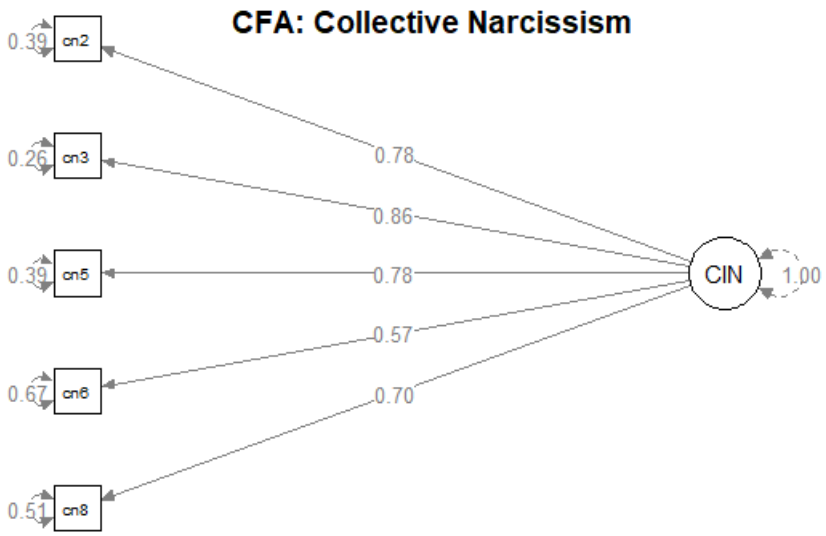


Figure 16

# of missingness patterns	4
Robust χ2 (df):	24.621***(5)
Scaling correction factor for the Yuan-Bentler correction	1.521
Robust CFI:	0.984
Robust TLI:	0.967
Robust RMSEA (P-value) 90 % CI:	0.085 (0.68)0.053 0.119
SRMR:	0.024
McDonald's omega (ω) $_{total}$	0.86
ω $_{Collective\ .narcissism}$	0.86
All paths are significant at p < 0.001 level.	

National Identification Scale – (Leach et al., 2008)

All indicators yield acceptable psychometric qualities. The goodness of fit statistics of the measurement model indicate a good fit.

Table 20

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
nice01	2.096	-0.937	-0.09	0.77	1.799
nice02	3.405	-1.151	-0.576	-0.022	0.935
nice03	4.203	-0.742	-0.134	0.543	1.333

Table 21

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
niso01	3.952	-1.634	-1.112	-0.435	0.835
niso02	2.994	-1.951	-1.313	-0.456	0.978
niso03	2.968	-1.182	-0.547	0.119	1.124

Table 22

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
nisa01	3.535	-1.717	-1.3	-0.303	0.719
nisa02	3.453	-1.815	-1.297	-0.436	0.815
nisa03	3.629	-1.525	-0.969	0.002	0.997

Table 23

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
niss01	3.765	-1.554	-0.673	0.178	1.441
niss02	4.538	-1.423	-0.566	0.252	1.51
niss03	4.117	-1.323	-0.511	0.335	1.533

Table 24

Variable Name	Discrimination	Category Thresholds			
	α	β_1	β_2	β_3	β_4
niho01	2.534	-2.186	-1.104	-0.096	1.714
niho02	2.359	-1.514	-0.401	0.702	2.183
niho03	3.207	-1.67	-0.681	0.239	1.8

