Focusing on social attributes, not group categories

Quantifying social group mentions

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Abstract

Research increasingly examines how political actors refer to social groups in their communication. Existing studies typically classify such references — *social group mentions* — into mutually exclusive group categories (e.g., economic, gender, ethnic). While this approach has advanced comparative analyses of group-based political discourse, it constrains how scholars capture the semantic diversity and intersectionality of social group references. This paper proposes a novel methodological framework that reconceptualizes social group labeling by focusing on the social attributes invoked in group mentions rather than on pre-defined group categories. We define social group mentions as statements that name or describe collectives of people through shared attributes and argue that each mention can involve one or more such attributes. Building on this conceptual shift, we introduce a multilabel classification approach that distinguishes between vertical and horizontal group attributes. Vertical attributes include markers of social stratification such as class, occupation, or income, while horizontal attributes encompass dimensions such as age, gender, place, ethnicity, religion, or shared values, behavioral patterns and experiences. We further identify ”universal” group references, that is, undifferentiated collectivisms (e.g., “everyone,” “society”). out attribute-centered ontology allows researchers to capture intersectional and compositional patterns of

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group-based discourse with greater nuance, flexibility, and cross-context comparability. We illustrate the analytical advantages of this framework through an application to party manifestos of populist radical-right and Green parties, demonstrating how an attribute-centered perspective enriches our understanding of how political actors construct, differentiate, and mobilize social groups in political communication.

Word count: 8745

1 Introduction

Political actors routinely refer to social groups, and such invocations play a central role in structuring political alignment between parties and constituencies. Although social groups have long occupied a central place in the social sciences, research has primarily focused on how groups are defined by social structure (e.g., Blau and Duncan 1967; Lipset 1960; Lipset and Rokkan 1967; Goldthorpe 2007; Dalton 1984, 2008; Kriesi et al. 2008, 2012; Piketty et al. 2018, 2021) or experienced through identity (e.g., Tajfel 2010; Tajfel and Turner 2004; Achen and Bartels 2017; Huddy 2001; Brubaker 2024). Much less attention has been devoted to how social groups are invoked and mobilized by political actors themselves. Despite the recent emergence of supply-side approaches that measure group references (Licht and Sczepanski 2025; Farahani et al. 2024;) and group appeals in party communication (e.g., Thau 2019, 2024; Dolinsky 2021, 2023; Stuckelberger 2019; Stuckelberger and Tresch 2024; Huber 2022; Riethmüller et al. 2024; Horne et al. 2025; Dodeigne 2025; Dausgard and Hjorth 2025; Amarales et al. 2025), scholars still lack a theoretically grounded and empirically scalable taxonomy for analyzing party references to social groups from a communicative perspective.[1]

This article addresses that gap. We develop a taxonomy of social group references from the perspective of political parties built around three principles. First, group references are identified through the **attributes** political actors explicitly invoke rather than through presumed social positions or identity categories. Second, we organize these attributes in a **hierarchical** taxonomy that captures how parties vary the level of abstraction at which groups are invoked, ranging from universal categories such as "the people" to highly specific groups such as "self-employed foreign nurses." Third, our attribute-centered taxonomy takes **intersectionality** seriously by recognizing that political actors routinely combine multiple attributes when referring to social groups such as for "self-employed foreign nurses."

Taken together, this framework provides an attribute-centered, hierarchical taxonomy that accommodates intersectional group references, improves comparability across contexts, reduces information loss, and minimizes bias by defining groups consistent with how parties

[1] We kept the categories' order fixed across examples to ease the cognitive load at annotation time.

themselves invoke them. These principles further highlight that political actors possess substantial leeway not only to respond to existing social structures but also to shape and reconfigure social group boundaries (see also Brubaker 2004; Chandra 2012; De Leon 2015; Damhuis 2020; Westheuser and Zollinger 2025) through the combination of attributes and shifts in levels of abstraction.

`TODO: Add methodological contribution`

`TODO: Add key findings`

This perspective provides a theoretically grounded starting point for addressing a central question in contemporary research: whether parties primarily respond to existing (Lipset and Rokkan 1967) and shifting group structures (Dalton 1984, 2008; Kriesi et al. 2008, 2012; Piketty et al. 2018, 2021; Bornschier et al. 2024) and/or actively participate in constructing them in an era of mass political communication (Brubaker 2004; Chandra 2012; De Leon 2015; Westheuser and Zollinger 2025; Damhuis 2020). We thus show that developing a supply-side taxonomy of social groups is not merely a classificatory exercise but a prerequisite for an improved understanding of how political actors not only respond but also shape the social boundaries underlying democratic competition.

2 Structuring Invocations of Social Groups

A central challenge in studying group references lies not in detecting that political actors refer to social groups, but in determining how such references should be structured analytically. The scale of this challenge is substantial. Even within a single country, party discourse contains thousands of distinct group references. For example, party manifestos of the UK Labour and Conservative parties between 1964 and 2015 contain more than 2,700 unique mentions of social groups (Thau 2019; Licht & Sczepanski 2025).

A growing body of research has begun to measure and map such references, often linking group mentions to specific frames, such as positive or negative appeals (Riethmüller and Franzmann 2025; Dodeigne 2025; Horne et al. 2025 ; Huber 2022), representational claims (Gevers et al. 2024; De Mulder et al. 2025), or distinctions between identity and non-identity groups (Stuckelberger and Tresch 2024) and social classes (Thau 2019, Thau et al. 2022).

These approaches have generated important insights when applied to specific research questions. However, we argue that such frameworks are less suitable as general taxonomies of social group references, as they often inherit classifications shaped by demand-side perspectives or conflate group attributes with the framing of groups. As a result, they may limit our ability to capture the full variety of group appeals observable from a supply-side perspective as well assume positional or Identity frames where they need to be measured first.

For example, women, ethnic or sexual minorities are often associated with cultural or identity conflicts, whereas the working class is commonly framed in predominantly economic terms (Bornschier, 2015; Kriesi et al., 2008, 2012; Stuckelberger & Tresch, 2022). While such associations may appear plausible in some perspectives, they should not be assumed when analyzing how parties invoke social groups. In practice, groups such as women or the working class can be framed in multiple ways, combining cultural, identity-based, and economic-redistributive narratives. Even class politics depended on organizational mediation and strategic articulation by parties rather than simply reflecting pre-existing social structures (Przeworski & Sprague, 1986; Thau 2021), and parties may actively construct class identities and group boundaries through political discourse (De Leon, 2015). Similarly, feminist scholarship has long emphasized that gender injustice is simultaneously economic and cultural, requiring attention to both redistribution and recognition (Fraser, 2013). More broadly, Polanyi's ([1944] 2001) insight that economic and social orders are co-constitutive suggests that conflicts over redistribution are inherently also conflicts over social belonging and moral order. Together, these perspectives caution against treating particular groups as inherently economic or identity-based and instead point to the flexibility with which political actors frame social groups in practice.

We therefore propose to separate the classification of group references from the analysis of group framing. Structuring the observed variation in group references instead requires addressing three interrelated questions: on what basis group mentions should be distinguished, at what level of abstraction these distinctions operate, and whether—and how—to account for intersectionality. We address these questions in turn.

2.1 From Classes and Identities to Attributes

We first address how social group references should be distinguished analytically. While scholars broadly agree that understanding when, why, and how political actors invoke social groups is important, there is less agreement on what constitutes a social group in the first place.

Our central claim is that social groups should be defined by the attributes political actors invoke in discourse. Attributes are measurable properties, and a single attribute—or a combination of attributes—can delineate a collective of people. Following Sczepanski and Licht (2025, 1), we therefore define social groups as collectivities sharing one or more attributes, which may include economic characteristics, nationality or ethnicity, shared values, or other meaningful attributes. This attribute-centered perspective serves two purposes. First, it keeps the analysis open to the full universe of supply-side group references, avoiding restrictions inherited from demand-side or socio-demographic classifications. Second, it separates the identification of social groups from their political framing, allowing groups to be classified independently of whether they are invoked in economic, cultural, moral, or identity-based terms, which can then be analyzed in a distinct step.

This view is not incompatible with existing approaches but departs from much current work, which often relies on predefined socio-demographic categories or survey-based group lists (Wlezien & Miller, 1997; Dolinsky, 2021, 2023; Huber, 2022; Riethmüller et al., 2024). Such strategies facilitate links to demand-side perspectives and its indicators but restrict analysis to groups assumed to be salient in socio-demographic classifications, thereby excluding many groups invoked in political discourse. Recent efforts to systematize group appeals similarly aggregate references into sets aligned with traditional cleavages (Dolinsky, 2023; Horne et al., 2025; Stuckelberger & Tresch, 2024), implicitly carrying assumptions about which groups matter politically and how they are framed.

These tendencies reflect the long dominance of structural and identity-based perspectives. Structural accounts define groups through positions in enduring social relations and institutions (Lipset & Rokkan, 1967; Dalton, 1984, 2008; Kriesi et al., 2008, 2012; Piketty et al., 2018, 2021), treating groups as products of social structure rather than objects of political communication. Identity-based approaches, drawing on social identity theory, conceptualize groups through processes of self-categorization and belonging (Ashforth & Mael, 1989; Hogg, 1992, 2016). While both traditions provide important insights, they are less suited as foundations for a supply-side taxonomy.

In constrast, other approaches move closer to a supply-side perspective by defining social groups as collectives sharing meaningful attributes, including values and lived experiences (Chandra, 2012; Zuber et al., 2025; Wolkenstein & Wratil, 2021). Empirical work shows that attributes such as being "hard-working" or "morally upright" play an important role in political boundary-making (Zollinger, 2022; Sczepanski, 2023), and that even economically defined groups often anchor claims in cultural terms (Zollinger, 2024). However, these approaches often lack scalable strategies for systematic measurement and equally struggle to separate the attribute basis of a group references from its accompanying frames. We like to reiterate that we are agnostic about whose perspective is the most powerful in explaining the formation of political alignments between social groups and parties, but we provide a taxonomy of social group references that is open to validate the different views empirically.

In short, a strictly attribute-centered perspective allows us to map the universe of invoked groups without importing structural or identity-based assumptions into supply-side analysis. While this approach enables us to group diverse verbatim references into meaningful categories, attributes alone do not yet provide a workable taxonomy, as many attributes are nested within hierarchical levels of abstraction that must also be systematically accounted for.

2.2 A Hierarchy of Attribute Abstraction

Political parties do not only choose *which* social groups to invoke but also vary the level of abstraction at which these groups are defined. Group appeals may target highly specific collectivities—such as "nurses," "small business owners," or "single mothers"—or broader and more abstract categories, including "working people," "ordinary citizens," or even "the people" (see also Thau 2019 or Horne et al. 2025). This flexibility reflects a central dimension of party communication: the capacity to adjust the inclusiveness and vagueness of group boundaries to expand or narrow potential appeals (Damhuis and Karremans, 2017; Evans and Tilley, 2017; Horn et al., 2021).

This flexibility motivates the second core element of our taxonomy: the hierarchy of abstraction. Social group appeals differ systematically in how concretely or abstractly group boundaries are drawn, ranging from highly specific collectivities to universalized categories that approach claims of general representation. Treating all social groups as operating at the same level of abstraction obscures a central dimension of group references and limits comparability across contexts. By explicitly capturing variation in abstraction, our taxonomy enables a more precise and generalizable analysis of how parties potentially construct, expand, or narrow social groups.

Classic theories of political representation already emphasize the importance of abstraction in political claims-making. Pitkin (1967) distinguishes between descriptive references to concrete constituencies and more abstract claims to represent general interests. Similarly, Downsian models of electoral competition imply incentives for parties to frame appeals in increasingly inclusive terms as they seek to maximize electoral support (Downs, 1957). From this perspective, abstract group appeals can function as coalition-expanding devices, allowing parties to appeal simultaneously to heterogeneous constituencies without committing to narrowly defined distributive claims.[2]

This logic has been further developed in research on populism and mass politics. Populist appeals are having been characterized precisely by their reliance on highly abstract and universalized group categories—most notably "the people"—which remain intentionally vague and elastic (Laclau, 2005; Mudde & Kaltwasser, 2017). Such abstraction enables parties to fuse diverse grievances and social positions under a common label, facilitating broad but internally heterogeneous coalitions. Importantly, this strategy is not limited to populist actors. Mainstream parties also rely on abstract categories such as "ordinary consumers," or "citizens," which combine inclusiveness with normative evaluation while avoiding precise socio-structural specification (Zollinger, 2024).

Research on cleavage politics and realignment further shows that shifts toward more abstract group references often accompany periods of social and electoral change. As tra-

[2]We omitted options for "No" because not choosing "Yes" or "Unsure" for a given attribute category implied this coding choice.

ditional class or religious anchors weaken, parties increasingly rely on higher-level group categories that cut across established divisions, such as “the middle class,” “the majority,” or “society at large” (Kriesi et al., 2008, 2012; Dalton, 2008). These appeals are rationalized allow parties to bridge fragmented electorates while retaining interpretive flexibility regarding who is included in the invoked group. Other studies have suggest that parties nowadays increasingly refer to the same broad and neutral groups, considering all classes as potential constituencies (Damhuis and Karremans, 2017; Evans and Tilley, 2017; Horn et al., 2021).

From a constructivist perspective, varying levels of abstraction are best understood as a discursive resource. Laclau and Mouffe’s (1985) theory of articulation highlights how abstract signifiers can function as nodal points that temporarily stabilize meaning while remaining open to multiple interpretations. Abstract group appeals thus enable parties to construct equivalences between otherwise disparate social groups, whereas more concrete appeals emphasize differentiation and targeted representation.

Recent research on social group appeals has made important strides in systematically identifying and categorizing group mentions. These studies differ in how they handle levels of abstraction. Several adopt a single-level approach, such as Huber (2022), who relies on fixed survey items, or Riethmüller et al. (2024), who use CSES socio-demographic variables. Other contributions implement two-level hierarchies, where concrete mentions are aggregated into broader categories: Thau (2019; 2024) distinguishes economic versus non-economic groups, Dolinsky (2021; 2023) clusters mentions into socio-demographic classes, and Stückelberger and Tresch (2024) combine concrete mentions with alignment-based categories.

While these approaches provide merit for specific research questions, the hierarchical organization of group categories has typically been treated as a technical step rather than a central analytical dimension. Explicitly incorporating levels of abstraction as a feature allows us to better capture how parties may vary the inclusiveness or universality of their appeals as well as avoiding problematic comparison across levels or across nested group categories. We suggest to think of at least three level, (1) attribute dimensions, (2) attribute categories, (3) specific group attributes.

Attribute Dimensions

Many existing approaches implicitly distinguish between "economic" and "non-economic" or a "cultural" group dimensions (e.g., Thau, 2019; Horne et al., 2024). We adopt this intuition but reformulate it in attribute-centered terms. At the most abstract level, social groups can be organized along three broad attribute dimensions: universal, vertical, and horizontal. First, some references invoke universal groups, such as "the people" or "society," which include everyone and therefore do not distinguish between insiders and outsiders.

All other groups are defined by attributes that differentiate between those who belong and those who do not. These attributes may relate either to economic positions and activities or to attributes unrelated to economic roles. To avoid importing framing assumptions, we refer to these dimensions as vertical (economic) and horizontal (non-economic), drawing on terminology from inequality research while not adopting its broader theoretical implications.

Our terminology builds on Stewart's (2000, 2008) distinction between vertical and horizontal inequalities but adapts it for a different analytical purpose. Whereas Stewart distinguishes inequalities between individuals (vertical) from inequalities between culturally defined groups (horizontal), we use the distinction to categorize the attributes invoked in group references. Vertical group references are defined by attributes linked to economic positions or activities, while horizontal references rely on non-economic attributes. We prefer this terminology because the labels "economic" and "non-economic" can easily be conflated with economic or cultural framings of groups. Our taxonomy, by contrast, makes no assumptions about inequality structures or how groups are framed; it focuses solely on how parties delineate groups through attributes. Vertical groups are thus defined by attributes linked to economic roles or activities, horizontal groups by attributes unrelated to economic roles, while universal groups refer to collectivities for which boundary-making is absent.

Attribute Categories

Defining abstract group dimensions naturally leads to a second level of abstraction: group categories. At this level, the literature shows considerable agreement on the types of categories that structure social group references. These categories are based on attributes that are mutually exclusive at the categorical level but broad enough to encompass a wide range of specific groups.

For example, employment-related categories include groups such as the unemployed, employees, or the self-employed, all defined by attributes related to employment status. Similarly, a gender category encompasses women, men, LGBTQ+ persons, and other groups defined by gender-related attributes.

Our taxonomy assembles a nearly comprehensive list of such attribute-based categories, designed to capture almost all empirical group references while ensuring that categories remain hierarchically coherent. Categories must therefore avoid to be nested within the attribute categories: highly specific groups are not treated as separate categories if they fall under a broader attribute category. For instance, health professionals do not constitute a separate category, as they are more appropriately included within the broader category of occupation- or profession-related groups.[3]

2.2.3 Specific group references

Different to the attribute dimensions and the attribute categories, specific groups are often context-dependent and hierarchically nested within broader categories. At this level, groups are best understood as clusters of more concrete references that fall under shared attribute categories. For example, the gender category typically includes references to women, men, or individuals defined by LGBTQ+ attributes. While references to women or men are frequently specified through intersectional combinations—such as working women or older men— other social groups such as LGBTQ+ references can also become more specific without necessarily invoking additional attributes. Moreover, identical group mentions may carry different meanings across historical and societal contexts. A party's reference to "families consisting of mothers, fathers, and children," for instance, might have appeared politically neutral in the 1960s but could be interpreted in more recent contexts as excluding non-traditional family forms. Conversely, different expressions may refer to the same group, as there are multiple ways of invoking men, workers, or occupational groups in political discourse.

