Appendix A

Literature Review

We conducted a literature review to identify commonly used operationalizations of online deliberation in recent quantitative content analyses. This review does not claim completeness. We stopped adding more literature after the most important dimensions had become clear and operationalizable definitions had been found. We searched on Web of Science (https://www.webofscience.com) in October 2021 for articles that included "deliberation AND comment* AND (online OR social media)" in any field. The results were narrowed down to articles published in in political science or communication journals between 2015 and 2021. From the resulting 94 hits, we identified 34 articles that were relevant for our task by reading the abstracts. After a cursory reading, we excluded studies that did not include suggestions about how to operationalize deliberation in quantitative content analyses. Thereby, we dropped most studies that relied on qualitative or survey methods. We added some frequently cited older contributions that focused on theory (Friess & Eilders, 2015; Papacharissi, 2004) or offline communication (Stromer-Galley, 2007).

From the remaining 18 studies, we identified the suggested construct dimensions and extracted definitions and operational coding instructions. We clustered similar dimensions and operationalizations, taking particular care of studies that used the same label for different constructs. This was the case for "impoliteness" and "incivility", which are sometimes used interchangeably (Coe et al., 2014), considered distinct (Papacharissi, 2004) or interrelated (Rega & Marchetti, 2021). From all suggested dimensions, we distilled five key dimensions of online deliberation for our operationalization: Reciprocity, argumentation, sourcing, impoliteness, and incivility. These concepts are discussed in the main text. Our selection criteria were frequency of operationalization in previous studies, conceptual clarity, and feasibility of the operationalization given our material. Additionally, we decided to code the positioning of replies towards parent comments, to get a better understanding of the dynamics of this reciprocal communication. Table A1 lists the reviewed literature and indicates which of the conceptual dimensions were operationalized or suggested for operationalization in these studies. The column names in this table follow our definitions of these concepts, as discussed in the main text.

Table A1. Literature review of online deliberation.

Authors[1]	Year	Cit.[2]	Meth.[3]	Rec.[4]	Pos.[5]	Arg.[6]	Sour.[7]	Imp.[8]	Inc.[9]	Else[10]
Beckert and Ziegele	(2020)	2	c, s	0	0	1	1	1	X	elaborateness, information value, polarization, simplification, humor
Coe et al.	(2014)	342	c	1	1	1	1	1	X	meta-talk
Collins and Nerlich	(2015)	39	c	1	0	1	0	M	M	topic relevance
Esau et al.	(2017)	32	c	1	1	1	0	1	0	topic relevance, engagement, constructiveness
Friess and Eilders	(2015)	68	t	1	0	1	1	M	M	
Friess et al.	(2020)	3	c	1	0	1	1	1	1	genuine question, relevance, solution, appeal
Gervais	(2015)	106	c, e	0	0	0	0	1	X	
Klinger and Russmann	(2015)	7	c	1	1	1	0	1	0	doubts, solutions
Maia and Rezende	(2016)	21	c	1	1	1	0	1	0	
Manosevitch et al.	(2014)	17	c, e	1	1	1	0	0	0	elaborateness
Marzinkowski and Engelmann	(2022)	1	c	1	1	1	1	1	0	negative emotions
Oz et al.	(2018)	53	c, e	0	0	1	1	1	1	
Papacharissi	(2004)	515	c, t	0	0	0	0	1	1	
Rega and Marchetti	(2021)	0	c	0	0	0	0	M	M	
Rossini[11]	(2020)	32	c	1	1	1	0	1	1	
Stromer-Galley	(2007)	269	c	1	1	1	1	0	0	
Stroud et al.	(2015)	120	c, e	1	0	1	1	M	M	relevance, genuine question
Ziegele et al.	(2020)	8	c	1	0	1	1	M	M	elaborateness, relevance, questions
Total				13	8	15	9	16	9	

Notes: 1: References at the end of the Appendix; 2: Citation count, according to Web of Science on 2022-04-22; 3: Main methods used, "c" indicates quantitative content analyses, "e" experiments, "s" surveys, "t" theory; 4: Reciprocity; 5: Positioning; 6: Argumentation; 7: Sourcing; 8: Impoliteness. The letter "M" indicates that the study merges aspects of impoliteness and incivility (as defined here) into one dimension; 9: Incivility. The letter "M" indicates that the study merges aspects of impoliteness and incivility (as defined here) into one dimension. The letter "X" indicates that the study operationalizes only "impoliteness" (as defined here) but labels it as "incivility"; 10: Abridged.; 11: Rossini 2020 differentiates "incivility" and "intolerance". The former matches our understanding or "impoliteness", while the latter matches our understanding of "incivility".

Appendix B

Dictionaries for the Topic of Migration

Step 1 and Step 2 of our analysis make use of a sample of manually coded comments and replies. In Step 1, this sample was used to optimize and validate our automated measurements. In Step 2, this was sample used to investigate the impact of right-wing populist parent comments on the deliberative quality of replies. The sample consists of 535 parent comments and 1,413 replies, which were drawn from comments that reacted on posts about migration. Here, we document the dictionary that we used to detect the topic of migration.

Dictionaries are lists of keywords that are used in automated content analysis. Here, we considered a Facebook post to cover the topic of migration if at least one of the migration keywords documented below were present in the text of the post, in the headline or in the sub-headline of a hyperlinked article. We developed two language-specific dictionaries, one for Austria and one for Slovenia. The dictionary development started from an existing German dictionary for the topic of migration, which was constructed by one of the authors for a different paper (Thiele, 2022a). The construction process of this dictionary is documented in detail in the online supplementary material of that article.

To arrive at a Slovenian dictionary, we followed a multi-stage process. First, one author translated the German dictionary by hand, assisted by the online translation website Linguee (https://www.linguee.de/). This translation website relies on the DeepL engine and provides context for the suggested translations, which helped us to remove ambiguous words. Next, the Slovenian project team reviewed this list, added, or removed keywords, and placed wildcards where feasible. We then applied this preliminary dictionary, drew a random sample of 400 positive matches, and machine-translated these posts into German, using the DeepL API (https://www.deepl.com). Judging from these results, the German speaking author modified or removed ambiguous terms from the dictionary. The list of words was then expanded with synonyms and related words using nearest neighbor queries from the fasttext models, which are described in Appendix D. We used keywords-in-context searches to identify other related terms. Again, we translated all Slovenian words into German and inspected this list for unprecise or incongruous terms.

We optimized the dictionaries and evaluated their accuracy using a random sample of 400 Austrian and 400 Slovenian Facebook posts, drawn from all posts considered in Step 1 of the analysis. The Slovenian posts were machine-translated into German using the DeepL API and coded by the German speaking author along a binary variable, indicating the presence of the topic of migration. This topic was considered present if the text of a post referred in any way to migration, borders, asylum, flight, or integration. Validity of our dictionary measurement was assessed by comparing it with the human coding, quantified by the measures Recall, Precision, and F1, which are introduced in the main text (Stryker et al., 2006). The Austrian dictionary reached a very satisfactory Recall of 0.97, a Precision of 0.98 and a F1 score of 0.98. The Slovenian dictionary performed somewhat less well, but still satisfactory, with a Recall of 0.78, Precision of 0.88, and F1 of 0.87. Both dictionaries are documented in Table B1.

Table B1: Migration Dictionaries

Concept (n terms)	**Words**[1]
German: Migration (105)	*außengrenz*, *einwanderer*, *grenzschutz, *migrant*, *migration*, *zuwander*, abgeschoben*, abschiebe*, abschiebung*, abwandern, abzuschieben, anlandeplattform*, asyl*, auffanglager, aufzunehmen, ausgewandert, ausländerbehörde, ausländerin*, ausländern, ausländische, ausländischen, ausreise, aussengrenzen, balkanroute, camp, deutschkenntnisse, deutschkurs*, eingewandert, einreise, einreisebeschränkungen, einreisebestimmungen, einreisen, einreisende, einreisenden, einreisestopp, einreiseverbot, einreiseverbote, einreist, einwandern, einwanderung, einwanderungsland, einwanderungspolitik, festung europa, flucht, flüchtete, flüchtling*, flüchtlingsquartier*, fluchtursachen, geflohen, geflohene*, geflüchtet, geflüchteten, gernzzaun, grenze, grenzen dicht, grenzgänger, grenzgebiet, grenzkontrolle*, grenzöffnung, grenzöffnungen, grenzschließung, grenzschließungen, grenzsicherung, grenzübergang, grenzübergänge, grenzübertritt*, grenzverkehr, grenzzäune, heimatländer, herkunftsländer, idomeni, immigrant*, integration*, integrieren, integriert, integrierte, integrierten, islam kindergärten, kara tepe, kriegsflüchtlinge, lampedusa, landesgrenzen, lesbos, masseneinwanderung, massenflucht, migration*, migrationsdeal, mittelmeerroute, rackete, refugee*, rückführen, rückführung*, rückgeführt*, schlepper*, schleuser, seenot, seenotrettung, spielfeld, sprache, staatsbürger, syrer*, traiskirchen, wiedereinreise, wirtschaftsflüchtlinge, zugewandert*
Slovenian: Migration (67)	azil*, balkansk* pot*, beg, begu, begun*, begun* tok*, begun* val*, deport*, drž* izvor*, državljanstv*, drzavljanstvo, državn* mej*, dublinsk* konvenc*, evrop* azil* polit*, evrop* migr* polit*, frontex, idomeni, ilegal* migr*, imigra*, immigr*, integrac*, izgn*, izgnati, izgon*, kontrol* mej*, kontrol* zunanj* mej*, lampedus*, lesbos*, mednarodn* zašcit*, mej* preh*, mejn* nadzor*, mejnem, migr*, migr* tok*, migr* val*, migr* žep*, množicni *beg, moria, nadzor* mej*, nadzor* zunanj* mej, obaln* straž*, prebéžnic*, prebežnik*, preck* mej*, preh* mej*, priseljen*, priseljevanj*, prosil* za azil, rackete, refugee, sirec, sirij*, sirsk*, sredozemsk* pot*, subsidiarn* zašcit*, tihotap*, tihotap* ljudi, traiskirchen, trdnjav* evrop*, upravljanj* zunanj* mej*, utrdb* evrop*, varovanj* mej*, zap* mej*, zašcit* mej*, združ* družin*, ženevsk* konvenc*, zunanj* mej*

Notes: 1: A * represents a wildcard, it matches any number of characters or digits.