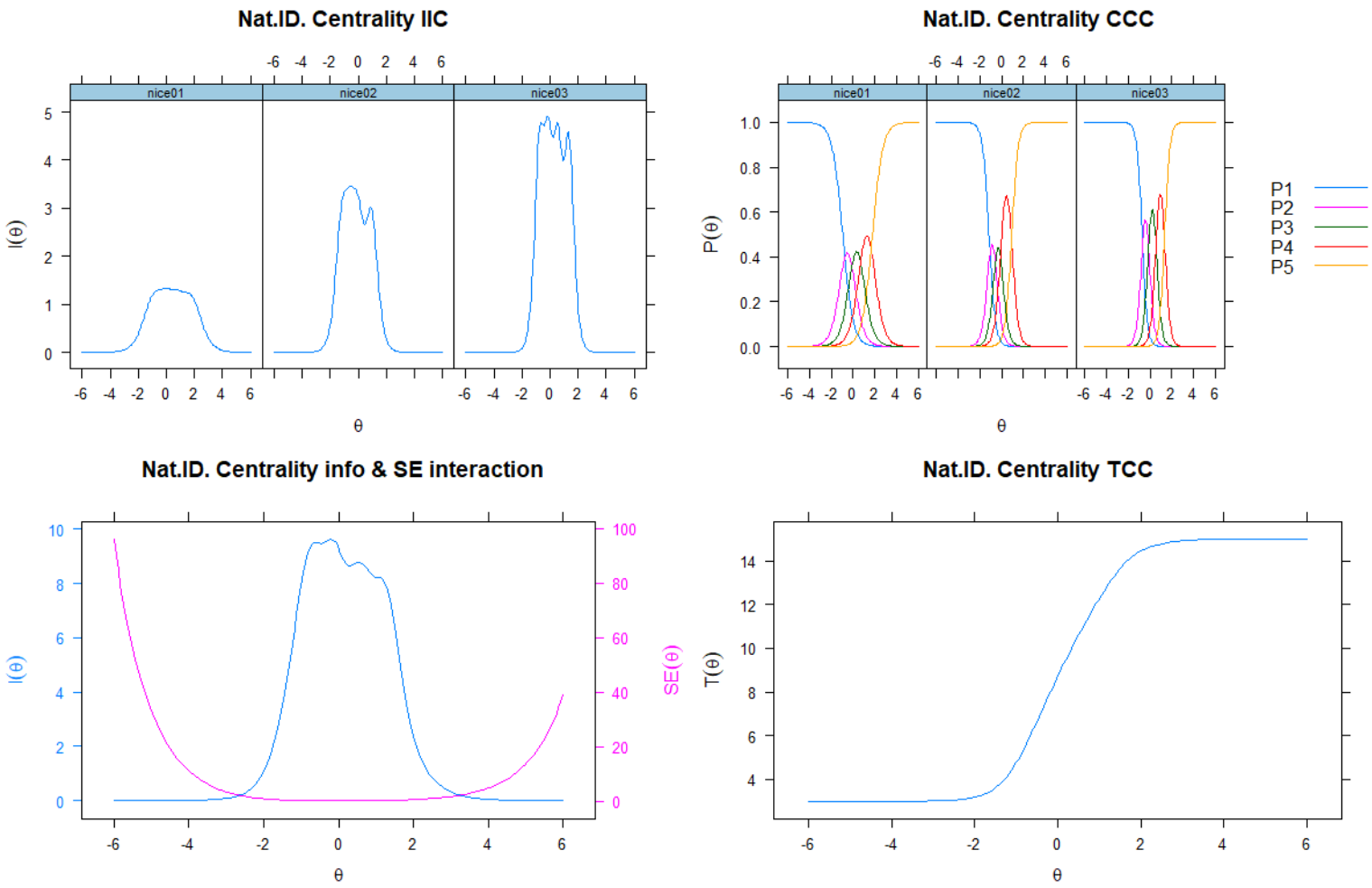


Figure 17 Results from the IRT Graded Response Model

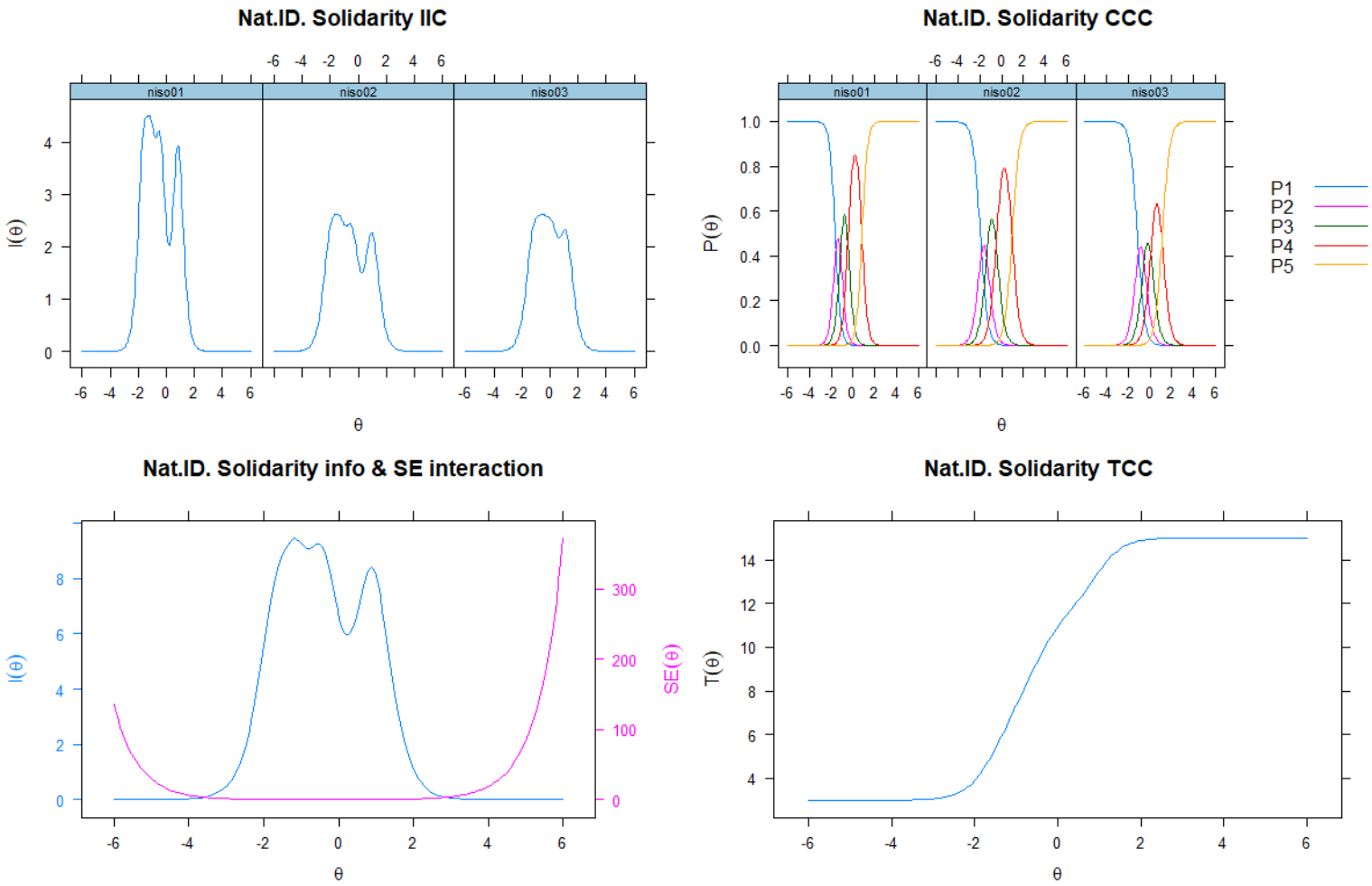


Figure 18 Results from the IRT Graded Response Model

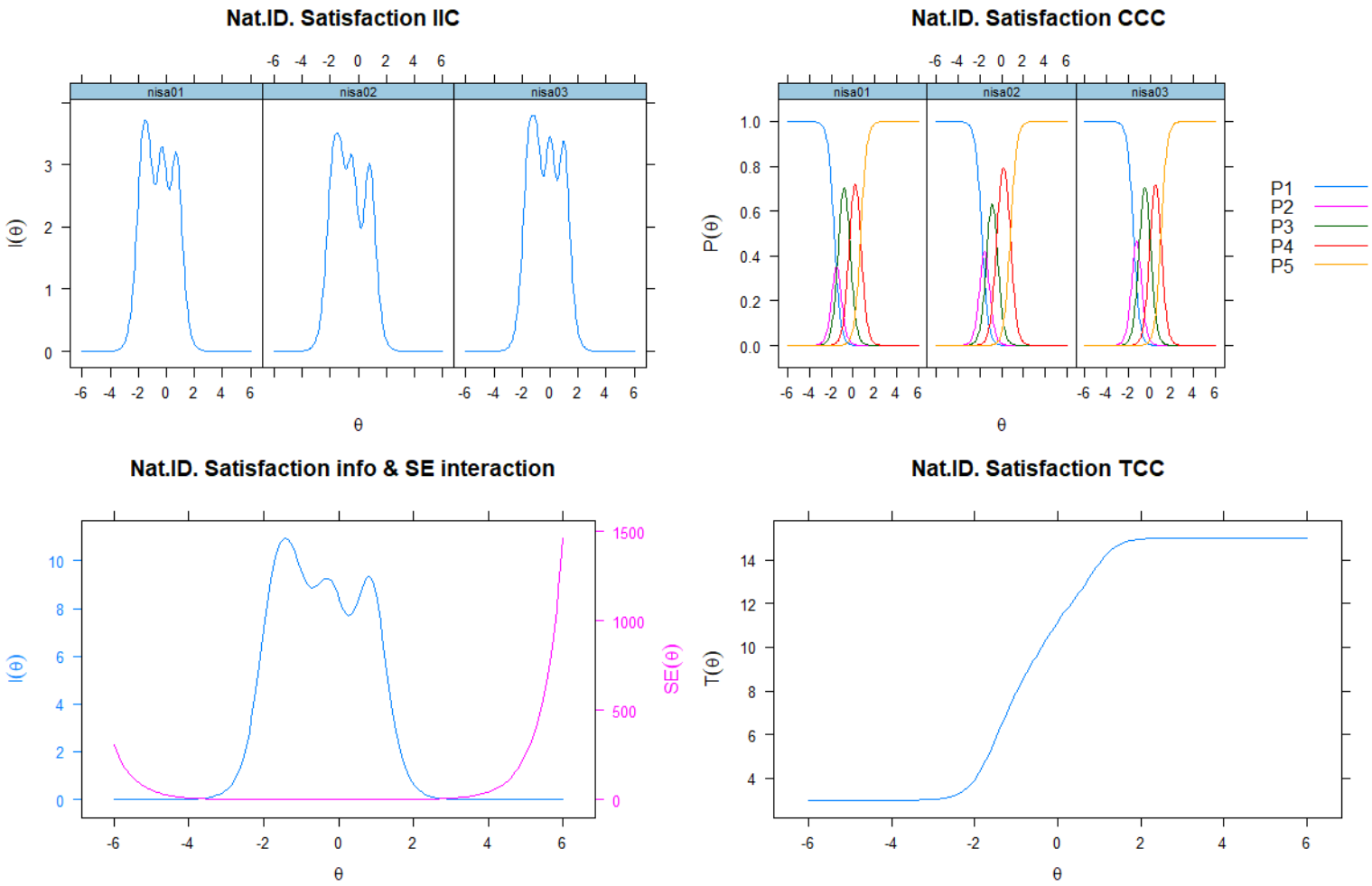


Figure 19 Results from the IRT Graded Response Model

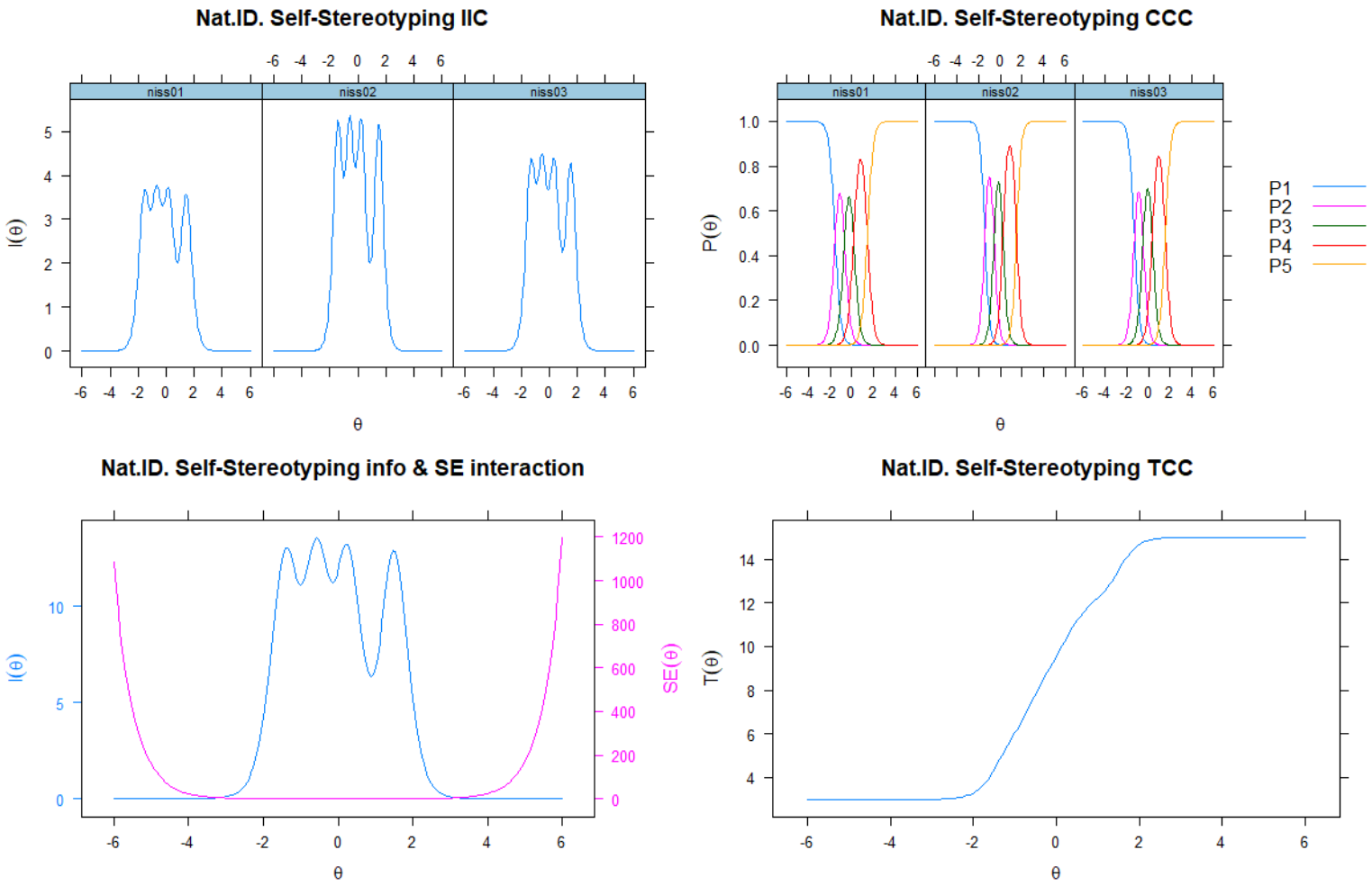


Figure 20 Results from the IRT Graded Response Model

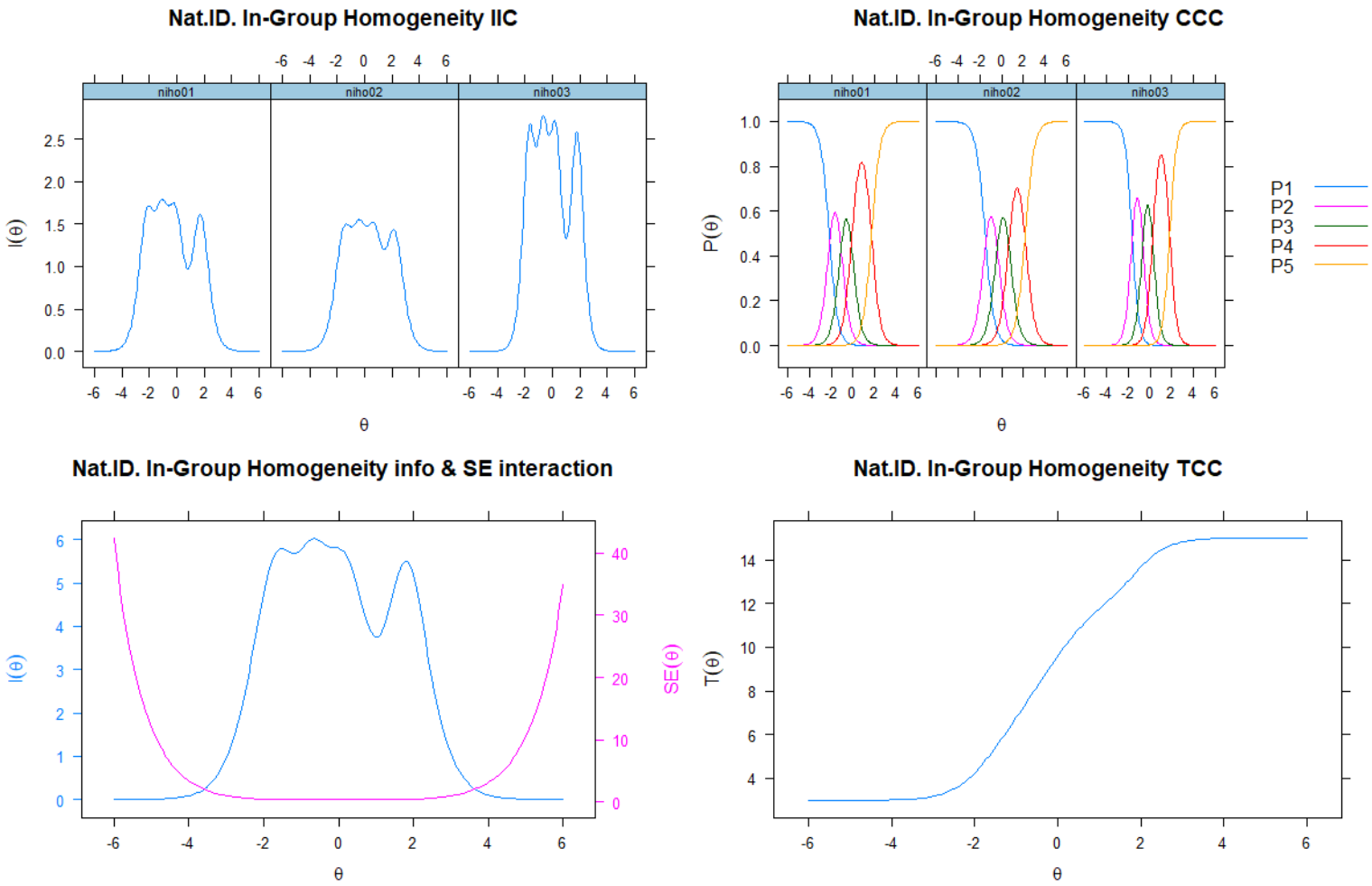


Figure 21 Results from the IRT Graded Response Model

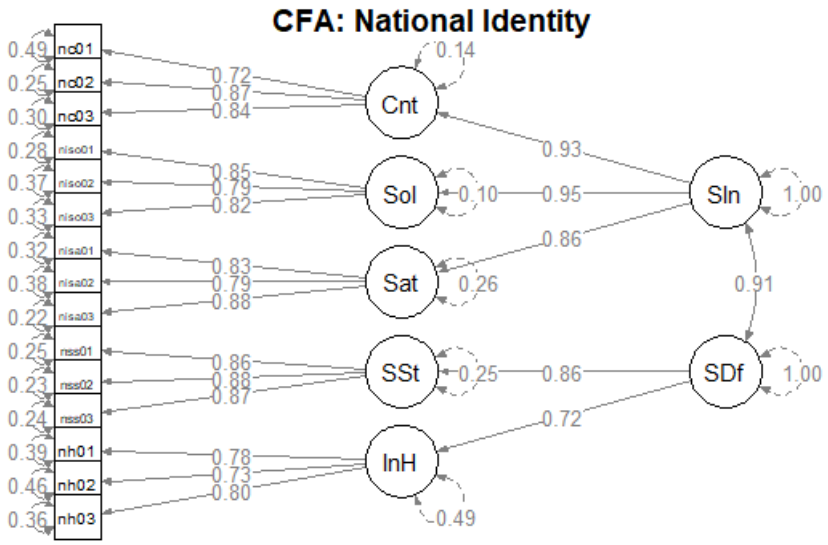


Figure 22

# of missingness patterns	21
Robust χ2 (df):	218.711***(84)
Scaling correction factor for the Yuan-Bentler correction	1.374
Robust CFI:	0.979
Robust TLI:	0.974
Robust RMSEA (P-value) 90 % CI:	0.050 (0.930) 0.042 0.059
SRMR:	0.030
McDonald's omega (ω) $_{total}$	0.96
ω $_{Centrality}$	0.85
ω $_{Solidarity}$	0.86
ω $_{Satisfaction}$	0.87
ω $_{Self\text{-}stereotyping}$	0.91
ω $_{In\text{-}group\ homogeneity}$	0.81
Self-Investment: Reliability values at level 1: 0.88; Reliability values at level 2: 0.95; Partial reliability value at level 1: 0.94 ***Self-Definition***: Reliability values at level 1: 0.71; Reliability values at level 2: 0.79; Partial reliability value at level 1: 0.89	
All paths are significant at $p < 0.001$ level.	

