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SIMZ51
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The Effect of Party System Ideological Polarisation on Individual Affective Polarisation in Europe

Multilevel Evidence from 29 European Countries from 1996 to 2021

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18 May 2026

Abstract

This thesis looks into how ideological polarisation of party systems (X) influences affective polarisation (Y) on the individual level. Taking off from social identity theory, I assume that larger ideological divergence between parties fosters more emotionally charged evaluations of political opponents because of identity-based in-group and out-group dynamics as well as due to being by virtue differences in beliefs. The latter are exemplified against the rise of cultural cleavages in political campaigns, which centralise more sensitive issues than traditional economic ones. Using data from Comparative Studies of Electoral Systems, the sample consists of around 170 thousand individual observations in 300 regions, nested in 29 European countries, throughout 115 elections from 1996 to 2021. Running three-level hierarchical models (individual-region-country), I found high heterogeneity between countries in both baseline affect levels and the slopes of the focal relationship that rejected any clear pan-European trends. Income inequality had no statistically significant average effect on affect, although individual extremism average estimates held positive, significant, and nearly identical both between- and within-countries. While the influence of party ideology on individual affect seems substantially contingent on political contexts, the extremity of individual beliefs reliably contributes to higher affect even when controlling for space and time.

Key words: polarisation, party ideology, affect, multilevel analysis, Europe.
Words: 16 105

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1 Introduction

In late April of 2026, a failed assassination attempt on the US president Donald Trump made headlines worldwide. This was not the first attempt on Trump during his political career but the latest of two (Kleinman et al., 2026), five (Faris, 2024), or even ten (Mallon, 2026), depending on how sources count. In a similar vein, late 2025 marked the assassination of Charlie Kirk, a conservative debater. Both individuals could be described as *polarising* figures in that their political statements consistently attracted heavily charged rhetoric from (and between) supporters and opponents alike alike. Kirk's murder especially sparked new discussions over political violence having grown more common, if not to some degree accepted, in the US. Assassination attempts are, without doubt, extreme cases. Further, partisan news media oftentimes exaggerate the degree of animosity in the public by amplifying and exaggerating stories of clashes between vocal, but ultimately minor extremist groups (Fiorina et al., 2005/2011). Regardless, both the occurrence of such violent acts against political figures and the character of the public uproar at their wake paints a picture of a concerningly polarised American society. It may seem that such hostility may have become, for many people, intricately connected with the presidential US electoral system of only two and constantly clashing parties. Yet, even though the degree of partisan hostility in the US indeed has proven above average and growing over recent decades, some European countries rank even higher in that metric (Gidron et al., 2020, p. 69), despite receiving disproportionately little attention in polarisation studies until recently.

Political polarisation at its core signifies the extent to which individuals arrange themselves in mutually exclusive groups by some attribute, typically by political beliefs. The US is a classical example whereas most voters choose between two parties that represent distinct belief systems. Accordingly, it is the US that holds most of the rather extensive tradition of polarisation research which traces back to the 1950s studies of how individuals form public opinions (Converse, 2008). Yet, for decades political polarisation broadly meant divergence in ideology, and it was not until the 2010s that the concept of affective polarisation—negative sentiment towards political opponents (Iyengar et al., 2012)—gained substantive traction in academic circles in the US and is still a relatively understudied phenomenon in multiparty European systems. This new approach of studying polarisation proved notably distinct from disagreements over belief systems and allowed further inquiries into how partisan identities and/or idea differences may lead to feelings of hostility towards out-groups.

Political polarisation deserves attention for multiple reasons. For one, ideological disagreements to some degree benefit democracies by fostering some forms of political participation (Kleiner, 2020, pp. 592–593; Barber & McCarthy, 2015, as cited in Reiljan, 2020, p. 377). Affect towards opponents, however, manifests itself in more negative ways like lowering political trust (ibid.), and in some cases may even lead opposing groups from online arguments to violence in real-life protests (Gallacher et al., 2021, p. 12). Further, ideology and affect are distinct, yet interconnected dimensions of political polarisation that are known to interact. Ideological polarisation tends to be positively associated with affective polarisation (Reiljan, 2020, p. 392), thus likely acting as one of the enablers of affective sentiment and its undesirable consequences. Yet, research on how macro level ideological polarisation may cause micro-level affect is scarce outside of the US. In response to this gap, my thesis aims to probe at the extent to which more polarised party ideology supply contributes to individuals feeling more negatively towards political opponents. I formulate the research question as follows.

RQ: what is the effect of party system polarisation on individual affective polarisation in Europe?

The main contribution of this study lies in the methodological approach that chiefly relies on multilevel modeling where affective polarisation is on the individual level while also accounting for variation in regions within countries. To my knowledge, no prior cross-national study examined affective polarisation on the individual level, or at least not in conjuncture with party system ideological polarisation.

The rest of my thesis is structured as follows. Chapter 2 defines the key terms, overviews the theoretical framework along with relevant prior literature, before deriving hypotheses. Chapter 3 presents my methodology, research design, data from the Comparative Studies of Electoral Systems dataset, and operationalisation of variables. Chapter 4 presents the descriptive statistics of the sample, preliminary tests, and overall results. Chapter 5 goes over conclusions, limitations, and recommendations. Multilevel model outputs are provided in the Appendix, wheras code and data are to be submitted digitally.

2 Conceptual Framework

The primary aim of this thesis is to investigate the effect of party system ideological polarisation on individual affective polarisation in Europe. This chapter provides definitions of these key concepts, presents the theoretical lens of this study rooted in social identity-based studies of affect, and discusses relevant prior research, listing emergent hypotheses along the way.

2.1 Defining Political Polarisation

Polarisation in the broadest sense can be seen as concentration of data points around the extremes of an axis, rather than, for instance, around the centre. A classic text from econometrics offers a comprehensive illustration whereas a sample is polarised by some attribute when its data points fulfil three conditions: 1) data points are clustered into several groups of significant size; 2) any two data points in one group are similar to each other; and 3) any two data points from different groups are different from each other (Esteban & Ray, 1994, p. 824). Applied to a political context, a textbook example of a polarised society is one where most of the public is either strongly on the political left or on the political right, with a minority around the centre. Such a society, in line with these criteria, contains a small number of groups (*the left* and *the right*) of significant size, with high homogeneity *within* groups (any two people in *the left* will hold similar views) and high heterogeneity *across* groups (someone from *the left* and someone from *the right* will disagree on most political issues). This society would be considered polarised along ideological grounds, although polarisation can be visualised on the basis of other attributes (e.g., sentiment towards political opponents) or specific policy attitudes (e.g., migration, European integration), and can emerge on the party level as well as that of the individual.

Political polarisation is a notoriously multifaceted concept with an extensive research history, especially in the US. A seminal text on ideological belief formation (Converse, 2008), originally published in 1964, cites surveys on individual ideological leanings from the early to mid 1950s (p. 18). Later work on political opinion formation planted the seeds for the study of polarisation as one particularly fascinating and simultaneously concerning trend. Cross-national studies on polarisation trends in other democracies, have also gained traction more recently elsewhere, including Europe.

This long history and extensive inquiry into political polarisation has created a landscape of conceptual distinctions with various often interconnected and/or overlapping features. Subsections 2.1.1 and 2.1.2 decode the different types of polarisation with special attention to literature on affective polarisation which is the main focus of my study. Afterwards, subsection 2.2 overviews the more general trends in political polarisation observed in prior studies both in the US context as well as comparative cross-national studies, focusing on observed effects of party system polarisation on individual affective polarisation.

2.1.1 Ideological Polarisation: Masses and Elites

Political polarisation is generally seen as the extent to which adherents of a certain political position distance themselves from adherents of other positions. Over time, different traditions have come to adopt distinct conceptualisations. Most research until recently equated political polarisation with i*deological polarisation* (hereafter *IP*) which describes distance on the left/right spectrum (Reiljan, 2020). At its core, IP represents the ideological distance between individuals or parties, typically as placement on the left/right spectrum or stated positions on particular policy issues. On the party system level, IP describes the ideological context of party competition in a nation, typically based on the ideological positions of parties in a government for a particular election context (Dalton, 2008).

Accordingly, IP has often been narrowed down to mass polarisation and elite polarisation. Mass IP refers to polarisation on the level of individual belief systems whereas elite IP covers ideological position of political elites. Literature shows variation in defining who constitutes this political class. Some include broad classifications whereas the umbrella of political elites includes politicians alongside political activists, journalists, and infotainers as all these actors are involved in political messaging (e.g. Fiorina et al., 2005/2011, p. 166). In the context of this thesis, I restrict restrict the *political elite* to political parties that are holding office. Further, I use the terms *mass ideological polarisation / mass IP* and *individual ideological polarisation / individual IP* interchangeably. Likewise, I do so with *elite ideological polarisation / elite IP* and *party system ideological polarisation / party system IP*.

2.1.2 Affective Polarisation

Affective polarisation (hereafter *AP*) is a more recent concept that emerged in polarisation research as per the seminal article by (Iyengar et al., 2012). AP, drawing from theories of social identity and social distance, defines polarisation in terms of feelings towards the political "other", placing emphasis on sentiment rather than differences in ideological beliefs. In essence, AP describes the strength of negative emotions that an individual feels towards political opponents, often in contrast to the positive feelings he or she holds towards like-minded individuals. Past this point, views diverge on how to adequately measure AP and a clear consensus of how to do so in multiparty contexts (which constitute most of European states) has not been achieved to date (Bettarelli et al., 2023, p. 647). Typically, the key distinguishing factor in measurements of AP in cross-national studies has been the treatment of partisan identity. Some scholars conceptualise political affect on the basis of *in-party* vs *out-party* sentiment: looking at individuals who are members of a party or sympathise with one (i.e., partisans) and viewing their levels of affect as the difference in how much they like their own party against how much they dislike other parties (e.g. Boxell et al., 2024; Iyengar et al., 2012; Reiljan, 2020). The other approach drops the *in-party* / *out-party* distinction and instead focuses on general dispersion of individuals' feelings towards political political parties without the requirement for them to prefer, support, or lean towards one party more so than others (Wagner, 2021). As such, this view does not require grouping individuals by the party they feel closest to, which makes it more applicable to conceptualising AP on the individual level and thus more suitable for my thesis. I discuss these measures and elaborate on this choice in more detail in later sections.

Affect further branches out into different types. By object, affect can mean disliking specific groups like party X *in corpore*, or voters of party X, or leaders of party X (e.g., Reiljan et al., 2024, p. 654). Alternatively, the type of affective experience can be specified, typically as either negative emotions felt towards the opponents or avoidance of social contact with them (e.g., "How would you feel if your child married a Democrat?" or "How open are you to having a friend who is Republican?"). Finally, affect manifests itself on different levels, namely individual or aggregate, with the latter as more common in literature overall (Wagner, 2021, p. 2). In this thesis, I view *affect* as *individual* sentiment towards specific political parties and *affective polarisation* as the range of such sentiment in an individual's judgments of different parties in the same party system.

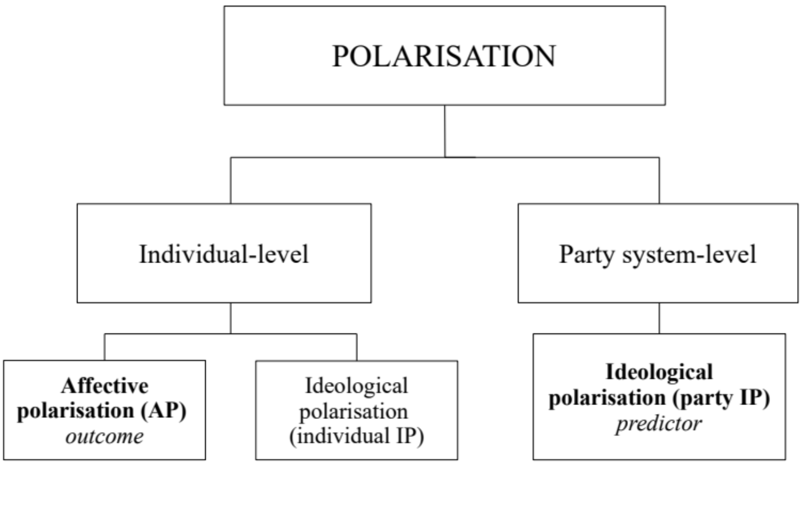

Figure 1. Flow chart of key terms with most relevant ones in bold.

Throughout the rest of the thesis, I abbreviate *affective polarisation* as *AP* and *ideological polarisation* as *IP.* With definitions out of the way, the primary aim of this thesis is thus as follows: to examine how party system ideological polarisation (party IP, X) affects individual-level affective polarisation (AP or mass AP, Y). The following section presents the theoretical model I use for this study.

2.2 Ideology and Individual Affect

While the article that pioneered studies of AP delineated affect as "a more appropriate indicator of mass polarization than ideology" (Iyengar et al., 2012, p. 427), subsequent scholars have found that ideology and affect far from redundant. Rather, affect and ideology constitute two distinct and even complementary dimensions of polarisation (Reiljan, 2020, p. 380) in that the emergence of negative sentiment towards opposing parties might partly result from ideological grounds. This relationship, although at times ambiguous, has been observed nonetheless both in terms of affect being shaped by individual's own larger ideological distance from the other party (Rogowski & Sutherland, 2016, p. 504) or by higher party system IP (e.g., Banda & Cluverius, 2018).