Appendix C

Codebook

We manually coded 535 parent and 1,413 reply comments along the categories for right-wing populism, people-centrism, anti-elitism, and anti-immigration, and along four dimensions for the quality of deliberation, argumentation, sourcing, impoliteness, and incivility. Additionally, we coded the positioning of the reply comment towards the parent comment. This manually coded sample is the basis for our analysis in Step 2 and was used for validation and optimization of our measurements in Step 1. Here, we document the codebook.

1. Previous Codebooks

Our coding instructions are based on existing codebooks. The instructions for coding right-wing populist content are closely aligned with the codebook developed by Blassnig et al. (2016, 2019). The instructions for coding the quality of online deliberation draw on the codebook developed by Ziegele and Friess (2018), which was used in Friess et al. (2020). An abridged version of our coding instructions is documented below. We cite the source of each instruction. The citations were hidden in the codebook used during the coding process to improve readability. The columns of the tables indicate the coded construct, the level on which it was coded (1 = parent comments, 2 = replies), the instructions, and the values of the codes. Examples were taken either from existing codebooks or from translated comments from our corpus. One author constructed the codebook. Both authors conducted the coding. Reliability measures are reported in the main text. One category, expressing anger, was dropped due to low reliability scores.

2. General Coding Guidelines

We used holistic grading to code each comment. That means, coders were asked to read the comment and to assign one code for the whole comment. Following Blassnig et al. (2016, p. 1), our coding instructions followed these general guidelines: "Only code explicit statements. Implications, hints, and context knowledge must not be coded. If in doubt, don't code it. If you have to ask yourself whether a statement is explicit enough to code it, it is not. […] Hypothetical statements are coded. Statements that are future-oriented or in subjunctive mood are coded as normal statements. Hypothetical does not mean implicit." Additionally, the coding instructions made clear that the coded categories are not mutually exclusive.

3. Right-wing Populist Content

Construct	Lvl	Instructions	Codes
People-Centrism	1&2	<u>Question:</u> Does the comment invocate **the people** or **demand sovereignty** for the people? (Aslanidis, 2018, p. 1255) <u>Definitions:</u> **People-centrism** is one core dimension of populist communication. It is defined here as an ideological discourse that invocates 'the people' (Aslanidis, 2018, p. 1255). It values 'the people' as something positive or worth protecting, constructs it as an in-group, i.e., as a group to which the author of the text belongs to, and/or suggests that 'the people' are the "rightful political sovereign within a given polity" (Aslanidis, 2018, p. 1255). '**The people**' are defined as the "overwhelming majority" (Aslanidis, 2018, p. 1255) of the "population of a country" or polity that is assumed to "share a common origin or culture" (Blassnig et al., 2016, p. 14). "The people may be regarded as nation, ethnos, demos, class, or strata" (Blassnig et al., 2016, p. 14). It is essential that the commenter regards himself or herself as part of the people and values the people. The people may be addressed directly ("the people", "the Austrian population"), "as a metaphor ('man on the street', 'the common man'), or as a subgroup that is regarded as representing" (Blassnig et al., 2016, p. 14) the overwhelming majority ('the hardworking people', 'voters', 'we taxpayers'). <u>Instructions:</u> Please code "1", if the coded text **refers to 'the people'** in one of the ways described above **and** is characterized by at least one of the **following aspects**: • The people are attributed with **virtues** and **positive traits**. For example, the people may be described as good, honest, hard-working, modest, moral, credible, intelligent, competent, consistent, considerate, benevolent, or similar (Blassnig et al., 2016, p. 17). *(e.g., "Why does every normal citizen actually know about this madness, only the politicians do not?")* • The people are seen as responsible for **positive developments**, events, or situations (Blassnig et al., 2016, p. 17). *(e.g., "I am glad to be a tiny part of this. a lot of work and sweat has built this country and made it what it is now.")*	0: not present 1: present

		• The people are described as a **homogeneous group**: The "people is seen as sharing a common understanding of the world, common feelings [...], common opinions [...], or a common will [...]. *(e.g., 'The voters want immigration controlled, they declared that loud and clear.')"* (Blassnig et al., 2016, p. 18). • The people are constructed as a **collective of victims**, that suffers from elite actions, or external threats, or needs to be protected (Hameleers, 2019). *(e.g.: "Who is protecting us????")* • The comment demands to listen to the **people's will**, or addresses the people to **wake up**, or to **stand up** for their will (Blassnig et al., 2016, p. 20) *(e.g., "let's unite and take the streets! together we can make a difference!")* • The comment criticizes institutions or elites for **not reflecting the people's will**, for deceiving or silencing the vast majority. *(e.g.: "The people will not be deceived any longer by this clown.")*	
Anti-Elitism	1&2	<u>Question:</u> Does the comment **discredit** or **blame the elite** or suggest that the elite is **detached** from the people? (Blassnig et al., 2016, pp. 18–19) <u>Definitions:</u> **Anti-elitism** is the second core dimension of populist communication. It is defined as "references against a slim minority of unaccountable power holders [that allegedly engage] [...] in the misappropriation of popular sovereignty" (Aslanidis, 2018, p. 1255). It constructs 'the elite' as the antagonist of 'the people', which illegitimately rules and deceives the latter (Mudde, 2004, p. 543). '**The elite**' is defined as minority groups of power holders within a society that are (assumed to be) powerful and influential because of its "political power, wealth, or privilege" (Blassnig et al., 2016, p. 14). Not the factual power is decisive, but the assumption of such power in the coded text. Elites "can be allocated to the areas of politics, administration, economy, law, media, science, and culture" (Blassnig et al., 2016, p. 14). "The elite may either be addressed in general terms [(e.g., 'those above', 'politicians', 'the rich', 'the media')] or specific members [or institutional representatives] of the elite may be addressed by name" (Blassnig et al., 2016, p. 14) or nickname (e.g., "Wall Street", "Brussels", "Soros"). <u>Instructions:</u> Please code "1", if the coded text **refers to 'the elite'** in some of the ways described above **and** is characterized by at least **one of the following aspects**: • Elites are **discredited** or denounced: "Negative personality traits, mistakes, and unlawful or immoral behavior of the elites are stressed. The elites [...] are portrayed as corrupt, evil, incapable, malevolent, [mendacious], criminal, lazy, stupid, undemocratic [or in any other similar negative way]. The elites or its representatives are denied of morality, charisma, credibility, intelligence, competence, consistency etc." (Blassnig et al., 2016, p. 18) *(e.g., "It is minister Mikl Leitner who, apart from incompetence, only attracts attention with embarrassing statements."; "Down with this sell-out government!")* <u>Caution:</u> If a text criticizes elites in a balanced way, without suggesting a fundamental or moral degeneracy of the elite or the established system it is <u>not</u> considered anti-elitist. • Elites are **blamed** for fundamentally negative developments or situations: elites are held responsible for undesirable situations that are depicted as serious harm for the society (Blassnig et al., 2016, p. 18). *(e.g., "Our politicians have managed to make Austria an unsafe country. The politicians who are responsible should be locked up")* • Elites are depicted as **detached** from the people, **unaccountable** to the people's will, or **manipulating** the people: The elite is described as "not being close to the people, not knowing the people and their needs, not speaking for the people, [...] not listening to the people," (Blassnig et al., 2016, p. 19) not representing the people, betraying or deceiving the people, lying to the people, manipulating the public opinion, or as being distanced from the people in any other way (Blassnig et al., 2016, pp. 19–20). *(e.g., "when will our so-called representatives of the people finally open their eyes"; "The politicians do not listen to us")* • Elites are denied **sovereignty**. "The speaker argues in favor of granting less power to the" or some elites (Blassnig et al., 2016, p. 21). *(e.g., "I hope that the EU breaks apart so that Austria can finally close the borders!")*	0: not present 1: present
Anti-Immigration	1&2	<u>Question:</u> Does the comment speak out **against immigration**? <u>Definitions:</u> **Anti-immigration** discourse is a third core dimension of right-wing populist communication. It is defined as any statement that refers to immigration or immigrants as a threat, ascribes migration or migrants with negative attributes, or demands measures that limit, stop, or reverse migration processes. By such discourse, immigration and immigrants are frequently constructed as threat to 'the people's' (often: the nation's) security, economy, or culture (Callens & Meuleman, 2017, pp. 368–369). '**Immigrants'** here are defined as a minority that is excluded from 'the people' in right-wing populist statements, on the grounds of an (alleged) origin, culture, or ethnicity (Blassnig et al., 2016, pp. 15, 31). Statements may refer to 'immigrants' or the phenomenon of 'immigration' in different ways, either by addressing a collective (e.g. "refugees", "migrants", "foreigners", etc.), by addressing the phenomenon of migration abstractly (e.g. "migration", "illegal migration"), by naming specific ethnic groups (e.g., "Afghans", "African refugees"), by referring to geographical locations that are associated with migration or flight, like	0: not present 1: present

specific border crossings or refugee camps (e.g., “the Balkan route”, “Lesbos”), or by referring to other societal groups or institutions that are involved in migration processes (e.g., “human traffickers”, “illegal migration networks”, “asylum industry”), or involved in policing migration processes (e.g., “our border police”).