[3] $1\times$ universal + $5\times$ vertical attributes + $11\times$ horizontal attributes

Scholarship on ethnic politics and social categorization has long emphasized these features of social group construction. Constructivist approaches show that group categories are not fixed entities but context-dependent classifications activated and reinterpreted in political practice (Brubaker, 2004; Chandra, 2012). Similarly, research on symbolic and social boundary-making demonstrates how political actors continuously reshape group boundaries through discourse, allowing categories to shift meaning over time and across contexts (Lamont & Molnár, 2002). Studies of classification systems further underline that social categories are historically contingent and hierarchically organized rather than natural or stable groupings (Bowker & Star, 1999).

Importantly, much of this literature originates in ethnic and identity politics research. While our taxonomy is not limited to ethnic or identity-based groups, these studies provide valuable insights into how political actors invoke, reshape, and contest group categories in practice. We generalize these insights beyond ethnic politics by proposing a taxonomy applicable to all social group references, allowing specific groups—regardless of context—to be systematically organized along broader attribute categories such as gender, occupation, nationality, or other defining attributes.

However, such a view indicates an "ontological break" in the taxonomy of social groups. Attribute dimensions and attribute categories can be deductively derived from the literature and provide a generalizable attribute taxonomy across contexts. In contrast, specific groups cannot be captured comprehensively through deduction., in fact a purely deductive approach would risk to miss important variation in the scope of relevant social groups as well as its meaning. We thus, suggest to approach these specific groups as empirical clusters within defined attribute categories such as occupation or gender; asking questions such as which social groups within the domain of gender are actually mentioned by whom. Even with allowing for such a fine-grained distinction of social groups, ranging from attribute dimensions over categories to specific groups, variation in social group references in not only introduced by varying degrees of abstraction, e.g. specificity but inflated by the opportunity of political actors to fuse different attributes across and/or within the layers of abstraction. In short, intersectionality of group attributes is a defining feature of political communication.

2.3 Intersectionality

Intersectionality has become central across the social sciences because it reconceptualizes social structure and inequality as the product of interacting rather than additive dimensions of difference, such as class, race, gender, culture, and territory (Crenshaw, 1989; Collins, 2000; McCall, 2005). From this perspective, social groups cannot always be reduced to single attributes: intersectional positions are more than the sum of their components and reflect historically specific configurations that cannot be inferred from any single attribute alone (Cho, Crenshaw, & McCall, 2013).

Despite broad agreement on its importance, empirical research on group appeals has not yet fully exploited intersectionality's analytical potential. Existing measurement strategies rarely deny its relevance, but typically operationalize group appeals by assigning each reference to a single defining category or attribute (e.g., Thau 2019, 2024; Dolinsky 2021, 2023; Huber 2022; Riethmüller et al. 2024; Stuckelberger & Tresch 2024; Licht & Sczepanski 2025). As a result, a central feature of political communication—the combination of attributes in group appeals—often remains invisible in empirical analyses.

This gap motivates the third core pillar of our taxonomy: intersectionality. We treat intersectionality not as a property of specific groups but as a general feature of group references. Ignoring intersectionality forces classifications to choose between attributes, producing both conceptual conflation and substantial information loss. For example, appeals to "working mothers" simultaneously invoke employment, family, and gender attributes; restricting classification to a single category obscures how frequently these attributes co-occur in political discourse.

Importantly, intersectionality operates at different communicative levels. It can occur within a single reference, when multiple attributes explicitly define a group, as in "working mothers." But it can also arise across references, when separate group mentions are discursively linked to construct coalitions that are likewise more than the sum of isolated constituencies. Existing measurement strategies typically miss the former because they assign only one category per mention, whereas the latter may still be observable when multiple group references are analyzed jointly. Intersectional effects may also emerge through discursive or organizational linkages that bind constituencies into broader political projects.

This logic is consistent with dominant approaches in party competition research, which show that political actors rarely mobilize groups in isolation. Coalition theory highlights how parties aggregate heterogeneous constituencies whose support can be jointly mobilized (Riker, 1962). Historical accounts of class politics demonstrate how labor parties combined class appeals with national, religious, gendered, or moral constituencies to build durable coalitions (Przeworski & Sprague, 1986; Eley, 2002; Howe et al., 2022). Contemporary realignment research shows how economic and cultural attributes jointly structure electoral coalitions (Kriesi et al., 2008, 2012; Piketty, Gethin, & Martínez-Toledano, 2018, 2021), while discursive approaches emphasize how heterogeneous demands are symbolically linked into broader political identities (Laclau & Mouffe, 1985; Mudde & Kaltwasser, 2017; Zollinger, 2024). Capturing intersectionality at the level of individual references is therefore crucial to preserve analytical granularity and avoid overlooking how parties explicitly construct social groups.

Taken together, combining attribute-centered classification, hierarchical abstraction, and intersectionality yields a comprehensive taxonomy of social group references, summarized in Figure 1

3 Application

To demonstrate the scalability of our approach, we apply automated text analysis methods to, first, extract social group mentions from party manifestos, and second, classify these mentions according to the attribute categories they feature.

3.1 Case selection and data

We focus our application on the social group mentions of populist radical-right (PRR) and Green parties and have compiled a corpus of the party manifestos these parties in 36 Western countries between 1966 and 2021. The contrasting ideological profiles of the PRR and Green party families should provide for wide range of group references and therefore a broad coverage of attribute categories. However, to allow for comparisons to mainstream parties, we have also included the party manifestos of mainstream center-left/social democratic and center-right/conservative parties in four selected countries (Germany, Sweden, United Kingdom, and the United States). Figure A1 shows and overview of the cases included in our application.

We have obtained the texts of party manifestos from secondary sources[4] and filled gaps through original data collection whenever possible. We created sentence-level data from raw texts through automatic sentence segmentation[5] and machine-translated all sentences into English using the open-weights M2M model (Fan et al. 2020). In total, we processed 495 party manifestos into a corpus comprising 436,984 sentences.

3.2 Measurement

We proceeded in two steps to quantify the attributes used in social group mentions in this corpus. We first identified social group mentions in manifesto sentences, applying the methods described in Licht and Sczepanski (2025). We then labeled the extracted social group mentions by classifying the attributes they contain with a custom multi-label classification approach. In each step, we collected manual annotations for a sample of texts to produce labeled data for (few-shot) supervised machine learning.

Social group mention detection

Studying what types of attributes political parties emphasize when they mention social groups in their manifestos presupposes data that records the verbatim social groups mentions contained in each manifesto sentence (if any) (Licht and Sczepanski 2025; Horne, Dolinsky, and Huber 2025). Given the broad coverage of our case selection, we could neither rely on full manual annotation nor on existing labeled data or pre-trained classifiers.

Accordingly, we produced the labeled data necessary for our application following the approach proposed by Licht and Sczepanski (2025). Their approach combines sequence annotation (i.e., marking relevant phrases in sentences) and supervised token classification

[4]The *Manifesto Project Dataset* (Lehmann et al. 2023) and PoliDoc (Benoit, Bräuninger, and Debus 2009).

[5]Using the `stanza` library (Qi et al. 2020).

to extract any verbatim words or phrases used in a sentence to refer to social groups.

In particular, we proceeded in three annotation rounds, building on an active learning-like logic with the goal of maximizing the reliability and generalization of supervised classifier trained on the collected annotations. In the first round, we applied a informativeness-based sampling (Kaufman 2024) to maximally diversify the selection of examples distributed for annotation, selecting 4,454 sentences for annotation (stratifying by manifesto, i.e., party and election). To manually annotate social group mentions in this sample, we recruited a research assistant (RA) that already had experience with this annotation task from prior projects and proved very reliable.[6]. To prepare the second annotation round, we used the RA's annotations from round one to train a preliminary token classifier, applied it to the remaining sentences in our corpus, and computed classification uncertainty for each sentence based on the predicted probabilities of the preliminary classifier. We then sampled 2,472 sentences (again, stratifying by manifesto) with high prediction uncertainty for annotation for the second round. Importantly, this sampling strategy allowed us to progressively focus the human annotation effort on difficult cases. We repeated this process one more time – annotation, classifier training, uncertainty-based sampling – to sample another 987 sentences for annotation in a third round.

We combined all sentences annotated in these three rounds, set aside 15% of sentences for evaluation, and trained a token classifier using the same model architecture and training procedure as described in Licht and Sczepanski (2025). The final classifier trained on our data achieved a span-level F1[7] of 0.927 and a sentence-level F1 of 0.981 in held-out sentences.

Attribute classification

To classify the attributes contained in the social group mentions identified in the previous step, we collected multilabel annotations for a sample of mentions extracted by our supervised mention detection classifier.

[6]In addition to being qualified for the task through prior experience, they received detailed coding instructions explaining the concept of social group mentions with definitions and examples and we performed two rounds of training with the RA using 231 respectively 238 sentences sampled from our target corpus. This allowed us to assert the coder's ability to identify social group mentions in the target data and provide them with feedback.

[7]The span-level F1 is 0.831 when only considering exact span matches (as per the strict `seqeval` metric, cf. Licht and Sczepanski 2025).

Annotation

We recruited two RAs to annotate the attributes contained in the social group mentions identified in the previous step. Our coding instrument showed one mention at a time in its respective sentence context, first asked whether the group mention qualifies as "universal" group reference, and, if not, prompted the annotator to select all veritical and horiztonal attributes conained in the focal group mention.[8] While a mention's classification as "universal" ruled out economic and non-economic attributes classification, non-universal mentions could be labeled with one or more of the available attribute categories, resulting in multi-label annotations (Erlich et al. 2022).

Based on prior empirical work on parties' group focus (e.g., Thau 2019; Huber 2021; Dolinsky, Huber, and Horne 2025), we expected that some social attribute categories are much less prevalent in social group mentions than others. We therefore again proceeded in several annotation rounds to hedge the risk of label class imbalance in our group attributes classification annotations and diversify our sample of annotated examples.[9] We describe these steps in detail in the Supporting Materials and highlight the main points here. Our first annotation rounds focused on sampling diverse examples, tackling difficult cases, and balancing attributes' prevalence in the annotated data. Inter-annotator agreement (ICA) was overall very high in these rounds and for most attribute categories, except in those rounds that focused on difficult examples and low-prevalence attribute categories for which estimating ICA is difficult (see Table B1 and Table B2). To further improve the quality of our annotations, the author team arbitrated cases with disagreeing annotations in each round. Further they implemented a conceptually-driven annotation consolidation round and reviewed cases where an ensemble of classifiers tended to disagree with the then current annotations. This process resulted in consolidated multi-label attribute annotations for 600 mention-in-context examples.

Automation

The collected annotations only covered a small fraction of the 209,351 (predicted) social

[8] Please refere to Section B.1 for a detailed description of our coding instrument.

[9] Label class imbalance is a common problem in social science classification tasks that can harm classifiers' predictive performance. Iteratively sampling texts can be an effective strategy to mitigate this harm.

group mentions in our corpus, however. Classifying which attributes are contained in each of these mentions thus required automating this classification task. This proved practically challenging. The high per-example effort required for full multi-label annotation during human annotation stressed our fixed annotation budget, so we could only annotate a 600 mention-in-context examples. Yet, supervised machine learning for multi-label classification from few examples with many label classes and label class imbalance is a difficult problem (cf. Erlich et al. 2022).

The current computational text analysis literature offers two approaches to address this problem: few-shot finetuning with "small" transformer encoder-only models and few-shot in-context learning (Brown et al. 2020) with large decoder-only language models (LLMs). We opted for the first option because it is more compute-efficient and has been shown to be effective (cf. Tunstall et al. 2022; Laurer et al. 2024; Burnham et al. 2025), and leave the second option for future work.

Specifically, we opted for the few-shot sentence transformer finetuning (SetFit) approach proposed by Tunstall et al. (2022). In this framework, the labeled examples in the training set are first used to construct pairs for contrastive embedding model finetuning. In our application, this effectively specializes a general-purpuse sentence embedding model to represent social group mentions. In the second step, the finetuned embeddings serve as input to a classification head and the embedding model plus the classification head are trained end-to-end for multilabel classifiction of the training examples.[10]

We adopted the SetFit approach to train two separate multi-label classifiers, one for economic attributes and one for non-economic attributes. Since our application has not been examined in prior work, we have thoroughly evaluated several implementation choices such as the base embedding model, input formatting strategy, and hyperparameter choices, which we detail in the Supporting Materials. Table 1 summarizes the performance of these classifiers averaged across five held-out test folds.[11] The economic attribute classifier achieves a macro-

[10]Tunstall et al. (2022) demonstrate that this two-pronged finetuning strategy enables impressively effective few-shot learning. A further advantage of SetFit is that it is very efficient at prediction time in contrast to NLI commonly applied for few-shot supervised classification in political science (Laurer et al. 2024; Burnham et al. 2025).

[11]These are the results of models trained on folds' respective training examples using "optimal" hyperparameters identified using stochastic hyperparameter grid search. Specifically, at the end of each hyperparameter sweep on a fold's training examples, we selected the hyper-parameters that yielded the best

Table 1: Evaluation results of group mention attribute classifiers. Values report the mean precision, recall, and F1-score averaged across five folds for each attribute category, along with the prevalence of each category in the training set.

	F1-Score	Precision	Recall	prevalence
economic attributes				
micro average	0.785	0.822	0.758	
weighted average	0.784	0.831	0.758	
macro average	0.800	0.842	0.788	
education	0.942	0.933	0.967	0.033
employment status	0.721	0.770	0.733	0.059
income/wealth/economic status	0.751	0.857	0.675	0.093
occupation/profession	0.787	0.809	0.776	0.166
non-economic attributes				
micro average	0.829	0.881	0.782	
weighted average	0.826	0.896	0.782	
macro average	0.804	0.871	0.768	
age	0.872	0.918	0.841	0.106
crime	0.764	0.842	0.719	0.052
ethnicity	0.921	1.000	0.860	0.065
family	0.905	0.873	0.972	0.098
gender/sexuality	0.765	0.825	0.725	0.074
health	0.732	0.863	0.666	0.056
nationality	0.819	0.890	0.764	0.128
place/location	0.750	0.837	0.702	0.033
religion	0.759	0.770	0.776	0.050
shared values/mentalities	0.753	0.889	0.660	0.135

averaged (micro) F1 of 0.8 (0.785); the non-economic attribute classifier a macro-averaged (micro) F1 of 0.804 (0.829). And while classification reliability varies across attribute categories, it is overall very good, with most categories achieving an F1 of 0.75 or higher. We consider these strong results given the low number of few-shot training examples and strong label class imbalance (see the prevalence column, Erlich et al. 2022). In particular, the classifiers prove similarly reliable as trained human annotators (see Table B2) in classifying economic attributes and even more reliable in classifying non-economic attributes.

macro-averaged F1 on the fold's validation examples, finetuned the model with these hyper-parameters, and evaluated it in the corresponding fold's test examples.

4 Results

4.1 Prevalence and intersectionality

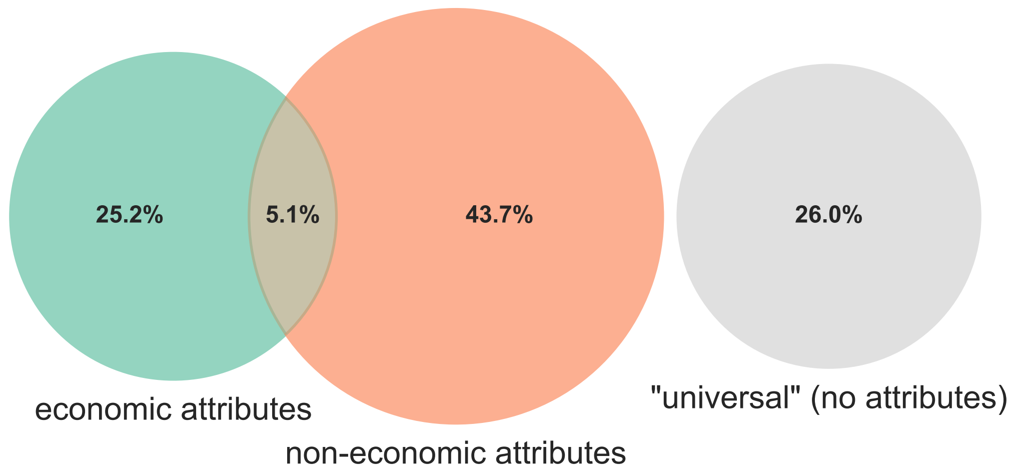

Figure 1: Distribution of social group mentions across attribute dimensions. The venn diagram shows the share of mentions featuring economic attributes, non-economic attributes, both types of attributes (intersection), or neither ('universal' mentions, gray). Areas are proportional to the relative frequencies in the data. Numbers show the share of mentions in each category. For example, 43.9% of mentions feature only non-economic attributes, not considering the 5.6% of mentions that feature at least one attribute of both attribute dimensions.

Figure 1 reveals that most social group mentions in the analyzed party manifestos are characterized by at least one economic or non-economic attribute. While about every fourth social group mention (26%) is predicted to contain no attributes at all and consider a "universal" group reference in our scheme, 30.3% of mentions feature at least one economic attribute, and 48.8% feature at least one non-economic attribute.

Overall, we observe intersectionality in 15.6% of all mentions, including "universal" group references without attributes, and in 21% of all mentions that feature at least one attribute. Further, 5.1% of mentions (6.9% of mentions with at least one attribute) are predicted to contain at least one attribute from both attribute dimensions, and thus exhibit cross-dimensional intersectionality.