Prior empirical work has detected links between ideology and affect towards out-parties. In the US, the two parties have been consistently distancing from each other for multiple decades (Dalton, 2018, p. 205; also Hetherington, 2001; McCarthy et al., 2005, p. 3), clarifying their policy positions and disagreements, and thus encouraging voters to side with one party and against the other (Banda & Cluverius, 2018, p. 97; Hetherington, 2001, p. 629). Furthermore, the positive association between individual ideology and affect was found in multiple democracies, including but not limited to those in Europe (e.g., Bettarelli et al., 2023; Boxell et al., 2024; Reiljan, 2020; Reiljan et al., 2024).

Yet, even though some common ground exists in that a positive relationship between ideology and affect is present, debates over the causal mechanism are unresolved. As per (Turkenburg & van Erkel, 2025, pp. 216–217), scholars tend towards either one of two explanations. The earlier school of thought argues that ideologies cause affect in that they represent different party identities: supporters of one party become hostile to supporters of other-minded parties primarily because of the latter's identity as an out-party. In this view, AP results from the activation of us-them identity dynamics based on party alignment, rather than from the divergence in personal ideological beliefs.

Another, more recent school of thought holds that ideology shapes affect via both party identity and ideological differences side by side. In this view, an individual expresses negative sentiment towards opposing parties because they represent opposing ideas, not just because of their identity as out-parties (ibid.). This view presents a distinction in that clearly predefined party identity is not a prerequisite for affect formation. Individuals may not prefer any particular party over others, or prefer more than one, and still display affective evaluations towards certain parties or the party system as a whole because these groups represent opposing ideas—in addition to activation of in- and out-group identity dynamics. This latter view, I argue, fits the context of my thesis better. Party identification and its salience to voting outcomes in Europe have been declining over decades as political decision-making became more individualised rather than rooted in party identities (Garzia et al., 2022, pp. 318–319), in contrast to the US where identity-centred AP research originates. As a result, party identity activation alone fails to offer a sufficient explanation of how elite IP forms individual affect in Europe. Another motivation is that singling out partisan alignment as the proxy for identity might conceal the effects of other non-political identities that may contribute to affect (Iyengar & Krupenkin, 2018, p. 215) as the extent partisan sorting by sociodemographic profiles of each party has shown notable positive relationships with AP even in countries where overall AP is comparably low, like the Netherlands (Harteveld, 2021, p. 8). Partisanship, while important, does not represent the only type of identity whose activation may contribute to affect, inviting a broader conceptualisation. That being said, I assume that growing party system IP causes individual AP simultaneously in two ways as: 1) increasingly other-minded parties look more distant from one's own, thus activating identity-based out-group hostility mechanisms; and 2) opposing parties represent ideas and beliefs that are contrary to one's own, prompting affective responses when the opinion differences exceed the threshold where finding common ground is feasible—this applies for partisans and non-partisans alike.

An alternative explanation might reverse the direction of causality in that it is not individuals getting more polarised as parties grow apart, but that parties are readjusting policy positions to maximise their electoral outcomes with an increasingly polarised electorate (ibid., pp. 13-14; Dalton, 2018, p. 97). This view might even make more sense as European multiparty systems offer more alternatives for voters to support or punish parties and therefore place less pressure on voters to support a party or candidate whose views grew apart from one's own. Yet, these explanations do not contradict each other and the effect almost undoubtedly extends both ways—(Wagner, 2021, p. 8) finds a significant positive relationship between Party IP as the outcome and AP as the predictor, which is the reverse of the focal relationship I examine in this thesis. Further discussions over which phenomenon is more prevalent, while intriguing, lie outside the scope of this thesis. My goal strictly focuses on the top-down effects of party IP on individual AP, taking place via identity activation and perceived ideological differences.

Accordingly, the picture is that as political parties shift further away from the ideological centre and from each other, their voters are pulled along (Zaller, 1992/2012, pp. 8–9) and face a more polarised choice of parties in subsequent elections. Eroding common ground between parties laid ground for increasingly harsh rhetoric between the parties has been associated with the public's affective polarisation (Banda & Cluverius, 2018, p. 97; Iyengar et al., 2012, p. 427).

The 2016 American presidential election (and to some degree, both subsequent elections) serves as an example: the rise of MAGA and the victory of Donald Trump painted the picture of the American electorate having shifted substantially towards the right. Yet, a more faithful interpretation posits the event as not so much a sign of public opinion having swinging rightwards, but rather as a response of the voters to a significantly more polarised party system (Dalton, 2018, p. 205). Americans, in this sense, voted for more extreme candidates not necessarily because their own views became more extreme but because the candidate options on the ballots had become more extreme compared to earlier elections. Still, even in the absence of any substantive shift in the degree of disagreements within the electorate, affective polarisation since the 1990s grew in the US regardless—more sharply so than in much of Western Europe over the same period (Gidron et al., 2020, p. 70). Higher party system IP thus seemingly contributes to higher individual AP even if individual-level IP remains more or less stagnant. One compelling explanation for why this happens comes from a shift in party competition dynamics over the recent few decades, observed in the US and in much of Europe, namely the re-emergence of the cultural cleavage.

Traditionally, voter choices (and thus, party agendas) in Western Europe were mostly determined by issues that were economic in character, even if unique across local contexts. Since the 1970s and especially into the 21st century, however, multiple states saw cultural cleavages match or exceed economic ones in terms of determining electoral outcomes (Dalton, 2018, p. 3; Kriesi et al., 2008, p. 324). Following (Gidron et al., 2020, p. 70), the economic and cultural cleavages at their core address questions of resource distribution and self-interest ("who gets what") in the former and matters of at time deeply personal values and social identities ("who we are") in the latter. Accordingly, disagreements along the cultural cleavage often invoke more sensitive themes (e.g., religious or moral principles, national identity, etc.), are often framed in normative terms, and thus are more prone to invoke affective reactions within the public (Dalton, 2018, p. 44; Gidron et al., 2020, p. 70). When cultural issues determine party competition, parties distancing from one's own positions begin to seem less as adversaries to compete against and more as an antagonistic force or a threat to one's core beliefs.

Yet, despite the growing prevalence and importance of the cultural cleavage in European politics and its higher potential to mobilise affect, overall pan-European trends in Europe are ambiguous. Prior studies consistently find how AP has increased in some countries such as Switzerland, declined in others like Germany, and remained the same in yet others over time. Depending on the data sources and conceptualisations of AP, results for the same countries at times appear contradictory (e.g., Sweden in Bettarelli et al., 2023, p. 652; vs Boxell et al., 2024), with no evident trajectory to unite all or even most of the continent's democracies (Reiljan, 2025, p. 128). Drawing from these findings, I expect substantial cross-country variation in affect and its relationship to elite ideological divergence to take place, determined by country- or region-level contextual factors. In other words, I theorise that party system ideological polarisation positively affects individual affect, and that this effect is more prominent within countries than between countries.

H1: Party System Ideological Polarisation positively affects Individual Affective Polarisation within countries.

2.2.1 Other Determinants of AP

Several characteristics on the individual and country-level may also determine AP. This section overviews such potential factors. Notably, no prior cross-national study to my knowledge has investigated AP strictly on the individual level, which makes me rely on prior analyses with mostly aggregated measures in determining potential controls.

Individual extremism (as self-placed distance from the centre) is positively associated with individual affect (Rogowski & Sutherland, 2016, p. 497; Wagner, 2021, p. 8), in line with prior discussions on how ideological divergence creates conditions for AP. Therefore, I hypothesise individual extremism to have a slight positive effect on AP.

Hypothesis 2: individual extremism positively correlates with individual affective polarisation.

Literature on the effect of sociodemographic factors on individual AP is inconclusive. Higher education allows for individual belief systems that are more consistent internally and with those of like-minded political elites (Converse, 2008; Zaller, 1992/2012). Accordingly, the solidified political positions may suggest that people with higher education might be more prone to affective evaluations of opponents. However, various studies found the effect of education on AP to be slightly positive (Stewart et al., 2020, p. 42), statistically insignificant (Iyengar et al., 2012, p. 426), and even negative, while age had a positive effect or no effect (Banda & Cluverius, 2018, p. 95; Riera & Madariaga, 2023, p. 7). AP was also found to be higher among women and less affluent individuals (ibid.) and marginally lower among white than non-white individuals (Stewart et al., 2020, p. 42). More generally, partisans whose sociodemographic profile fits that of their party (such as the average US Republican being white, male, etc) tend to display significantly higher AP across various democracies (Harteveld, 2021, p. 8). This finding suggests that AP may emerge from the activation of non-political identities as well, since non-political identities partly determine how individuals sort themselves by party allegiance (as discussed in the previous subsection on how ideology causes affect), which would mean that AP is determined by party-based sociodemographic profiles rather than individual sociodemographic indicators. Yet, my project concerns multiple countries with multiple parties in each, which renders such inquiry into profiles for every major party simply infeasible. Instead, I include separate sociodemographic variables in my analysis which I elaborate upon in the next chapter.

Higher levels of political information signal that a person is more engaged in politics, and therefore has more exposure to political messaging which is one of the drivers of polarisation (Converse, 2008; Zaller, 1992/2012). Likewise, higher political interest has also been observed to amplify AP (Banda & Cluverius, 2018, p. 96; Riera & Madariaga, 2023, p. 8; Rogowski & Sutherland, 2016, p. 497). However, the measurement of these indicators on the international scale poses unique challenges which have not yet been resolved. Data from CSES, which I use for this study, has no measure for political interest, but offers proxies for political knowledge of the respondents as quizzes of three to four questions of increasing difficulty. Despite the parsimony, however, these items did not perform well as question difficulty between nations varies significantly and some questions, when regressed with political knowledge, sometimes showed negative associations or standard errors that exceeded the estimates themselves (Elff, 2009, pp. 10–11), in addition to altogether missing data for some countries. Even assuming that measurements improved since 2009 (although no scholarly text to my knowledge has addressed this issue since), these limitations nonetheless compromise the larger half of my 1996-2021 sample, time-wise. Therefore, despite theoretical interest, I exclude political information from my analysis due to data limitations.

Only one cross-national study to the extent of my knowledge has attempted to examine region-level variation of AP, although it found over half of the variation in affect to be present within states (Bettarelli et al., 2023). Because of this, as well as due to the scarcity of data for region-level factors and to avoid overcomplicating my analysis, I only employ region identifiers on the region-level to control for unobservable time-invariant characteristics. I elaborate on my sample, data structures, and measurement choices in the next chapter.

For country-level characteristics, majoritarian electoral systems and higher income inequality have been associated with higher affective polarisation (Gidron et al., 2020, p. 71; Stewart et al., 2020, p. 42), while higher numbers of legislative parties resulted in lower individual AP and per capita GDP and national unemployment had no effect (Riera & Madariaga, 2023, p. 11). To avoid bias, I do not include party system fragmentation and electoral institutions in my analysis as these factors inherently correlate with my main predictor, party system polarisation. I keep income inequality and expect it to correlate positively with affect.

Hypothesis 3: country-level income inequality positively correlates with individual affective polarisation.

Having discussed my theoretical expectations and prior literature, I continue to my methodology and research design in the following chapter.

3 Data & Methodology

To test the hypotheses presented in the preceding chapter, I pick multilevel modeling as the primary method. This chapter presents my specifications of the research design, choice of data sources, and variable operationalisation.

3.1 Research Design

This thesis takes a quantitative approach since the main interest lies on statistical trends of the interplay of party ideological polarisation and individual affective polarisation in a pan-European context. Namely, I analysed a cross-national sample of individuals in European democracies which I describe in more detail in later sections. Further, as my research question concerns a macro-to-micro effect of party system ideological polarisation on individual affective polarisation, I choose multi-level modelling (also referred to as hierarchical modelling or mixed effects) as my primary tool of analysis since this method is tailored to examine relationships between variables on different levels. Aside from multilevel models, preliminary testing involves several OLS linear regression tests to probe and test the data structure under different specifications, and ANOVA testing used to further designate the optimal model structure for that data at hand. The following subsection expands on hierarchical modeling in more detail.

3.1.1 Method

This thesis employs multi-level modelling (MLM) to test the hypotheses, relying mostly on the textbook on hierarchical modelling by (Gelman & Hill, 2006). As per this text, two potential ways a classical regression may handle hierarchical data are complete pooling and no-pooling. Complete pooling refers to regression that omits group identifiers and in so doing pools all observations together, producing a straightforward relationship estimate but ignoring differences of that relationship in different groups. Meanwhile, at the other extreme, no-pooling includes group IDs which produces separate estimates for every group, although it treats separate groups completely separately and tends to exaggerate estimate groups with fewer observations (pp. 255-256). As no-pooling examines variation within groups and omits variation between groups, complete pooling does the opposite. One way or another, both approaches oversimplify reality where essentially any sample will show variation in the outcome both within- and between-groups. MLM offers a comfortable middle ground to this issue via partial pooling. It takes into account both individual- and group-level variation, with estimates ranging between those of complete pooling and no-pooling, depending on whether group- or individual-level data contains more information. This is determined by sample sizes in each sampled group: a group with a large sample shows lower errors and so yields more information on the individual-level, whereas a group with a small sample shows larger uncertainty within individuals which leads to an estimate more reliant on the group-level calculations (ibid., p. 253). Since samples in any real-world setting land between these two extremes, MLM outputs for groups accordingly produces estimates between no-pooling and complete pooling, leaning towards one or the other in line with the sample structure.

Since my analysis looks at a total of three levels (individual, region, and country), MLM provides a suitable approach to analysing my data—by virtue of the data being hierarchical and as a result of preliminary classical regression tests. MLM allows for varying intercepts and/or varying slopes for different groups in the sample which substantially expands the possibilities to account for heterogeneity in distinct groups.