<u>Instructions:</u> Please code “1”, if the coded text **refers to ‘immigrants’ or ‘immigration’** in some of the ways described above **and** is characterized by at least **one of the following aspects**:

- Immigrants are portrayed as a **threat** to the **security, culture, or economy** of the country or of Europe (Callens & Meuleman, 2017, pp. 368–369). *(e.g., “They flood our country, get everything shoved in the ass and as return they rape our children!!!!!!”, “They come and take away the jobs of the Austrians!”)*
- Immigrants are attributed collectively with **negative traits** or are said to behave in a unpleasant way *(e.g. “If Islam was peaceful, there wouldn't be so much terror in Islamic countries. Islam is the problem.”)*
- Migration is described as a process that have gotten **out of control**. *(e.g., “At the border crossings they simply overrun our officials”; “we have to control the borders!”).* This may be indicated by using metaphors of natural disasters *(e.g., “asylum-catastrophe”, “they flood our country”).*
- Problems of **integration** are stressed, or it is demanded that immigrants should adapt to ‘our’ culture or society. *(e.g., “How will you explain to future generations that we are strangers in our own country?!!!”)*
- The comment speaks out against “**illegal migration**” or labels migration per se as a problem *(e.g., “the refugee-problem”).*
- Refugees are suspected to **cheat** the asylum system and to be economic migrants, not refugees in the sense of the Geneva Convention *(e.g. “These are not refugees. … these are illegal immigrants!”)*
- **Protective measures** that protect the borders, the country, or the people against migration are demanded. *(e.g., “the borders should be controlled!”)*
- **Deportations** of asylum-seekers, migrants, or cultural minorities are demanded. *(e.g. “I have a perfect solution send all the men back and only give asylum to women and children”)*
- **Violence** against asylum-seekers, migrants, or cultural minorities is supported *(e.g., “they should be fucked in prison … If he survives his sentence, he should be deported directly to his home country”).*
- **“Refugee welcome” or “multiculturalism” policies,** culture, and supporters are attacked, or mocked (e.g. “*asylum industry*”).

4. *Online Deliberation*

Construct	Lvl	Instructions	Codes
Position	2	<u>Question:</u> How does the reply position itself towards the parent comment? (Stromer-Galley, 2007, p. 24; Ziegele & Friess, 2018, pp. 34–35) <u>Definitions and Instructions:</u> Here we code the **position** of the reply towards the parent comment. We code if it… • **1: agrees** with the ‘parent comment’. This is the case when an reply expresses its agreement with the parent comment, re-affirms statements from the parent comment, or generally exhibits a positive, supporting tone directed towards the parent comment or its author (Ziegele & Friess, 2018, p. 34). • **-1: disagrees** with the ‘parent comment’. This is the case whenever the reply explicitly states its disagreement, confronts the parent comment with different views or facts, or expresses a negative tone directed towards the parent comment or its author. (Ziegele & Friess, 2018, p. 35) • **0: takes a neutral** or unclear position towards the parent comment. • **33:** If you think that the ‘reply’ is written by the **author of the ‘parent comment’**, code 33. The position sometimes must be inferred from the tenor of the comment (Ziegele & Friess, 2018, p. 34). If you are unsure, code 0. Sarcastic statements that mock the parent comment are considered as disagreement. We only code the positioning towards the parent comment; positioning towards the post, the news article, or other comments are ignored here. (e.g. agreement: “👍👍”, *“I’m afraid about this, too!*”; disagreement: “*This is not true at all*.”; neutral/unclear: *“To what extent?”*)	1: agrees 0: neutral / unclear -1: disagrees 33: same author

Argumentation	1&2	Question: Does the comment provide **reasons** for its claims? (Friess et al., 2020, p. 11; Stromer-Galley, 2007, p. 10; Ziegele & Friess, 2018, p. 24) Definitions: An **argument** is a statement that substantiates or rebuts a specific **claim** by providing **reasons** (Ziegele & Friess, 2018, p. 24). A **claim** is either • a statement that something is **true** or is a **fact** (e.g., *"Austria now is an unsafe country"*). This includes normative assessments (e.g., *"Slovenia is the greatest country"*). • or a **demand** for or against something. This is often expressed by comments that something "should" or should not happen (e.g., *"we need to go to the streets"*), or by indicating what the commenter "would" do if he or she was in charge. (e.g., *"I would cut his salary"*). A **reason** is a statement that explains **why** the something is the case or should be done. It provides a justification for a claim and provides an answer to the question "Why?". The reason given must be logically related to the claim. It can be either explicitly marked by words like "because", "since", "as", "consequentially", etc., or may be presented as a cause or consequence of the claimed fact or in some other way as a justification for the claimed demand (Ziegele & Friess, 2018, p. 24). • Factual claims may be justified by either pointing out causes or justifications explicitly (e.g., "x because y"), or by providing other forms of justification for the claimed fact or assessment in a separate sentence (Ziegele & Friess, 2018, p. 24). If a comment refers to the sources of a given information, this counts as providing a reason. (e.g., claim: *"Immigration is bad for our country",* reason: "*they take away our jobs"*; claim: *"Austria now is an unsafe country"*, reason: *"The criminal statistic is rising since 2015.")* • Demands can be likewise justified by stating the reason for a demand explicitly ("x because y.") or by presenting additional justification (e.g., claim: *"we need to go to the streets"*, reason: *"we need to show them that we don't want them."*; claim: *"I would cut his salary"*, reason: *"He is corrupt."*; claim: *"It's time that we do something against these asylum seekers."* reason: *"They cost us money, and they bring insecurity to this country.*") Please note that the quality, persuasiveness, or correctness of a reason given is <u>irrelevant</u> here. It is <u>not</u> required that the reason given is particularly elaborate, convincing, accurate or true (Stromer-Galley, 2007, p. 10; Ziegele & Friess, 2018, p. 24). Instructions: Please code if the comment presents any form of **reason** for its **claims**. To do so, please 1) **Identify the claims** (as defined above) made in the comment. If you cannot identify any claim, code 0. 2) **Identify reasons** given (as defined above) in the comment for any of the claims. If you cannot identify any reason, code 0. Help: If the statement does not explicitly mention "because", and you are in doubt if two parts of the comment form a claim-reason relation, try the following: Try to insert a "because" between the part that you believe to be a claim and the part that you suspect to be a reason. Only use the explicit sentences. If the parts connected in this way form a (more or less) reasonable statement, code 1 (Ziegele & Friess, 2018, p. 24). If you are in doubt, code 0.	0: not present 1: present
Sourcing	1&2	Question: Does the comment refer to **sources** of **external knowledge**? (Stromer-Galley, 2007, p. 10; Ziegele & Friess, 2018, p. 29) Definitions and Instructions: Here we code, if the comment refers to any kind of **external knowledge** that is verifiable in the broadest sense by providing the **source** of this knowledge. This is the case if the comment includes a hyperlink/URL; or refers to a specific study, author, legal framework; or some other kind of identifiable source, including general references to the position or program of a specific institution. Anecdotal evidence, such as personal experiences here does not qualify as "external" knowledge (Marzinkowski & Engelmann, 2022, p. 9; Stromer-Galley, 2007, p. 10; Ziegele & Friess, 2018, p. 29). (e.g. "*Article 7 of the EU Treaty provides...*", "*The action originated from Ms. XY: https://www.foo.bar*", "*in the coalition contract the parties have agreed …"*)	0: not present 1: present
Impoliteness	1&2	Question: Is the comment characterized by an **impolite tone**? (Friess et al., 2020, p. 11) Definitions and Instructions: Impoliteness is defined as an "unnecessarily disrespectful tone toward the discussion forum, its participants, or its topics" (Coe et al., 2014, p. 660). Coding scheme: Please code "1", if you find at least **one passage** in the coded text that contains one or more of the following aspects: • **Name-calling**: Using abusive words, insults, derogatory, offensive, or belittling statements toward persons, groups, or institutions (Coe et al., 2014, p. 661; Friess et al., 2020, p. 11; Rega	0: not present 1: present