Figure 2 breaks down these numbers by attribute dimensions. It shows that among

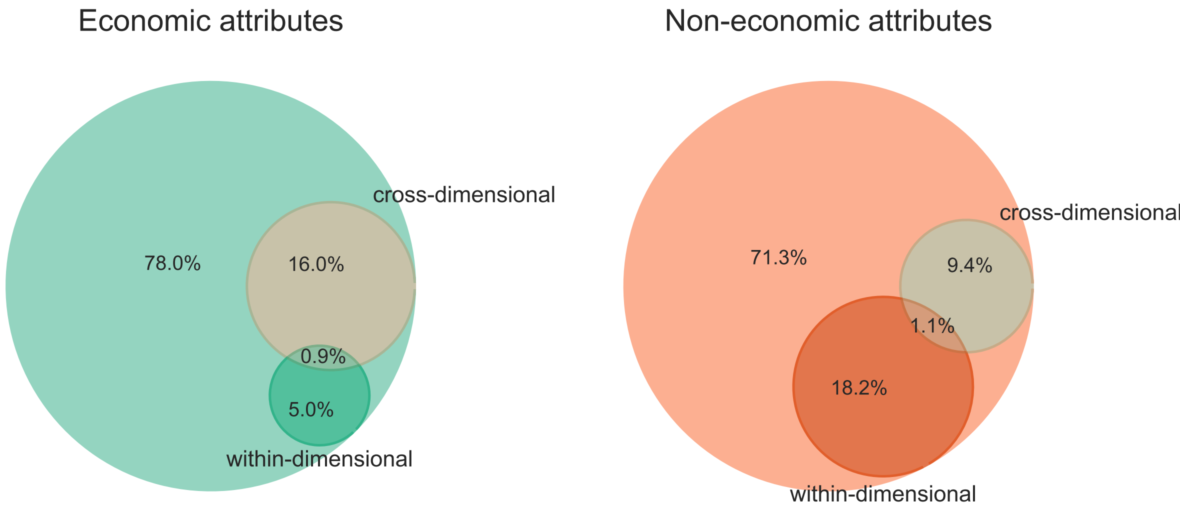

Figure 2: Attribute intersectionality patterns by attribute dimension. The venn diagrams show the for each attribute dimension the share mentions that feature only one attribute (outer circle) versus those that feature multiple attributes, either of the same attribute dimension (within-dimensional intersectionality) or with at least one attribute category of the other attribute dimension (cross-dimensional intersectionality). The small intersecting area of these two inner circles in both diagrams represents mentions that both feature more than one attribute of the same dimension and at least one attribute of the other dimension.

the 30.3% of mentions featuring at least one economic attribute, 21.9% of mentions are intersectional and combine multiple economic attributes (5.0%) at least one economic with at least one non-economic attribute (16%), or both (0.9%). Similarly, among the 48.8% of mentions featuring at least one non-economic attribute, 28.7% of mentions are intersectional and combine multiple attributes from within the same attribute dimension (18.2%), combine with at least one economic attribute (9.4%), or both (1.1%).

Interestingly, within-dimension intersectionality is more common for non-economic attributes. In particular, for economic attributes, interesctionality is about four times more likely to be cross-dimensional than within-dimensional. Viewed together with the higher prevalence of non-economic attributes (Figure 1), this underscores the importance of non-economic attributes in parties' group mentions.

We turn next to the prevalence of specific attribute categories, that is, the share of social group mentions that are predicted to feature a given attribute category. We exclude universal group references from this analysis to focus on the prevalence of specific attributes.

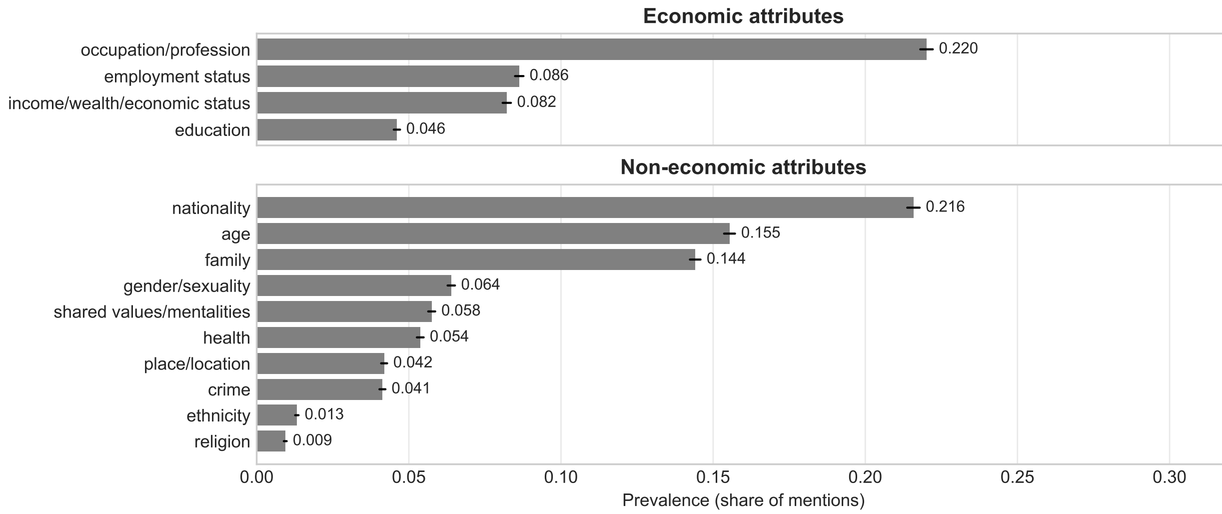

Figure 3: Prevalence of attribute categories across all social group mentions (excluding universal mentions with no specific attributes). Bars show the share of mentions featuring each attribute, with 95% confidence intervals. Top panel: economic attributes; bottom panel: non-economic attributes.

Figure 3 shows the overall prevalence of each attribute category across all social group mentions that contain at least one attribute. Economic attributes are shown in the top panel, non-economic attributes in the bottom panel. Overall, the most prevalent attribute categories are *occupation/profession* and *nationality*. In the economic dimension, the second and third most prevalent attributes – *employment status* and *income/wealth/economic status* – are relatively far less prevalent than the second and third most prevalent non-economic attributes *age* and *family*, which showing substantially higher prevalences. This disparity may partially reflect the lower prevalence of within-dimension intersectionality among economic attributes compared to non-economic attributes (see Figure 2), where, as shown further below, categories like *family* and *age* frequently co-occur in the same mentions.

To gain a more granular understanding of interesectionality patterns, we next compare attribute categories' co-occurrences. In particular, we focus on how frequently each attribute category appears alone in a group mention versus in combination with other attributes and therefore *intersectionally*.

Figure 4 reveals substantial variation in how different attributes tend to be used alone versus intersectionally. Among economic attributes, *occupation/profession* is mentioned most frequently as the only attribute of a social group (82%), which is about 1.3 times more often

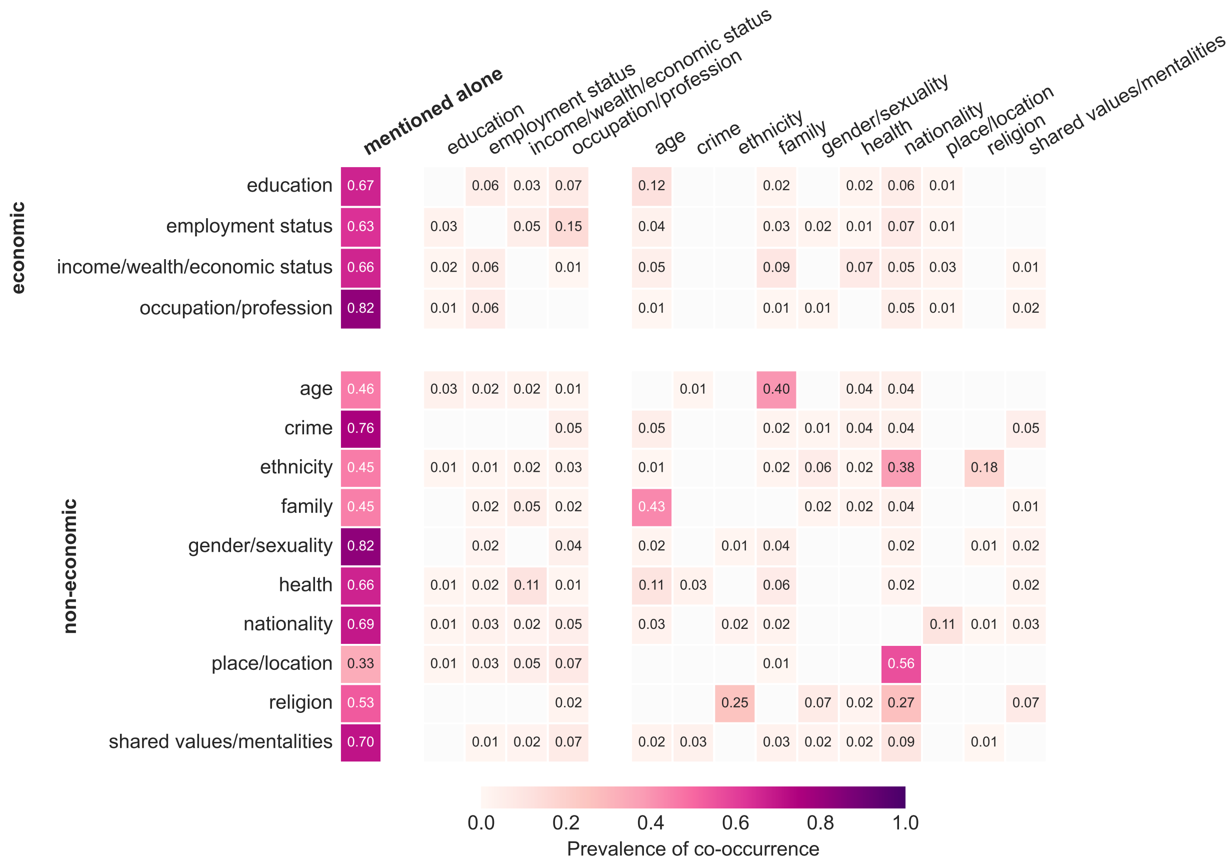

Figure 4: Co-occurrence patterns of attribute categories in social group mentions. Heatmap cells show the share of mentions where each focal attribute (rows) co-occurs with other attributes (columns). The first column ('mentioned alone') shows the share of mentions where the focal attribute appears without any other attributes. Top panel: economic attributes; bottom panel: non-economic attributes. Values below 0.01 are not displayed.

than the economic attribute that is most frequently used intersectionally: *employment status* (63%). Among non-economic attributes, *gender/sexuality* is mentioned most frequently alone (82%) – almost 2.5 times more often than *place/location* (33%).

Figure 4 also allows examining intersectionality patterns by focusing on the two right-most heatmap columns that show attributes' co-occurrence tendencies.[12] This view reveals that most of economic within-dimension intersectionality is driven by the co-occurrence of *employment status* with other economic attributes. Conversely, we have noted above

[12]Figure C2 and Figure C3 report alternative visual presentations of co-occurrence patterns. Figure C2 analyzes co-occurrence rates in the population of "potentially intersectional" mentions by subsetting the data to all group mentions that feature at least two attributes. Figure C3 analyzes co-occurrence patterns using *conditional probabilities* of co-occurrence for all attribute category pairs. Table C2 shows concrete examples sampled from our corpus.

that within-dimensional intersectionality is more common for non-economic attributes than cross-dimensional intersectionality. Figure 4 shows that this is driven by the very frequent co-occurrence of *age* and *family*, and of *ethnicity*, *place/location*, or *religion* with *nationality*.

Regarding cross-dimension intersectionality, economic attributes are frequently combined with *age* (especially *education*), *family*, *health*, and *nationality*, while the non-economic attribute *health* is often combined with *income/wealth/economic status* and *place/location* and *shared values/mentalities* are often combined with *occupation/profession*.

These patterns revealed by Figure 4 are particularly interesting because they add depth to the analysis of parties' group attribute focus. For example, while social group mentions featuring desscriptions of *shared values/mentalities* are comparatively rare, their tendency to co-occur with *occupation/profession* and *nationality* suggests that parties use such attributes to differentiate their group focus strategies and specify which kind of people they mean exactly when referring to groups.

4.2 Convergence with other categorization schemes

We turn next to a comparison of our *attribute*-centered scheme with two existing *group* categorization schemes, focusing on the schemes by Thau (2019) and Horne, Dolinsky, and Huber (2025). These analyses illustrate patterns of alignment between our and existing schemes but will also highlight important differences between them. Our goal is not to compare schemes' accuracy but to illustrate how our attribute-centered, hierarchical approach adds analytical value.

Comparison to Thau's social group category classifications

We begin with a comparison to the group categorization scheme developed by Thau (2019) for his analysis of group-based appeals in British party manifestos (cf. Thau 2021). His scheme differentiates between five group types, including the types *Social group* and *Professional group*. Within *Social group* mentions, he further distinguishes between nine group categories (including one *Other* category).

Below, we use the group category classifications of the 4,018 social and professional group mentions recorded in Thau's data, which he collected from trained annotators. To show how our multilabel attribute annotations compare to Thau's single-label group category annotations, we have applied our classifiers to this sample of social group mentions.

Figure 5: Correspondence of Thau's social group categorizations with our group attribute classofications. Numbers report the probability that a mention assigned by Thau's coders to one of his social group categories (shown on y-axis) has been labeled as featuring a given social attribute in our classification scheme (shown on x-axis). *Note:* Values below 0.009 not plotted to ease readability.

Figure 5 shows how Thau's group category and our attribute category classifications co-occur in this sample. Specifically, Figure 5 reports the conditional probability that our classifiers have labeled a given mention as featuring the attribute category reported on the x-axis, given that the mention was labeled as belonging to the respective group category (y-axis labels) in Thau's data. For example, 91% of mentions in Thau's *Age/generation* category were labeled as featuring the non-economic attribute *age* by our classifier; and because we adopt a multilabel logic, 19% mentions in Thau's *Age/generation* category were (also) labeled as featuring the attribute *employment status*.

This comparison reveals two general patterns. On the one hand, Thau's categories *Age/Generation*, *Geography*, *Health*, *Nationality*, *Professional group* and *Religion* show a strong correspondence to specific attribute categories in our scheme. We argue that this validates our scheme since these group categories in Thau's scheme are already attribute-centered.

However, on the other hand, other categories in Thau's scheme are characterized by more heterogeneous attribute expression patterns. For example, group mentions in Thau's *Economic class* category are not particularly strongly associated with any single attribute category but with several, especially *employment status* (29%), *income/wealth/economic status* (36%), and *occupation/profession* (23%). Similarly, instances in Thau's *Gender* category are frequently labeled as featuring *gender/sexuality* (49%) and/or *family* (31%) as attributes.

The examples of *Economic class* and *Gender* in Thau's scheme point to an important strength of our hierarchical, attribute-centered taxonomy. The case of *Economic class* shows how we disaggregate this abstract sociological construct into more manifest indicators. Accordingly, our taxonomy awards new possibilities for detailed analysis of how the notion of social class and status are communicated in concrete social group refrences by adding granularity. The same applies to instances in the broad *Gender* category, which are frequently labeled more specifically as *gender/sexuality* or *family* (or both) in our measurements.

In the Supporting Materials Section C.3, we present further analyses relying on Thau's annotated data that empirically substantiates our argument that multi-label classification of group mentions is crucial to capture the intersectional nature of many group mentions like "low-income families". First, we analyze the 9.4% of social group mentions recorded in Thau's data that were classified into different group categories despite being verbatim identical. Second, we discuss how our attribute annotations distribute across selected social group categories in Thau's data, showing that typically up to one third of Thau's singly-labeled mentions are intersectional according to our scheme. These analyses underscore the relevance of intersectionality in social group mentions.

Comparison to Horne et al.'s group categorizations

Next, we compare the annotations produced with our attribute-centered group mention labeling scheme to a more recent group classification scheme proposed by Horne, Dolinsky, and Huber (2025). Horne et al.'s group categorization scheme features 44 group categories. Notably, Horne et al. also account for intersectionality by allowing for the classification of group mentions into multiple categories – similar to our approach. However, their scheme also differs in important ways from ours. First, like Thau's scheme, their scheme is centered on group *categories* rather than *attributes*. Second, their scheme comprises many more group categories than our scheme (12) and Thau's (10). Third and related, Horne et al. do not explicitly organize their group categories in a hierarchical taxonomy. This means that some of their categories, like *Ethnic And National Communities* are rather broad, and combine attributes we separate into different attribute categories. Other group categories in their scheme, like *Health Professionals* are more specific. Overall, this leads to a "ragged" taxonomy with categories that vary in their level of abstraction/breadth, and in some instances even leads to hierarchical "nesting" of categories, such as *Health Professionals* being an instance of *White Collar Workers* profession.

Below, we examine how these differences affect how their and our approaches label and partition the group mentions in a sample drawn from our data. Specifically, we have sampled 10% of the social group mentions in our machine-labeled corpus and applied Horne et al.'s group category multi-label classifier to them.[13]

First, it is notable that the annotations produced with both schemes show strong convergence. A χ^2-test computed on the label category co-occurrence count matrix indicates a highly significant overall association between the two classification schemes ($\chi^2 = 108{,}311.55$, $p < 0.001$, Cramér's $V = 0.631$).