Construct Level Descriptive Statistics and Multiple Imputation

We used semi-parametric predictive mean matching algorithm implemented in the R mice package (van Buuren & Groothuis-Oudshoorn, 2011) to impute the missing values in the normalized factor scored displayed in Table 25 below (min. missing: 1.91 %; max missing: 2.5 %). This approach ensures plausible values with the help of an iterated process. The algorithm utilizes observed values of the predictor and the predicted variables to impute the missings. Once predicted values of the missing observations are calculated with linear regression, they are matched to the closest three values in the observed predicted values, and one of these three values is randomly imputed. This process is iterated, and with each iteration, a new dataset of observed values is created.

We imputed 10 chain datasets with 1000 iterations and used the imputed values in the last created dataset. Judging by the descriptive statistics, visual inspection of the density plots (before & after the imputation), and diagnostic plots, we see no result to bias our following estimations.

Table 25

Construct level descriptive statistics before imputation

Construct	*Abbreviation*	*Missings*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
People-Centrism	PC	1.91 %	0.76	0.21	-1.16	0.96	0.83	0-1	0.01
Anti-Elitism	AE	1.91 %	0.62	0.25	-0.37	-0.8	0.64	0-1	0.01
Manichean View of Politics	MV	1.91 %	0.42	0.17	0.21	-0.32	0.42	0-1	0.01
Right-Wing Authoritarianism	RWA	1.91 %	0.5	0.25	-0.04	-0.87	0.50	0-1	0.01
Collective Narcissism	CN	2.38 %	0.33	0.25	0.58	-0.39	0.29	0-1	0.01
Self-Investment	SInv	2.50 %	0.57	0.22	-0.24	-0.36	0.59	0-1	0.01
Self-Definition	SDef	2.50 %	0.56	0.21	-0.15	-0.27	0.56	0-1	0.01

Table 26

Construct level descriptive statistics after imputation

Construct	*Abbreviation*	*Missings*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
People-Centrism	PC	0.00 %	0.76	0.21	-1.15	0.94	0.83	0-1	0.01
Anti-Elitism	AE	0.00 %	0.62	0.25	-0.38	-0.8	0.64	0-1	0.01
Manichean View of Politics	MV	0.00 %	0.42	0.17	0.2	-0.34	0.42	0-1	0.01
Right-Wing Authoritarianism	RWA	0.00 %	0.5	0.25	-0.04	-0.87	0.51	0-1	0.01
Collective Narcissism	CN	0.00 %	0.33	0.25	0.58	-0.38	0.29	0-1	0.01
Self-Investment	SInv	0.00 %	0.58	0.22	-0.26	-0.33	0.59	0-1	0.01
Self-Definition	SDef	0.00 %	0.56	0.21	-0.17	-0.25	0.56	0-1	0.01

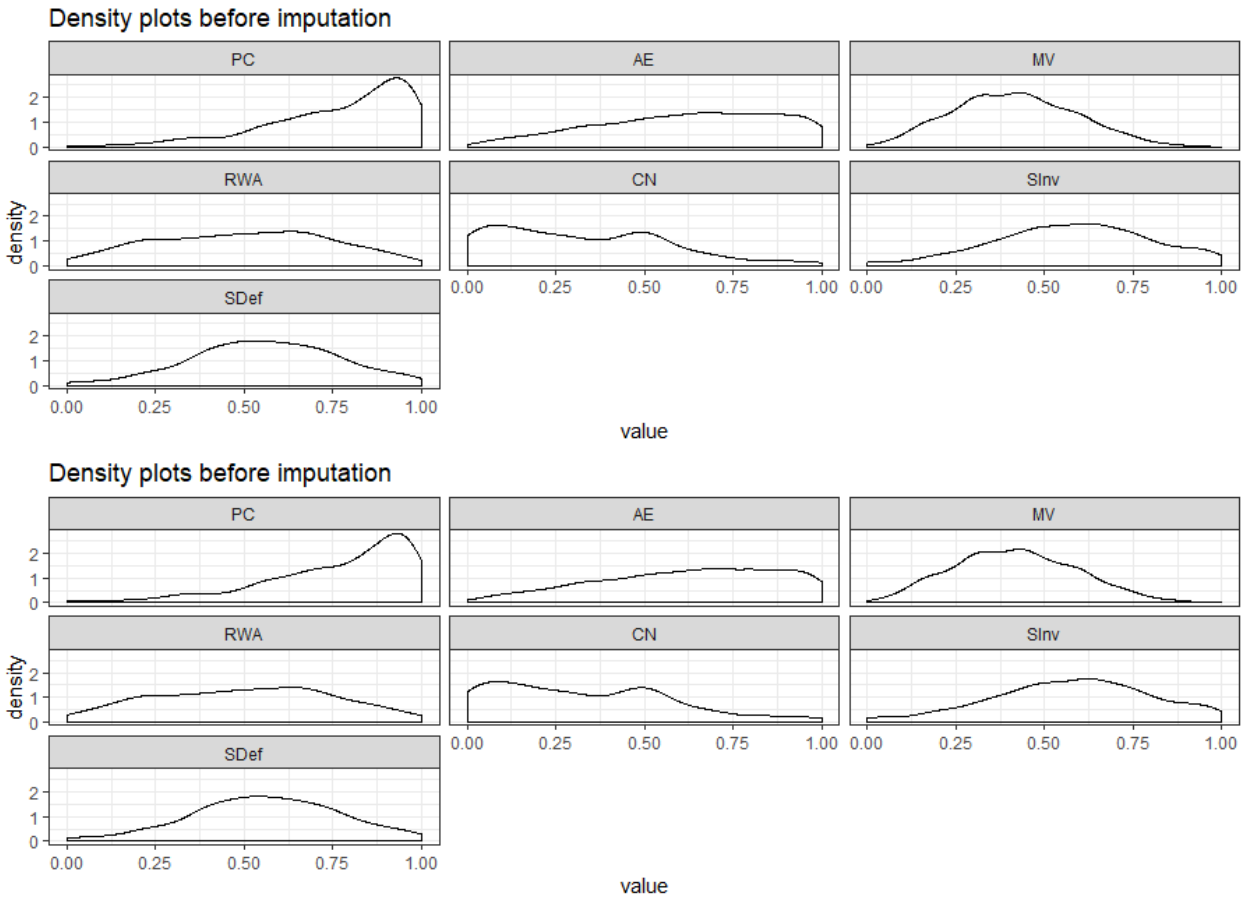

Density plots before imputation
PC
AE
MV
RWA
CN
SInv
SDef
density
value
Density plots before imputation
PC
AE
MV
RWA
CN
SInv
SDef
density
value

Figure 23

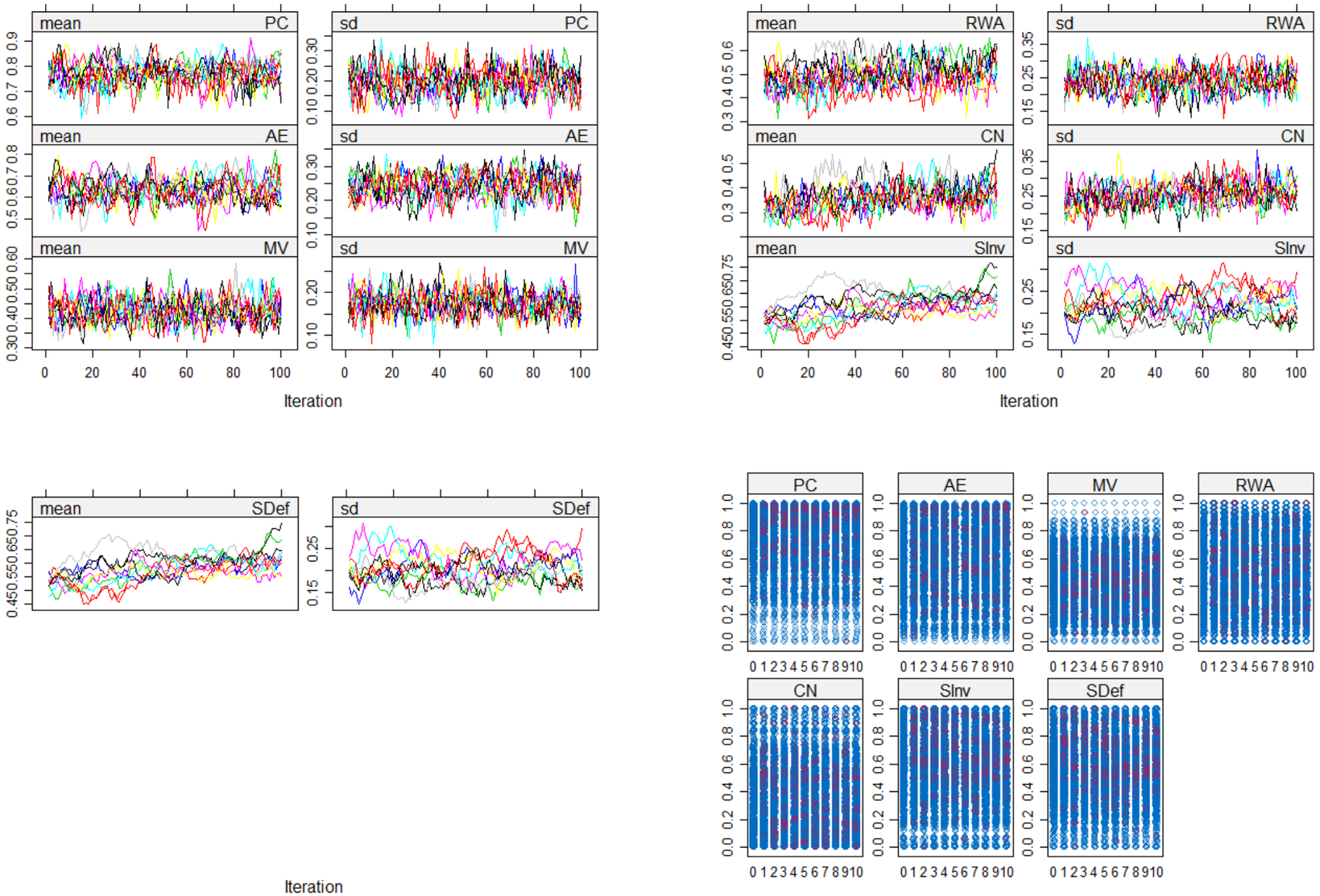


Figure 24 Multiple imputation diagnostics plots

Extended Latent Profile Analysis Results

We implemented model-based clustering and relied on mclust (Scrucca, Fop, Murphy, & Raftery, 2016), tidyLPA (Rosenberg, Beymer, Anderson, & Schmidt, 2018) and factoextra (Kassambara, 2017) packages in the R environment to estimate the latent profiles. The approach we adopt considers the data coming from a mixture of density and assumes a normal distribution of variables. The model parameters are estimated with the Expectation-Maximization algorithm initialized by hierarchical model-based clustering. Each cluster in the data is centered at the mean with increased density around the mean. The geometric features like shape, volume and orientation rely on the covariance matrix for all the profiles (Kassambara, 2017).