		& Marchetti, 2021, p. 112) (e.g.: "*How stupid are you, anyway? … these assholes think our women are fair game*") • **Profanity/Vulgarity**: Use of obscene or rude language inappropriate for public or professional discourse (Coe et al., 2014, p. 661; Friess et al., 2020, p. 11) (e.g.: *"I could puke if I read this.", "Keep your shit!"*) • **Cynicism, sarcasm, or mockery:** "Reckless, biting mockery aimed at denunciation/devaluation of the addressee" (Friess et al., 2020, p. 11) or ironic statements that aim at devaluating persons, groups, ideas, or institutions (e.g., *"Congratulations, the next MILLION social parasites are already on their way here!*", "*Austria is sooo rich and we can afford it!!*") • **Depreciation***:* Intentionally depreciating a person, group, or idea (Friess et al., 2020, p. 11). *(e.g. "they are thieves and so are their fathers. ")* • **Shouting**: The user underlines his or her comment by "raising its volume" through the excessive use (three or more) of exclamation marks, question marks, writing some words or the complete comment in all capital letters (Friess et al., 2020, p. 11) (e.g. "*the next MILLION social parasites", "Send them back!!!!")*	
Incivility	1&2	Question: Is the comment characterized by **incivility**? Definitions and Instructions: Incivility here is defined as discourse that threatens democratic values, denies people their personal freedoms, or stereotypes social groups (Friess et al., 2020, p. 11; Papacharissi, 2004, p. 274) Coding scheme: Please code "1", if you find at least **one passage** in the coded text that contains one or more of the following aspects: • **Dehumanization**: "Dehumanization of opponents through the assignment of pejorative and exclusionary animal or debris names or through objectification" (Friess et al., 2020, p. 11). (e.g.: *"Politicians are pigs!", "should we adapt to these subhumans?"*). • **Negative stereotypes**: "Simplifying and generalizing prejudices against a person or a group based on certain (negative) characteristics attributed to the respective group" (Friess et al., 2020, p. 11). (e.g.: "*Muslims are terrorist sympathizers*" (Oz et al., 2018, p. 3407)) • **Sexism**: "Discrimination, degradation of a person/group on grounds of gender." (Friess et al., 2020, p. 11) Sexism often implies the expression of stereotypes. Seemingly "positive" stereotypes can be sexist as well. (e.g., *"Women cannot drive cars"; "Women are simply more talented than men at raising children"*) (Ziegele & Friess, 2018, p. 15) • **Racism**: "Discrimination and degradation of a person/group on grounds of race" (Friess et al., 2020, p. 11) or culture. (e.g., *"In their culture, you aren't supposed to even see the women's hair but with our women these assholes think they're fair game. I am not generalizing – most of them think like this!")* • **Threat of violence**: "Threat of or incitement to violence or crime" (Friess et al., 2020, p. 11). (e.g., *"Migrants are welcome from my side, as long as they all volunteer to be castrated."*) • **Silencing**: Denying or threatening other's freedom to speak (Oz et al., 2018, p. 3407) or attempts to silence someone (e.g.: "*You foolish Republican better shut up!*" (Oz et al., 2018, p. 3407))	0: not present 1: present

Appendix D

Automated Text Analysis

In Step 1 of our analysis, we measured right-wing populism in user comments using an automated text analysis method called "distributed dictionary representation" (DDR) (Garten et al., 2018). This method augments dictionaries with information from word embedding models (Garten et al., 2018). Below, we document how we implemented this method. We first introduce the concept of word embeddings and document how we trained the models used here. Secondly, we describe the DDR measurement in general. Thirdly, we describe the dataset used for optimizing and validating our measurements. Fourthly, we describe how we evaluated measurement validity. We then describe how we improved our measurements by optimizing the short dictionaries. While the resulting dictionaries are documented in the main text, we conclude this Appendix by providing plots and examples for face validity. The DDR method and all functions used for optimizing and validating the measurement are implemented in our R-package *dictvectoR* (Thiele, 2022b). Figure D1 illustrates the workflow described in the following sections.

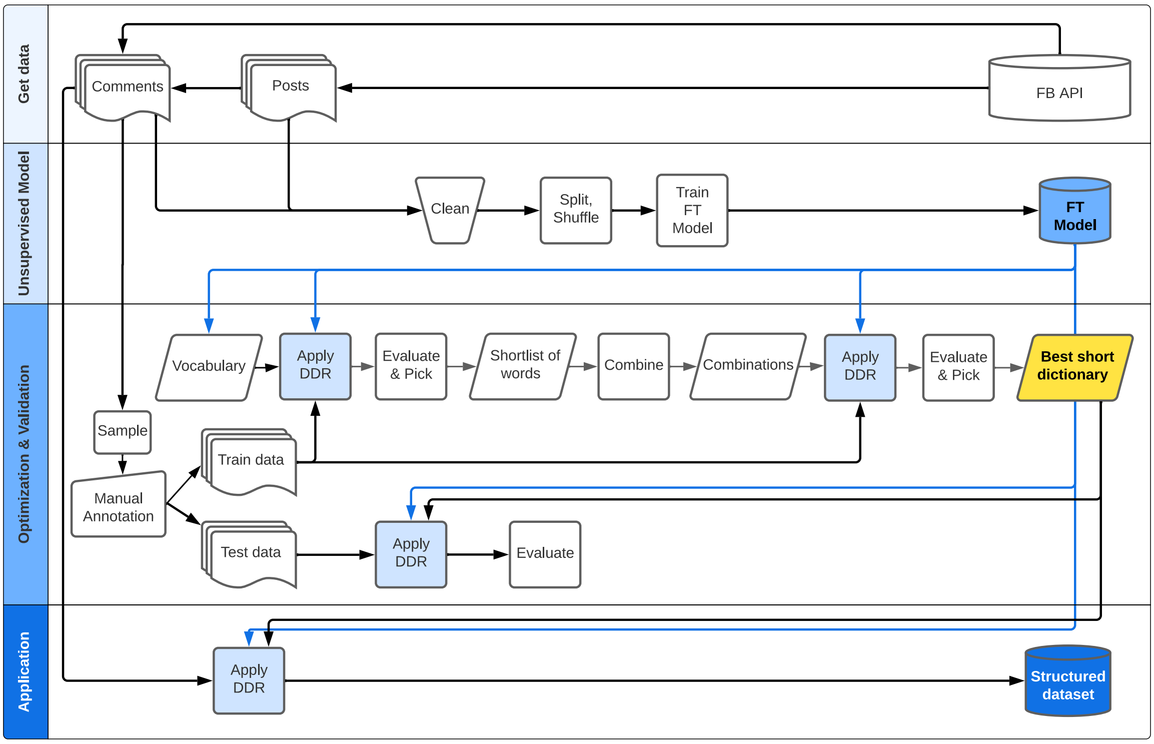


Figure D1. Schematic illustration of the pipeline for our DDR measurements.

1. Word-vectors and Fasttext Models

Word vectors, also called word embeddings, aim to represent semantic proximity of words in a vector space (Mikolov et al., 2013). They result from machine learning algorithms that learn vectors for each word from large corpora of texts by drawing on the basic idea that words with similar meaning appear in similar contexts (Mikolov et al., 2013). For our task, we trained two *fasttext* word vector models (Bojanowski et al., 2017), one for the German-speaking Austrian corpus and one for the Slovenian corpus. Compared to other word embedding models (e.g., Mikolov et al., 2013), fasttext models have the advantage that they are robust against misspellings, can return vectors for out-of-vocabulary words, and perform well on morphological rich languages (Bojanowski et al., 2017). Compared to state-of-the-art BERT models (Devlin et al., 2019), training fasttext models is computationally less expensive. Moreover, user comments are often very short, which makes the central advantage of BERT models, namely to be context-sensitive, less relevant. For our task, we considered it preferrable to use custom-trained word vector models over pre-trained models to capture authentic user-generated communication. Pre-trained models are often trained on general corpora, such as text from Wikipedia. Fasttext models can be trained from R (Benesty, 2019).

We compiled two training datasets, one for each language consisting of all textual data from posts and user comments analyzed in Step 1. For Austria, we this data consisted of 4,293 posts and 232,935 parent comments. For Slovenia, we considered 3,365 posts and 50,274 user comments. From each post we also considered the headlines and sub-headlines of linked articles, as presented on Facebook. For each language, all textual data was split into sentences, using the quanteda (Benoit et al., 2018) tokenizer, and randomly shuffled. Text was cleaned by removing hyperlinks, punctuation, and excessive white space, replacing self-defined lists of emojis by German, respectively Slovenian words for "anger", "joy", and "fear", replacing numbers by words, keeping only letters, and lowercasing all characters. The cleaned training sample consisted of 235,540 sentences for the Austrian model and 63,245 sentences for the Slovenian model.

We used the R-package fastrtext (Benesty, 2019) to train two fasttext models, one per language, with the following specifications: 200 dimensions, context window size 5, learning rate .05, learning rate update 100, epochs 5, minimum count 7, bucket 2,000,000, ngrams 3-6, sampling threshold 1e-04. The Austrian model includes a vocabulary of 20,192 words, the Slovenian model 12,701 words. The row labelled "Unsupervised Model" in Figure D1 illustrates this step of our workflow. Both models are made available with the replication material.

2. *DDR Measurement*

In the DDR method, word embedding models are used to calculate the similarity between an average vector representation of a dictionary and vectors for each document (Garten et al., 2018). The resulting similarity score can be interpreted as indicator for how strongly a concept is represented in a document. Here, we obtained these measures by first querying the *fasttext* models for vectors of each word in a dictionary and averaging across the vectors for all words. This procedure was equally applied to each document. Textual data was previously cleaned in the same way as the training data described above. Additionally, we removed frequent stopwords, excluding such words that indicate in- and out-groups (e.g., "we", "our", "they"). The vectors were L2 normalized to ignore differences in the length of the vectors. We then calculated the cosine similarity between the concept and each document vector. Cosine similarity can range from -1 to +1. We replaced missing values, induced by empty text fields, by the country-level mean minus 1 SD.

3. *Validation and Training Data*

To validate our DDR measures and to optimize the short dictionaries, we used the manually coded comments and reply comments used in Step 2. This dataset contains 1,040 parent comments and replies from Austria and 973 comments and replies from Slovenia. We split both datasets randomly into train and test samples, using a 70% (AT: 728, SI: 682) to 30% (AT: 312, SI: 291) ratio. The comments were manually coded along binary categories, indicating whether a message was anti-elitist, people-centric, and/or anti-immigrant, or nothing thereof, as described in detail in Appendix C. To simplify, we considered a comment populist if it was coded as people-centric or anti-elitist, or both.

4. *Evaluation*

To evaluate our DDR measures, both for validation and optimization, we tested how well the continuous DDR measurements perform in predicting our binary, human coding (Grimmer & Stewart, 2013, p. 275). To obtain the prediction, we ran logistic regressions with the binary, human coding as dependent variable and the continuous DDR measurement as independent variable. We considered predictions with probabilities greater 50% as positive. These predictions were then compared to the manually coding by calculating Recall, Precision and F1 (Stryker et al., 2006). Recall indicates the proportion of correctly identified positive hits in all truly positive documents. Precision indicates the share of correctly identified positive hits in all predicted positives. F1 is a harmonic mean of both.