Figure 6 visually illustates how this overall strong correspondence arises. The heatmaps show normalized pointwise mutual information (nPMI) values to quantify the strength of association between our economic and non-economic attribute categories (y-axis) and Horne et al.'s group categories (x-axis). The theoretical range of PMI values ranges from -1 (system-

[13] Using model `rwillh11/mdeberta_groups_2.0` hosted on the Hugging Face model hub (accessed on Jan 23, 2026).

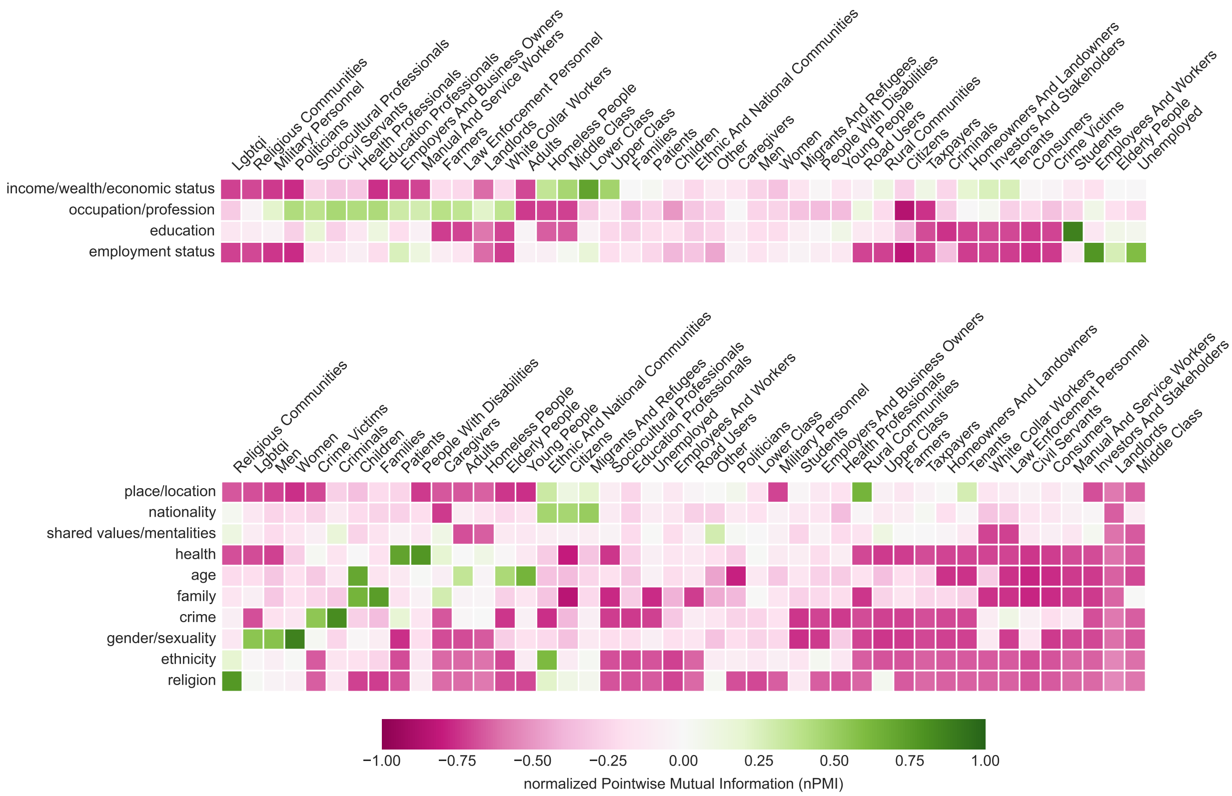

Figure 6: Patterns of convergence between group mention classifications of our attribute-centered classifier and Horne et al.'s group category classifier. The figure reports normalized Pointwise Mutual Information (nPMI) values that measure the strength of association of label classes on a scale ranging from -1 (systematic disassociation) through 0 (independence) to +1 (perfect co-occurrence). y-axis labels indicate the attribute category in our scheme; x-axis labels the group categories Horne et al.'s scheme. Plot panels separated by economic and non-economic attributes. *Note:* heatmap columns sorted (for each attribute dimension) using hierarchical clustering to better reveal conceptual overlap.

atic disassociation) through 0 (independence) to +1 (perfect co-occurrence). Positive nPMI values (shaded green) in Figure 6 reveal expected convergence patterns, such as the strong association between our *occupation/profession* attribute and Horne et al.'s occupation-related categories (e.g., *Civil Servants*, *Farmers*, *Health Professionals*, etc.), between our *gender/-sexuality* attribute and their *Women*, *LGBTQI*, and *Men* categories, or between our *health* attribute category and their group categories *Patients* and *People With Disabilities*.

Negative nPMI values (shaded magenta), on the other hand, indicate systematic disassociation where specific attribute categories do not co-occur with certain group categories in Horne et al.'s scheme. For example, non-economic attributes like *religion*, *ethnicity*, and *family* show consistent negative associations with occupation- and class-based group categories, because the group mentions sampled from our corpus are typically either categorized as either occupation/class-based or non-economic but rarely both at the same time. These negative associations are analytically meaningful because they reveal systematic patterns in how the two classification schemes partition the social group mention space: attributes that Horne et al.'s classifier treats as separate categories (e.g., occupation versus family status) show mutual exclusivity in their co-occurrence patterns.

The strong association and disassociation patterns revealed in Figure 6 indicate that both classification schemes capture similar underlying patterns in how social group mentions are categorized. However, it also shows that our attribute-centered approach groups some of Horne et al.'s more granular categories together (e.g., all occupation-related categories) while featurizing some of their broader categories with more specific attributes (e.g., *Ethnic And National Communities* as mixture of *ethnicity*, *nationality*, *religion*, and *place/location*).

In the Supplementary Materials Section C.4, we present further analyses focusing on occupation/profession and gender/sexuality-related mentions. These analyses demonstrate that our attribute-centered framework, while strongly aligning with Horne et al.'s scheme, also allows capturing mentions related to these attributes that are not covered by pre-defined group categories.

4.3 Differences between Green and Populist Radical-Right party families

Above, we have validated our hierarchical attribute-centered group mention labeling scheme and documented with it that attribute categories' vary in their overall prevalence in party manifestos as well as their tendencies to be used intersectionally through combinations with other attributes. We turn next to the question how much parties' strategic calculus and group focus strategies contribute to the observed patterns of attribute prevalence and co-occurrence in party manifestos. On the one hand, it is very likely that the cultural, socio-political, historic, and thematic context act as constraints on parties possibilities to combine different attributes creatively to refer to social groups in their election programs. On the other hand, the literature on political parties' group-based strategies suggests that parties strategically select which social groups to appeal to in their election programs (**cites?**). We examine this question next by comparing attribute prevalence and co-occurrence patterns between the Green and Populist Radical-Right (PRR) party families.

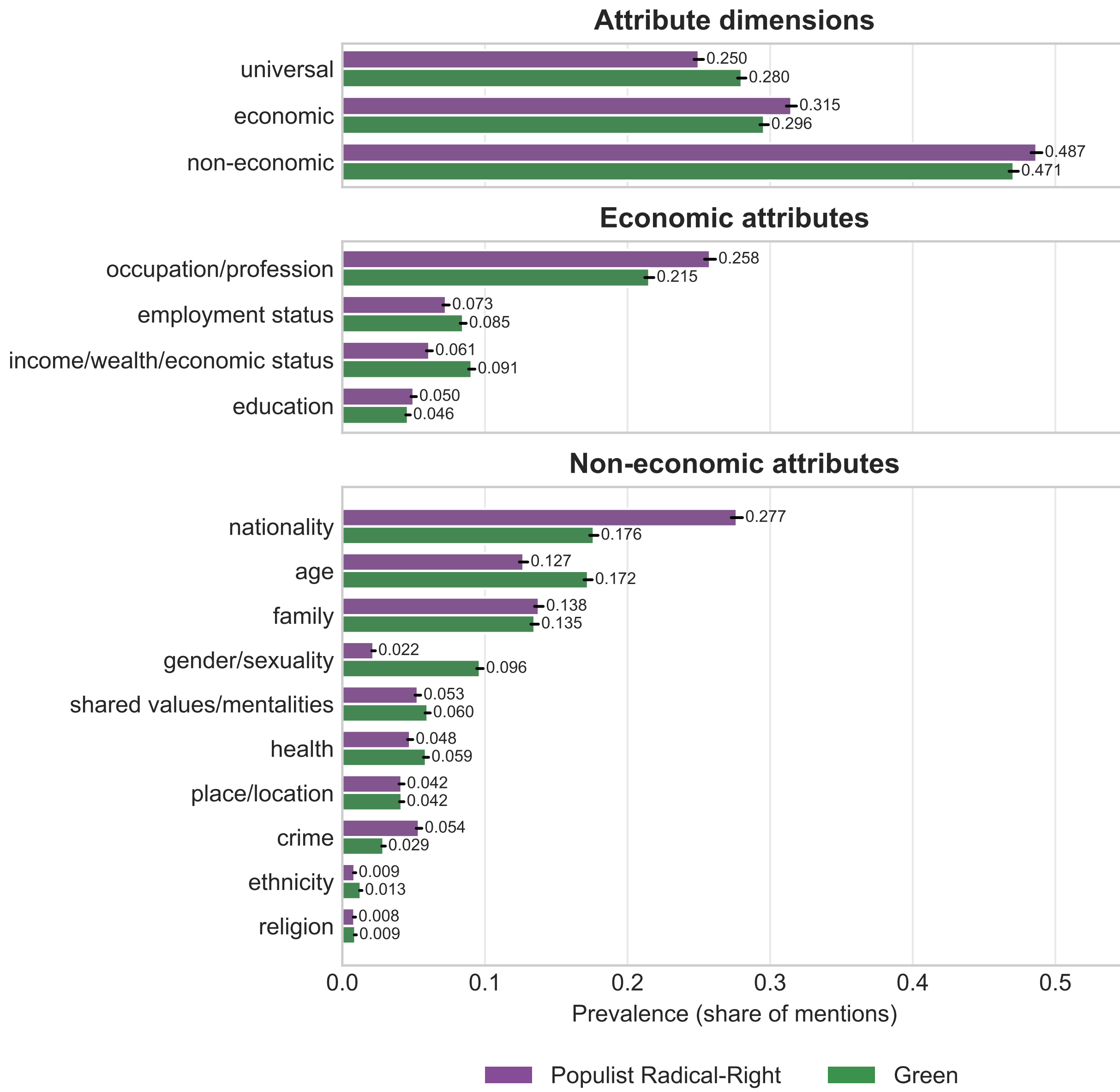

Figure 7: Prevalence of attribute dimensions, economic and non-economic attributes in social group mentions in Populist Radica-Right and Green parties' election manifestos. Bars show share of mentions containing each attribute, with 95% confidence intervals. *Note:* Top panel shows prevalence in all mentions, while middle and bottom panels show prevalence in mentions containing at least one attribute.

Figure 7 reports the prevalence of attribute dimensions and categories in PRR and Green parties' manifestos, revealing several noteworthy patterns. First, we find no or only minor differences in these two party families' overall tendency to characterize groups they mention with economic or non-economic attributes. In particular, while Green parties tend to use "universal" group references to slightly more frequently than PRR parties, the magnitude of this difference does arguably not indicate a substantially higher degree of "universalism" in Green parties' group focus strategies.

However, notable differences between PRR and Green parties arise when focusing on the prevalence of specific attribute categories in the set of group mentions with at least one attribute. In the case of economic attributes, PRR parties focus more heavily on *occupation/profession* and less on *income/wealth/economic status* than Green parties. This is consistent with the notion that PRR parties' group focus strategies are more oriented towards appealing to specific occupational groups (e.g., "working class", "small business owners") and less towards emphasizing economic inequality and redistribution as a core issue. Notably, despite its well-established role as a driver of voting behavior and its rising issue salience in recent decades (**cite?**), *education* is relatively infrequently expressed in social group mentions by both party families.

Regarding non-economic attributes, PRR parties emphasize *nationality* and *crime* more prominently than Green parties, while Green parties place greater emphasis on *age* and *gender/sexuality* as salient attributes for identifying and mobilizing social groups. However, *religion* and *ethnicity* are very uncommon in both party families' group mentions, and any prevalence differences between them are thus in the permille range.

?@fig-prevalence_by_family_w_mainstream in the Supporting Materials extends this comparison by adding prevalence estimates for center-right/conservative and center-left/social democratic mainstream parties based on data from three countries (Germany, Sweden, and the UK). This comparison reveals how Green and PRR parties differentiate through their focus on certain group attribute categories from their mainstream competitors. It shows that Green parties' in these countries tend to differentiate through their non-economic attribute emphasis profile, which is characterized by a pronounced focus on *gender/sexuality* and little emphasis on *crime*. In contrast, their economic profile is very similar to that of Social Democratic parties, with similarly strong focus on *income/wealth/economic status* albeit somewhat less emphasis on *employment status*. PRR parties, in turn, distinguish themselves primarily through their emphasis on *occupation/profession* and *nationality* and thus adopt a intersectional differentiation strategy. Interestingly, their focus on *crime* is not markedly different from that of conservative/center-right parties, suggesting this is not a unique dimension of PRR parties group attribut focus.

Further, the differences between PRR and Green parties' group attribute focus shown in Figure 7 exhibit interesting temporal patterns. For example, Figure C7 shows that while their relative emphasis differences are overall very stable across decades, PRR parties' overall stronger focus on the *occupation/profession* attribute is more pronounced in the 1970s than in later decades. Regarding non-economic attribute prevalence, Figure C8 shows that Greens parties' *age* focus stands out especially in the 2000s and 2010s, whereas their *gender/sexuality* focus has been relatively more pronounced before the 2000s. PRR parties' group focus, in turn, shows a sharp increase in the prevalence of *family* from 2010s to 2020s.

We next turn to attribute category co-occurrence patterns in Green and Populist PRR parties' group mentions. In Section 4.1, we have shown that the co-occurrence patterns of attributes in group mentions differ across attribute categories and dimensions and reveals interesting patterns of intersectionality in parties' group focus strategies. Comparing these patterns between PRR and Green parties, in turn, allows us examining these parties group focus strategies through the lens of intersectionality.

To compare the co-occurrence patterns of attributes in group mentions between PRR and Green parties, we compute the differences in conditional probabilities of attribute co-occurrence between these two party families. Conditional probabilities measure how likely a group mention contains attribute B when it contains attribute A. This quantitity is ideal for quantitative-descriptive comparisons between party families as it provides a comparable and interpretable quantity that answers the question: How likely is it that a party uses attribute B to describe a group when it has choosen to describe it with attribute A?[14]

Figure 8 reports the results of this descriptive analysis. Positive values (green) indicate

[14]We discuss the rationale for using conditional probabilities as a co-occurrence metric in more detail in the Supplementary Materials, **?@sec-cooc_metrics**.

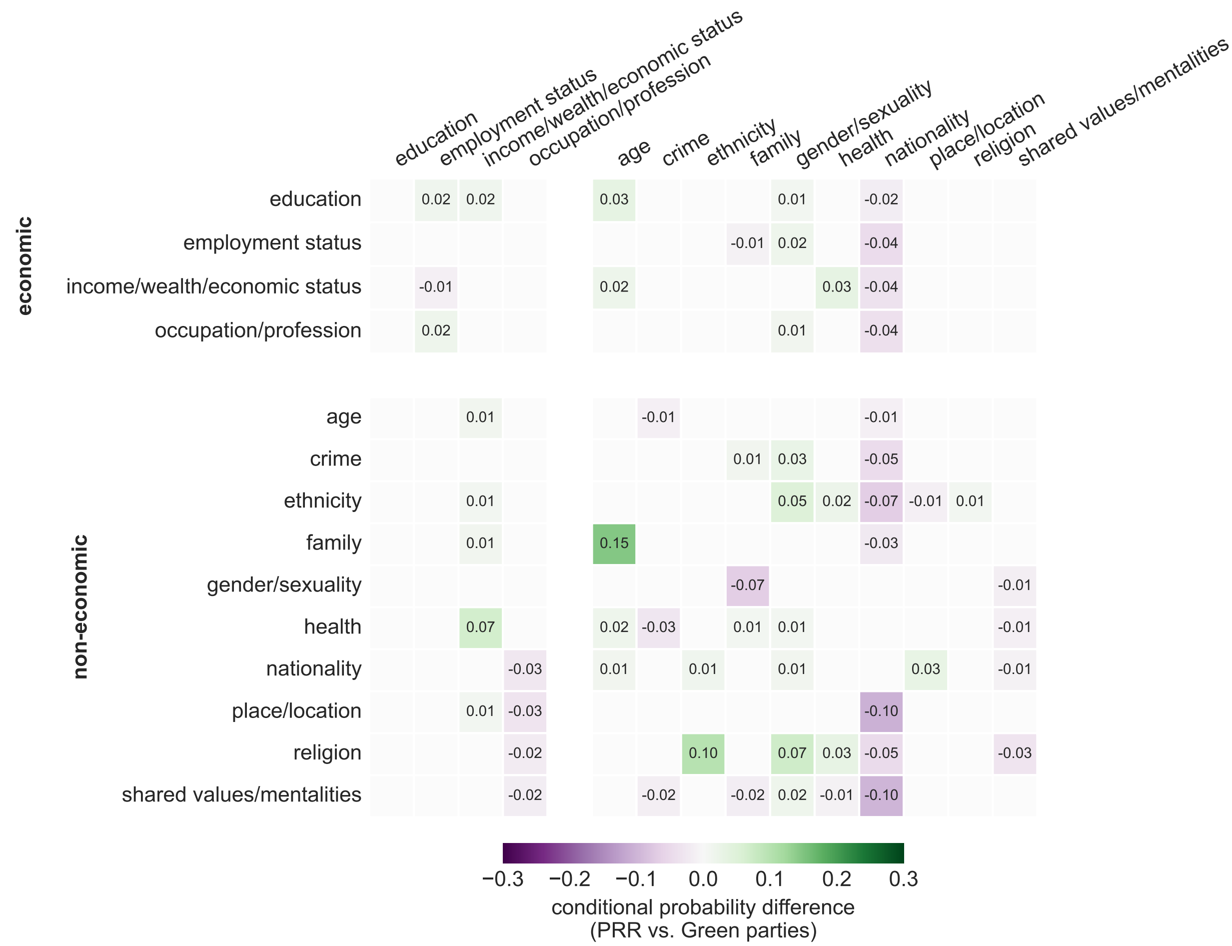

Figure 8: Differences in conditional probabilities of attribute co-occurrence between Green and Populist Radica-Right (PRR) party manifestos. Heatmap cells show the difference in P(B|A) between Green and PRR parties (Green – PRR). Rows indicate "attribute A" (the conditioning attribute) and columns indicate "attribute B" (the outcome attribute). Positive values (green) indicate that attribute B is more likely to be mentioned given attribute A in Green party manifestos compared to PRR manifestos, while negative values (purple) indicate the opposite. *Note:* Values below 0.01 in absolute value are not displayed.

that attribute B (shown in columns) is more likely to be mentioned given attribute A (shown in rows) in Green party manifestos compared to PRR manifestos, while negative values (purple) indicate the opposite.[15]

Several interesting patterns stand out in Figure 8. The purple-shaded vertical band in column *nationality* clearly shows that PRR parties are overall more likely to combine *nationality* with a range of other attributes than Green parties. This difference applies

[15]Please refer to Figure C9 for the results of statistical tests that assess whether observed differences in parties co-mentioning patterns are statistically and substantively significant.

to the non-economic attribute categories *place/location*, *shared_values/mentalities*,*ethnicity*, *crime*, and *religion* as well as economic attribute categories. Further, PRR parties' focus on *occupation/profession* is also slighty higher than that of Green parties when they refer to non-economic group attributes like *nationality* or *place/location*.