The research design is as follows. First, after cleaning the data (section 3.2) and presenting descriptive statistics (section 4.1), I ran preliminary analyses based on various specifications of classical regression (section 4.2). Afterwards, I fit preliminary multilevel models with ANOVA to determine the optimal structure for the final models in regards to the appropriateness of adding varying slopes (subsections 4.3.1-2). Finally, I tested the hypotheses using the five finalised models that focus on intercepts of Y, within-country variation, and between-country variation (subsections 4.3.3-4).

3.2 Data

In line with much of prior cross-national scholarship on polarisation, this study relies on data from the Comparative Studies of Electoral Systems, or CSES, namely the CSES Integrated Module Dataset, or IMD (https://cses.org/data-download/cses-integrated-module-dataset-imd/). This dataset contains harmonised data from modules 1 through 5. In total, CSES IMD contains around 395 000 individual-level observations, structured around 230 elections in 59 countries from 1996 to 2021, including respondent evaluations of the relevant political parties in each polity. Although some data from module 6 (2021-2026) are available as well, I do not include it in my research, partly due to time constraints with harmonising it with the IMD, and partly because the IMD contains enough data for this analysis. CSES IMD is the optimal choice for my research because it contains a large sample across Europe, includes individual like/dislike evaluations of relevant political parties which are the basis of most measures of affective polarisation, and contains identifiers of individuals' region of residence that allow me to look into disaggregated, regional trends.

For this study, the data was organised as follows. First, I excluded observations that do not fit the criteria for my sample: countries outside of Europe, sub-country units (Belgium (Flanders) and Belgium (Wallonia), since Belgium is in the dataset), and authoritarian regimes (Belarus, Russia). Then, I computed the indices for AP and party system IP and excluded rows with missing data for these indices. The resulting final sample contained 174 498 individual-level responses, corresponding to 115 elections in 29 countries, consisting of 300 regions within a time frame from 1996 to 2021. Region IDs and income quintile data for wave 5 (2016-2021) was not available in CSES IMD, but it was part of the separate wave 5 file in different coding—I added these values to my dataset manually. As CSES IMD does not contain data on income inequality, Gini index was sourced from the Databank of the World Bank (https://data.worldbank.org/indicator/SI.POV.GINI). Chapter 4 opens with an in-depth overview of the descriptive statistics for all variables.

The data structure, as this analysis specifies, has three levels: individual, region, and country. The individual level consists of the CSES respondent ID, focal variables, sociodemographic indicators (age, gender, education, household income), individual extremism. The region level contains only the region identifier as per the default CSES classification for the analysis. The country level includes country indicators and income inequality. This structure accounts for the clustering of focal variable values by space, although given the repeated cross-section structure of CSES IMD, clustering by time must be present as well. If the latter is to be included, election IDs may serve as an indicator of unique electoral contexts in time. However, I do not include this dimension for several reasons. First, both the country- and individual-level are integral to this research design as one holds X and the other holds Y, and the region-level was warranted due to its significance in prior research. As such, election-level would add a fourth layer on an already complex structure, not to mention also making it non-nested which complicates interpretation and uncertainty estimations. Second, while clustering by time is likely non-trivial, the time frame of 25 years in the sample is relatively short for a phenomena as entrenched as polarisation to vary substantially, especially in the mostly stable European electoral contexts throughout that period. Still, to mitigate this limitation at least in part, I separately computed standard errors by country and by election, and displayed these estimates side-by-side in the results section.

Having overviewed the data, the following section describes my variable operationalisation.

3.3 Operationalisation

I present the measurements and their indicators in my analysis starting from the focal variables, moving on to individual-level controls, and to country-level controls.

3.3.1 Focal variables

The focal relationship, i.e., the relationship between my predictor (X) and outcome (Y) variables, is that between **perceived party IP** and **individual AP**, respectively. The initial research plan aimed to measure party IP as an expert estimate of party IP for each country-year that I would compute using the Chapel Hill Expert Survey data and the perceived party IP index formula by (Dalton, 2008); however, data limitations discarded this option—merging CHES trend data from 1999 to 2024 and CSES IMD data reduced the total sample to only 25 elections, or less than a quarter of the current sample size.

The focal variables were measured as follows. The predictor, perceived party IP, follows the formula of the CSES Polarisation index by Dalton (2008), as per formula 1. This index is based on CSES survey items which ask respondents to rank every relevant party in their country on the left/right scale, and calculates the average party system ideology *PartySystemAverageLR*. Then, it subtracts that average from the evaluation of party *i*'s left/right score $PartyLR_i$, divides by 5 (as the midpoint of the left/right scale going 0 to 10), weighs by vote share of that party in the most recent election $vote_i$, and sums up the values, resulting in the Polarisation Index (PI) score. This index fits my purposes because it encapsulates perceived distribution of party ideology assessments in a straightforward manner, showing the average distance in respondents' minds between political parties, with weighted scores allowing to place more emphasis on larger parties. In my analysis, I use index values that are aggregated to the country-year level, by taking the mean of each country-year. This is to reduce noise and mitigate same dataset bias as both my X and Y variables are computed from data in the same dataset.

$$PI = \sqrt{\sum vote_i * (\frac{PartyLR_i - PartySystemAverageLR}{5})^2}$$

Formula 1. CSES Polarisation Index (CPI), by Dalton (2008, p. 906). I use this measure for Party System IP throughout the text.

For the outcome variable, individual affective polarisation, two options emerged due to a lack of clear scholarly consensus on the optimal measurement: the Spread-of-Scores index by (Wagner, 2021) and the Affective Polarisation Index by (Reiljan, 2020. pp. 380-381). These indices are inter-correlated (Reiljan, 2025, p. 119), based mostly on the CSES feeling thermometer items towards specific parties and are both weighed by party vote shares where affect towards larger parties is heavier, although their main difference is in the treatment of partisanship.

The Affective Polarisation Index presupposes a clear distinction of the in-party and all others as out-parties, and treats AP as distance from one's evaluation of their most liked party to their evaluation of other parties (formula 2). Respondents are grouped by the party they feel close to, i.e., the in-party *n,* and within these groups, average evaluations of the in-party and every out-party are computed. The relative AP of a party is then calculated as the distance between the average in-group evaluation *Like*$_n$ and the average out-group evaluation *Like*$_m$, weighted by the out-party *Vote share*^{m}. This calculation is repeated for every out-party and summed up into that party's relative AP, then by the same process relative AP is calculated for every other party in the party system. The final Affective Polarisation Index is a sum of these relative AP scores for each party, weighted by that party's own vote share.

$$API = \sum_{n=1}^{N} \left[\sum_{m=1, m \neq n}^{N} (Like_n - Like_m) \times \left(\frac{VoteShare_m}{1 - VoteShare_n} \right) \times VoteShare_n \right]$$

Formula 2. Affective Polarisation Index, by Reiljan (2020, p. 381). Common alternative measure, not used in my analysis for reasons presented in the text.

Overall, API offers a reliable method for measuring affective polarisation even in a multiparty environment, although two key issues arise when attempting to integrate it in my project. Firstly, API presupposes individual partisanship, excluding individuals with no clear party preference or more those sympathising with more than one party, all against the backdrop of declining relevance of partisanship towards electoral outcomes (Garzia et al., 2022, p. 328). Yet, even more crucially, the final estimates of API are by design aggregated and fixed to the country level as calculations are based on respondent groupings by their respective in-party. This index thus cannot measure AP on the individual level, which is the main focus of my analysis.

Instead, my thesis employs the Spread-of-Scores index by Wagner (2021) which addresses these limitations. The Spread-of-Scores index also begins with taking evaluations of all relevant parties in the party system, but does not designate in- and out-parties, which allows staying on the individual level as grouping respondents is not required. The value of the index (*Spread*$_i$ as per formula 3) for the individual *i* in a party system with *p* relevant parties refers to the distance between each party score *Like*$_{ip}$ and the mean of all evaluations by that individual *Like*$_i$, weighted by the *VoteShare*$_p$ from the most recent election to reduce distortions by weighting attitudes towards larger parties as heavier. (There is an unweighted version as well with a slightly different formula, but I omit it from my analysis: partly because of aforementioned concerns about data distortion by heavily polarising but small parties with limited relevance for their party systems, and partly due to how descriptive statistics in chapter 4 show nearly identical trajectories of both measures in most states of the sample.)

$$Spread_i = \sqrt{\sum_{p=1}^{p} VoteShare_p * (Like_{ip} - \overline{Like_i})^2}$$

Formula 3. Spread-of-Scores Index by Wagner (2021), weighted by vote shares. This is the measure I use for individual AP throughout the analysis.

Unlike API, the Spread-of-Scores does not require respondents to identify any specific in-party. As a result, the measure may comfortably stay on the individual-level as no groupings of respondents are required since no in-group and out-group distinctions allow the inclusion of non-partisans in the analysis. This broader treatment allows me not only to operationalise AP on the individual level, but also to see its trends on the regional level as per (Bettarelli et al., 2023), in addition to between-country variation which has almost exclusively been the focus of cross-national scholarship.

I used the polaR package in R (https://gitlab.com/felixgruenewald/polaR/-/blob/main/Readme.md) by Felix Gruenewald, who build the package as an addition to the online Encyclopedia of Political Polarisation. Namely, I employed functions to import the CSES IMD dataset directly together with the ready-computed values for both country-level CPI for each year and the non-aggregated, weighted version of Spread-of-Scores for each individual.

3.3.2 Other variables

Aside from focal variables, this analysis employed indicators, individual-level variables, and one country-level variable. The indicators are codes for identifying units and groups. I included the identifiers for respondents, regions, and countries in my dataset from CSES. Additionally, I created country-year and election (country + full date) identifiers that I used for descriptive statistics but not in any of the tests.

Individual-level variables include respondent age in years, gender as “male” or “female”, education on five levels (“No education / illiterate”, “Primary or lower secondary”, “Upper secondary”, “Post-secondary non-university”, and “University degree”), household income quintile (adjusted by CSES to each polity), extremism as the self placement on the left/right scale recoded to the distance from the centre, on a scale of 0 (centrist) to 5 (extreme left or right). Country level factors include only the Gini coefficient for income inequality, with values of 0 to 100 where higher values mean more inequality. Region and country IDs are included in the multilevel model as group indicators. For all of the above variables, where applicable, responses such as “Don’t know” or “Refused to answer” were recoded as missing values. For parsimony sake, education and income were recoded as numeric in MLM tests (whereas they were used as leveled factors in the preliminary tests).

Having described the methodology, data structure, and operationalisation, I conclude chapter 3 and transition to the results of the analysis.

4 Results

The current chapter overviews descriptive statistics of the sample, four preliminary OLS analyses, and hypothesis testing, concluding with additional findings that were not part of formal hypothesis testing.

4.1 Sample Description

In this section, I overview the descriptives of my sample. To reiterate, choosing only relevant rows resulted in a total sample of 174 498 individual responses from 281 regions in 29 countries, over 115 elections in the time spanning from 1996 to 2021, displayed in figures 2. Germany leads the chart with nearly 16 thousand of the respondents over seven elections while Croatia, Estonia, Montenegro, and Serbia only contain data from one election each. Sample mean lies at 4,0 elections and around 6 400 respondents per country. Each state has an average of 9,7 regions and each region has an average of 625 respondents.

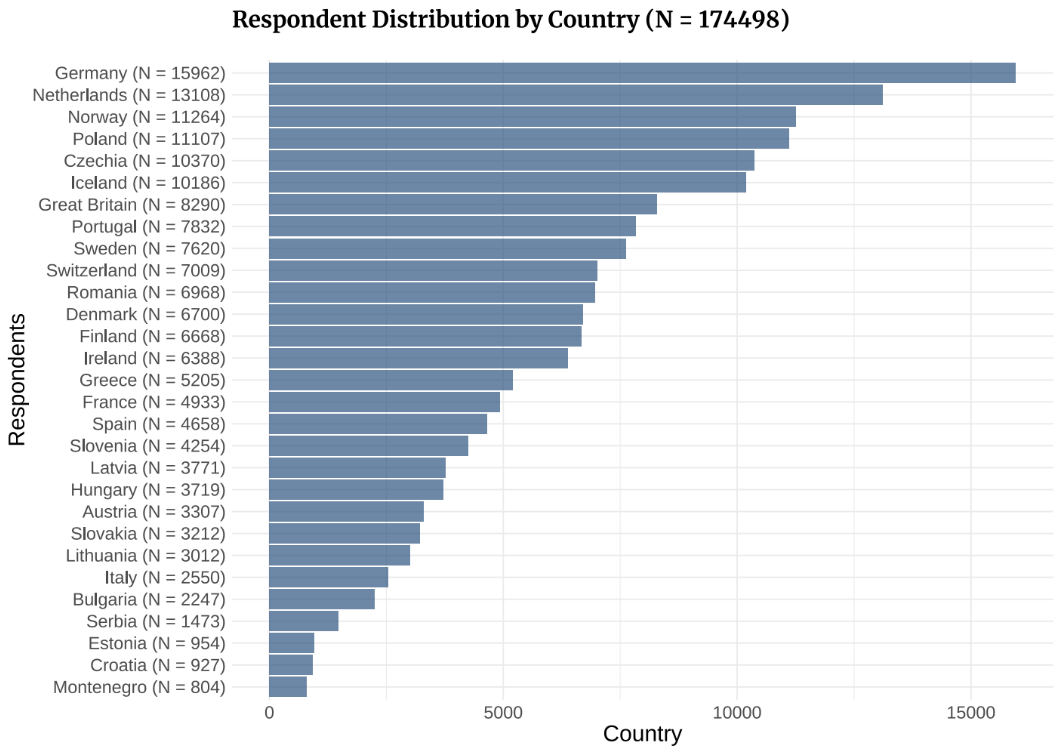

Figure 2. Total distribution of respondents by country.