5. *Optimizing Short Dictionaries*

For the DDR method, short, clear-cut dictionaries perform better than long lists of words (Garten et al., 2018). Our aims for the dictionary development were to find short dictionaries, which (a) reflect the language used in the analyzed comments, (b) perform well in predicting the human coding, (c) reflect the key dimensions of our concepts, and (d) reflect equivalent dimensions in both languages. We tried to meet these objectives by following both inductive and deductive logic. The row "Optimization & Validation" in Figure D1 illustrates the steps described below. The R-code for all steps is also presented in the vignette "from text to measurement" in our R-package *dictvectoR* (Thiele, 2022b).

We started, inductively, from the vocabularies of both fasttext models, which are the most common words found in the observed user comments. We narrowed down this vocabulary to the 80% most frequent words and obtained F1 scores for each individual word, treating each word as a single-word dictionary for a DDR measure, and the train dataset as counterpart for evaluation. From these results, we picked the quartile with the highest F1 scores. From working with the material, we knew that right-wing populist expressions frequently use combinations of words that contrast in- and out-groups (e.g., “our border”). Hence, we expanded our list of words by identifying frequently used multiword expressions in our corpus that contained one of the words found so far. We obtained F1 scores for these multiword expression in the same way as described above. Additionally, we counted the number of occurrences of each term. We narrowed down this list of terms by dropping expressions that occurred less often than three times in the complete corpus, and by keeping only the top performing quartile.

Switching to a deductive logic, the resulting lists of terms were annotated by hand. Only the German speaking author was involved in this process. Hence, the Slovenian terms were machine-translated into German, using the DeepL API. These lists contained between 330 and 450 words for each concept (populism, anti-immigration). The terms were annotated ad-hoc for their theoretical plausibility, relevance, and discriminatory power and boiled down to a shortlist of 20 populist and 15 anti-immigrant words per language. Additionally, the terms were assigned with labels for conceptual subdimensions. For populism, these subdimensions included elite actors, incompetency of elites, moral degeneracy of elites, invocations of the people, virtues of the people, victimization of the people, and defending the people. For anti-immigration, these subdimensions were migrants as a group, constructions of economic, and security threats from migration, and calls for defense against immigration. The selected terms reflect country-specific discourses but match equivalent subdimensions. For example, the Slovenian anti-immigration discourse was focused on events at the border, compared to the Austrian discourse, which was more concerned with issues of integration. These differences plausibly reflect different realities in both countries, as Slovenia received only very few applications for asylum, while Austria clearly is a destination country.

From these shortlists of words, we obtained all possible dictionary combinations of lengths between four and eight words. This resulted in 22,243 uniquely combined dictionaries for anti-immigration, and 60,525 for populism. We excluded dictionaries that exclusively reflected anti-elitism or people-centrism. For each combination, we applied the DDR method and used the hand-coded training data for evaluation to obtain F1 scores. The resulting F1 scores ranged from .44 to .77. From the best performing short dictionaries, we picked those four short dictionaries that maximized the F1 score per country and concept and had the largest conceptual overlap across countries. Finally, we tested how these picks performed on the validation test sample. The results are reported in the main text.

6. Examples for Face Validity

In addition to the formal validity test reported in the article, Figures D2 to D5 present examples of our measurements for face validity. The jitter-plots show the distribution of all hand-coded comments (AT: n=1,040, SI: n=973) across the binary hand coding of each category on the x-axis and the respective DDR measurement on the y-axis. The boxplot shows the mean of the DDR measure and the +/- 1 SD bars. Additionally, the figures present 30 examples in text labels, indicating the value of the respective DDR measurement and a snipped from the comment, DeepL-translated into English. Figure D2 shows the performance of the populism measurement for the Austrian data, Figure D3 populism for Slovenia, Figure D4 anti-immigration for Austria, and Figure D5 anti-immigration for Slovenia.

This example illustrates how to read these plots: In Figure D2, the comment picked as example with the highest DDR score for populism has a value of .7 and reads “…the fooling and corruption negotiations continue. […]”. Its black color indicates that it was manually coded as “populist”. The least populist comment displayed as example has a DDR score of .37. Its clumsy machine-translation reads “Woman… what do you think how you annoy me”. It has been manually coded as non-populist, indicated by its grey color. The grey dots and the bar on the left-hand side of the plot show that hand-coded non-populist comments had a mean DDR score of about .48. The black dots and the bar on the right-hand side show that populist-coded comments have a mean DDR score of about .60.

Figure D2. Hand-coding, DDR measurement, and examples of populist and non-populist comments in the Austrian sample.

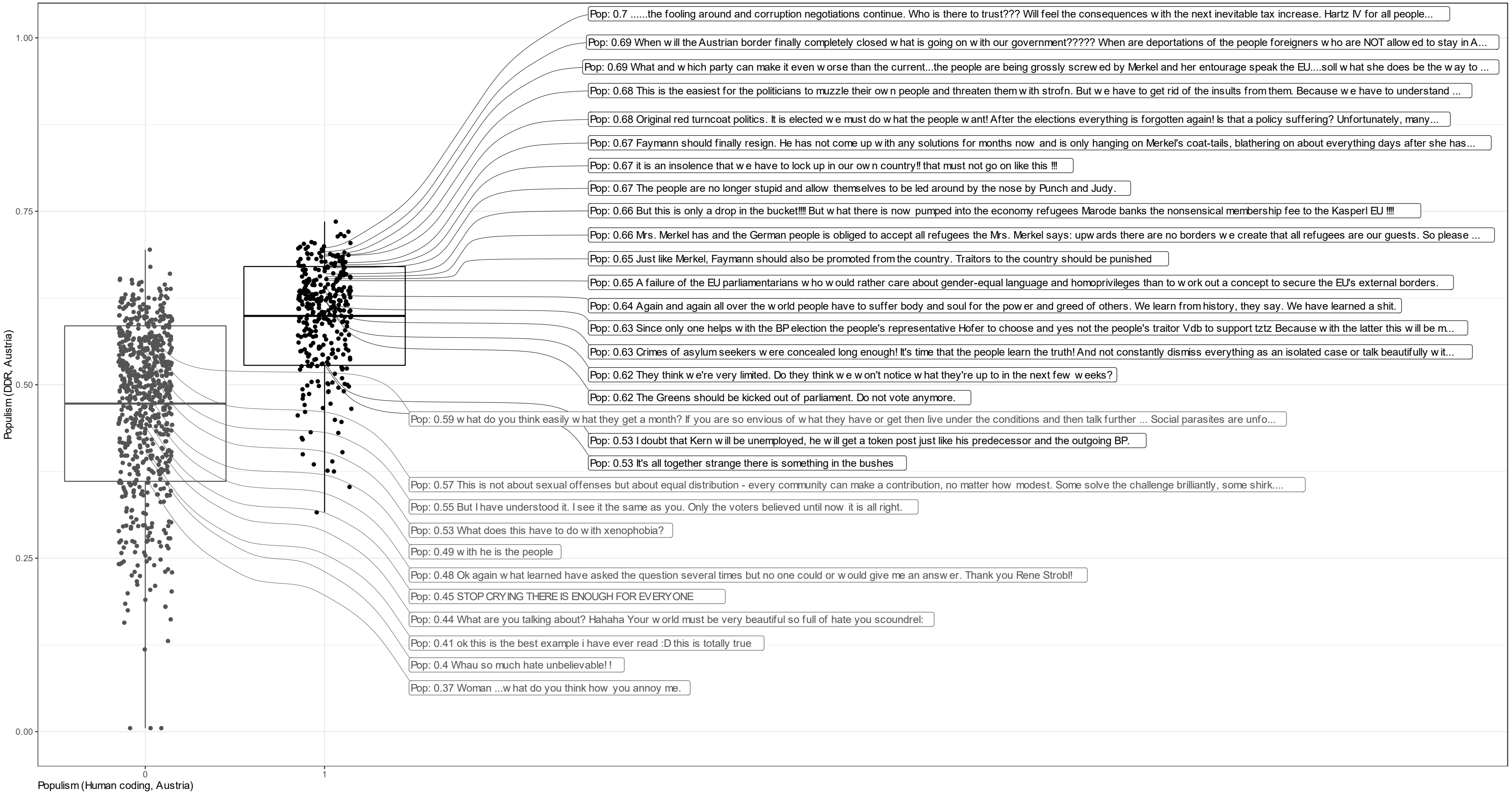


Figure D3. Hand-coding, DDR measurement, and examples of populist and non-populist comments in the Slovenian sample.