Green parties, in turn, are comparatively more likely to mention *age* when they refer to *family*. They are more inclined to mention the attributes *ethnicity*, *gender/sexuality*, and *health* when they refer to a *religion*-based group, and *family*, *gender/sexuality*, and *health* when the mention *ethnicity*. Last but not least, they are more likely to mention *gender/sexuality* when they refer to *crime*-related groups, such as victims or perpetrators.

Viewed together, the comparative analysis of attribute prevalence and co-occurrence patterns in Green and PRR parties' manifestos reveals that these two party families differ in their group focus strategies in several interesting ways. More generally, it demonstrates the added analytical value of our attribute-centered taxonomy for the analysis of parties' group focus strategies, as it allows us to capture and compare the intersectional nature of parties' group appeals in a systematic and detailed way.

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Supplemental Materials

Focusing on social attributes, not group categories

A Dataset

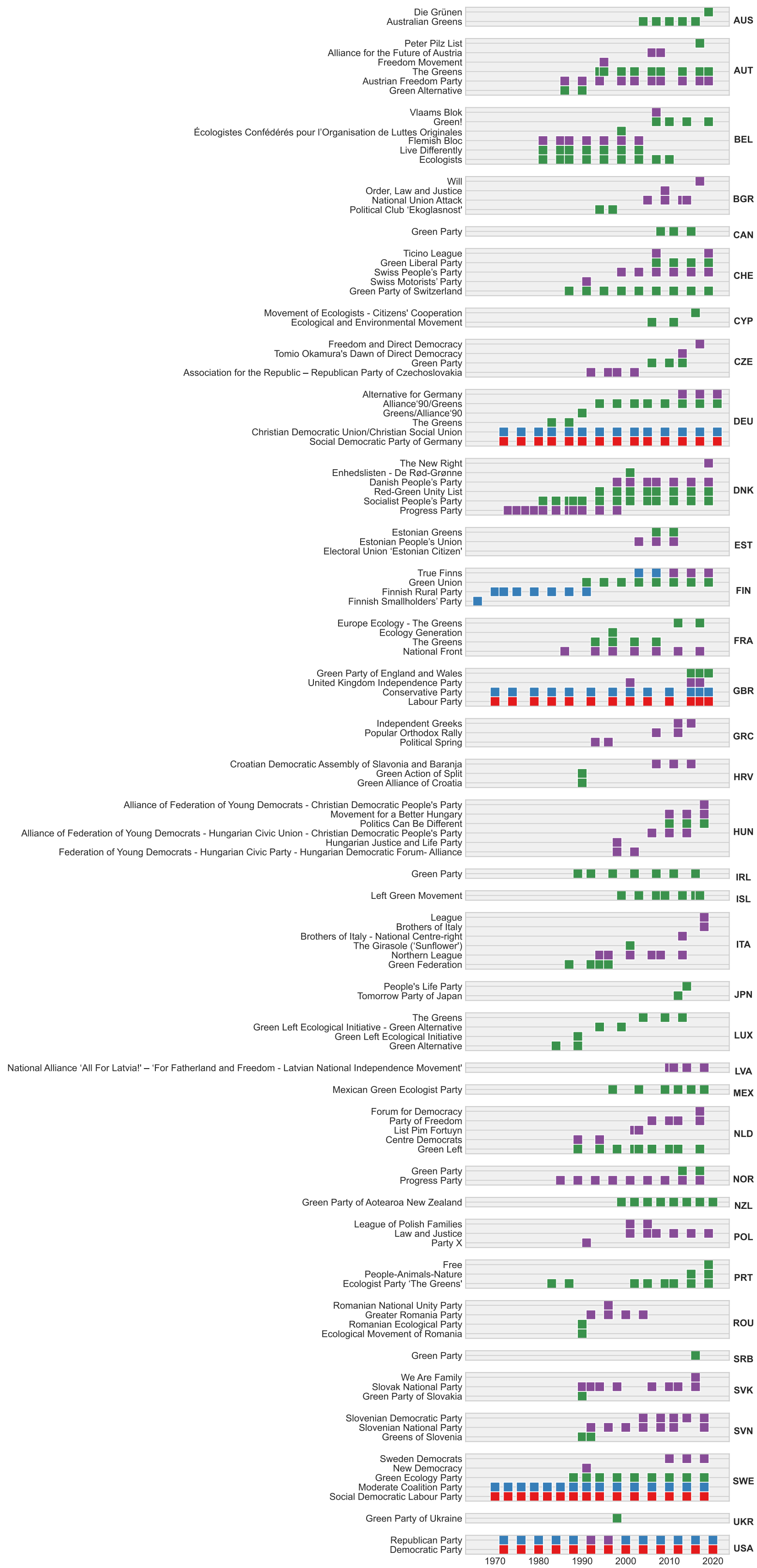

Figure A1: Overview of cases included in out corpus. Each square represents a party in a given year, colored by its party family.

B Attribute classification

B.1 Coding instrument

Our coding instructions introduce the vertical/horizontal distinction, each of the attribute categories, as well as our "universal" group mention category, explain the available coding choices, and give examples. Our coding instrument, implemented as a Qualtrix survey, presents annotators independently with one social group mention at a time (i.e., per page) in their respective sentence context, marking the mention in bold.

Below the display of the sentence, the annotator is first asked to indicate whether the highlighted mention is an "universal" mention per our definition. If the annotator chose "Yes" for this coding dimension, our coding instructions asked them to proceed with the next instance on the next page.

If not, the annotator proceeds with coding the attribute categories for the vertical and horizontal attribute dimensions in turn. For each of the dimensions, we tasked the annotator to indicate which of the respective attribute categories was contained in the highlighted social group mention, displaying the attribute categories below each other[16] in a multiple-choice grid with the answer options "Yes" or "Unsure" horizontally aligned.[17] This procedure results in 17 annotations[18] per mention-in-sentence-context instance and annotator.

B.2 Annotation

In a first round of annotations, we have sampled 300 mentions-in-sentence-context examples from all sentences with at least one predicted social group mention, again using an informativeness-based sampling strategy. Table B1 reports the micro inter-annotator agreement (ICA) by attribute dimension from this round and indicated that our coders produced overall reliable annotations. To resolve examples with disagreeing annotations, the authors team reviewed any mention-in-sentence-context example with at least one disagreeing annotation to determine their final labels.

[16]We kept the categories' order fixed across examples to ease the cognitive load at annotation time.

[17]We omitted options for "No" because not choosing "Yes" or "Unsure" for a given attribute category implied this coding choice.

[18]$1\times$ universal + $5\times$ vertical attributes + $11\times$ horizontal attributes

However, as expected, the prevalence of attribute categories in the labels collected in this first round turned out to be very imbalanced and we observed variation in ICA estimates across categories that could only partially be explained by low prevalence (see Table B2). We therefore dedicated a second annotation round to collecting more annotations for difficult examples. To this end, we fine-tuned a multilabel classifier to predict mentions-in-sentence-context examples' binary labels on the universal, vertical, horizontal indicators based on the consolidated annotations collected in the first round. We applied this classifier to the mention-in-sentence-context instances not yet distributed for attribute annotation to obtain predicted probabilities. We then computed classification uncertainty at the example level and selected the 150 most uncertain examples into a second annotation batch.

Table B1 and Table B2 show that, due to our focus on difficult examples, ICA was generally lower than in the first round. We therefore used zero-shot in-context learning (Brown et al. 2020) to generate large language model (LLM) annotations for the examples in the second-round batch. We then presented our annotators the instances where the LLM disagreed with their judgment and tasked them to (independently) judge which annotation they viewed as more valid while blinding them towards the source of the respective annotations. The author team arbitrated the cases in which our annotators' independent judgments disagreed. All instances from this second round were then consolidated into final labels and added to those of the first round.

Table B1: Inter-coder agreement estimates for attribute classifications computed at the level of attribute dimensions: universal, economic, and non-economic. Estimates are based on Krippendorff's and the prevalence of 'yes' annotations (prevalence) across all annotated examples in each annotation round.

	Krippendorff's α			prevalence		
annotation round	1	2	3	1	2	3
universal	0.697	0.259	0.000	0.275	0.144	0.006
economic	0.791	0.731	0.806	0.410	0.687	0.318
non-economic	0.754	0.474	0.752	0.563	0.727	0.844

In a third round of annotation, we then addressed the problem of label class imbalance that clearly showed in the pooled set of multi-labeled mention-in-sentence-context instances from rounds one and two. In particular, we focused on over-sampling likely examples of so

Table B2: Inter-coder agreement estimates for attribute classifications computed at the level of economic and non-economic attribute categories. Estimates are based on Krippendorff's α and values in parentheses indicate the prevalence of 'yes' annotations (prevalence) across all annotated examples in each annotation round.

dimension	annotation round category	1	2	3
economic	education	+0.799 (1.0%)	+0.847 (8.0%)	+0.888 (8.9%)
	employment status	+0.527 (8.8%)	+0.607 (12.8%)	+0.650 (6.7%)
	income/wealth/economic status	+0.694 (6.9%)	+0.903 (13.0%)	+0.745 (2.8%)
	occupation/profession	+0.804 (18.7%)	+0.694 (28.8%)	+0.241 (12.9%)
non-economic	age	+0.832 (17.5%)	+0.704 (12.8%)	+0.442 (10.7%)
	crime	+0.659 (3.4%)	+0.847 (8.0%)	+0.842 (11.2%)
	ethnicity	+0.664 (1.3%)	+0.658 (4.0%)	+0.822 (25.1%)
	family	+0.765 (8.4%)	+0.650 (6.7%)	+0.753 (10.7%)
	gender/sexuality	+0.830 (2.4%)	-0.021 (4.7%)	+0.842 (25.8%)
	health	+0.906 (4.0%)	+0.359 (10.7%)	+0.607 (15.3%)
	nationality	+0.804 (12.9%)	+0.581 (16.0%)	+0.443 (20.8%)
	place/location	+0.662 (2.0%)	+0.854 (2.7%)	+0.496 (1.7%)
	religion	+0.666 (0.7%)	+0.322 (3.3%)	+0.959 (16.8%)
	shared values/mentalities		+0.567 (23.4%)	+0.484 (5.0%)

far under-represented attribute categories in the vertical and horizontal attribute dimensions. To identify likely examples for the given label categories, we used the attribute category definitions to define queries and used a pre-trained sentence embedding model to rank so far unannotated mention-in-sentence-context instances based on their cosine similarities to each of these queries. To oversample likely examples of so far underrepresented categories, we defined quotas for each attribute category in inverse proportion to the categories prevalence in the labeled instances from round one and two, using a annotation budget of 200 examples for round 3. We then chose as many of the so far unanottated mention-in-sentence-context instances as the quote prescribed in descending order of their embeddings' similarities to the embedding of the respective attribute category definition query. In total, this resulted in a samole of 180 mention-in-sentence-context examples for annotation in round 3.[19]

Table B1 shows that the attribute annotations of examples in this third round were overall highly reliable, which is likely explained by focusing on identifying *likely* examples of each attribute category in this final round (in contrast to difficult instances in round

[19]Deviations from the annotation budget of 200 cases are explained by rounding in the computation of quotas and some mention-in-sentence-context instances that were ranked high for multiple attribute queries.

2). Further, the consolidated labels from round 3 showed that our over-sampling strategy was effective as it helped to reduce the label class imbalance across the set of vertical and horizontal attribute categories.

A last round of annotation focused on conceptual consolidation and was performed by the authors. Specifically, we manually reviewed any annotated examples that were labeled as combining certain attribute categories to determine whether the combination of these categories was conceptually valid and consistent with our attribute definitions.

B.3 SetFit finetuning

We have first carefully split the 600 annotated examples into five training, validation and test folds to minimize leakage between the training and evaluation sets. This is generally a crucial step in any supervised machine learning application, but it is particularly important in our application for several reasons. First, simple random sampling does not account for the facts that (a) mentions are embedded in sentences so that the same mention can appear in multiple sentences and (b) some mentions are near duplicates of each other and having these in different splits can lead to overestimation of predictive performance. Second, in the context of few-shot learning, it is particularly important to minimize leakage between the training and evaluation sets because the small number of training examples makes it more likely that a given example in the evaluation set is very similar to one in the training set, which can lead to overestimation of predictive performance.

We have then used the training and validation split to examine the average performance of different base embedding models[^fn:embedding_model_selection] and input formatting strategies[^fn:inpiut_formatting_strategies] and select the best-performing model and formatting strategy for each classifier.

Finally, we have trained the two classifiers on the full training set using the selected embedding model and input formatting strategy and evaluated their performance on the held-out test set.

C Additional analyses and results

C.1 Universal group references

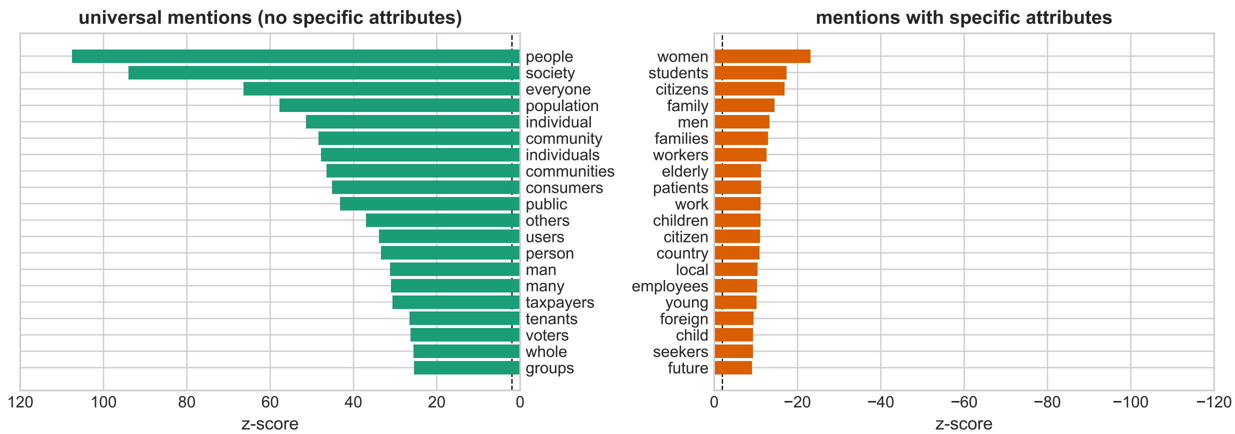

Figure C1: Most distinctive words for mentions with no specific attributes (*universal* mentions, left) vs. mentions with at least one economic or non-economic attribute (right). Values plotted are z-scores from "fighting words" analysis. Values above ± 1.96 (vertical dashed line) can be considered significantly distinctive.

We consider predicted group mentions that are predicted to contain no attributes as "universal" group references, that is, references to groups in general without specifying which kind of people they mean exactly. To validate, that the predicted absence of attributes in these mentions indeed reflects this conceptual category, we examine the most distinctive n-grams of these mentions by applying the "fighting words" method (Monroe, Colaresi, and Quinn 2008) to all group mentions in our corpus, using a binary indicator of whether a mention is predicted to be a "universal" group reference as grouping variable.

Figure C1 shows the top 20 most distinctive n-grams of "universal" group references and compares them The set of most distinctively "universal" terms includes tokens like "people", "society", "everyone", and similar terms that are used as generic collectivisms in the English language. The most distinctively non-"universal" terms, in turn, include denotational group labels like "women", "students", "citizens", and "family".