To estimate the profiles, we used the normalized factors scores of populist attitudes, RWA, collective narcissism, and the higher-order factors of the national identification scale. The mclust function suggests two clusters/latent profiles with varying volume, shape, and orientation based on the observed data – this model estimates the variances and the covariances freely across profiles. Despite not being parsimonious, the procedure allows us to understand many aspects of the variables that are used to estimate the profiles and how they are related (Rosenberg et al., 2018). The bootstrapped likelihood ratio test (Nylund, Asparouhov, & Muthén, 2007) confirmed that a two cluster is significantly better, and three clusters lead to estimation problems. All these results suggest that two latent profiles are likely. 58 % of the sample is categorized as Profile 1, and the remaining 42 % is Profile 2.

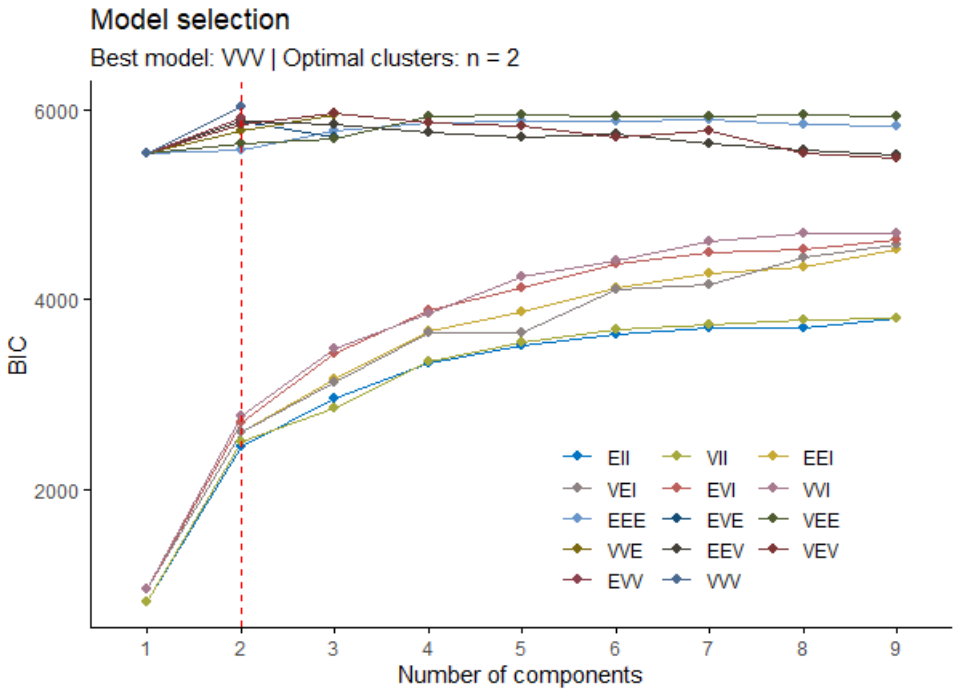


Figure 25

Table 27

Bootstrap sequential LRT for the number of mixture components		
Model = VVV (ellipsoidal, varying volume, shape, and orientation // varying variances and varying covariances)		
Replications = 999		
	LRTS bootstrap	p-value
1 vs 2	730.2594	0.001

Table 28

Class	LogLik	AIC	AWE	BIC	CAIC	CLC	KIC	SABIC	ICL	Entropy	prob_min	prob_max	n_min	n_max	BLRT	p-val
1	2888.110	-5706.220	-5201.965	-5540.592	-5505.592	-5774.220	-5668.220	-5651.741	5540.592	1	1	1	1	1	NA	NA
2	3253.239	-6364.479	-5339.099	-6028.492	-5957.492	-6504.885	-6290.479	-6253.965	5912.079	0.797	0.938	0.947	0.417	0.583	730.2594	0.001
3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

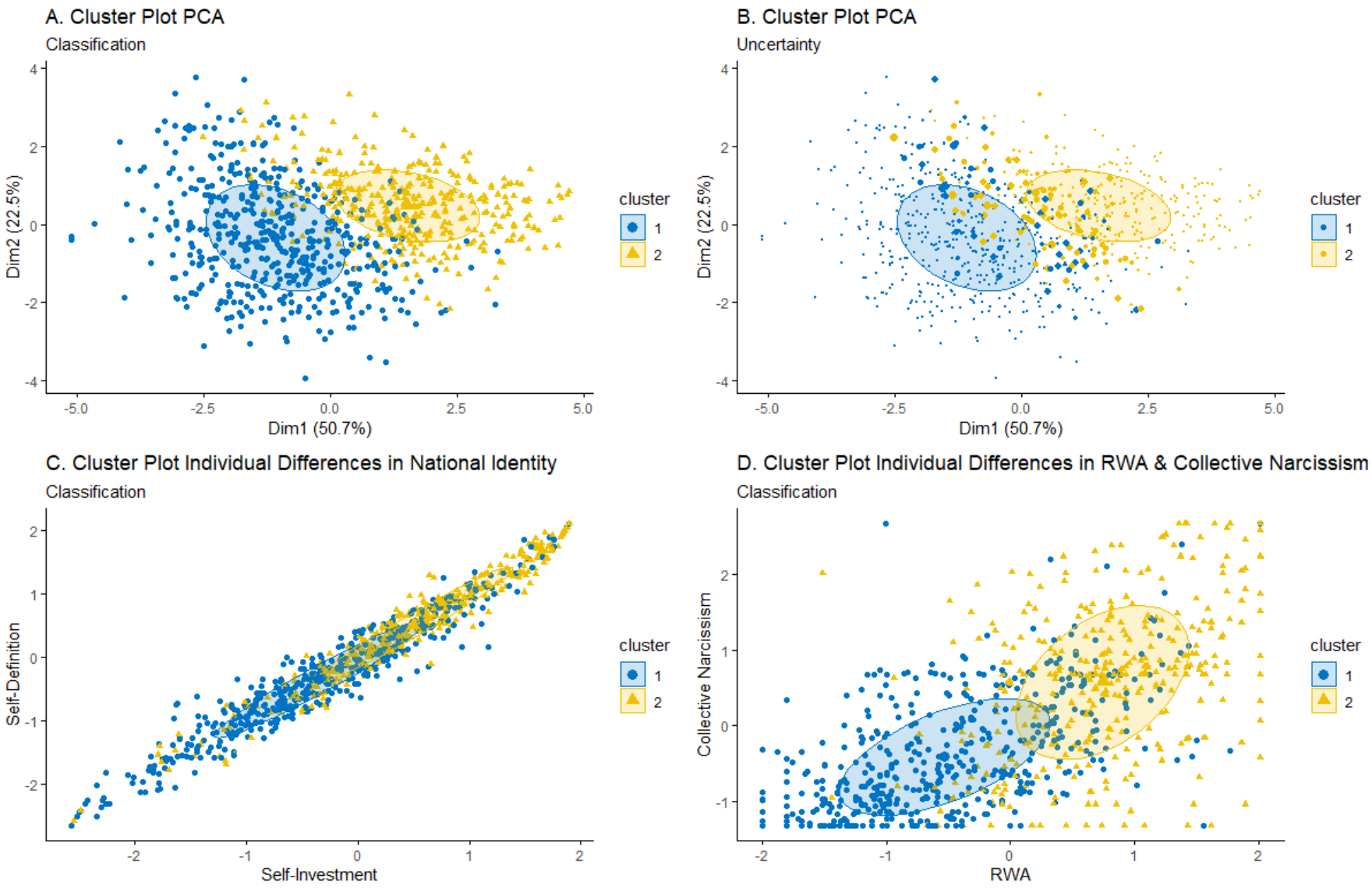


Figure 26 Estimated latent profiles.

Entropy estimate (.80) is acceptable to make a decision on the number of profiles. When we plot the estimated profiles on a two dimensional space (determined by principal component analysis; the first dimension explains 51 %, the second dimension explains 23 %), we see that the profiles do not have a considerable overlap and the predicted probabilities of belonging to these profiles have negligible uncertainty, which again indicates the distinctiveness of the profiles (***see*** Figures 26 A & B). We also plotted the profiles against one another using four variables on the x & y-axis. In the plot where we have the national identification dimensions (self-investment & self-definition), Profile 2's position, in general, seems to be higher compared to Profile 1. When it comes to RWA and collective narcissism, Profile 1 is again lower on both constructs (***see*** Figures 26 C & D).

All this evidence suggests that Profile 2 is higher on the spectrum that includes all these psychological constructs. Descriptive statistics for each profile are listed in the following Tables 29 and 30.

Table 29

Construct level descriptive statistics for Profile 1

Construct	*Abbreviation*	*N*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
People-Centrism	PC	489	0.65	0.19	-0.87	0.55	0.68	0.97	0.01
Anti-Elitism	AE	489	0.49	0.22	0.03	-0.70	0.49	0.99	0.01
Manichean View of Politics	MV	489	0.39	0.17	0.18	-0.24	0.40	1.00	0.01
Right-Wing Authoritarianism	RWA	489	0.37	0.21	0.35	-0.52	0.35	1.00	0.01
Collective Narcissism	CN	489	0.23	0.19	0.90	0.65	0.18	1.00	0.01
Self-Investment	SInv	489	0.50	0.21	-0.12	-0.30	0.50	1.00	0.01
Self-Definition	SDef	489	0.48	0.19	-0.10	-0.06	0.49	1.00	0.01

Table 30

Construct level descriptive statistics for Profile 2

Construct	*Abbreviation*	*N*	*Mean*	*SD*	*Skew*	*Kurtosis*	*Median*	*Range*	*SE*
People-Centrism	PC	350	0.93	0.05	-0.59	-0.74	0.94	0.20	0.00
Anti-Elitism	AE	350	0.81	0.15	-0.71	-0.27	0.83	0.67	0.01
Manichean View of Politics	MV	350	0.45	0.18	0.19	-0.55	0.44	0.86	0.01
Right-Wing Authoritarianism	RWA	350	0.68	0.17	-0.22	-0.30	0.69	0.88	0.01
Collective Narcissism	CN	350	0.47	0.25	-0.01	-0.59	0.50	1.00	0.01
Self-Investment	SInv	350	0.69	0.20	-0.62	0.51	0.70	1.00	0.01
Self-Definition	SDef	350	0.66	0.19	-0.51	0.30	0.67	1.00	0.01

The density plots in Figure 27 display the distribution of profiles (in the sample) with regards to gender, self-placed political orientation, and East vs. West German federal states.