Country	Elections	Country	Elections	Country	Elections
Austria	3	Greece	5	Poland	6
Bulgaria	2	Hungary	3	Portugal	5
Croatia	1	Iceland	7	Romania	5
Czechia	7	Ireland	4	Serbia	1
Denmark	4	Italy	2	Slovakia	3
Estonia	1	Latvia	4	Slovenia	4
Finland	5	Lithuania	2	Spain	4
France	3	Montenegro	1	Sweden	5
Germany	7	Netherlands	6	Switzerland	4
Great Britain	5	Norway	6		

Table 1. Sampled elections by country.

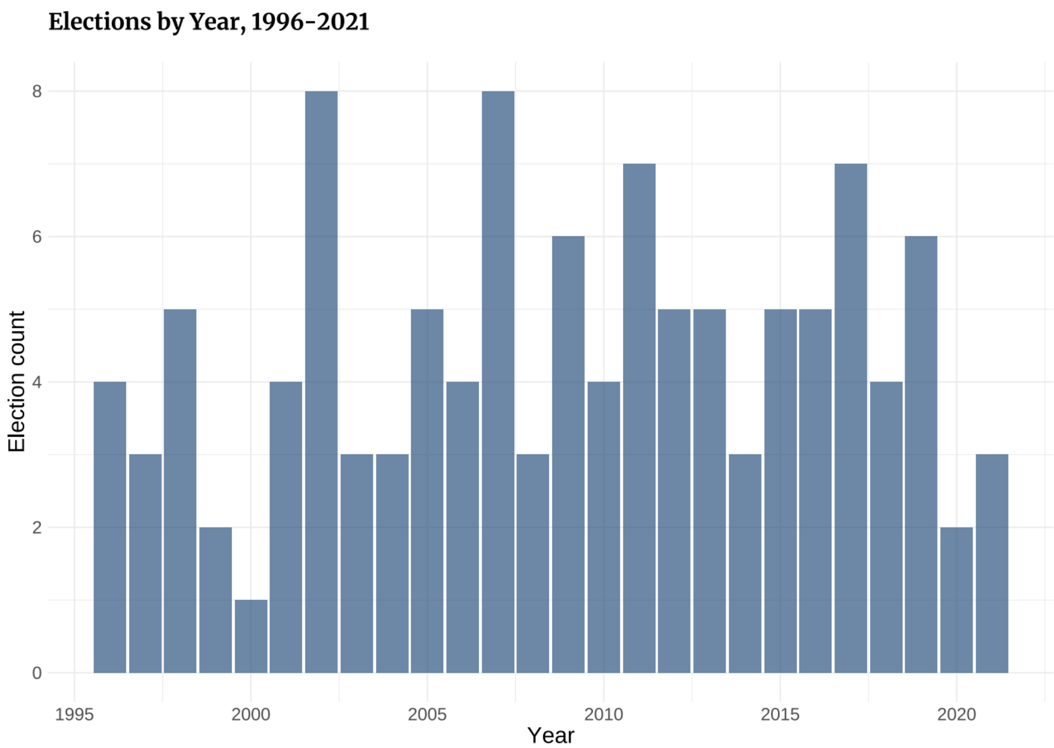

Figure 3. Sampled elections by year.

The following subsections present the distribution of respondents in terms of demographic factors and focal variables. I present two graphs for each variable: one facet plot representing variable distribution in every country, and one graph to display the overall sample trend with central tendency statistics where applicable. Total N slightly varies due to the removals of missing values before every graph generation.

4.1.1 Individual- and Country-Level Descriptives

Starting with individual sociodemographics, Figures 4 and 5 represent distribution by age. The former figure employs density plots instead of histograms due to large variation in respondent count between countries (see Figure 2 above) which would otherwise obscure distribution shapes in countries with fewer respondents. Regardless, most countries seem to follow a somewhat normal distribution in regards to respondent age, as does the sample overall.

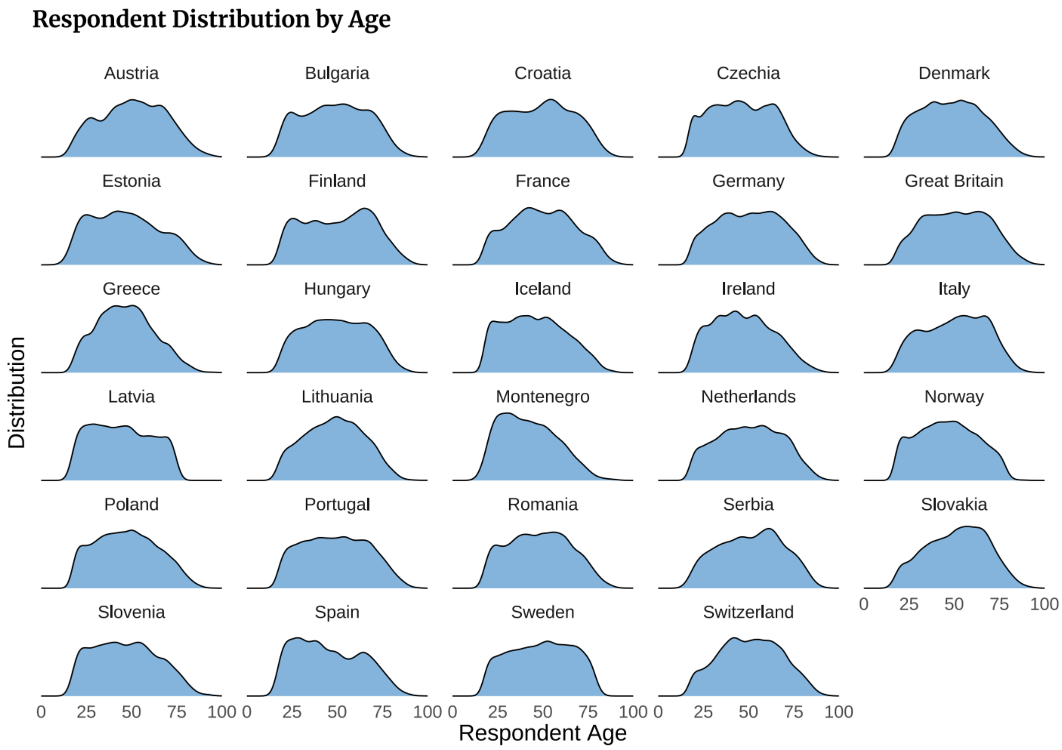

Figure 4. Density plot of respondent distribution by age in every sampled country.

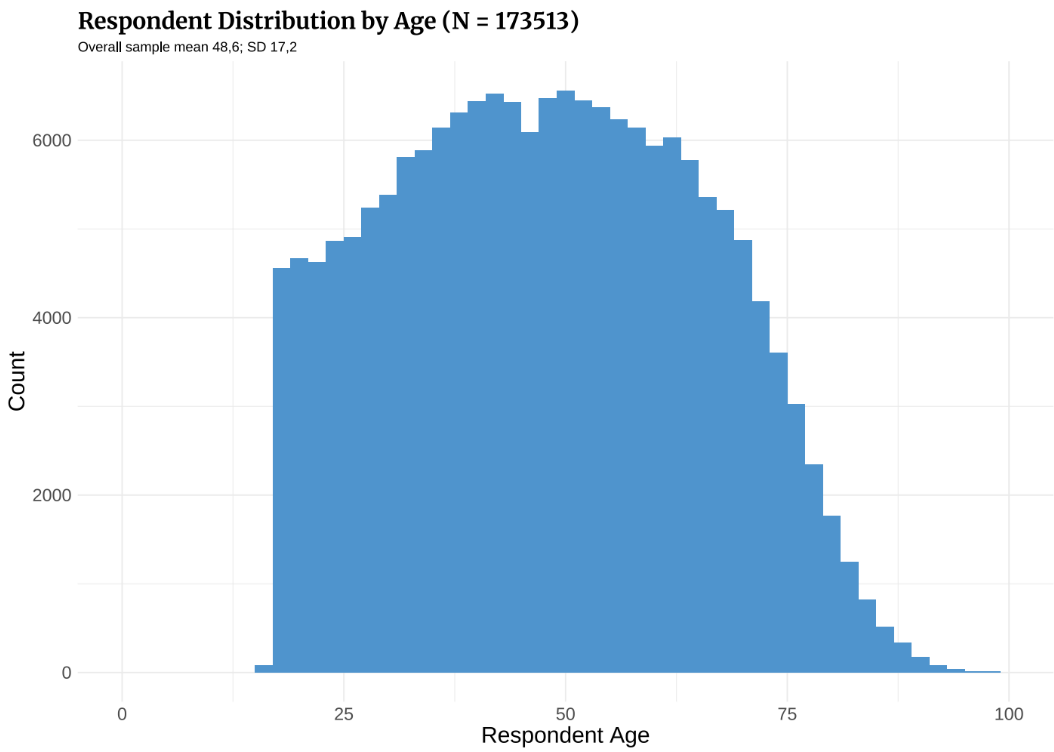

Figure 5. Overall sample respondent distribution by age.

Figures 6 and 7 display respondent distribution by gender. Both overall and in individual states, the sample is fairly balanced.

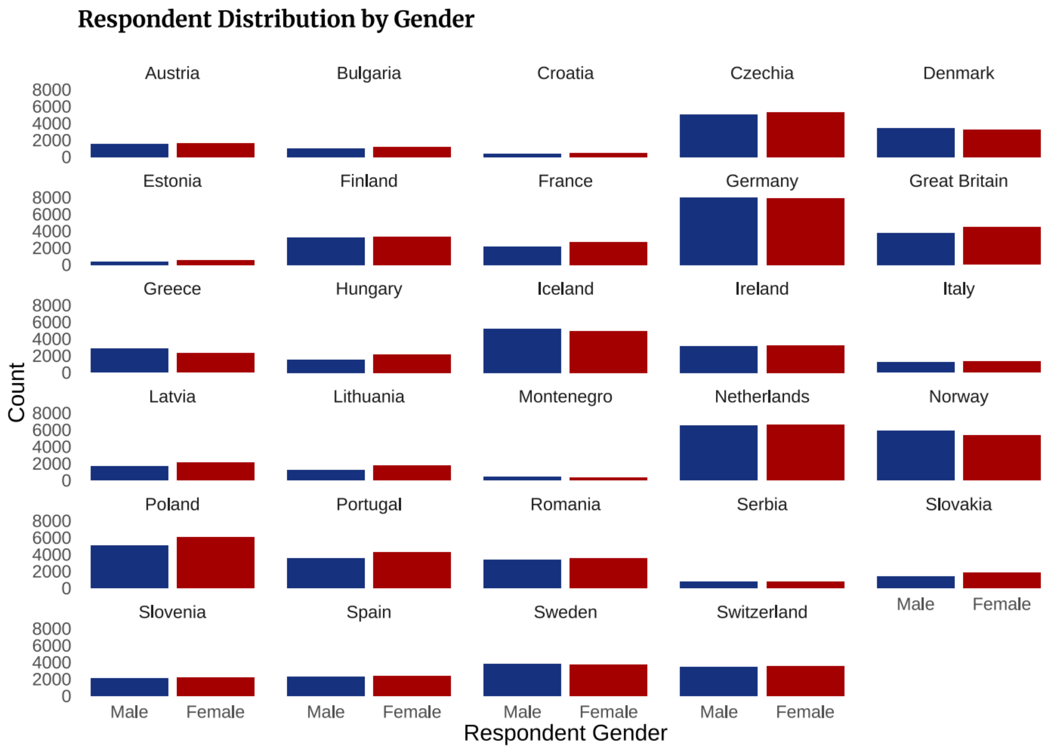

Figure 6. Cross-national respondent distribution by gender.

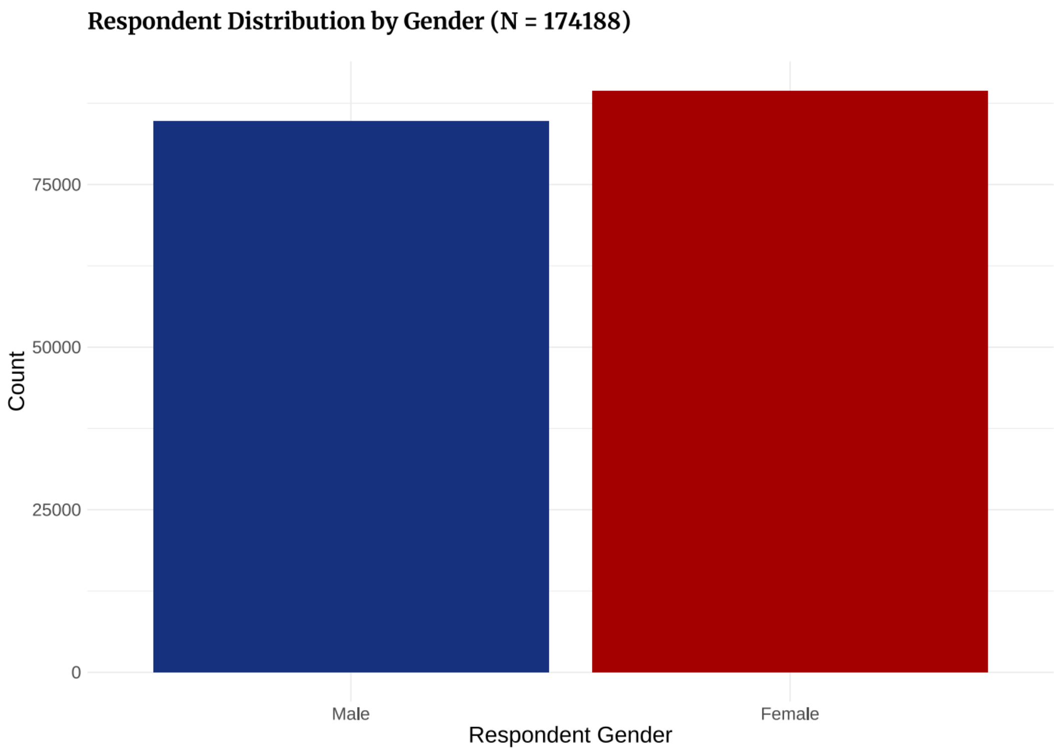

Figure 7. Overall respondents by gender.