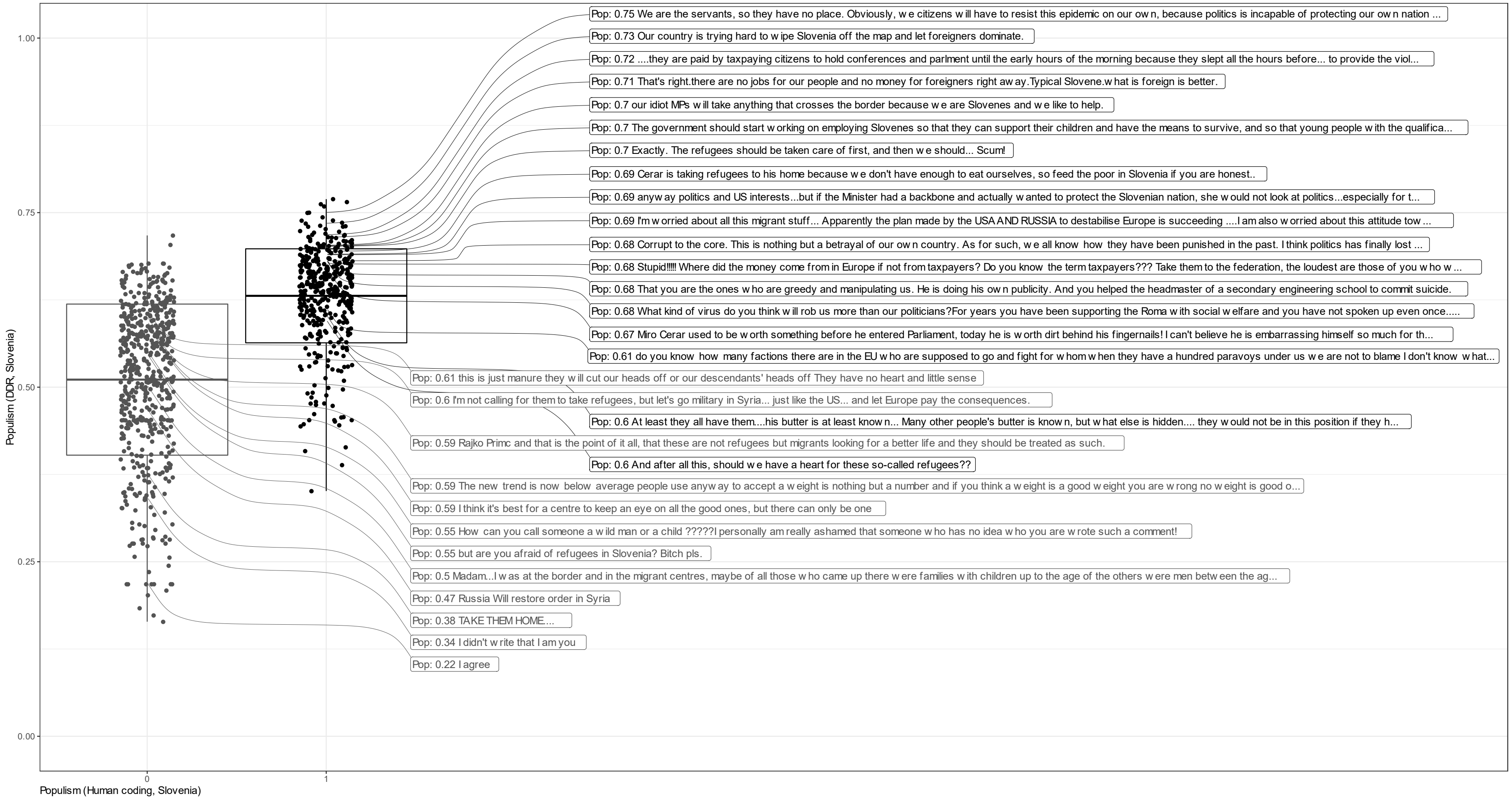


Figure D4. Hand-coding, DDR measurement, and examples of anti-immigrant and non-anti-immigrant comments in the Austrian sample.

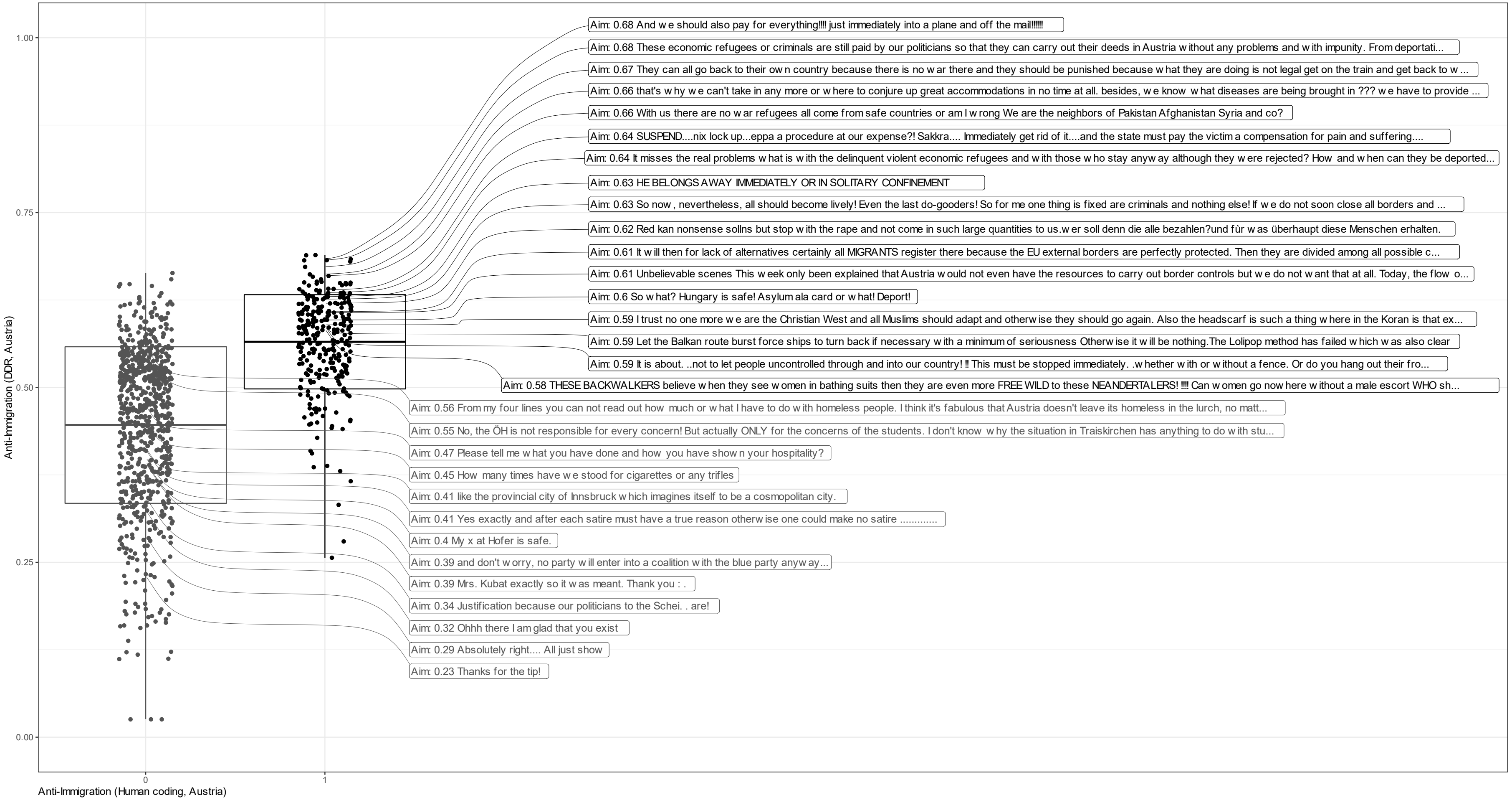
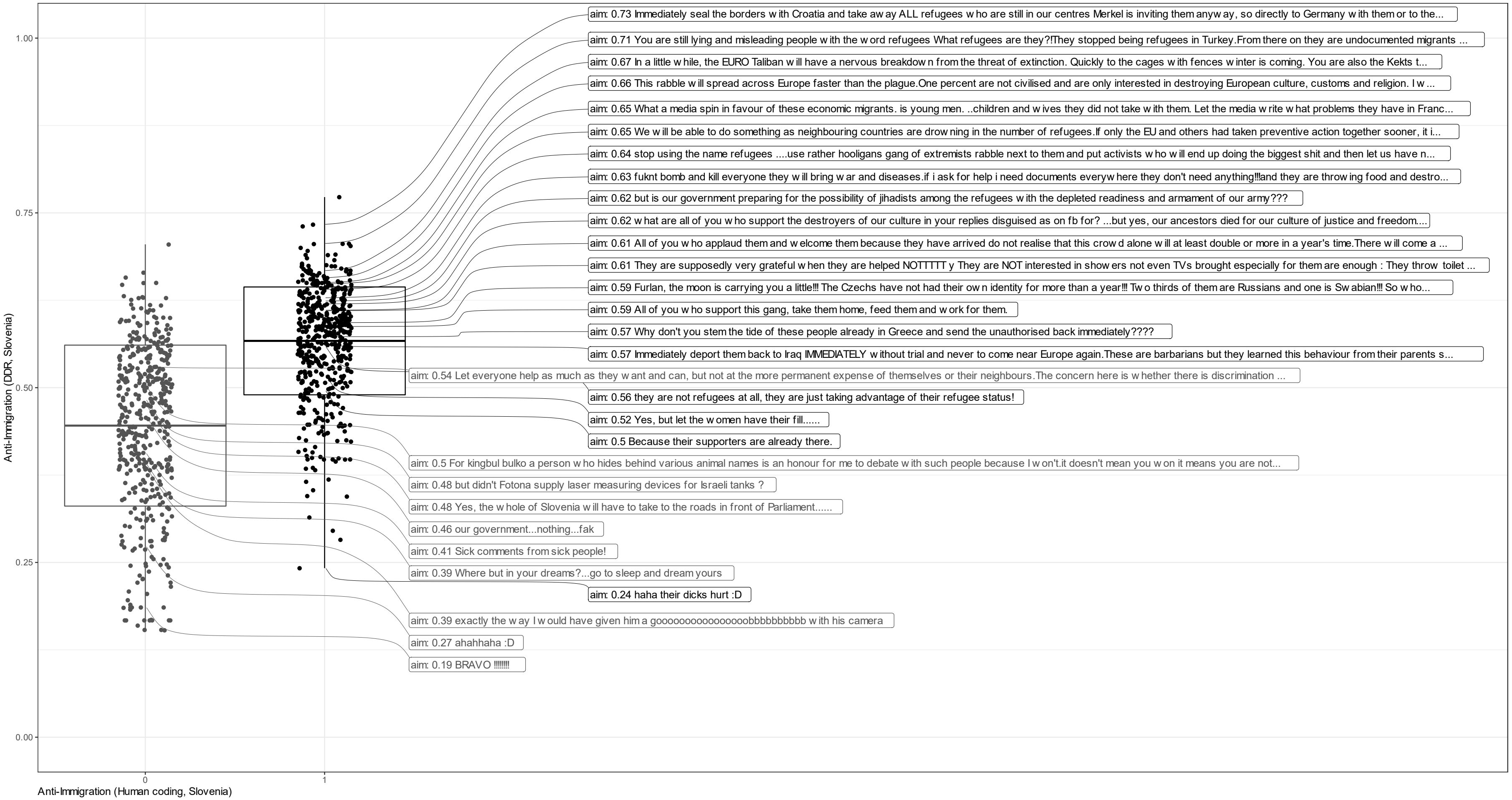


Figure D5. Hand-coding, DDR measurement, and examples of anti-immigrant and non-anti-immigrant comments in the Slovenian sample.