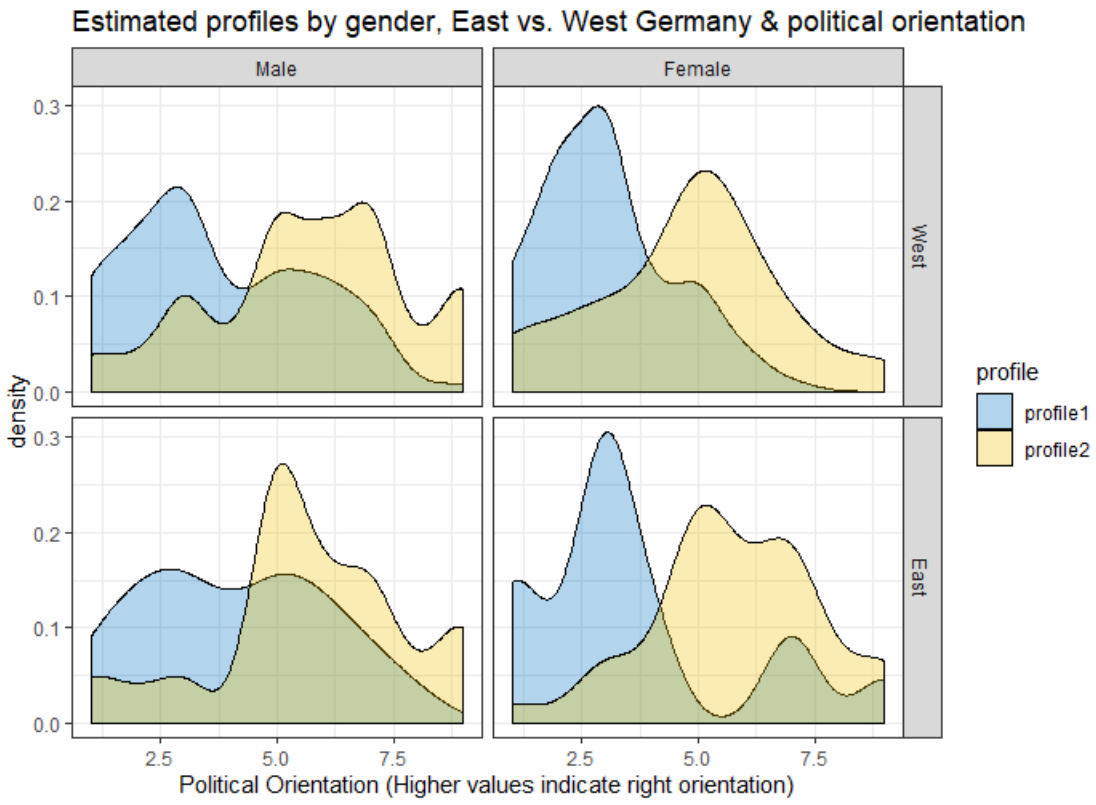


Figure 27

We used these socio-demographic variables and age in a logistic regression to check the associations. Results indicate that all are positively associated with being categorized as Profile 2. The strongest predictor is being born in one of the Eastern German federal states. Table 31 below shows the coefficients from the logistic regression model.

The average marginal effect of being an Eastern German on the probability of being Profile 2 is 13 percentage points (SE = .037, CI = .06 - .20). That is to say, being born in one of federal states from the former GDR is on average predicted to be 13 points more likely to be categorized as Profile 2; all control variables are held at their observed values. The second strongest predictor is political orientation with an average marginal effect of 8 percentage points (SE = .006, CI = .07 - .09). This means leaning towards the right side of the political spectrum is on average predicted to be 8 points more likely to be categorized as Profile 2; all control variables are held at their observed values. The marginal effect of gender is also on average 8 percentage points (SE = .037, CI = .008 - .15), indicating that females are more likely to be associated with the second profile. We used the reported age as a continuous variable rather than categorizing it into intervals. Due to this continuous nature, interpreting the effect does not make sense.

All these relationships are depicted in Figure 28. The overlapping confidence intervals of gender and political orientation call for caution; therefore, we choose only to emphasize the effect of East vs. West German differences on the profile.

Table 31 Logistic regression results; profile explained by socio-demographics.

	Profile 1 vs. 2
(Intercept)	-3.95*** (0.32)
Gender [a]	0.44* (0.20)
Born in East vs. West [b]	0.70*** (0.19)
Age	0.03*** (0.00)
Political Orientation [c]	0.45*** (0.04)
Nagelkerke's R^2	33 %
AIC	826.83
BIC	850.03
Deviance	816.83
Num. obs.	764

***p < 0.001, **p < 0.01, *p < 0.05

[a] Reference category: Male
[b] Reference category: West
[c] Higher scores indicate right orientation

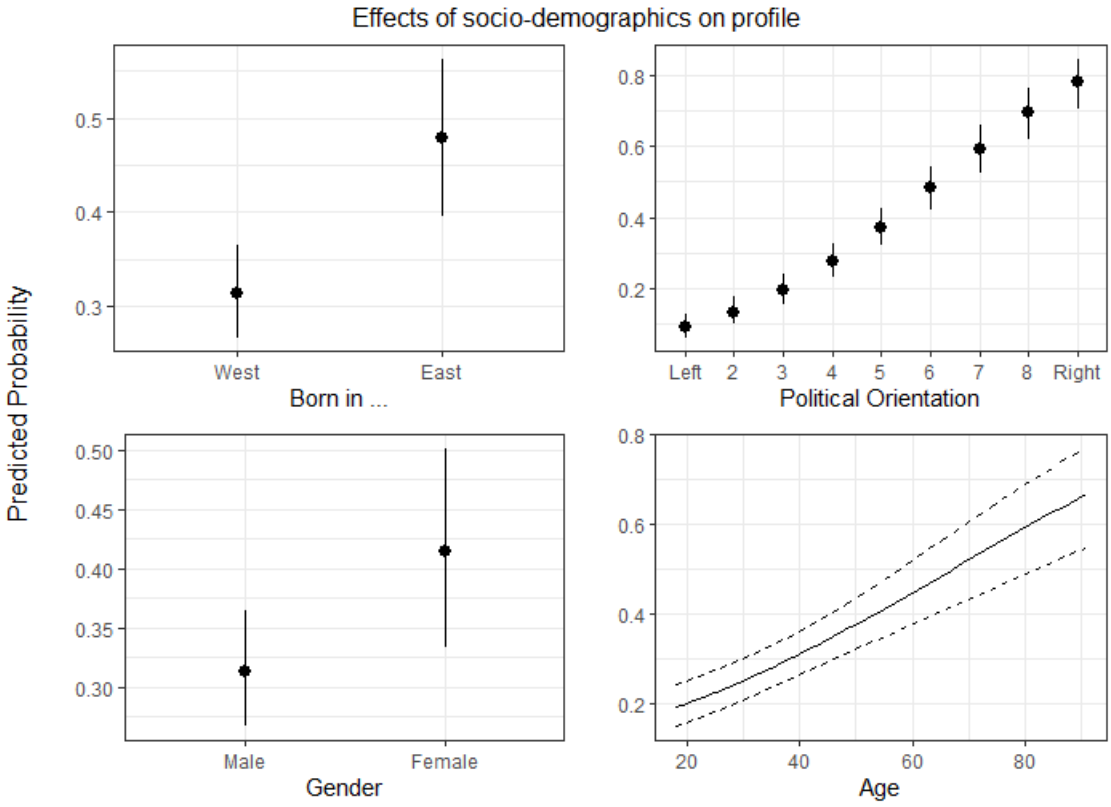


Figure 28

Figure 29 displays the distribution of the estimated latent profiles across experimental - conditions after the random assignment; $\chi 2$ (2, N = 839) = 4.72, p =.09453. The non-significant association indicates a balanced distribution of the profiles across conditions.

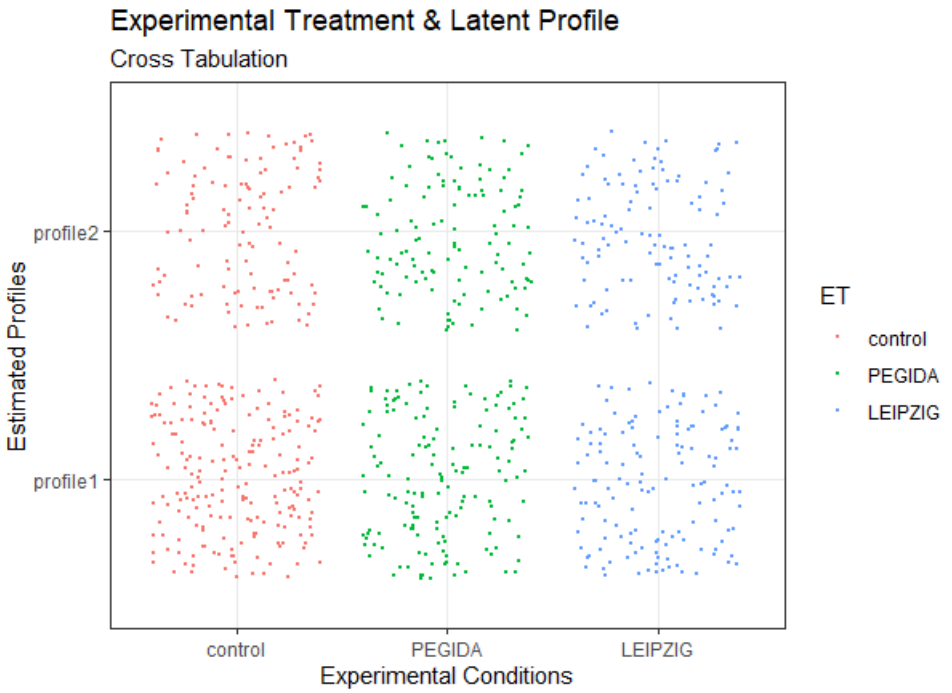


Figure 29

Extended Structural Topic Modeling Results

Structural topic modeling (STM) is a general framework that has somewhat of a similarity to fuzzy clustering. It can classify different texts into estimated topics in a mixed-membership model (Lucas et al., 2015; M. E. Roberts et al., 2014). In our research design, the estimated topics correspond to different viewpoints on the populist slogans administered in different settings. We utilize STM because this approach does not assume an exclusive/unique subjective viewpoint per person; it is unrealistic to expect that participants who are exposed to the different demonstration contexts will frame their open-ended responses in a monolithic manner.

Therefore, using STM that assigns portions of the open-ended responses to multiple estimated topics is particularly useful.

With STM, not only we detect the subjective viewpoints but we also check the correlates of each viewpoint separately. To estimate the topics, we used the experimental treatment and the estimated latent profiles as two nominal variables assuming that each profile perceives the demonstrations subjectively different.

Suggested number of topics

Although some solutions are available in the general topic modeling framework, determining the number of topics (subjective viewpoints of the demonstrations) is not the strongest feature of the technique. Nonetheless, we implemented two approaches to decide on the number of topics to be estimated.

Firstly, we turn to the features of the ldatuning R package. (Nikita, 2019). Here, the estimation relies on four metrics that stem from the previous literature on finding the optimal number of topics (Arun, Suresh, Veni Madhavan, & Narasimha Murthy, 2010; Cao, Xia, Li, Zhang, & Tang, 2009; Deveaud, SanJuan, & Bellot, 2014; Griffiths & Steyvers, 2004). These metrics are expected to minimize or maximize; we find that four topics are likely to be an optimal solution – to our corpus of open-ended responses. Figure 30 shows the results of the ldatuning number of topics estimation.

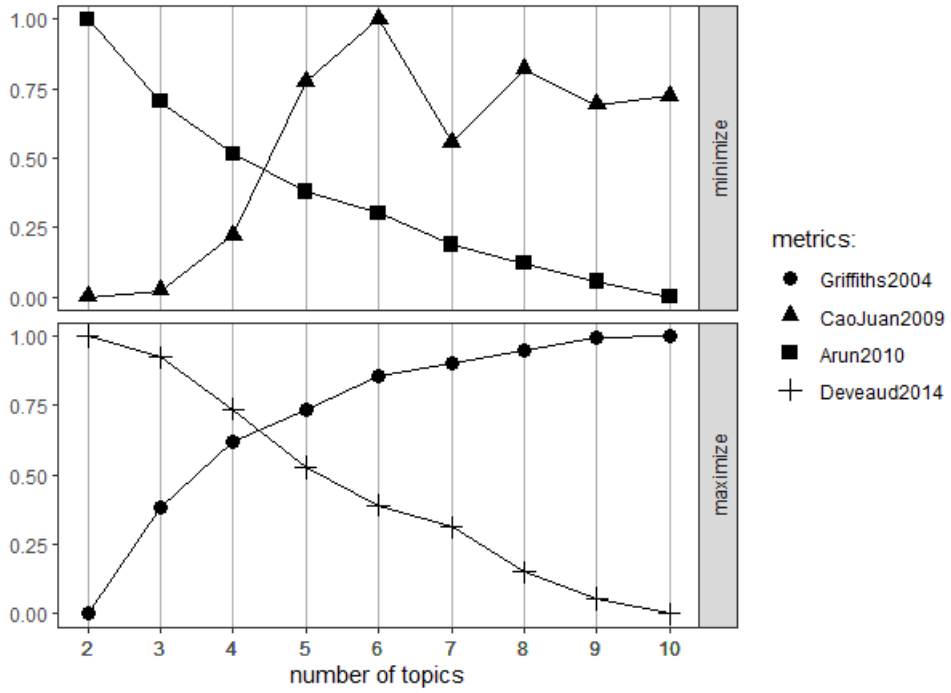


Figure 30 Metrics results for the optimal number of topics.