Further, figures 8 and 9 overview education. Distribution patterns vary across nations. The largest group of respondents in the overall sample graph has *primary or lower secondary education*, although country facets show that several countries with overall large samples push that figure upwards (e.g., Czechia and Germany with 7 elections each) while in some other countries that is a significantly less populous group. Unique national education systems undoubtedly shape these patterns, already suggesting a degree of within-country variation in the upcoming analysis, in the case that education proves a significant determinant of affect.

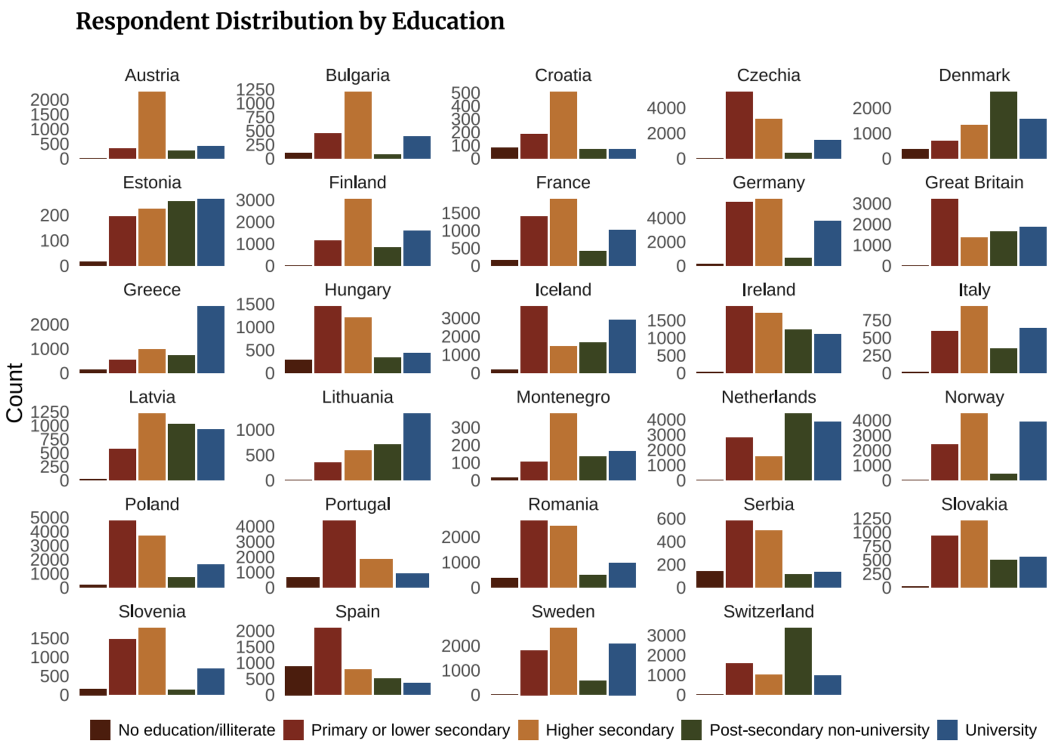

Figure 8. Cross-national distribution of respondents by education.

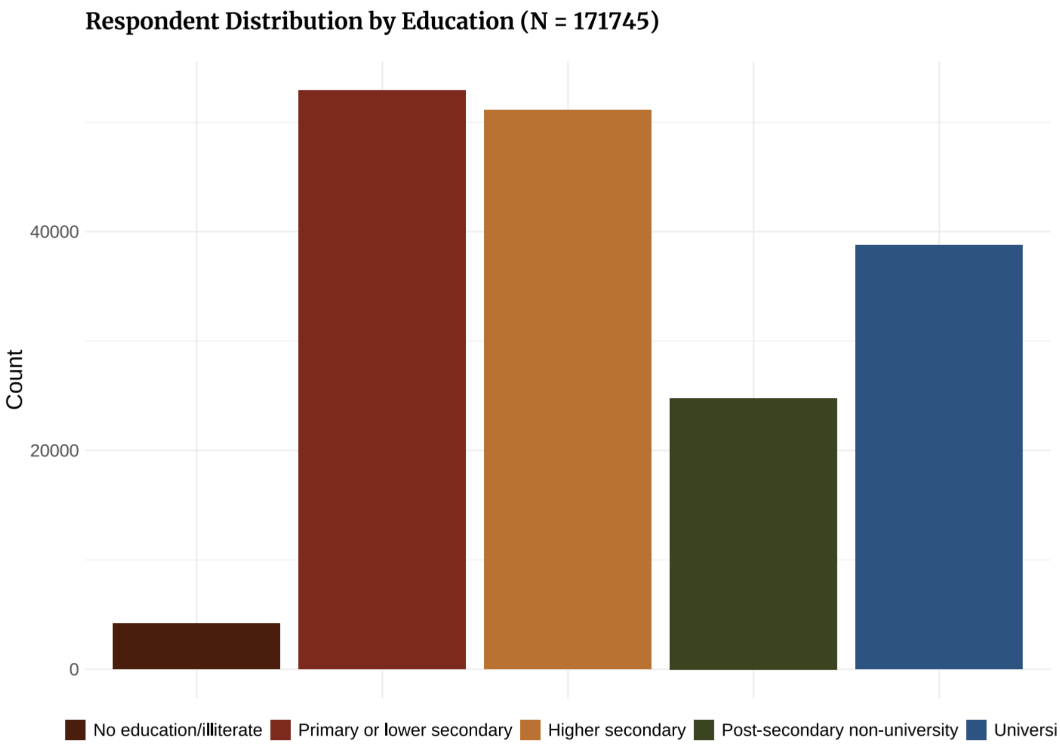

Figure 9. Overall sample distribution of education.

Next, figures 10 and 11 display respondents by household income quintile, adjusted to respective economies. Income distribution is fairly equal, which makes sense given that the operationalisation uses quintiles of the respective country sample and not quintiles of the entire sample or of the respective country's population. Still, Southern European states stand out with pretty drastic differences, especially Portugal. The largest issue about income data comes from the multitude of missing values. The CSES IMD as it stood had missing values here and there for most country-years, as usual, but income data was missing for all Lithuanian respondents as well as for all countries in the years 2017-2021 (module 5). Kept as is, this situation would have meant around 70 thousand missing values, leading to either excluding income from the analysis altogether or dropping these rows, thus discarding 5 most recent years of data and well over a third of all observations, including the entirety of one country. Thankfully, the income data for these years was available in the separate CSES Module 5 dataset which I manually added to the dataset. This way, 36 thousand values or 21% of all observations still have NAs for income, but the remaining missingness follows no obvious pattern and income data becomes visible for all sampled years up to 2021.

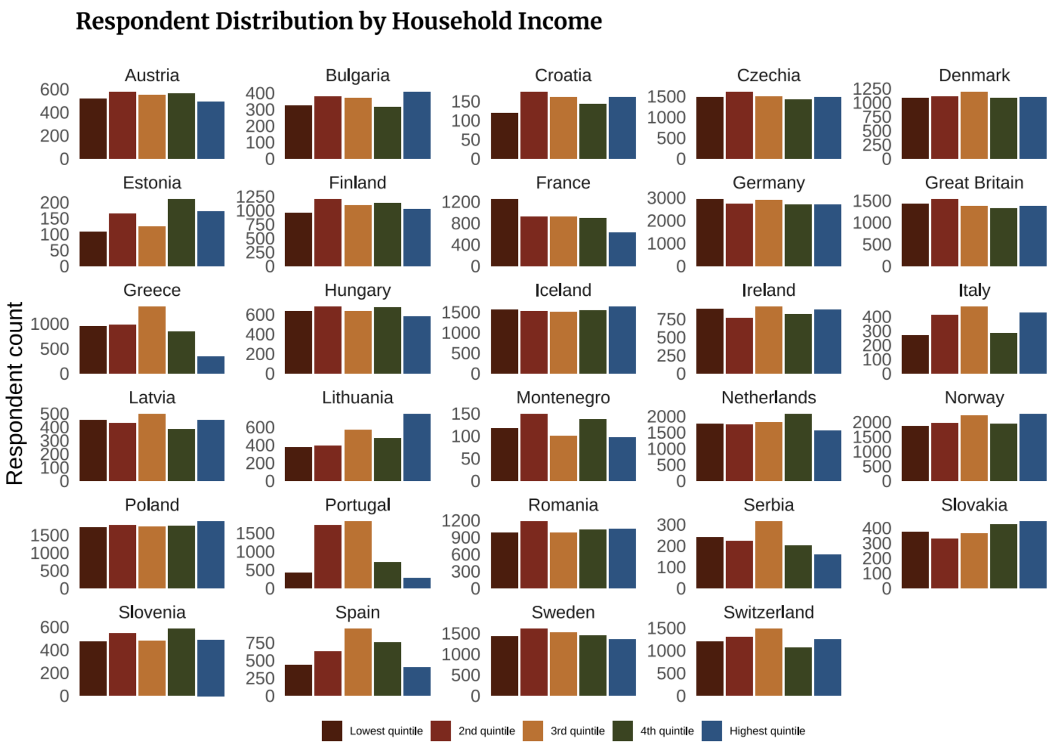

Figure 10. Cross-national respondent distribution by household income quintile.

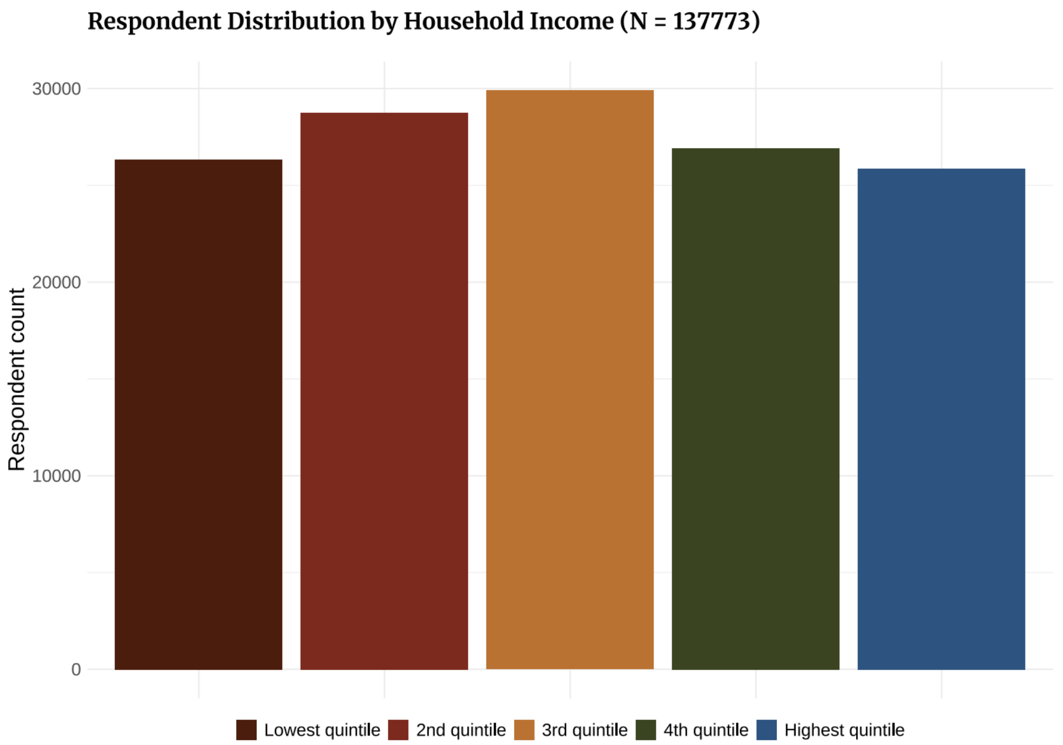

Figure 11. Overall sample distribution by household income quintile.

Following sociodemographics, figures 12, 13, and 14 show the distribution of individual extremism: faceted bar charts by country, overall sample bar chart, and line chart, in that order. A majority of respondents identify themselves as centrist or adjacent in nearly all countries. Notable exceptions are Montenegro and Romania where most see themselves as extremist and, surprisingly, the Nordics (excluding Iceland) where the most respondents place themselves as moderately left or right. Although country means over time varied somewhat, ideological extremism stayed largely stable and under the value 2, that is, closer to the centre than to the extremes, in most countries. Romania is the only clear outlier with mean extremism steadily rising, decreasing slightly, and shooting upwards to almost 4 as at 2021. Notably, around 20 thousand rows (nearly 12% of the sample) had NA for individual ideology with no distinct pattern of missingness.