Appendix E

Summary Statistics for Step 1 and Step 2

Table E1 reports the summary statistics for all variables used in Step 1, by country. The values can be read in the following way: The first variable, "reply comments" indicates that each parent comment in the Austrian sample received .7 replies at mean with a SD of 3.4. In the Slovenian sample, each parent comment received .5 (SD=2.4) replies at mean. In Austria, parent comments had a mean populism score of .4 (SD=.1). In 54,482 parent comments, that is 24% of the Austrian sample, the post was addressing the topic migration. Comments had a mean length of 71 characters. In 48,378 (21%) comments of the Austrian sample, at least one other user was tagged. At mean, 1,769.4 days passed since the publication of the comment until it was download by the authors. 3.6 days passed at mean between the publication of the post and the comment. A post received at mean 362.3 comments. This number is distributed extremely unevenly, indicated by the large SD=1,167. The column indicating the values for the Slovenian sample can be read correspondingly.

Table E2 reports the summary statistics of variables used in Step 2 of our study. The values indicate that of 1,413 analyzed replies, 308 (22%) included an argument, etc. The variables in the "Countering" group indicate that 218 replies were preceded by a reply that countered a populist parent comment. The control variables in the fourth group indicate that 519 (37%) reply comments reacted on parent comments that included an argument. Length indicates that the parent comments had a mean length of 358 characters (SD=563).

Table E1. Summary statistics, Step 1.

	Austria		Slovenia	
Variables	**Mean/n**	**(SD/%)**	**Mean/n**	**(SD/%)**
Dependent variable:				
Reply comments (count)	0.7	(3.4)	0.5	(2.4)
Explanatory variables:				
Populism	0.4	(0.1)	0.5	(0.1)
Anti-Immigration	0.4	(0.1)	0.4	(0.1)
Controls:				
Migration topic	54,482	(24%)	6,268	(12%)
Length	71.0	(114.8)	75	(245.5)
Tagged users	48,378	(21%)	2,288	(4.6%)
Download age	1,769.4	(250)	1,939.7	(219)
Days since post	3.6	(48.1)	1.3	(30.7)
Comments per post (count)	362.3	(1,167)	74.1	(75.3)
Facebook accounts				
Der Standard	20,724	(9.0%)		
Die Presse	11,034	(4.8%)		
Kronen Zeitung	44,963	(19%)		
Oe24.at	37,771	(16%)		
Zeit im Bild	116,415	(50%)		
24ur.com			33,290	(66%)
Delo			1,368	(2.7%)
Dnevnik			661	(1.3%)
RTVSLO.si			725	(1.4%)
Slovenske Novice			14,164	(28%)
Total (N parent comments)	**230,907**		**50,208**	

Table E2. Summary statistics, step 2.

Variables	**Mean/n**	**(SD)/(%)**
Dependent variables (R):		
Argument	308	(22%)
Sourcing	47	(3.3%)
Incivility	241	(17%)
Impoliteness	989	(70%)
Explanatory variables (P):		
People-centrism	656	(46%)
Anti-elitism	477	(34%)
Anti-Immigration	858	(61%)
Countering:		
Countering Populism	218	(15%)
Countering Anti-Immigr.	224	(16%)
Controls (P):		
Argument	519	(37%)
Sourcing	52	(3.7%)
Incivility	552	(39%)
Impoliteness	1,177	(83%)
Length	358	(563)
Facebook accounts		
Der Standard (AT)	47	(3.3%)
Die Presse (AT)	61	(4.3%)
Kronen Zeitung (AT)	288	(20%)
Oe24.at (AT)	75	(5%)
Zeit im Bild (AT)	268	(19%)
24ur.com (SI)	406	(29%)
Delo (SI)	58	(4.1%)
Dnevnik (SI)	5	(0.4%)
RTVSLO.si (SI)	10	(0.7%)
Slovenske Novice (SI)	195	(14%)
Country		
Austria	739	(52%)
Slovenia	674	(48%)
Total (N reply comments)	**1,413**	

Notes: (R) reply, (P) parent comments.

Appendix F

Right-wing Populism in Comments by Media Type

The plots below show the mean comparisons of the anti-immigration and populism DDR scores, used in Step 1 of our analysis, across media types. The plots report the p-values from the Kruskal-Wallis-tests, testing for significant differences between the groups. In Austria, all three media types (quality, tabloid, public TV) differ significantly in pairwise comparisons of their mean level of anti-immigrant and populist content in comments. In Slovenia, we do not find significant differences between quality press and public TV, but significant differences between tabloid and quality press, as well as tabloid and public broadcaster. All differences are very small, however.

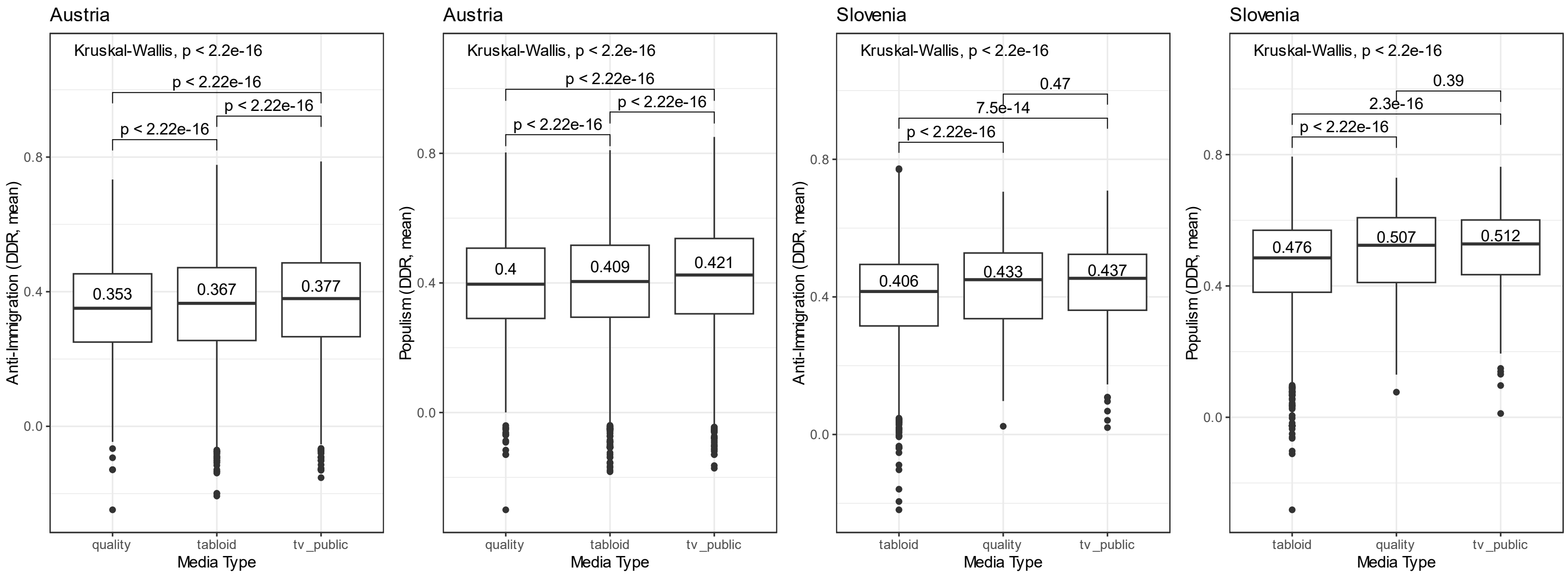


Figure F1. Mean comparison of populism and anti-immigration DDR scores across media types, by country.

Appendix G

Regression Tables for Step 1

Table F1 documents the results from the multilevel, negative binomial regressions on the number of reply comments fitted for step 1. Since our measurement of populist and anti-immigrant content is not directly comparable across languages, we analyzed the data from Austria (Model 1) and Slovenia (Model 2) separately. The data has a nested structure: comments are nested within the higher level of posts, while posts are nested within Facebook accounts. We account for this structure by fitting multilevel models, with random intercepts for the two higher levels posts and Facebook accounts. We used the R package *glmmTMB* (Brooks et al., 2022) to fit the models and restricted maximum likelihood (REML) estimation. The number of units on the account level is small (n = 5), which has been considered problematic for multilevel models for long (Stegmueller, 2013). However, Elff et al. (2021) have shown that these concerns are exaggerated, when using REML. The results are interpreted in the main text.

Table F1. Negative binomial multilevel regressions on the number of replies.