Secondly, we rely on the model diagnostic values with differing number of topics from the STM package. We envisaged the number of topics by paying attention to semantic coherence and residuals (smaller residuals and close to zero semantic coherence values are desired (M. Roberts, Stewart, & Tingley)). The overall results point to an optimal solution of four topics.

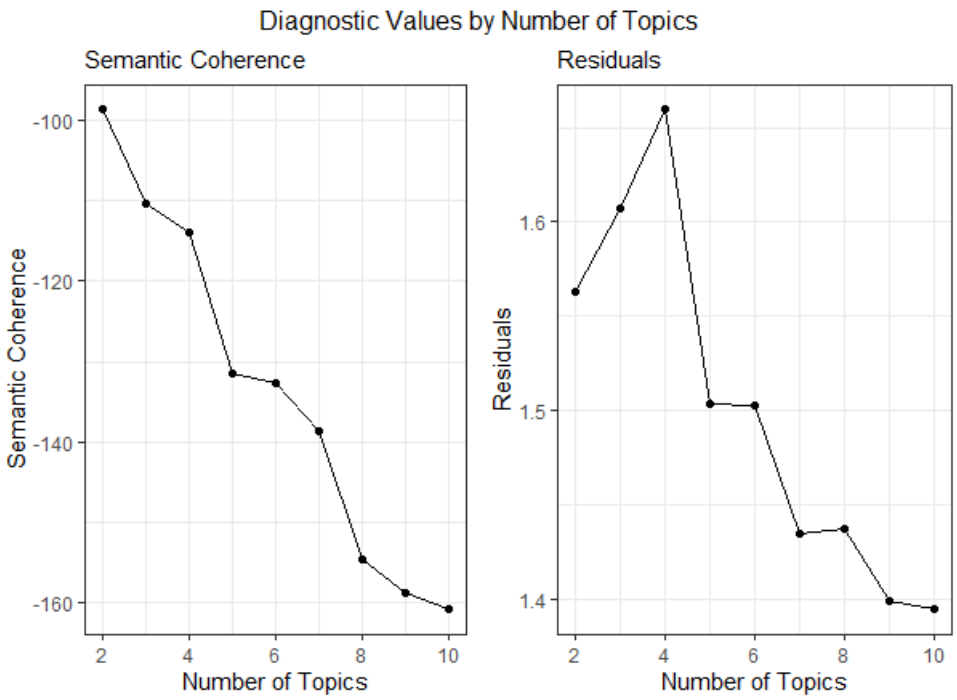


Figure 31 Diagnostic values from the STM package suggesting the optimal number of topics.

As the pre-processing strategy, we applied standard text preparation steps before the STM estimation (***see*** (Grimmer & Stewart, 2013; Lucas et al., 2015)). These steps are stemming (removal of "the endings of conjugated verbs or plural nouns"), removal of numbers, punctuation, and stopwords (which are common in a language, but do not have substantive meaning for analyses, such as "the" or "and").

Consequently, four topics solution provided the most meaningful results. The plots below summarize the estimation findings. Figure 32 A displays the words that have the highest probabilities associated with the estimated topics. Figure 32 B is the density plots of the profiles across the estimated topics, and Figure 32 C shows the correlations across topic proportions. Boxplots in Figures 33 and 34 provide cues about the experimental manipulation and profile and experimental treatment interaction, showing their influence on topic proportions. Figure 35 includes the ridge plots, also displaying the profile and experimental treatment interaction.

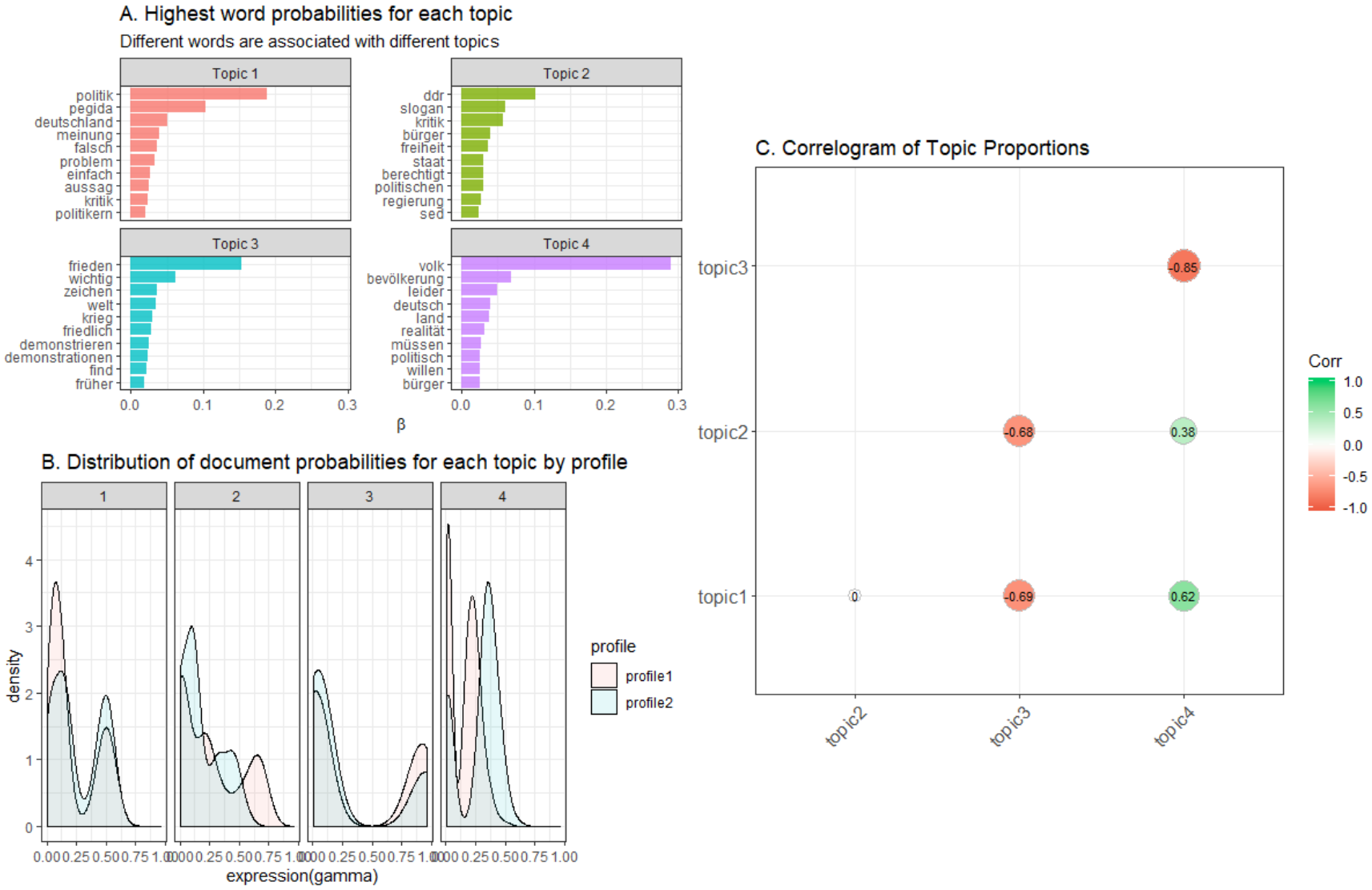


Figure 32 Structural topic model results.

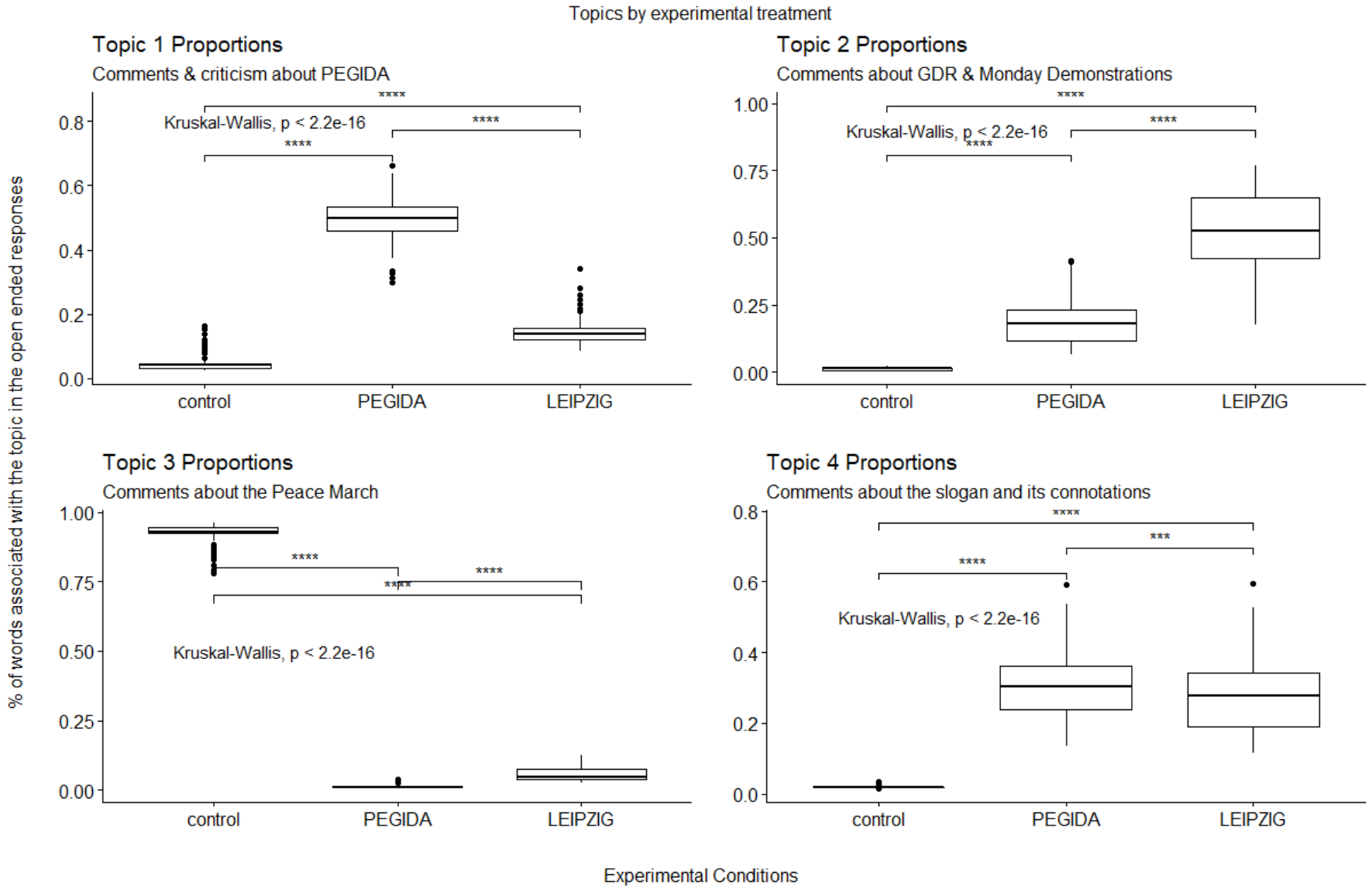

Topics by experimental treatment
Topic 1 Proportions
Comments & criticism about PEGIDA
Kruskal-Wallis, p < 2.2e-16
Topic 2 Proportions
Comments about GDR & Monday Demonstrations
Kruskal-Wallis, p < 2.2e-16
Topic 3 Proportions
Comments about the Peace March
Kruskal-Wallis, p < 2.2e-16
Topic 4 Proportions
Comments about the slogan and its connotations
Kruskal-Wallis, p < 2.2e-16
control
PEGIDA
LEIPZIG
% of words associated with the topic in the open ended responses
Experimental Conditions