Table C1: Distribution of social group mentions by number of attributes. Rows indicate the number of attributes predicted for each mention. Columns report absolute counts (N) and proportions (share) for overall attributes (combining economic and non-economic), economic attributes only, and non-economic attributes only.

	overall		economic		non-economic	
	N	share	N	share	N	share
N attributes						
0	54514	0.260	145923	0.697	107195	0.512
1	122279	0.584	59656	0.285	82417	0.394
2	29590	0.141	3673	0.018	18456	0.088
3	2760	0.013	99	0.000	1184	0.006
4	192	0.001	0	0.000	88	0.000
5	16	0.000	0	0.000	11	0.000

C.2 Attribute category co-occurrence analyses

We argue that intersectionality in parties' group mentions is an interesting facet of their group focus strategies. In this context, the question arises how to compare interesectionality patterns between groups. In our analysis, a key question along this line is whether PRR vs. Green parties combine attributes differently?

There are multiple ways to quantify and compare attribute co-occurrence patterns. Each approach has its strengths and weaknesses. Below, we discuss four possible approaches and provide recommendations for their use.

- **Comparing conditional probabilities**: We can compute Pr(attribute B | attribute A) by party family and compare the values. Conditional probabilities have the advantage that they are very interpretable, allowing statements like "When PRRP mentions class, 12% also mention gender." They thus directly answers substantive questions about co-occurrence patterns. Further, they do not suffer from base rate sensitivity issues like the PMI (see below). Subtracting the values for Green parties from thjose for PRR parties, for example, we obtain an indicator that is negative if PRR parties tend to combine the given attributs more frequently. Conditional probability differences can thus be compared across parties through simple subtraction, and the approach works well even with sparse data.

The downside is that the measure is asymmetric, requiring careful interpretation. Further, it does not account for statistical significance of observed differences.

We therefore use it solely for *descriptive* comparison of party families' attribute combination strategies.

- **Comparing statistical significance**: We can apply χ^2 or Fisher's exact tests for each attribute pair to determine whether co-occurrence patterns differ significantly between party families. These tests provide formal hypothesis testing and control for sampling variability. Effect size measures, such as Cramér's V, in turn, allow assessing practical significance beyond mere statistical significance.

  However, multiple comparison problems arise when testing many pairs simultaneously, requiring correction procedures like Bonferroni adjustment. The tests are also sensitive to sample size, meaning that with large N, nearly everything becomes statistically significant. Further, binary yes/no decisions do not capture the magnitude of differences.

  We therefore use significance testing for determining which attribute pair differences are statistically robust.

- **Comparing normalized Pointwise Mutual Information (nPMI)**: We can compute nPMI values by party family, which compare observed to expected co-occurrence under statistical independence. nPMI identifies unexpected patterns in both directions (positive associations where attributes co-occur more than expected, and negative associations where they co-occur less than expected). Being normalized to a [-1, +1] scale, it allows comparing different attribute pairs. This makes the nPMI metric useful for exploratory analysis.

  However, the measure is hard to interpret substantively in terms of party strategy. It is sensitive to base rates, and negative values tend to dominate in sparse data (as we observed in our analysis). Additionally, differences between parties can be small even when the underlying patterns differ substantially.

  We therefore use nPMI primarily for identifying which attribute pairs warrant further investigation.

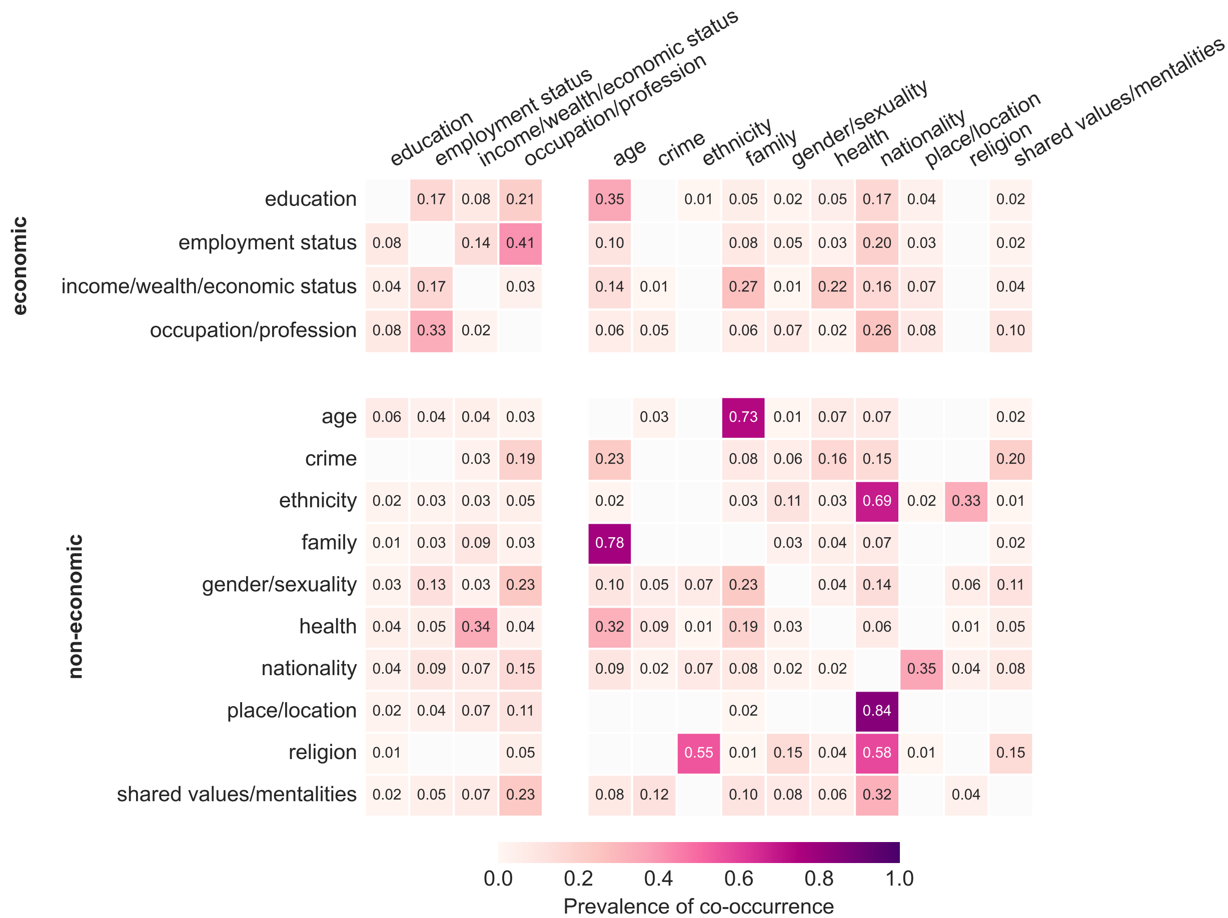

Figure C2: Co-occurrence patterns of attribute categories in intersectional social group mentions, that is, mentions that combine at least two attributes. Heatmap cells show the share of mentions where each focal attribute (rows) co-occurs with other attributes (columns). Top panel: economic attributes; bottom panel: non-economic attributes. *Note:* Values below 0.01 are not displayed.

Figure C2 allows examining specific intersectionality patterns by focusing on the 21.6% of non-universal mentions that feature at least two attributes and are thus intersectional. The heatmap reveals several notable patterns in how parties combine different attribute categories when making intersectional group references.

Among economic attributes, *employment status* emerges as the most "connective" attribute, frequently co-occurring with other economic categories such as *income/wealth/economic status* and *occupation/profession*, as well as with non-economic attributes like *age* and *health*. In contrast, *education level* shows more selective co-occurrence patterns, primarily combining with *age* and *nationality*.

The non-economic attribute patterns show even stronger associations. *Age* and *family* exhibit particularly high co-occurrence rates, potentially reflecting parties' tendency to frame generational concerns within family contexts (e.g., "young families"). Similarly, *ethnicity*, *nationality*, and *religion* form a tight cluster of frequently combined attributes, suggesting parties often invoke multiple aspects of cultural identity simultaneously. *Place/location* also frequently appears with *nationality*, indicating geographic and national identity are often linked in party discourse.

Cross-dimensional intersectionality patterns reveal strategic combinations that bridge economic and non-economic concerns. *Health* serves as a bridge attribute, frequently combined with *income/wealth/economic status*, possibly reflecting parties' attention to health inequalities. *Shared values/mentalities* often co-occurs with *occupation/profession*, suggesting parties frame certain occupational groups through ideological lenses.

Notably, some attributes rarely appear together even in intersectional mentions. *Gender/sexuality* shows relatively low co-occurrence with most economic attributes, potentially indicating that parties treat gender concerns as distinct from economic policy domains. These patterns suggest that while parties do engage in intersectional group appeals, they follow certain discursive templates that systematically combine some attributes while keeping others separate.

Conditional probabilities of co-occurrence

An alternative approach to quantatively describing attribute co-occurrence patterns is to compute the conditional probabilities of co-occurrence. We can compute Pr(attribute B | attribute A) for attribut category pairs and compare these values. Conditional probabilities have the advantage that they are very interpretable, allowing statements like "When a party uses economic status to describe a group, the propbability that it also uses gemnder/sexuality in the groip mention is 0.12." Conditional probabilities thus directly answers substantive questions about co-occurrence patterns. Further, they do not suffer from base rate sensitivity issues.

The downside is that the measure is asymmetric, requiring careful interpretation. Further, it does not account for statistical significance of observed differences. We therefore use it solely for *descriptive* comparison of party families' attribute combination strategies.

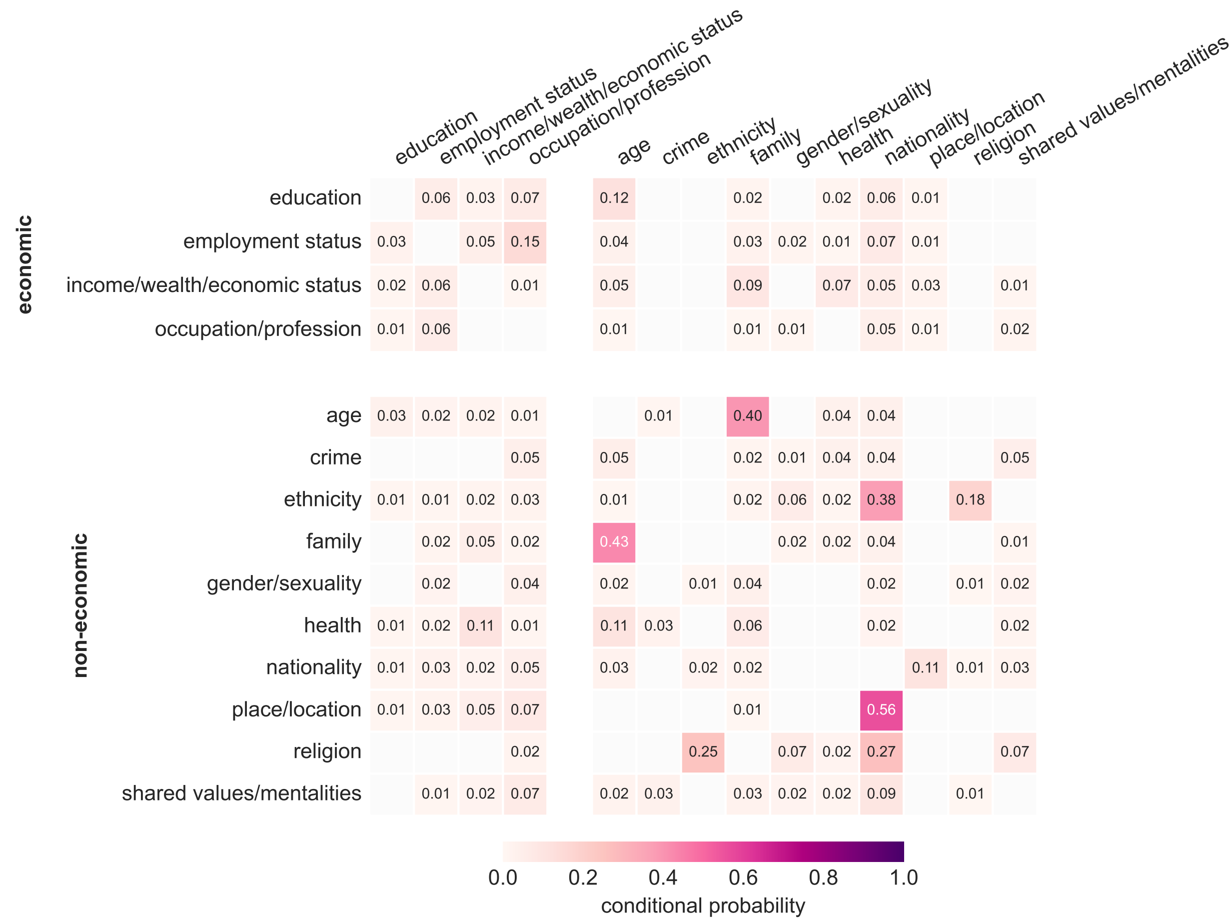

Figure C3: Conditional probabilities of attribute co-occurrence in social group mentions. Heatmap cells show P(B|A), the probability of mentioning attribute B given that attribute A is mentioned. Rows indicate "attribute A" (the conditioning attribute) and columns indicate "attribute B" (the outcome attribute). *Note:* Values below 0.01 are not displayed.

Table C2: Top attribute combinations by conditional probability $Pr(b|a)$, that is, the probability of attribute b being present in a mention given that attribute a is present. Only combinations with $Pr(b|a) > 0.1$ are included. Example mentions are randomly sampled from mentions that feature both attributes and no other attributes (i.e., mentions that only feature these two attributes).

attribute a	attribute b	Pr(b | a)	example 1
place/location	nationality	0.562	the population of Africa, including all Ara
family	age	0.429	children
religion	nationality	0.269	Muslims in France
religion	ethnicity	0.255	a multi-ethnic society
health	income/wealth/economic status	0.113	, who cannot afford the necessary "extras"
health	age	0.107	healthy and confident young people who h

C.3 Cross-validation against Thau's group category annotations

We use Thau's human-annotated social group categorization data to underscore the added value of taking intersectionality into account in group mention labeling. The idea of intersectionality is that social group mentions often involve multiple group attributes at the same time and that from a methodological point of view, this requires multi-label classification. Thau's coding scheme, however, is single-label, meaning that each group mention is assigned to one and only one group category.

Table C3: Examples of verbatim group mentions with conflicting group category annotations in data by Thau (2019) for category combinations that were confused more than 10 times. Each row shows (at most) three examples of verbatim group mentions that have been categorized into one of the following categories in different sentence contexts in the corpus and thus have "conflicting" labels. N reports the total number of mentions that exhibit the shown category confusion (in all 3,571 mentions).

attribute combination	N	examples
Age/generation + Economic class	50	"homeless 16 and 17 year olds"; "young people in full-time higher education"; "the young unemployed"
Age/generation + Other	29	"young users of hard drugs"; "secondary age pupils"; "persistent juvenile offenders"
Economic class + Gender	23	"women at work"; "men who work in the public services"; "Women at work"
Economic class + Geography	43	"the richest and poorest areas in our country"; "rural businesses"; "small local firms"
Economic class + Nationality	11	"migrant workers"; "People coming to Britain from the EU for work"; "skilled foreign workers"
Economic class + Other	94	"low income families"; "families where all parents are working"; "pensioner couples"
Geography + Other	13	"the community"; "pupils in less advantaged areas"; "community"

Table C3 illustrates the consequence of this annotation design choice by giving examples from Thau's data where the same verbatim identical group mentions were categorized into different categories at different times of the annotation process. For example, the group mention "homeless 16 and 17 year olds" has been classified as both *Economic class* and *Age/generation* in this data, and this label "confusion" occured for 50 group mentions in total.

Many of the examples in Table C3 are arguably clearly intersectional, such as “homeless 16 and 17 year olds” (economic status and age), “the richest and poorest areas in our country” (economic status and location or nationality), and “low income families” (economic status and family). In fact, about 9.4% of social group mentions in Thau’s data are affected by this problem.

Importantly, this observation does not indicate annotation errors *per se*. Instead, it illustrate why forcing a single-label classification scheme on a phenomenon that is inherently multi-dimensional can be problematic. Group mentions that exhibit multiple attributes, like “the richest and poorest areas in our country” (economic status and location or nationality) and “low income families” (economic status and family), are simply more accurately labeled if assigned to multiple categories *because* they are intersectional.

Examples from comparison to Thau’s social group category classifications

Next, we zoom in on three of Thau’s group categories: *Economic class*, *Age/generation*, and his *Other* group category. We focus on these three for different reasons. The category *Economic class* is interesting because it is an abstract, multi-facetted sociological construct that rarely manifests explicitly in social group mentions but is rather communicated through various indicators, such as occupation, income, or employment status. The category *Age/-generation* is interesting because it is appears conceptually more clearly delineated but is arguably an attribute-centered category in disguise, making it very prone to intersectionality with other attributes. The *Other* category is interesting because it is a catch-all category that is often used for mentions that do not fit well into the other categories, and thus is likely to be highly heterogeneous and intersectional.

Economic class

Having applied our multi-attribute classification approach to social group mentions categorized according to Thau’s group category scheme, we estimate that about 32% of mentions in his *Economic class* category are intersectional references. Table C4 shows that among the 68% of single-attribute mentions in this subset, most are classified as *income/wealth/eco-*

nomic status, *occupation/profession*, or *employment status* instances in our scheme.