	Model 1 Austria	**Model 2** Slovenia
Intercept	-0.87 (0.13) ***	-1.93 (0.38) ***
Explanatory variables (P)		
Populism	0.23 (0.01)***	0.24 (0.03)***
Anti-Immigration	0.43 (0.01)***	0.36 (0.03)***
Controls		
Migration topic	0.12 (0.03)***	-0.20 (0.10)*
Download age	0.04 (0.02)*	-0.01 (0.05)
Days passed since post	-0.09 (0.01)***	0.01 (0.02)
Length	0.30 (0.01)***	0.24 (0.04)***
Tagged users	0.41 (0.02)***	0.72 (0.07)***
Comments per post	-0.02 (0.03)	-0.03 (0.04)
AIC	401,863.31	73,635.54
Log Likelihood	-200,919.66	-36,805.77
Num. obs.	230,907	50,208
Num. groups: Post:Account	4,293	3,365
Num. groups: Account	5	5
Var: Post:Account (Intercept)	0.30	0.60
Var: Account (Intercept)	0.08	0.68

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

References in Appendices A-G

Aslanidis, P. (2018). Measuring populist discourse with semantic text analysis: An application on grassroots populist mobilization. *Quality & Quantity*, *52*(3), 1241–1263. https://doi.org/10.1007/s11135-017-0517-4

Beckert, J., & Ziegele, M. (2020). The Effects of Personality Traits and Situational Factors on the Deliberativeness and Civility of User Comments on News Websites. *International Journal of Communication*, *14*(0), Article 0.

Benesty, M. (2019). *Fastrtext 0.3.4*. https://CRAN.R-project.org/package=fastrtext

Benoit, K., Watanabe, K., Wang, H., Nulty, P., Obeng, A., Müller, S., & Matsuo, A. (2018). quanteda. An R package for the quantitative analysis of textual data. *Journal of Open Source Software*, *3*(30), 774. https://doi.org/10.21105/joss.00774

Blassnig, S., Engesser, S., Ernst, N., & Esser, F. (2019). Hitting a nerve: Populist news articles lead to more frequent and more populist reader comments. *Political Communication*, *36*(4), 629–651. https://doi.org/10.1080/10584609.2019.1637980

Blassnig, S., Engesser, S., & Esser, F. (2016). *Codebook: Populist online communication in Europe: Self-presentation, media representation, and audience reconstruction of political actors*. Courtesy by the Authors.

Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching Word Vectors with Subword Information. *ArXiv:1607.04606 [Cs]*. http://arxiv.org/abs/1607.04606

Brooks, M., Bolker, B., Kristensen, K., Maechler, M., Magnusson, A., McGillycuddy, M., Skaug, H., Nielsen, A., Berg, C., Bentham, K. van, Sadat, N., Lüdecke, D., Lenth, R., O'Brien, J., Geyer, C. J., & Jagan, M. (2022). *glmmTMB: Generalized Linear Mixed Models using Template Model Builder* (1.1.3). https://CRAN.R-project.org/package=glmmTMB

Callens, M.-S., & Meuleman, B. (2017). Do integration policies relate to economic and cultural threat perceptions? A comparative study in Europe. *International Journal of Comparative Sociology*, *58*(5), 367–391. https://doi.org/10.1177/0020715216665437

Coe, K., Kenski, K., & Rains, S. A. (2014). Online and uncivil? Patterns and determinants of incivility in newspaper website comments. *Journal of Communication*, *64*(4), 658–679. https://doi.org/10.1111/jcom.12104

Collins, L., & Nerlich, B. (2015). Examining User Comments for Deliberative Democracy: A Corpus-driven Analysis of the Climate Change Debate Online. *Environmental Communication*, *9*(2), 189–207. https://doi.org/10.1080/17524032.2014.981560

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *ArXiv:1810.04805 [Cs]*. http://arxiv.org/abs/1810.04805

Elff, M., Heisig, J. P., Schaeffer, M., & Shikano, S. (2021). Multilevel Analysis with Few Clusters: Improving Likelihood-Based Methods to Provide Unbiased Estimates and Accurate Inference. *British Journal of Political Science*, *51*(1), 412–426. https://doi.org/10.1017/S0007123419000097

Esau, K., Friess, D., & Eilders, C. (2017). Design matters! An empirical analysis of online deliberation on different news platforms. *Policy & Internet*, *9*(3), 321–342. https://doi.org/10.1002/poi3.154

Friess, D., & Eilders, C. (2015). A systematic review of online deliberation research. *Policy & Internet*, *7*(3), 319–339. https://doi.org/10.1002/poi3.95

Friess, D., Ziegele, M., & Heinbach, D. (2020). Collective civic moderation for deliberation? Exploring the links between citizens' organized engagement in comment sections and the deliberative quality of online discussions. *Political Communication*, *38*(5), 624–646. https://doi.org/10.1080/10584609.2020.1830322

Garten, J., Hoover, J., Johnson, K. M., Boghrati, R., Iskiwitch, C., & Dehghani, M. (2018). Dictionaries and distributions: Combining expert knowledge and large scale textual data content analysis. *Behavior Research Methods*, *50*(1), 344–361. https://doi.org/10.3758/s13428-017-0875-9

Gervais, B. T. (2015). Incivility Online: Affective and Behavioral Reactions to Uncivil Political Posts in a Web-based Experiment. *Journal of Information Technology & Politics*, *12*(2), 167–185. https://doi.org/10.1080/19331681.2014.997416

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political Analysis*, *21*(3), 267–297. https://doi.org/10.1093/pan/mps028

Hameleers, M. (2019). Putting Our Own People First: The Content and Effects of Online Right-wing Populist Discourse Surrounding the European Refugee Crisis. *Mass Communication and Society*, *0*, 1–23. https://doi.org/10.1080/15205436.2019.1655768

Klinger, U., & Russmann, U. (2015). The sociodemographics of political public deliberation: Measuring deliberative quality in different user groups. *Communications*, *40*(4), 471–484. https://doi.org/10.1515/commun-2015-0017

Maia, R. C. M., & Rezende, T. A. S. (2016). Respect and Disrespect in Deliberation Across the Networked Media Environment: Examining Multiple Paths of Political Talk. *Journal of Computer-Mediated Communication*, *21*(2), 121–139. https://doi.org/10.1111/jcc4.12155

Manosevitch, E., Steinfeld, N., & Lev-On, A. (2014). Promoting online deliberation quality: Cognitive cues matter. *Information, Communication & Society*, *17*(10), 1177–1195. https://doi.org/10.1080/1369118X.2014.899610

Marzinkowski, H., & Engelmann, I. (2022). Rational-critical user discussions: How argument strength and the conditions set by news organizations are linked to (reasoned) disagreement. *Digital Journalism*, *10*(3), 433–451. https://doi.org/10.1080/21670811.2021.1957968

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space. *ArXiv:1301.3781 [Cs]*. http://arxiv.org/abs/1301.3781

Mudde, C. (2004). The populist zeitgeist. *Government and Opposition*, *39*(4), 541–563. https://doi.org/10.1111/j.1477-7053.2004.00135.x

Oz, M., Zheng, P., & Chen, G. M. (2018). Twitter versus Facebook: Comparing incivility, impoliteness, and deliberative attributes. *New Media & Society*, *20*(9), 3400–3419. https://doi.org/10.1177/1461444817749516

Papacharissi, Z. (2004). Democracy online: Civility, politeness, and the democratic potential of online political discussion groups. *New Media & Society*, *6*(2), 259–283. https://doi.org/10.1177/1461444804041444

Rega, R., & Marchetti, R. (2021). The strategic use of incivility in contemporary politics. The case of the 2018 Italian general election on Facebook. *The Communication Review*, *24*(2), 107–132. https://doi.org/10.1080/10714421.2021.1938464

Rossini, P. (2020). Beyond incivility: Understanding patterns of uncivil and intolerant discourse in online political talk. *Communication Research*, 0093650220921314. https://doi.org/10.1177/0093650220921314

Stegmueller, D. (2013). How Many Countries for Multilevel Modeling? A Comparison of Frequentist and Bayesian Approaches. *American Journal of Political Science*, *57*(3), 748–761. https://doi.org/10.1111/ajps.12001

Stromer-Galley, J. (2007). Measuring deliberation's content: A coding scheme. *Journal of Deliberative Democracy*, *3*(1). https://doi.org/10.16997/jdd.50

Stroud, N. J., Scacco, J. M., Muddiman, A., & Curry, A. L. (2015). Changing Deliberative Norms on News Organizations' Facebook Sites. *Journal of Computer-Mediated Communication*, *20*(2), 188–203. https://doi.org/10.1111/jcc4.12104

Stryker, J. E., Wray, R. J., Hornik, R. C., & Yanovitzky, I. (2006). Validation of Database Search Terms for Content Analysis: The Case of Cancer News Coverage. *Journalism & Mass Communication Quarterly*, *83*(2), 413–430. https://doi.org/10.1177/107769900608300212

Thiele, D. (2022a). Pandemic populism? How Covid-19 triggered populist Facebook user comments in Germany and Austria. *Politics and Governance*, *10*(1), 185–196. https://doi.org/10.17645/pag.v10i1.4712

Thiele, D. (2022b). *Thieled/dictvectoR* (0.0.1) [R]. https://doi.org/10.5281/zenodo.7079600

Ziegele, M., & Friess, D. (2018). *Codebuch zur Erfassung von deliberativer Qualität in Online-Diskussionen*. Courtesy by the Authors.

Ziegele, M., Quiring, O., Esau, K., & Friess, D. (2020). Linking news value theory with online deliberation: How news factors and illustration factors in news articles affect the deliberative quality of user discussions in SNS' comment sections. *Communication Research*, *47*(6), 860–890. https://doi.org/10.1177/0093650218797884