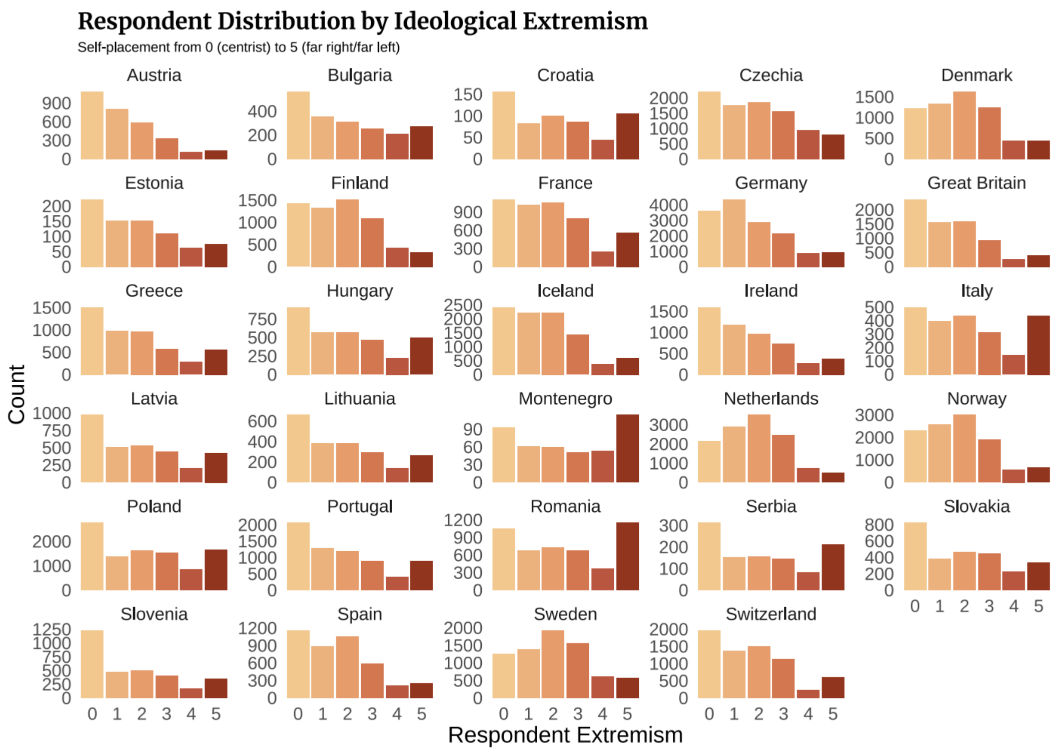

Figure 12. Cross-national trends of respondent ideological extremism.

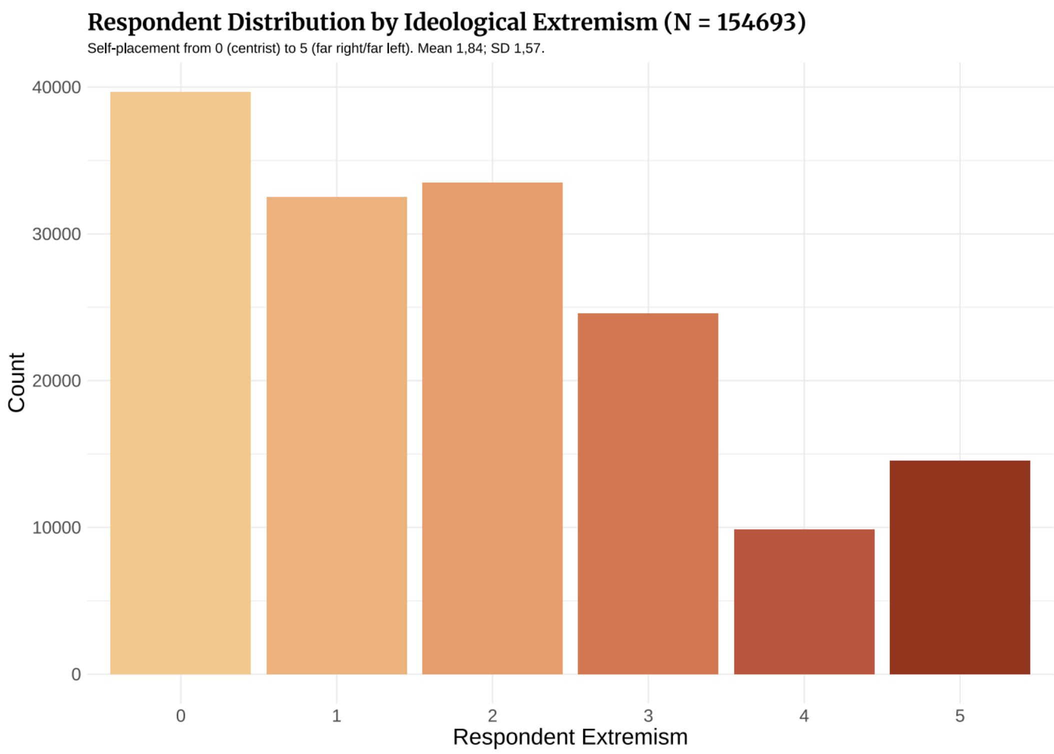

Figure 13. Overall sample trend of respondent ideological extremism.

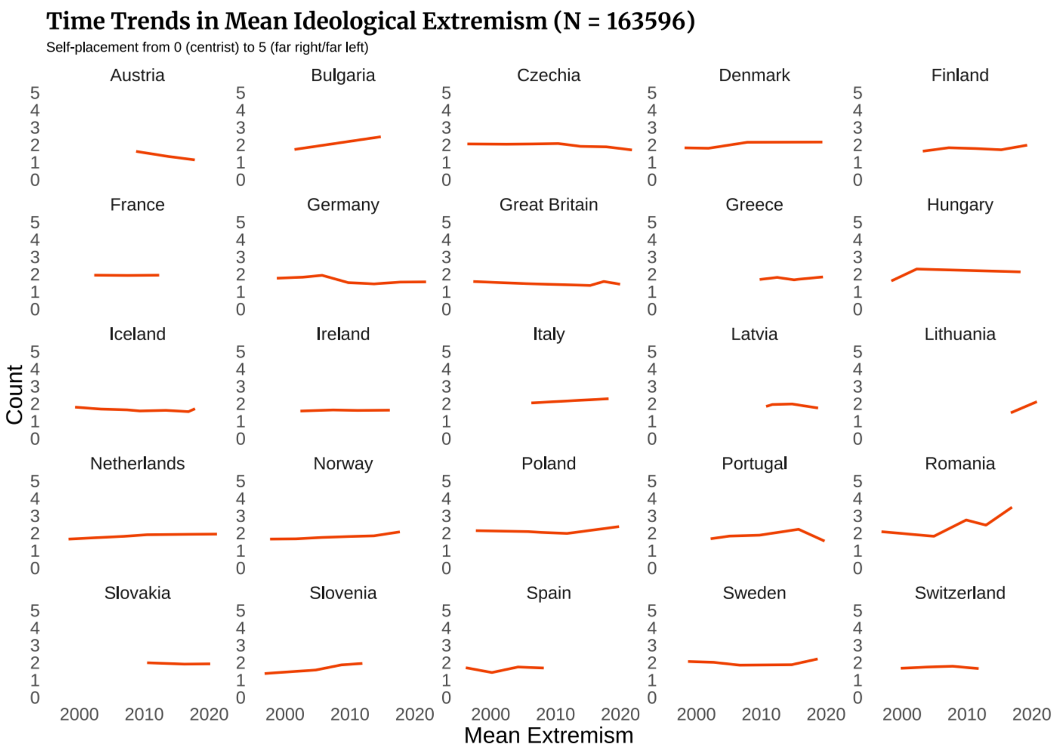

Figure 14. Cross-national trends in mean ideological extremism over time.

The final variable before moving to the focal variables is income inequality, measured here using the Gini coefficient. Croatia has only one election in the sample which comes from 2007 while the Gini index has no observations for that country-year, so that value is replaced with Croatia's value from 2008 and marked with an asterisk. Figure 15 and all subsequent time-series visualisations exclude countries with only one country-year in the sample (Croatia, Estonia, Montenegro, and Serbia). Income inequality ranges from least (24,5, Slovenia) to most prominent (41,2, Montenegro) with an overall mean of means at 31,9 and SD at 4,3. As per the Figure 15, income inequality values remain stable throughout the time frame, which is reasonable given how tangible changes in income inequality typically take generations.

Country	Gini mean	Country	Gini mean	Country	Gini mean
Austria	30,3	Greece	34,9	Poland	33,1
Bulgaria	35,5	Hungary	26,6	Portugal	35,3
Croatia	33,7*	Iceland	27,2	Romania	34,1
Czechia	26,2	Ireland	32,5	Serbia	39,9
Denmark	26,9	Italy	34,6	Slovakia	25,7
Estonia	32,5	Latvia	35,3	Slovenia	24,5
Finland	27,7	Lithuania	37,1	Spain	34,5
France	32,6	Montenegro	41,2	Sweden	28,6
Germany	30,5	Netherlands	27,8	Switzerland	33,6
Great Britain	34,1	Norway	27,7		

Table 2. Mean Gini index for every country of all sampled country-year observations.

Figure 15. Cross-national trends of income inequality over time, as mean Gini index for every country-year.

The following section overviews the descriptive statistics of the focal variables.

4.1.2 Focal Variable Trends

Focal variable visualisations in the subsequent figures focus on country-level trends in focal variables over the sampled time frame. To reiterate, these variables are perceived party system ideological polarisation (X) and individual affective polarisation (Y), operationalised as the CSES Polarisation Index and the Spread-of-Scores index, respectively. Perceived party system IP, notably, is aggregated to country level for these visualisations.

Figures 16 and 17 show the trends of party system polarisation. Notably, the Y axis is capped at 7 to prevent excessive white space in the graphs although the index values may range from 0 up to 10. Figure 16 shows that despite the rather sporadic data coverage, many states show an upward trend in party IP, even if some had seen decreasing values earlier, with only Italy consistently dropping across the whole time frame. Accordingly, the immediate takeaway of Figure 17 is an absence of any clear cross-national tendency, which is reasonable given that the documented lack of an evident pan-European direction of affective polarisation (Reiljan, 2025) might lead to analogous expectations to that of ideological disparities. Regardless, the data shows a general tendency towards higher party system IP in most European states.

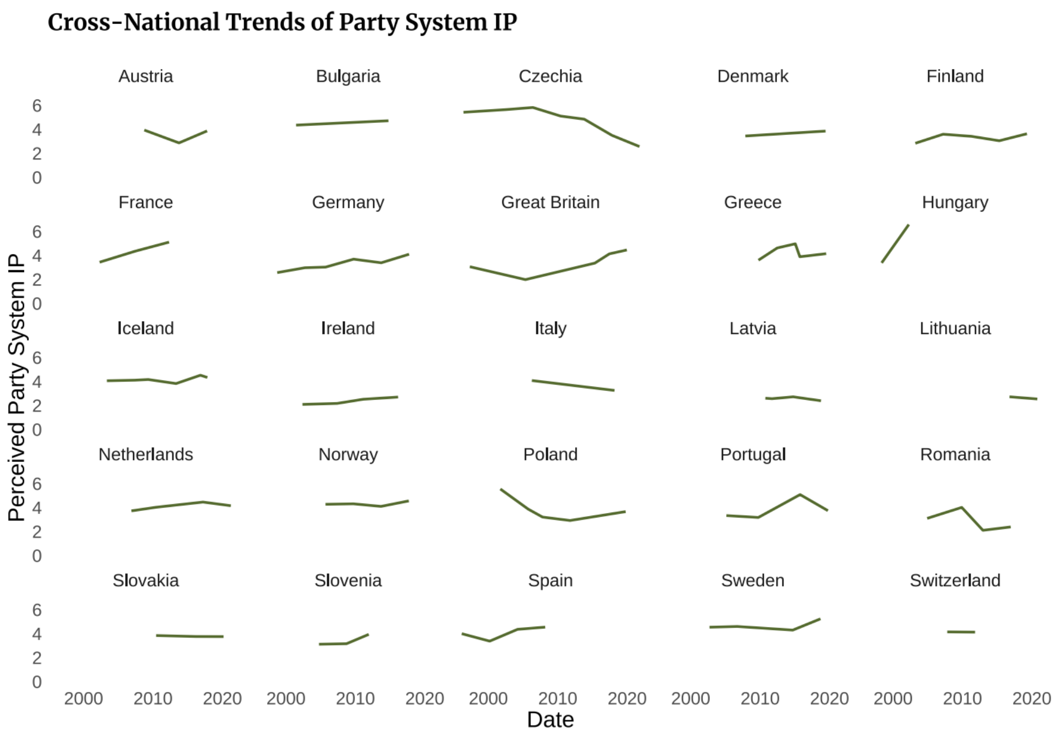

Figure 16. Cross-national trends of party system ideological polarisation.