Table C4: Social group mentions in Thau's *Economic class* group category that are assigned to a single attribute category according to our scheme and their absolute frequency. *Note:* Table only reports results for the six most prevalent attribute categories.

attribute category	N	examples
income/wealth/economic status	281	"Thousands i.e. who live in council homes"; "anyone earning less than Â£50,000"; "those in real need"; "ordinary people"; "those who pay for it "
occupation/profession	207	"established banksâ "; "management "; "major retailers"; "staff who work with the public"; "small companies"
employment status	184	"the worker"; "pensioner households"; "anyone who is unemployed for more than six months"; "those who are long-term unemployed for two years"; "Redundant workers"
education	39	"those who retired before 1956"; "those who learn"; "the school leaver"; "our students"; "the people often left out of good training opportunities"
nationality	18	"national and multinational capitalist groups"; "multi-national companies"; "first-time exporters"; "multinational oil companies"; "global companies"
family	13	"every family"; "the families that need them i.e. homes"; "families of strikers"; "family businesses"; "family "

However, other social group mentions in this subset of Thau's data are often labeled as combinations among these economic attributes or with other attributes, often non-economic ones like *family*, *age*, or *place/location*. Table C5 shows, for example, that mentions in Thau's *economic class* group category are often labeled as intersectional references featurin the attributes *income/wealth/economic status* and *family* or *employment status* and *age*, respectively.

Family

Thau's *Gender* group category is an example where our scheme is slightly broader be-

Table C5: Social group mentions in Thau's *Economic class* that are assigned to two or more attribute categories according to our scheme and their absolute frequency. *Note:* Table only reports results for the six most prevalent attribute combinations.

attribute combination	N	examples
employment status + income/wealth/economic status	54	"those who have suffered unemployment"; "the lower-paid"; "pensioners who save"; "people with personal pensions"; "working class"
employment status + occupation/profession	40	"employees who, through no fault of their own, find that their job has disappeared"; "employee-companies"; "the workers by hand and by brain"; "people engaged in especially hazardous work"; "welfare-to-work providers"
income/wealth/economic status + family	38	"families without a home or living in intolerable conditions"; "families with incomes of up to 59000 a year"; "families that need them "; "two thirds of families who own their house"; "single earner family on average earnings"
employment status + age	31	"highly able young people who cannot afford to work for free"; "the young worker"; "250000 young unemployed"; "people of working age"; "younger workers"
income/wealth/economic status + place/location	16	"residential leaseholders living in blocks of flats"; "the richest and poorest areas in our country"; "our poorest neighbourhoods"; "new town tenants"; "the most deprived areas in England"
occupation/profession + nationality	14	"british farmers"; "Asian staff in key public services"; "British businesses"; "UK farmers"; "British banks"

cause it also includes the aspect of sexual orientation. Mentions in this subset of Thau's data that are assigned to only one attribute in our scheme (55.1%) are typically categorized as *family* or *gender/sexuality* instances (see Table C6).

Yet, despite our gender-related category is already broader than Thau's, we still find that about 44.9% of the group mentions classified into Thau's *Gender* category are intersectional according to our annotations. Table C7 shows that the most common attribute combinations are *family* and *gender/sexuality* and *occupation/profession* + *gender/sexuality*, respectively.

Table C6: Social group mentions in Thau's *gender* group category that are assigned to only one attribute category according to our scheme and their absolute frequency. *Note:* Table only reports the results for the six most prevalent attribute categories.

attribute	N	examples
gender/sexuality	30	"three quarter million men and women"; "battered women"; "Women"; "the married man"; " women"
family	26	"fatherâ s"; "350000 mothers"; "dads"; "the wife"; "daughters"
occupation/profession	10	"trained men"; "service men"; "housewife"; "every housewife"; "housewives"
nationality	4	"thousands of British men"; "British men "; "some 19,000 British men and women"; "some 19,000 British men and women"
age	4	"women over 60"; "widow just under fifty"; "every boy and girl up to at least 18"; "every boy and girl up to at least 18"
employment status	3	"widows at work"; "men and women who earned their wages"; "men and women who earned their wages"

This is in parts driven by how we treat gendered references to familial roles, like father, mother, husband, wive, etc., which we consider intersectional. Other instances where we find intersectionality are not explained by this difference in coding appraoches, however, such as mentions that feature gender/sexuality alongside occpuation/profession ("service women"), employment status ("women part-time workers"), or nationality ("British women married to foreign husbands").

"Other"

Another intersting point of comparison to Thau's group category classifications are mentions in his *Other* category. Overall, about 22.5% of sopcial group mentions have been classified into this category by his annotators.

Our multilabel attribute classification approach assings 80.8% of mentions in Thau's *Other* category to at least one attribute in our scheme, while the remaining 19.2% of mentions in this category are not labeled as featuring any of our attributes and thus considered "universal" group references. As shown in Table C8, our approach thus makes 4 out of 5

Table C7: Social group mentions in Thau's *gender* group category that are assigned to two attribute categories according to our scheme and their absolute frequency. *Note:* Table only reports the results for the six most prevalent attribute combinations.

attribute combination	N	examples
family + gender/sexuality	15	"wives"; "fiancÃ©s"; "single mothers"; "wives and children"; "widowed mothers"
employment status + gender/-sexuality	10	"Women at work"; "working women"; "Women in Retirement"; "women at work"; "women workers"
occupation/profession + gen-der/sexuality	5	"women in the work-force"; "all women working in the NHS"; "service women"; "women who work in the public services"; "women of our Armed Forces"
age + family	4	"Our sons"; "children of servicemen and women killed while on active duty"; "moth-ers under 18"; "children of servicemen and women killed while on active duty"
crime + gender/sexuality	4	"women offenders"; "women escaping do-mestic violence"; "women victims of rape"; "women and ethnic minority offenders"
ethnicity + gender/sexuality	2	"women of every age, class, and ethnic ori-gin"; "men of every age, class, and ethnic origin"

mentions in Thau's general *Other* group analytically accesible by labeling them as featuring one (71.1%) or more attributes (28.9%) in our scheme.

C.4 Cross-validation against Horne et al.'s group category annotations

To shed more light on the convergence and divergences between our attribute classification and the group categtorization scheme by Horne, Dolinsky, and Huber (2025), we analyze two random samples of 5,000 mentions each labeled as featuring the *occupation/profession* attribute and mentions labeled as featuring the *gender/sexuality* attribute, respectively. These samples allow us to assess convergent validity by examining whether mentions our group attribute classifiers identify as featuring occupation-related or gender-related attributes are similarly categorized by Horne et al.'s group category classifier. The dual classification creates

Table C8: Social group mentions in Thau's *gender* group category that are assigned to two attribute categories according to our scheme and their absolute frequency. *Note:* Table only reports the results for the six most prevalent attribute combinations.

attribute(s)	N	examples
crime	141	"crime barons"; "criminals who donâ t go to prison"; "rape victims"; "the criminal who causes personal injury or damages property"; "survivors of sexual violence"
family	126	"Half a million families"; "the parents"; "parents of newborn children"; "broken families"; "busy families"
income/wealth/economic status	53	"a few"; "those householders living on small fixed incomes"; "ordinary savers"; "people living in flats"; "the privileged few"
income/wealth/economic status + family	35	"low-income families with children"; "two thirds of families who own their house"; "families without a home or living in intolerable conditions receive priority"; "better-off families"; "disadvantaged families"
education	31	"excluded pupils "; "pupils"; "top Maths and Science graduates"; "secondary school pupils"; "individual pupils"
age + family	23	"grandparents "; "those with children aged three"; "grandparents"; "each vulnerable child"; "older relatives"

overlapping annotations that reveal both areas of agreement (where both schemes identify similar patterns) and divergence (where our attribute-based approach captures distinctions not present in their categorical scheme). This comparison helps assessing to what extent our attribute-centered framework aligns with established categorization but also adds analytical value. Importantly, we examine these examples not to suggest that our classifiers have a higher accuracy but to illustrate how our attribute-centered approach seems to be better suited to accommodate interesectionality because it puts all attribute categories on the same analytical level.

Occupation profession

First, we focus on categories in Horne et al.'s classification scheme that capture references to specific occupational groups. In total, we identified 14 such categories in their scheme, ranging from *Caregivers* to *White Collar Workers*.[20]

Regarding convergence between their and our annotation scheme, we expect that our focus on occupation/profession-related attributes will lead to a high degree of overlap with mentions categorized into one or several of these categories by Horne et al.' classifiers. This is confirmed by our analysis, which finds that the share of mentions labeled as expressing an *occupation/profession* attribute by our classifier that are classified into an occupation group category by Horne et al.'s classifier is 83.8% – a high degree of correspondence.

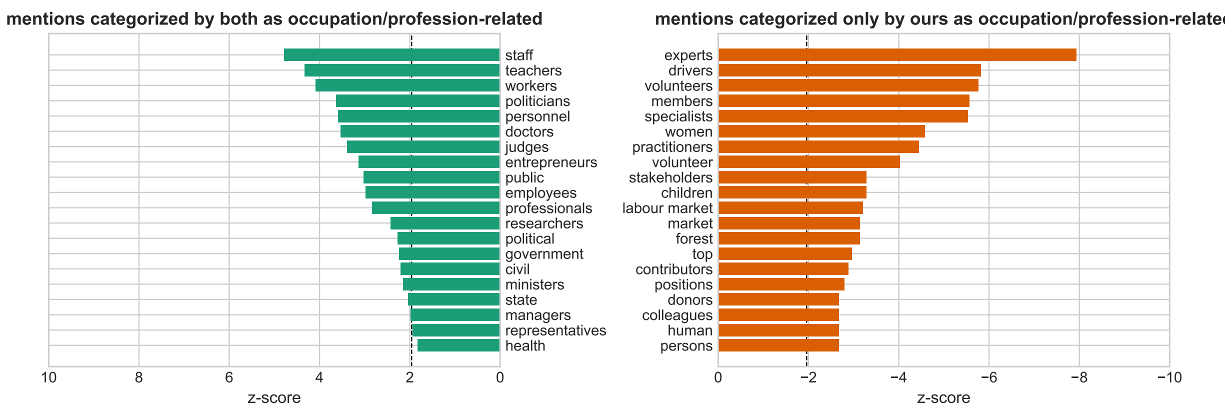

Figure C4: Most distinctive words for mentions labeled as featuring occupation/profession as an attribute by our classifier depending on whether by Horne et al.'S classifier has classified them into (at least) one of their occupuation/profession-related categories (left) or not (right). Values plotted are z-scores from "fighting words" on sample of 5000 occupation/profession mentions. Values above ±1.96 (vertical dashed line) can be considered significantly distinctive.

However, we also expect that due to being more encompassing and abstract than some of Horne et al's categories, such as *Civil servants*, *Farmers*, *Health professionals*, etc., our *occupation/profession* attribute will capture a broader set of mentions. We assess this question through a "fighting words" analysis (Monroe, Colaresi, and Quinn 2008), a method for identifying n-gram patterns that distinguish the 18% of social group mentions labeled as featuring the attribute of *occupation/profession* by our classifier that are not classified into any of Horne et al.'s occupation-related categories. Figure C4 and Table C9 show that our

[20]*Caregivers*, *Civil Servants*, *Education Professionals*, *Employees And Workers*, *Employers And Business Owners*, *Farmers*, *Health Professionals*, *Investors And Stakeholders*, *Law Enforcement Personnel*, *Manual And Service Workers*, *Military Personnel*, *Politicians*, *Sociocultural Professionals*, *White Collar Workers*

Table C9: Examples of social group mentions labeled as featuring occupation/profession as an attribute by our classifier that were not assigned to any of Horne et al.'s occupation-related group categories by their classifier. Values computed by summing "fighting words" scores as weights of mentions' tokens, normalized by number of tokens.

Mention	z-score	Horne et al. classification
experts	-7.937	
drivers	-5.820	Road Users
members	-5.562	
specialists	-5.535	
practitioners	-4.442	Other
external experts	-3.501	Other
experts in the field	-3.316	
contributors	-2.884	Other
non-political experts	-2.836	Other
more experienced) drivers	-2.835	Road Users
crafts-persons	-2.676	
working volunteers	-2.613	Lower Class
international experts	-2.566	
women in industry	-2.422	Women
members of cooperatives	-2.363	
the practising specialists	-2.354	
association members	-2.271	
the forest owner	-2.194	Homeowners And Landowners
women doing the same job	-2.019	Women
the industry stakeholders	-1.990	

occupation/profession classifications capture occupational and professional groups not covered by Horne et al.'s schemes, including broad categories like "experts" and "practitioners" as well as specific categories like "drivers".

Gender / Sexuality

Turning, to mentions that feature attributes related to gender and/or sexuality, we perform a similar cross-validation exercise by comparing their overlap with classifications into Horne et al.'s group categories *LGBTQI*, *Men*, and *Women*. Again, we find a high overlap between classifications. 91.4% of mentions labeled as expressing a *gender/sexuality* attribute by our classifier are classified into (at least) one of Horne et al.'s *LGBTQI*, *Men*, or *Women* group categories by their classifier.

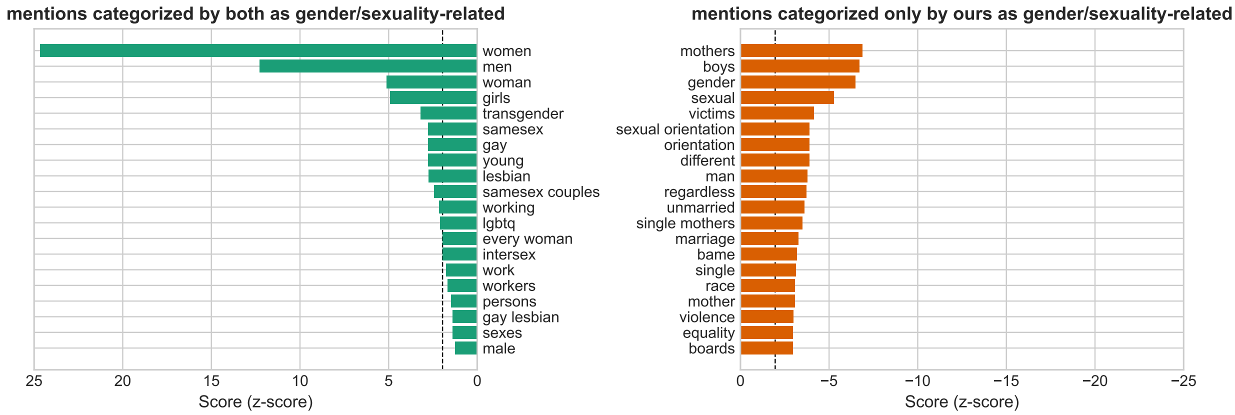

Figure C5: Top 20 most distinctive words for gender/sexuality mentions classified by Horne et al. (right) vs. not classified (left)

Table C10: Examples of social group mentions labeled as featuring gender/sexuality as an attribute by our classifier that were not assigned to any of Horne et al.'s Men, Women, or LGBTQI categories by their classifier. Values computed by summing "fighting words" scores as weights of mentions' tokens, normalized by number of tokens.

Mention	*z*-score	Horne et al. classification
all mothers or	-6.887	Families
co-mothers	-6.887	Families
boys	-6.703	Children
single mothers	-4.498	Families
A gender-friendly society	-4.498	
single-parent mothers	-3.525	Families
the unmarried co-mother	-3.335	Families
married mothers	-3.219	Families
breastfeeding mothers	-3.207	Families
the most vulnerable and gender-focused groups	-2.926	Lower Class
fellow mothers	-2.717	Families
mothers on MD	-2.671	Families
married and unmarried mothers	-2.425	Families
widowed mothers	-2.381	Families
married or	-2.206	Families
a mother who are married	-1.948	Families
the mother's wife	-1.875	Families
all genders	-1.867	
BAME groups	-1.782	Ethnic And National Communities
people on the basis of ethnicity, religion, sexual orientation or gender identity	-1.672	Other

However, looking at the remaining mentions that we label as *gender/sexuality*-related but not Horne et al.'s classifier, we again find interesting patterns. Most common are mentions including the familial role "mother" (see Figure C5), some of which combine this attribute with qualifiers (see Table C10).

C.5 Differences between Green and Populist Radical-Right party families

Comparing co-occurrence patterns

We argue that intersectionality in parties' group mentions is an interesting facet of their group focus strategies. In this context, the question arises how to compare interesectionality patterns between groups. In our analysis, a key question along this line is whether PRR vs. Green parties combine attributes differently?

There are multiple ways to quantify and compare attribute co-occurrence patterns. Each approach has its strengths and weaknesses. Below, we discuss four possible approaches and provide recommendations for their use.

- **Comparing conditional probabilities**: We can compute Pr(attribute B | attribute A) by party family and compare the values. Conditional probabilities have the advantage that they are very interpretable, allowing statements like "When Populist Radical-Right mentions class, 12% also mention gender." They thus directly answers substantive questions about co-occurrence patterns. Further, they do not suffer from base rate sensitivity issues like the PMI (see below). Subtracting the values for Green parties from thjose for PRR parties, for example, we obtain an indicator that is negative if PRR parties tend to combine the given attributs more frequently. Conditional probability differences can thus be compared across parties through simple subtraction, and the approach works well even with sparse data.

  The downside is that the measure is asymmetric, requiring careful interpretation. Further, it does not account for statistical significance of observed differences.

  We therefore use it solely for *descriptive* comparison of party families' attribute combination strategies.

- **Comparing statistical significance**: We can apply χ^2 or Fisher's exact tests for each attribute pair to determine whether co-occurrence patterns differ significantly between party families. These tests provide formal hypothesis testing and control for sampling variability. Effect size measures, such as Cramér's V, in turn, allow assessing practical significance beyond mere statistical significance.