Figure 33

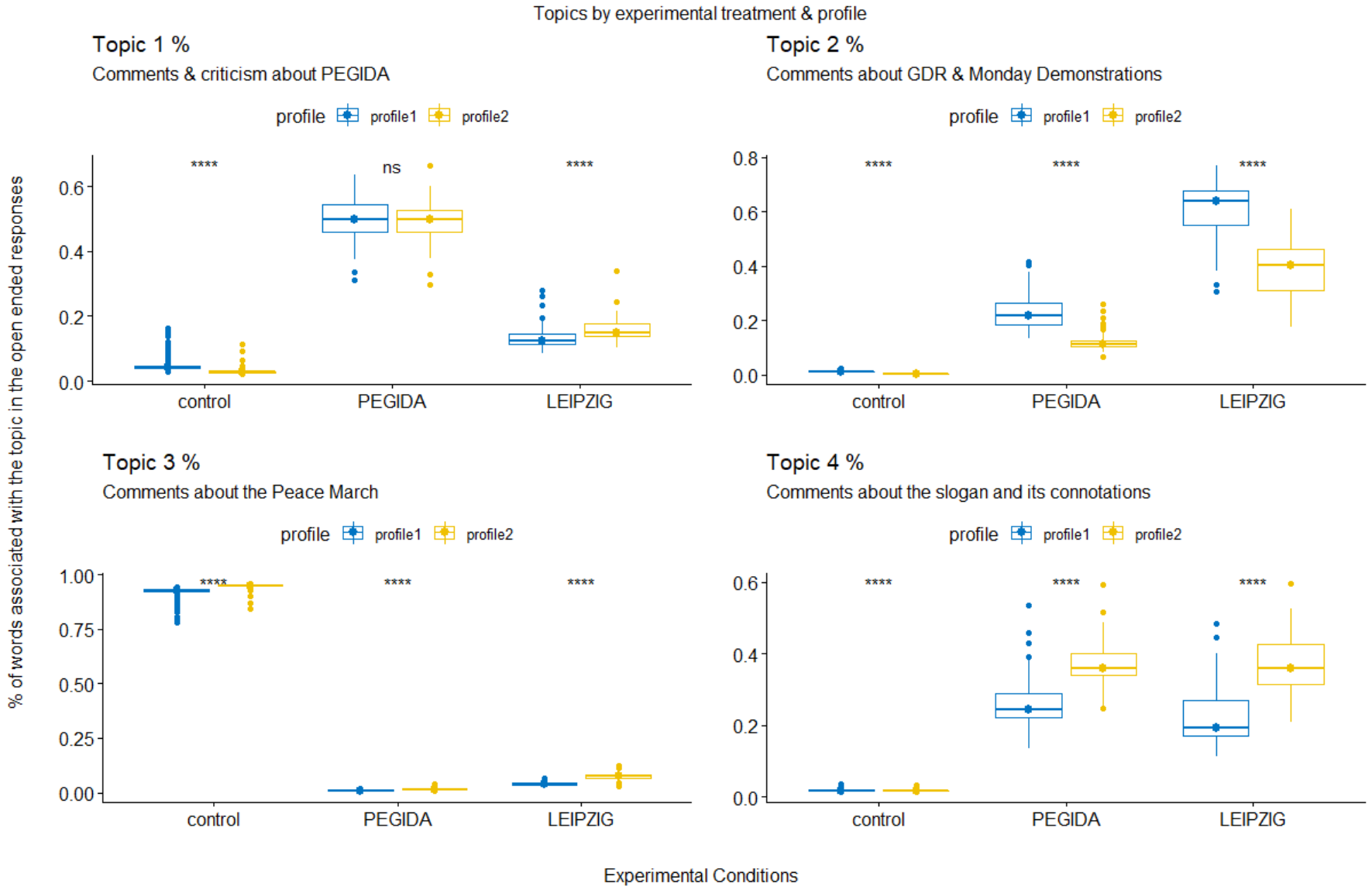

Topics by experimental treatment & profile
Topic 1 %
Comments & criticism about PEGIDA
Topic 2 %
Comments about GDR & Monday Demonstrations
Topic 3 %
Comments about the Peace March
Topic 4 %
Comments about the slogan and its connotations
profile
profile1
profile2
****
ns
control
PEGIDA
LEIPZIG
% of words associated with the topic in the open ended responses
Experimental Conditions

Figure 34

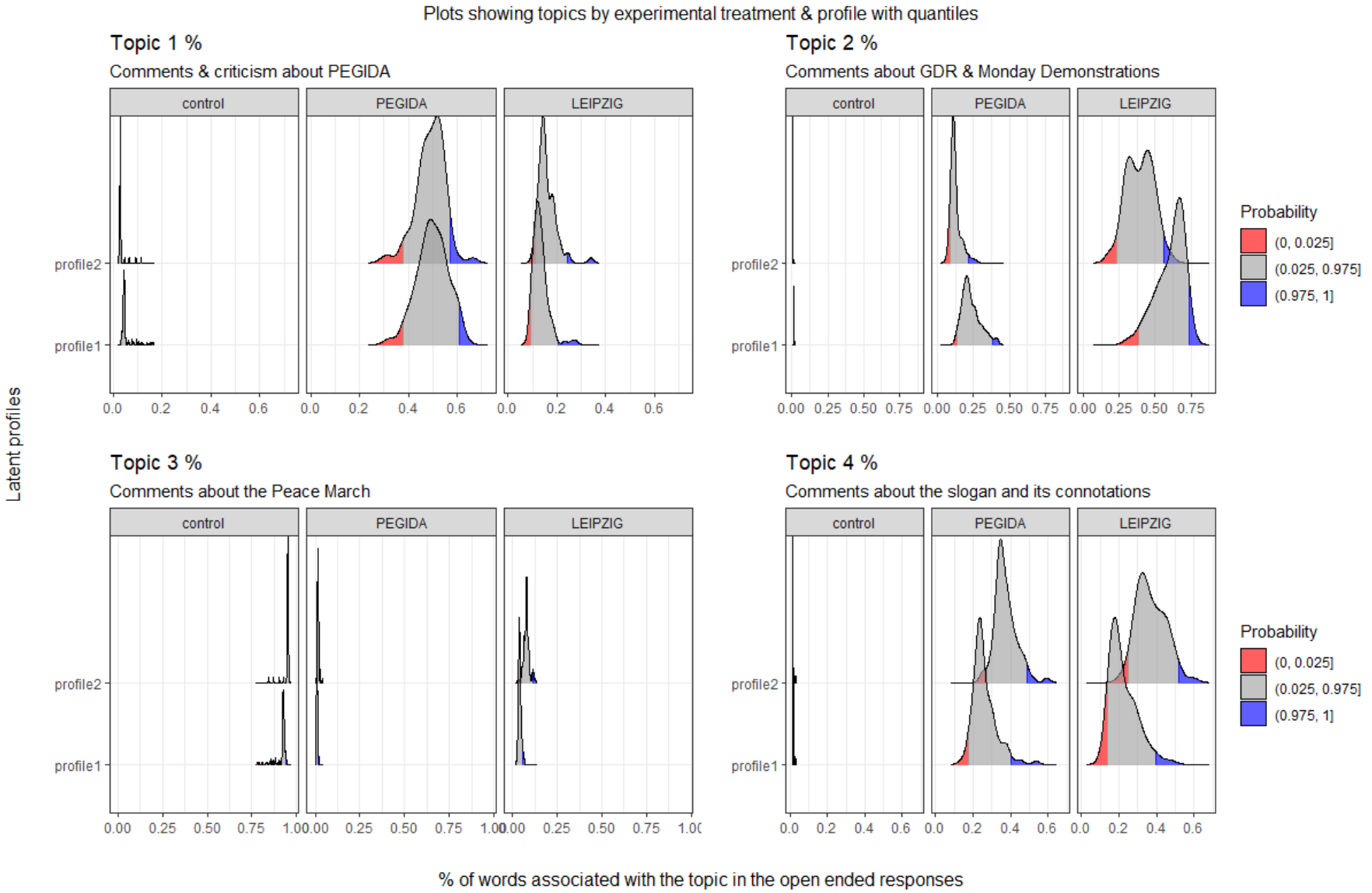

Plots showing topics by experimental treatment & profile with quantiles
Topic 1 %
Comments & criticism about PEGIDA
Topic 2 %
Comments about GDR & Monday Demonstrations
Topic 3 %
Comments about the Peace March
Topic 4 %
Comments about the slogan and its connotations
control
PEGIDA
LEIPZIG
profile2
profile1
Probability
(0, 0.025]
(0.025, 0.975]
(0.975, 1]
Latent profiles
% of words associated with the topic in the open ended responses

Figure 35

Topic labels

All the visuals above and representative quotes (Table 34) with the highest topic proportions make it clear that topic 3 is exclusively associated with the open-ended responses in the control group. We label this topic with *comments about the Peace March*. This topic is negatively associated with all the other topics.

Again, judging from the visuals above and the representative quotes with the highest topic proportions (Table 32), Topic 1 overwhelmingly deliberates on the PEGIDA with mixed reactions including corroboration and criticism. The semantic framings of this topic are clearly associated with the experimental treatment. We label this topic with *comments and criticism about PEGIDA*.

The parts of the open-ended responses that constitute Topic 2 are the outcome of the second experimental treatment – seeing the "Wir sind das Volk" slogan in the German Unification Movement Monday Demonstrations context. Responses here involve reflections on the unification movement itself as well as the slogan's contemporary associations (***see*** Table 33). We label this topic with *comments about GDR and Monday Demonstrations*.

The final estimated topic, topic 4, captures the portions of the open-ended responses that go beyond the experimental manipulation. The semantic frames within this topic elaborate on the slogan and its broader populist connotations such as people-centrism as well as anti-elitist sentiments. This topic seems to capture contemporary populist thoughts and reflections. We label this topic as *comments about the slogan and its connotations*.

Example representative quotes with some of the highest topic proportions are given in the tables below. The column on the right has the topic proportion (what percentage of the

open-ended responses includes words that are highly associated with the topic) and the profile category.