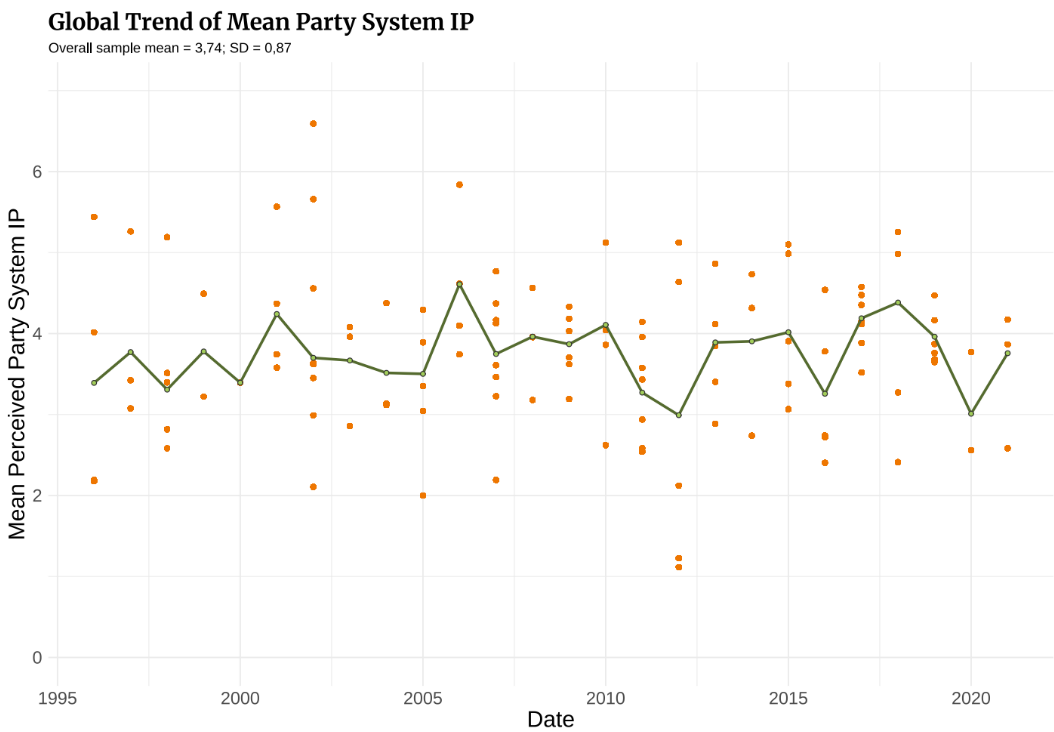

Figure 17. Overall sample trend of mean perceived party system ideological polarisation over time.

Finally, figures 18 and 19 show the time trends of individual AP. The Spread-of-Scores index comes in two variations: weighted by party vote share and unweighted, which I discuss in the operationalisation section. For my analysis, I chose the weighted version to reduce data distortions that may result from individuals feeling strongly negatively towards small parties that are hardly relevant to the party system at large. Another reason is that both versions show highly similar scores, which I illustrate in the following figures by picturing both variations of the index. The lines follow each other so closely that they often overlap, akin to the extremely close side-by-side comparisons of weighted and unweighted Spread-of-Scores in the seminal article (Wagner, 2021, p. 6). Since the empirical differences between the two measures are essentially negligible, I proceed with the weighted version onwards for reasons of theoretical interest.

Overall, AP seems remarkably stable in all sampled countries over the sample time frame. In figure 18, some curves bend slightly upward (e.g., Sweden) some turn downward (e.g. Portugal), others wiggle over time and end up almost the same as at the first observations (e.g. Germany, Greece). The latter tendency is even clearer in the global trend as per figure 19: fluctuations are common (mostly due to the estimates being tied to specific election dates and thus rather spread out), but are not extreme and seemingly pretty random as the curve hardly veers away from its initial value all throughout. The time series plots of AP indicate no evident trends aside from mostly subtle changes within countries over time.

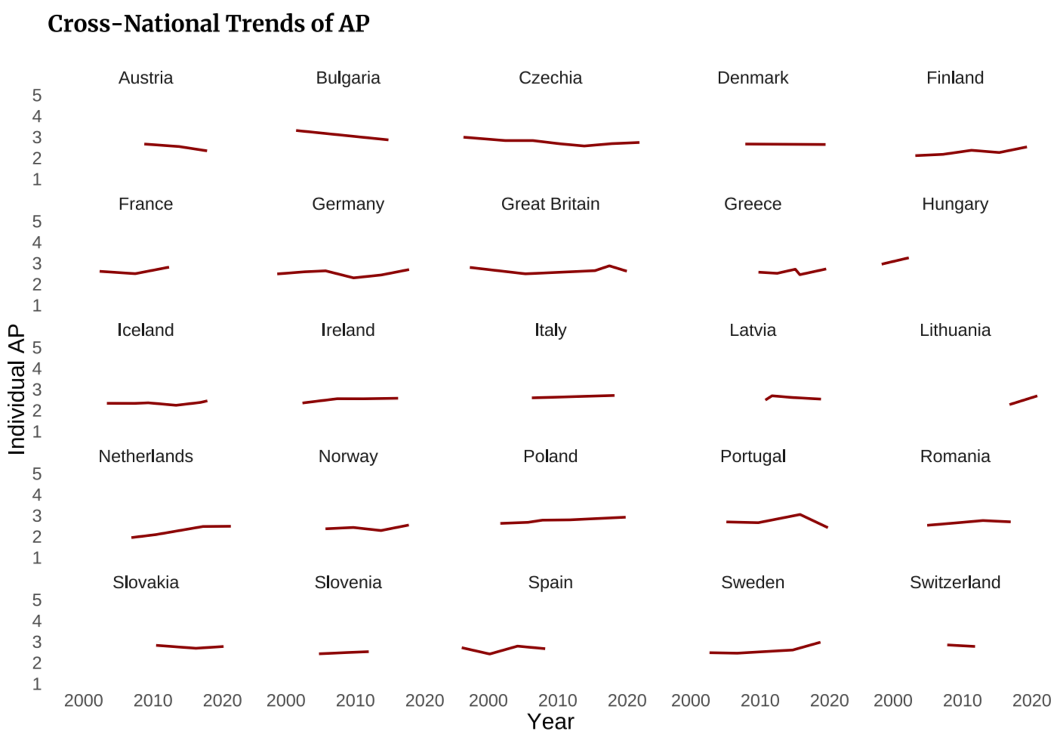

Figure 18. Cross-national time trends of individual AP, weighted and unweighted.

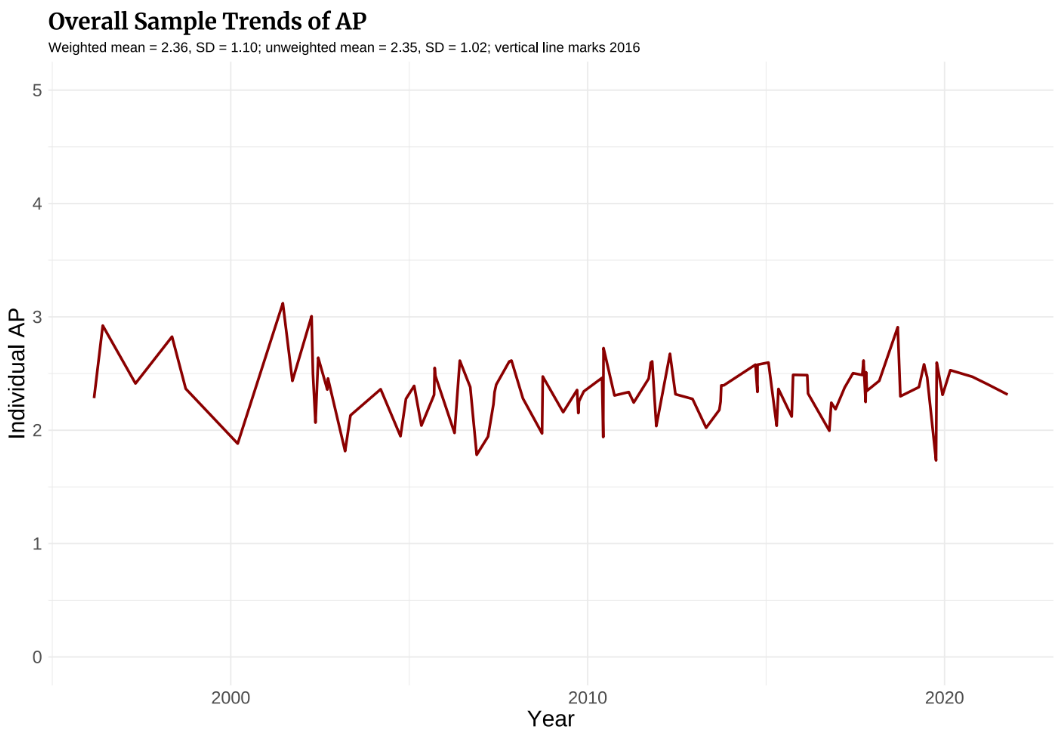

Figure 19. Overall sample trends of individual AP, weighted and unweighted.

Having overviewed descriptive statistics, I proceed to the preliminary testing.

4.2 Preliminary Modelling

Following Gelman & Hill (2006, p. 270), I conduct four initial tests on the final dataset to establish the relationship between party system IP and individual AP, variation different levels, and so prepare the ground for the final multilevel analysis. These steps are the complete pooling model, the no-pooling model, separate models for each country, and a two-step analysis (regression of the coefficients of the separate country models). I discuss the results of each step one-by-one.

4.2.1 Complete Pooling Models

The first test is a complete pooling model of the focal variables, ignoring group indicators. Such testing does not account for variation in the outcome over time nor between groups, but the simplicity of such a test makes it an appealing starting point to estimate the presence of any meaningful relationship between X and Y. I fitted two complete pooling models: one with only the focal variables, and one where I added controls but no region or country IDs. The results are displayed in tables 3 and 4.

Complete pooling model 1. The bivariate model, as per table 3, is highly statistically significant ($p < 0{,}001$) with barely any explanatory power ($R^2 = 0{,}008$). This is reasonable since the descriptive statistics (in line with literature) strongly suggested that no clear pan-European trend between party system IP and individual AP has been observed. Meanwhile, the focal relationship is evidently positive and remains statistically significant, even if weak: a 1-point increase in party system IP corresponds to only 0,107 point increase in individual AP. Figure 20 displays a density plot of the focal variables with a regression line for this bivariate model. Standard errors in all of the preliminary models are to be treated with caution as they are based on linear OLS models ("classical regression" in Gelman & Hill terms) which do not account for clustering—even though the data is by structure clustered both in space (countries, regions) and time (election years).

	Estimate	Std. error	95% CI
(Intercept)	1,957	0,011	1,94; 1,98
Perceived Party System IP	0,107	0,003	0,10; 0,11

Table 3. Estimates of complete pooling model 1.

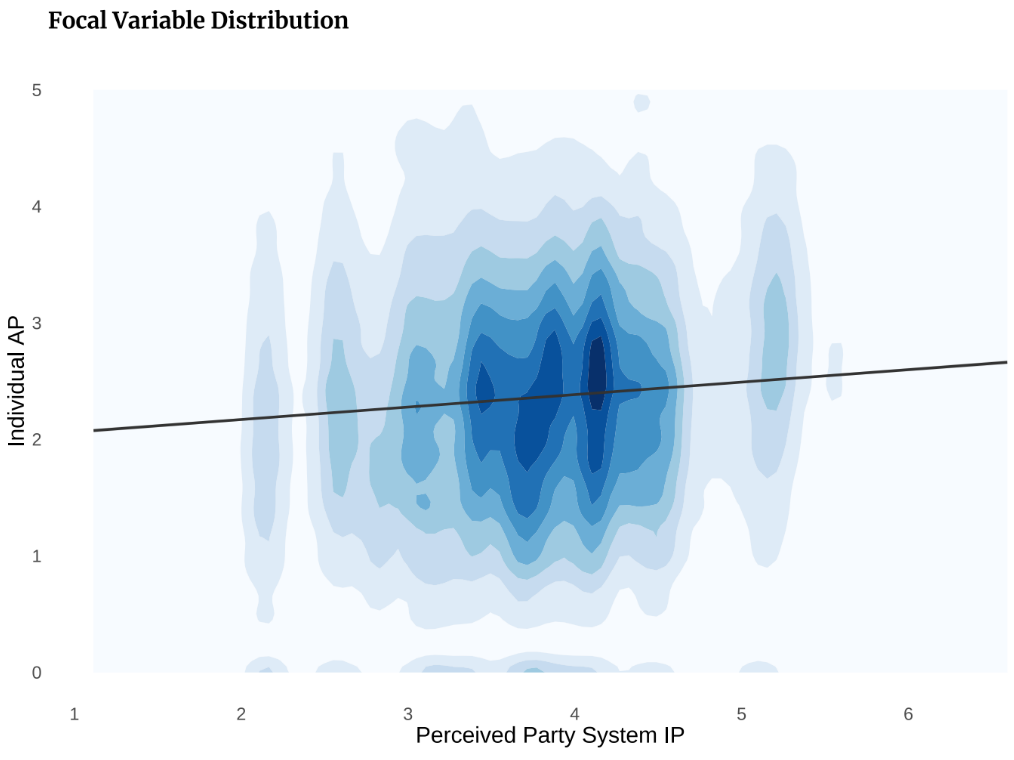

Figure 20. 2D density plot of the focal variables with a regression line representing the complete pooling Y ~ X bivariate model.

Complete pooling model 2. Table 4 presents the estimates for the second complete pooling model which adds controls (but no group dummies) to verify whether the focal relationship still stands. This model also shows high statistical significance ($p < 0{,}001$). The R^2 suddenly reaches up to 0,118 which affirms the role of other variables in explaining the link between party IP and individual AP.

Even though the 95% CI for all variables excludes 0, the focal relationship is slightly stronger in the expanded model. Interestingly, the effect of party IP is almost exactly the same that of extremism (given the former ranges 0 to 10, the latter from 0 to 5 and its estimate around double that of the former). This model reaffirms the significance of the focal relationship and suggests that its effect is not negated by the effects of sociodemographics, extremism, or income inequality.

	Estimate	Std. error	95% CI
(Intercept)	0,914	0,038	0,84; 0,99
Perceived Party System IP	0,115	0,004	0,11; 0,12
Age	0,004	< 0,001	0,004; 0,01
Gender: Female	0,076	0,006	0,06; 0,09
Education	-0,019	0,003	-0,02; -0,01
Income quintile	0,019	0,002	0,01; 0,02
Ideological extremism	0,213	0,002	0,21; 0,22
Income inequality	0,014	< 0,001	0,01; 0,02

Table 4. Estimates of complete pooling model 2.