However, tests are sensitive to sample size, meaning that with large N, nearly everything becomes statistically significant. Further, binary yes/no decisions do not capture the magnitude of differences.

We therefore use significance testing for determining which attribute pair differences are statistically robust.

- **Comparing normalized Pointwise Mutual Information (nPMI)**: We can compute nPMI values by party family, which compare observed to expected co-occurrence under statistical independence. nPMI identifies unexpected patterns in both directions (positive associations where attributes co-occur more than expected, and negative associations where they co-occur less than expected). Being normalized to a [-1, +1] scale, it allows comparing different attribute pairs. This makes the nPMI metric useful for exploratory analysis.

  However, the measure is hard to interpret substantively in terms of party strategy. It is sensitive to base rates, and negative values tend to dominate in sparse data (as we observed in our analysis). Additionally, differences between parties can be small even when the underlying patterns differ substantially.

  We therefore do not rely on nPMI analysis.

Statistical significance of co-occurrence differnces

We report differences between PRR and Green parties' attribute co-mentioning patterns in Figure 8 as a way to understand how these two party families' group focus strategies differ through the lense of intersectionality. Below, we report the results of χ^2 tests that assess whether observed differences in parties co-mentioning patterns are statistically significant. Further, we rely on Cramér's V to the practical significance of these differences – if any. Cramér's V measures association strength between two categorical variables, ranging from 0 to 1, where 0 indicats no association (complete independence) and 1 perfect association (complete dependence).

Figure C9 shows that Cramér's V estimates for attribute combinations with significant differences in party families' co-occurrence patterns (according to χ^2-tests) range from 0.006 to 0.054. Values in this range are commonly interpreted as very weak (Cohen, 1988). In particular, this means that even the "strongest" difference (*occupation/profession* $\times$ *nationality*) explains less than 0.2% of variance.

This understcores that statistical significance does not equate practical significance. While the χ^2-tests found the differences for the examined attribute combinations to be statistically significant ($p < 0.05$), the actual strength of association is very weak. However, it is important to recall that most mentions in our data have no or only one attribute. This makes our attribute co-occurrence data very sparse. Therefore, even small V values can represent meaningful political choices. Yet, intersectionality patterns *alone* do not produce strong separation between party families.

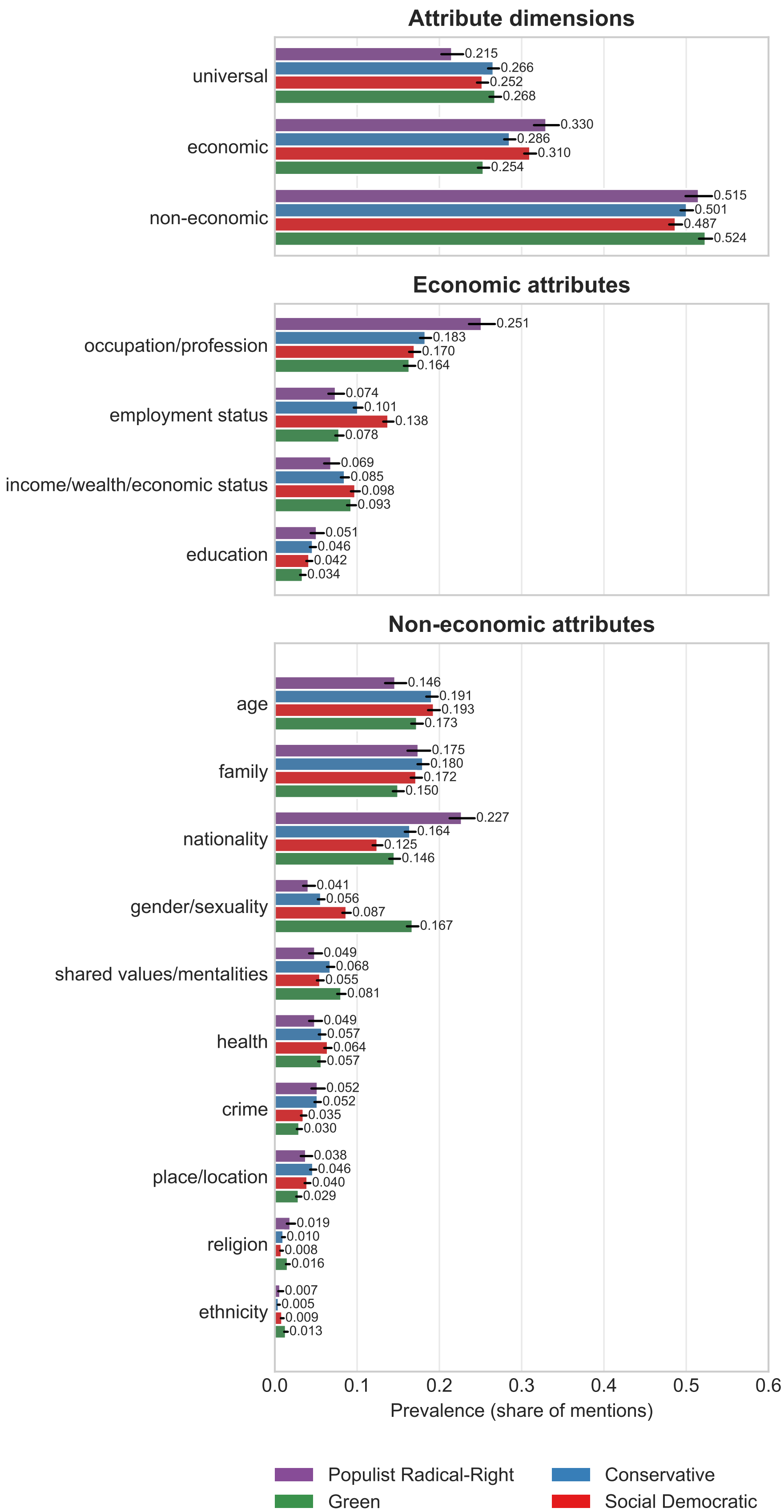

Figure C6: Prevalence of economic and non-economic group attributes in social group mentions in mainstream party manifestos (Conservative and Social Democratic) compared to PRR and Green parties. Bars show share of mentions containing each attribute, with 95% confidence intervals.

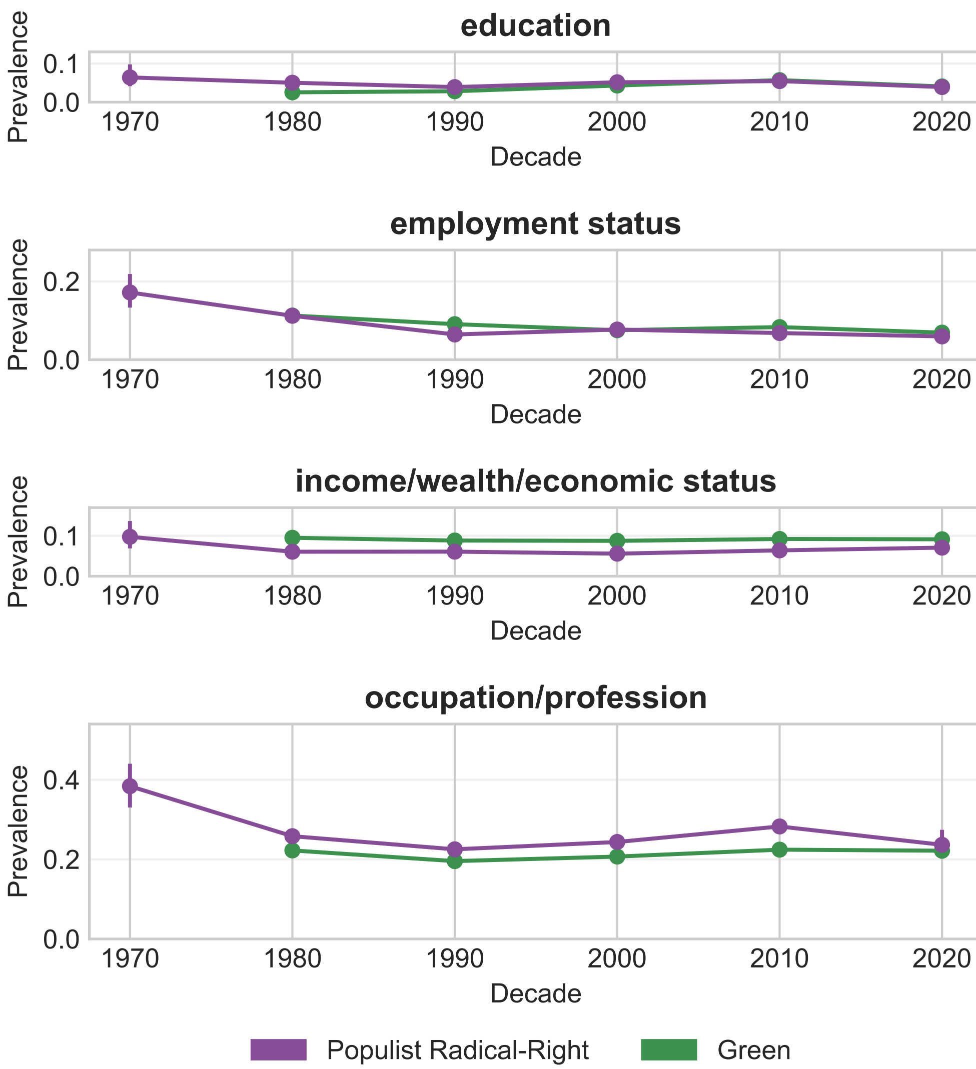

Figure C7: Temporal trends in the prevalence of economic attributes in social group mentions by PRR and Green parties across decades. Each panel shows one economic attribute category, with error bars representing 95% confidence intervals. Lines show the share of mentions containing each attribute over time.

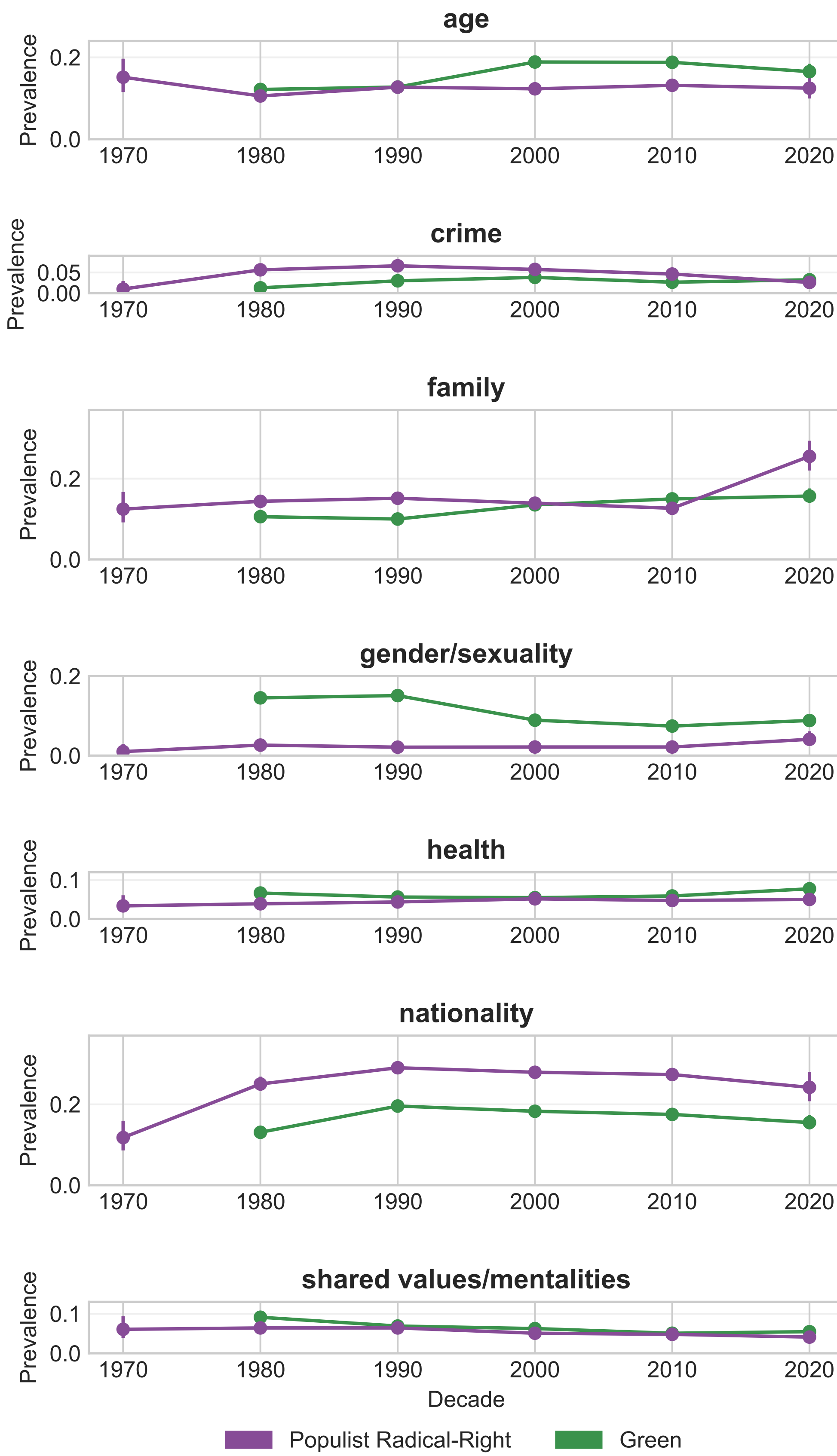

Figure C8: Temporal trends in the prevalence of economic attributes in social group mentions by PRR and Green parties across decades. Each panel shows one economic attribute category, with error bars representing 95% confidence intervals. Lines show the share of mentions containing each attribute over time.

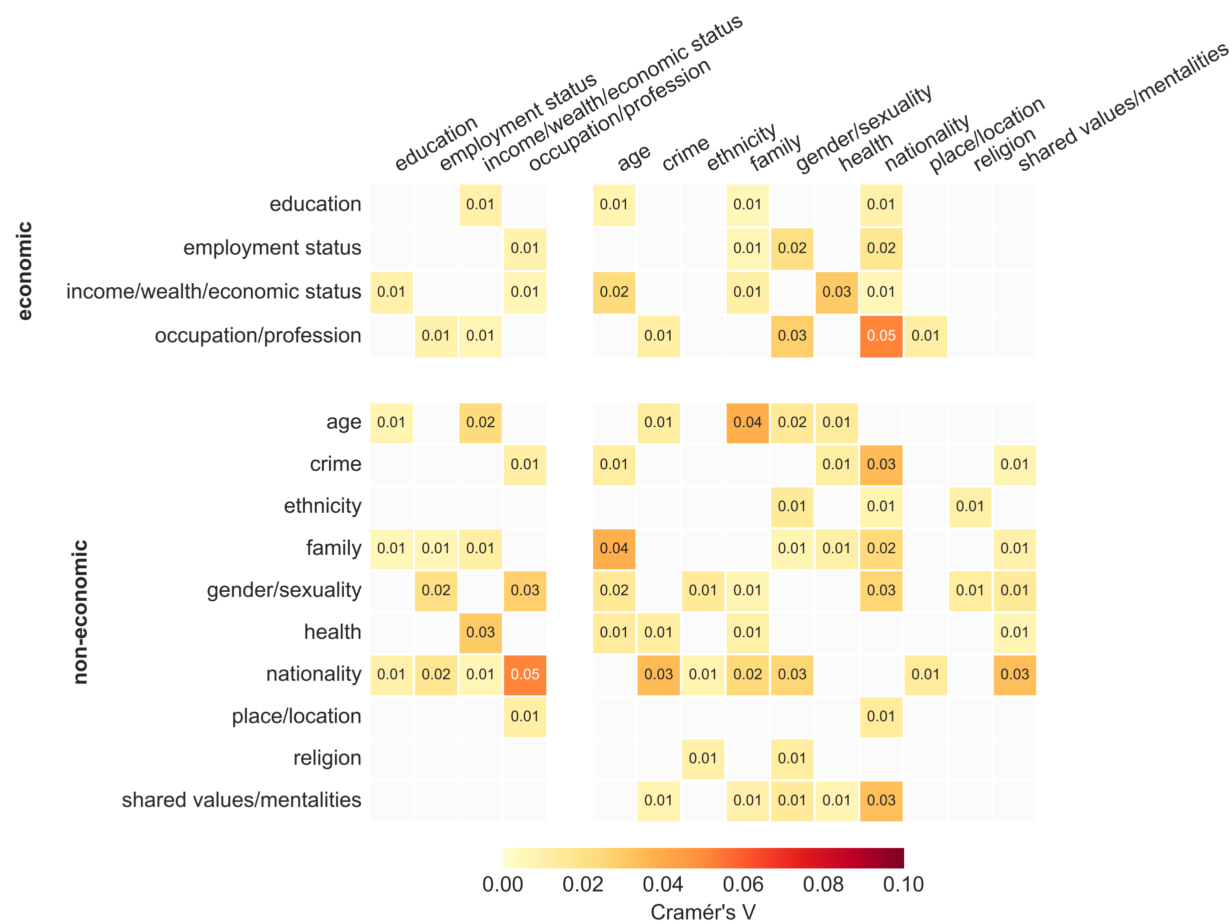

Figure C9: Substantive significance of differences in attribute co-occurrence patterns between PRR and Green parties. Heatmap cells show Cramér's V effect size for attribute pairs where co-occurrence significantly differs between the two party families (Chi-square test, $p < 0.05$). *Note:* Values on the diagonal are masked.