Table 32 Representative quotes with highest topic proportions

Topics 1: comments and criticism about PEGIDA	Profile, experimental condition & topic proportion in the open-ended response
Pegida (Dresden) ist ein Teil des Volkes, den Politik und Medien systematisch wahlweise ausgrenzen oder diffamieren. Dabei sind neben ein paar Spinnern, auf die sich Medien gerne stürzen, viel mehr dabei, die gehört werden sollten. In Dresden ging von Pegida nie Gewalt aus, allenfalls von Gegendemonstranten, die hinbestellt und teilweise sogar bezahlt werden, damit sie lärmen vor den Kameras.Deutschland wird beherrscht von einer Politikerelite, die mit Lobbyisten mehr die Interessen des Kapitals als die der Wähler vertritt. Warum sonst wird die Schere arm-reich immer größer? Politikern geht es zu viel um Macht und Rechthaberei um jeden Preis.	Profile 2, 0.66
Hass Angst Uninformiertheit Lebenskrisen, finanzielle Probleme Frust, Gefühl der Ungleichbehandlung und Benachteiligung fehlende Bereitschaft zuzuhören und sich auf andere (Ansichten als auch Menschen)einzulassenSchlechte Erfahrungen gemacht mit Politikern - mit Versprechen, dem Wahrheitsgehalt ihrer Aussagen, Nicht-Handeln Es ändert sich für viele Leute nichts konkret in ihrem Leben/ in ihrem Radius (zum Guten), wenn sie Volksparteien wählen bzw überhaupt wählen Keine spürbare Selbstwirksamkeit Frust, Enttäuschung	Profile 1, 0.64
Menschen, die eine Welt zurück wollen, die es nie gab. Viel Populismus (aka es gibt einen Volkswillen, und Aufgabe der Politik ist, diesen zu erkennen und umzusetzen, und sie sind in Besitz dieses Volkswillens), wenig Bereitschaft zu Demokratie als Aushandeln unterschiedlicher Interessen. Vielleicht, weil sie sich nicht gehört fühlen etc., aner das ist Spekulation, da sollen bitte die Soziologen und Politikwissenschaftler ran. Bedenken, daß aus Populismus gemischt mit Rassismus schlimmes wächst.Ich kann nachvollziehen, daß sich viele Menschen von dem, was in der großen Politik passiert, abgehängt fühlen, Ich glaube, daß viele einflußreiche Politiker häufiger Kontakt auf Augenhöhe mit Lobbyisten als mit bestimmten Teilen der Bevölkerung haben (ich habe ja persönlich auch sehr selten Kontakt mit Sozialhilfeempfängern mit prekären Lebensverhältnissen aus der Hochhaussiedlung). Ich kann nachvollziehen, daß die Haltung der Mainstreampresse einseitig wirkt (und dies nicht nur in den Kommentaren sondern auch in den Berichten selbst). Ich halte den Vorwurf der „Lügenpresse“ für falsch. Ich verurteile, daß sich die Wut der Demonstrierenden nicht gegen dieses Establishment wendet, sondern (teilweise gewaltsam) gegen Flüchtlinge, Ausländer, Andersdenkende.	Profile 1, 0.61

Table 33 Representative quotes with highest topic proportions

Topics 2: comments about GDR and Monday Demonstrations	Profile, experimental condition & topic proportion in the open-ended response
Mir fällt dazu spontan ein, dass dieser Satz seit geraumer Zeit von den Rechten missbraucht wird. Dadurch hat er eher so einen negativen Geschmack bekommen. Die Montagsdemonstrationen und dieser Satz standen ja ursprünglich mal für etwas Gutes.Ich kann ihre Wut und Kritik verstehen, weil sie auch berechtigt ist. Die DDR war eine Diktatur. Es gab viel Leid und Unrecht.	Profile 1, 0.77
Die Demonstranten brachten zum Ausdruck, dass das SED-Regime ihre Interessen ignoriert hat und wehrte sich gegen Unterdrückung.Berechtigte, aber auch sehr pauschale Form von Kritik. Forderungen nach Vergeltung sind aber nicht repräsentativ für die ostdeutsche Bürgerrechtsbewegung.	Profile 1, 0.74
Das war ein Signal für Freiheit und Demokratie, das für die damalige DDR sehr unerwartet, weil gefährlich war. Es erforderte viel Mut und nötige mir großen Respekt abfür mich waren die Demonstrationen ein Ausdruck des Wunschs nach Freiheit. Das Establishment hat die Bevölkerung klein gehalten und konnte sich selbst alles leisten	Profile 1, 0.74
Friedliche Revolution. Friedliche Proteste, die schließlich zum Mauerfall geführt (zumindest zu einem großen Teil dazu beigetragen) haben.Puh, ehrlich gesagt, verbinde ich damit gar nichts...	Profile 2, 0.60

Table 34 Representative quotes with highest topic proportions

Topics 3: comments about the Peace March	Profile, experimental condition & topic proportion in the open-ended response
Ich denke die Demonstration an sich ist wirkungslos. Niemand in einem anderen Land Juckt es ob hier Leute auf die Straße gehen und für mehr Frieden demonstrieren. Wir sollten glücklich mit dem Frieden bei uns sein und an uns selbst arbeiten. Solange geopolitisch noch interessenkriege herrschen bringt all das Jammern nichts. Am Ende müssen wir glücklich sein nicht die zu sein die von uns unterdrückt werden sondern die zu sein die davon profitieren. Also machen wir halt das beste draus.Siehe oben	Profile 2, 0.96
Es sollte das Recht eines jeden Menschen sein, sich friedlich und ohne Waffen zu versammeln, um für seine Ziele zu demonstrieren. Leider ist das nicht überall der Fall. Ob das Ziel der Ostermärsche jemals erreicht wird sei mal dahingestellt, aber der Wille der Teilnehmenden ist es, der zählt.Der Frieden überall auf der Welt ist ein hohes Ziel. Ich persönlich glaube nicht daran, dass ich ihn erleben werde. Aber ich hoffe für die zukünftigen Generationen, dass dieser Traum irgendwann vielleicht einmal wahr wird.	Profile 1, 0.96
In der Grundrichtung und Grundüberzeugung vollkommen richtig, an einigen Stellen doch etwas übertrieben in der Message/Forderungen (sofortige Beendigung aller Kriege etc.), kommt immer auf den Ort, die Gruppe, Veranstalter der Organisation an, im Grunde ist es eine schöne Sache. Geschichtlich brauche ich ihnen ja nicht zu erzählen, wie sie entstanden sind :PEs ist gut, dass die Grundidee und Überzeugung, dieser Idee (Frieden) bzw. die Zeichen inzwischen sehr weit verbreitet und geteilt werden. Aber es ist schade, dass das Zeichen durch die Häufigkeit auch die Idee etwas verschwindet in der Wirkung. Und das Frieden immer nur politisch und global gedacht wird und nicht persönlich.	Profile 2, 0.94
Ich finde es gut, dass sich Menschen treffen, um gemeinsam für Frieden zu demonstrieren. Meiner Meinung nach, wird heutzutage das Recht auf freie Meinungsäußerung durch Demonstrationen viel zu selten wahrgenommen. Gerade bei einen Anliegen wie Frieden ist es deshalb schön zu sehen, dass es den Menschen nicht egal ist, wenn Krieg herrscht, nur weil es in anderen Teilen der Welt stattfindet.Ich finde es gut, wenn Menschen den Mut aufbringen, ihre Anliegen nicht	Profile 1, 0.94

nur auf Demonstration vorbringen, sondern auch durch entsprechende Symbole Farbe bekennen. Meinungsfreiheit in jeglicher ist eines unserer wichtigsten Güter.	

Table 35 Representative quotes with highest topic proportions

Topics 4: Comments about the slogan and its connotations	Profile, experimental condition & topic proportion in the open-ended response
Heute leider sofort mit Nationalismus, Rechts, AfD, NPD etc. in Zusammenhang gebracht. Wir sind das Volk sollte zeigen, dass die Bevölkerung zusammenhält und für ein besseres Land ist und dass Politik die Lebensumstände der Bevölkerung verbessern sollte.	Profile 2, LEIPZIG , 0.60
Dieser Satz hat die DDR Bùrger motiviert und ihren Zusammenhalt repräsentiert. Es ist der Ruf an die Politiker, den Willen des Volkes wahrzunehmen.Privilegierte Menschen leben meist als Zaungast fern der Realität. Sie müssen dem Volk aufs Maul schauen, sonst regieren sie am Volk vorbei. Sie müssen den Willen des Volkes hören und nicht nur ihren eigenen Vorstellungen folgen. Die Bundesrepublik ist noch nie so schlecht regiert worden wie heute. Viele Könige regieren dieses Land. 830 € Diätenerhöhung, 2 € mehr Kindergeld und für mich persönlich waren es 20 € mehr Rente. Mehr muss man dazu nicht ausführen.	Profile 2 , PEGIDA 0.59
Gefährliche Umwidmung durch heutige Rechtspopulisten mit nationaler Gesinnung zur Stimmungsmache gegen ein weltoffenes, kosmopolitisches Deutschland, welches den Spagat zwischen Kultur- sowie Identitätsbewahrung und Globalisierung in der Realität bisher positiv vollbracht hat. „Wir sind das Volk“ Parolen als Zeichen eines Rechtsrucks unserer hysterischen Bevölkerung bei vermuteter Gefährdung der Komfortzone. (Streitthema Flüchtlingspolitik; bisher keine Auswirkungen oder persönliche Einschränkungen der Asylpolitik wahrgenommen-im Gegenteil; Freunde gefunden)Gefahr der Entfremdung zwischen Bevölkerung und politischem Alltagsgeschäft. Sinnkrise	Profile 1 , LEIPZIG, 0.48
Wenn demonstrierende Menschen rufen Wir sind das Volk , dann stimmt etwas grundsätzlich nicht - jeder Einzelne ist lediglich Teil eines Volkes. Übrigens: ich kriege immer Gänsehaut, wenn lauthals das Volk beschworen wird - wie wird denn Volk fefiniert?Aktuelles Beispiel dafür, wie gedankenlos und realitätsfern Politiker arbeiten: Sehr geehrte Damen und Herren, es wird allerhöchste Zeit, dass von allen verantwortlichen Stellen in unserem Land dieser inzwischen ausgeuferte Wahnwitz gestoppt wird, eine mögliche neue schwarz-gelb-grüne Koalition „JAMAIKA-KOALITION“ zu nennen. Hat sich eigentlich jemand einmal erkundigt, wie es die Bevölkerung Jamaikas und die politische Führung dieses Staates finden, dass die Bundesrepublik Deutschland dabei ist, eine „JAMAIKA-KOALITION“ zu bilden? Das ist doch eine alberne Clownerie! Der Respekt vor den Hoheitszeichen und der Nationalfahne eines jeden Landes gebietet es, dass dieser gedankenlose „Humbug“, den wir seit der Bundestagswahl mit der Bildung dieser Koalition tagtäglich bis zum Überdruss hinnehmen müssen, endlich beendet wird. Weil offensichtlich auch die Verantwortlichen in den politischen Führungs-Gremien gedankenlos dieses Spiel mitspielen, sind wir der Meinung, dass nur von allerhöchster Stelle – also von unserem Bundespräsidenten – hier mit klaren unmissverständlichen Worten Einhalt geboten werden muss. Es ist einfach hochgradig peinlich, wie sich die Bundesrepublik Deutschland innerhalb der Völkergemeinschaft damit aufführt. Das geht so weit, dass wir heute zum Beispiel im Radio in einem Kommentar des DLF hören mussten: „ ...ein Scheitern der Sondierungen wäre der Tod Jamaikas ... da wäre Jamaika am Ende ...“ Gerade einem international so hoch geschätzten und geachteten Mann, wie unserem Bundespräsidenten und früheren sehr erfahrenen Außenminister, kann dies alles nicht egal sein. Und zusätzlich ist es unerträglich, wie die Medien diese „Bezeichnung“ für die geplante Koalition geradezu genüsslich verwenden und es für nötig halten, uns permanent in der Berichterstattung mit penetranten Vermutungen und vagen sensationsgierigen Spekulationen usw. „auf dem Laufenden“ halten zu wollen - Ihre vornehmste Aufgabe sollte es ja eigentlich sein, uns TATSACHEN zu berichten und nicht, uns mit vorauseilenden Spekulationen und Vermutungen zu „befeuern“. Ganz zu schweigen von dem gedankenlosen	Profile 1, PEGIDA, 0.54

Sprachgebrauch, zum Beispiel in den politischen Talk-Shows. Sollen wir als einfache Bürger dieses Landes das politische Geschehen etwa nicht mehr ernst- nehmen?! Wir erwarten, dass endlich darüber nachgedacht wird und dass diese leider schon „eingeschliffene“ peinliche Bezeichnung für die geplante neue Koalition - auch im Hinblick auf ihre Glaubwürdigkeit - sofort beendet wird. Mit freundlichen - aber sehr zornigen - Grüßen	

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