The following subsection proceeds to the next step in preliminary testing: the no-pooling model.

4.2.2 No-Pooling Models

This stage of preliminary testing employs an inverted logic compared to the previous one. Whereas complete pooling ignored between-group variation, no-pooling exaggerates it by fitting a classical regression with only the focal variables and the group identifiers. Following (Gelman & Hill, 2006, p. 255), the no-pooling models all follow the basic structure: *Y ~ X + group ID - 1*. The *-1* in this case removes the global intercept for the whole model, due to which the model estimates represent the intercept of AP in that group, without taking any group as a reference. In my analysis, two variables act as group identifiers (region ID and country ID), therefore I fitted two no-pooling models: one with country IDs and one with region IDs. A third model with both group IDs might be possible, but not in this scenario since regions are fully nested in countries and such a test would thus be uninformative and largely redundant. The purpose of no-pooling tests is to establish whether intercepts of individual AP vary to a meaningful extent between countries and between regions.

No-pooling model 1. Table 5 presents some of the estimates of the first no-pooling model with only country IDs on top of the focal variables. This model adds 29 country dummies on top of the focal variables. As a result, the R^2 soars upwards to 0,82, which suggests significant share of variation in AP explained by differences between countries, but is likely inflated to some degree by the count of parameters and overfitting that tends to be inherent to no-pooling. The focal relationship, crucially, remains almost identical to that in the complete pooling models, showing that the association between perceived party IP and individual AP holds just as well when controlling for country differences.

	Estimate	Std. error	95% CI
Perceived Party System IP	0,114	0,004	0,11; 0,12
Austria	1,959	0,024	1,91; 2,01
Bulgaria	2,377	0,03	2,32; 2,44
…			

Table 5. Estimates of no-pooling model 1.

Figure 21 visualises the estimated country intercepts that correspond to the *Estimate* column in table 5. These values range from 1,52 to 2,38 with a mean at 1,97, and SD at 0,21, showing notable variation given that the total range of AP of 0 to 5. In line with literature and descriptive statistics, these results suggest that the base levels of polarisation are notably distinct in different European nations, which explains why no clear pan-European trend occurs in the data. Additionally, despite such local differences in affect levels, the positive effect of party IP on affect remains present and essentially identical to that in prior tests, meaning it is not explained away by the different AP baselines in countries.

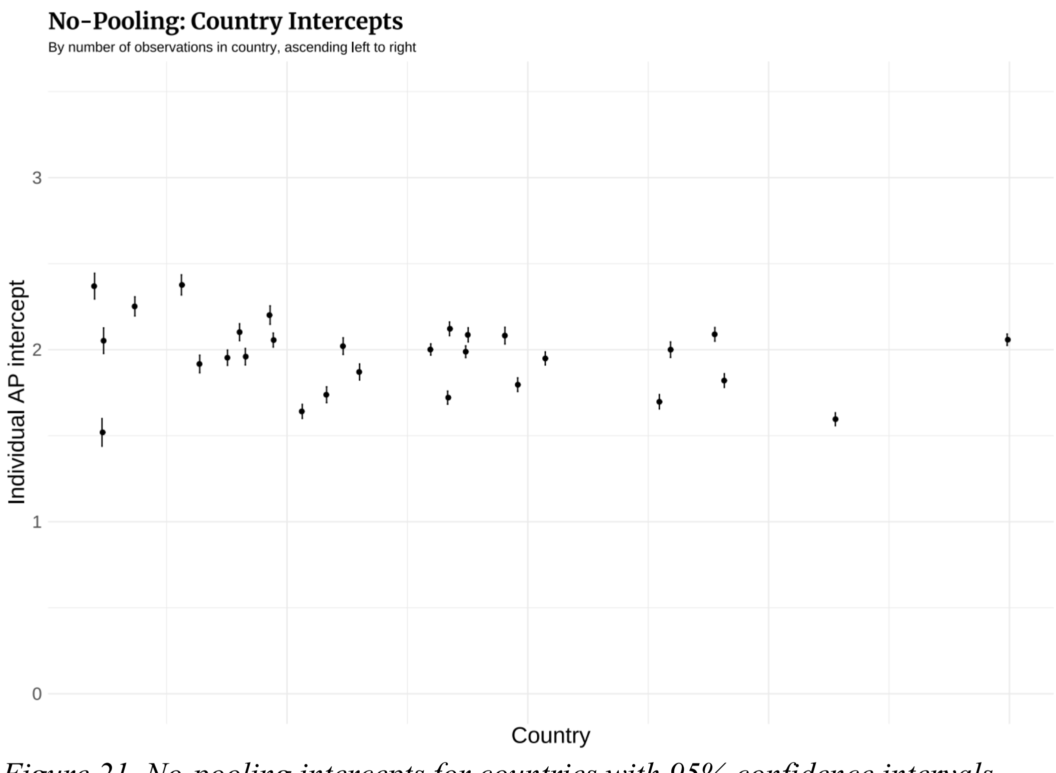

Figure 21. No-pooling intercepts for countries with 95% confidence intervals.

No-pooling model 2. The second no-pooling model conducted the same test with region IDs instead of countries with the results presented in table 6. With 301 region dummies added on top of the focal relationship, the resulting model displayed high statistical significance ($p < 0,001$). The R^2 at 0,829 is nearly identical to that of the first no-pooling model, likely resulting from how regions are nested within countries. Curiously, the focal relationship turned out slightly stronger than in prior models at 0,122 points increase in AP for 1-point increase in perceived party IP, although largely remains stable (compared to 0,114 in the prior model).

	Estimate	Std. error	95% CI
Perceived Party System IP	0,122	0,005	0,11; 0,13
Region 1040	1,937	0,100	1,74; 2,13
Region 1100	2,370	0,16	2,07; 2,68
…			

Table 6. Estimates of no-pooling model 2.

Figure 22 displays these estimates/region intercepts visually with bars for 95% confidence intervals. As respondent counts in regions was skewed towards the lower end, this figure order countries by log respondent count instead of raw values. With intercept value mean at 1,91 and SD at 0,27, AP varies notably among regions. Although region intercept values spread nearly twice as wide as country intercepts, uncertainty with regions is noticeably higher (particularly in regions with lower sample sizes) and partly contributes to the extremes. Still, even though the confidence intervals vary in width rather noticeably, the 95% CI does not include 0 for any region and the overall picture shows that intercepts vary among regions nonetheless.

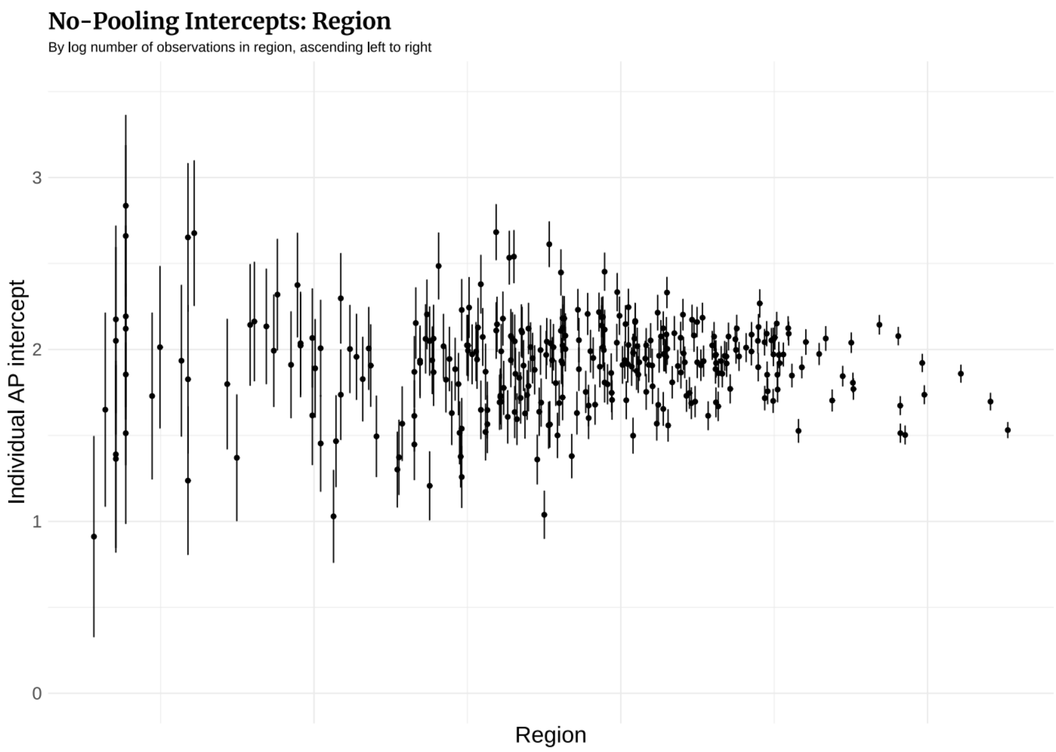

Figure 22. Individual AP intercepts for regions with 95% confidence intervals..

The no-pooling models presented the intercepts of AP for different countries and regions. The next section looks into the slopes of the focal relationship.

4.2.3 Separate Country Models

Step three of preliminary testing is fitting separate classical regression models for each group, i.e., every country and every region. The purpose of this step is to continue investigating within-group variation, but unlike no-pooling which estimated intercepts for groups, separate models estimate the different slopes, further probing into how appropriate the data structure is for a multilevel model. This section presents two sets of models, one for countries and one for regions. In both sets, the regression formula run on every group contains only the focal relationship and, to at least partially account for the particular contexts, the election ID. As a result, rows with only one election available (Croatia, Estonia, Montenegro, Serbia, and by extension their regions) are excluded from this step because they only have one value of X available since X is aggregated to the country level. Accordingly, a key limitation of these models opens up in this regard: separate groups only have between 2 and 7 distinct values of X throughout the whole sample. Still, the main goal of this step is to demonstrate that slope differences are present in an exploratory manner.

Separate country models. The first set of models computed such models for each country, containing 25 models. An immediate takeaway is that 4 of these models are statistically indistinguishable from zero: for Denmark and Spain, the focal relationship fails significance tests by either p-values or 95% CI, while Latvia and Slovenia show, in addition to the same issue, an overall model p-value of over 0,006. Figure 23 portrays the slopes of the remaining 25 countries, centered at the (0; 0) point for comparability. The results show extreme variation: 16 slopes are positive and 8 are negative; the mean slope rests at 0,326 (almost triple that of the coefficient estimated in complete pooling at 0,115) with SD at 2,27.

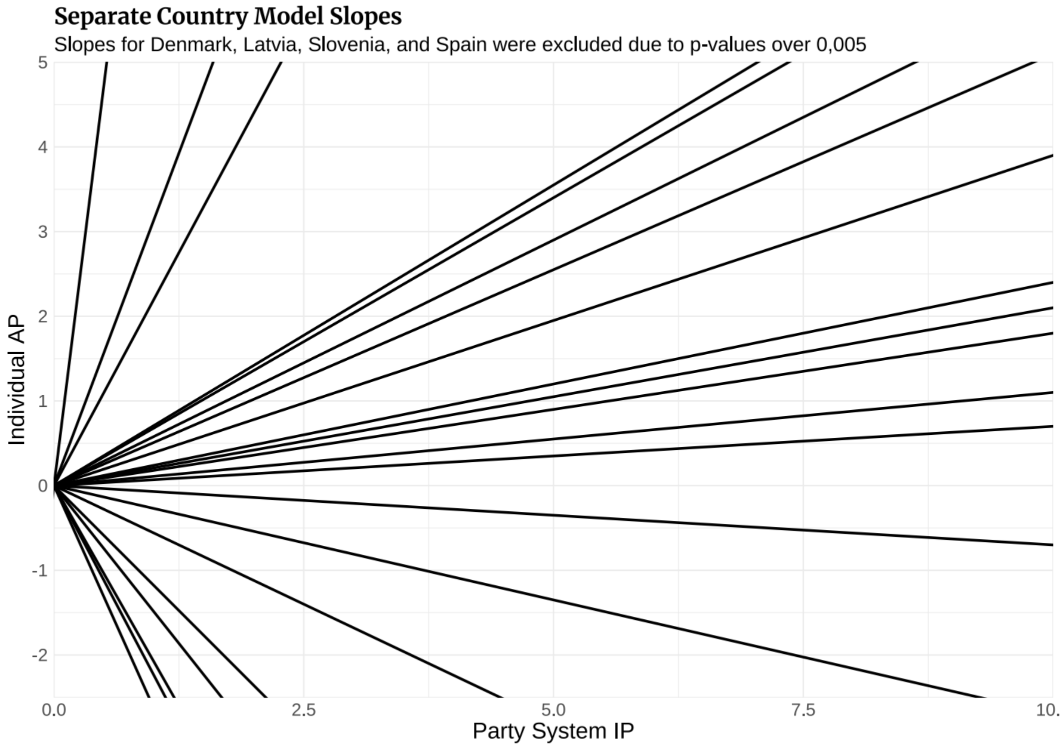

Figure 23. Focal relationship slopes for each country as per separate country models.

Separate region models. The second set of models computed the same for regions. After excluding regions in countries with only one election and regions with fewer than 100 observations, 236 region models were fitted within 24 countries. (Ireland is excluded from this part altogether as its region IDs are absent in the data altogether.) In 154 of these models, the focal relationship had a p-value over 0,006, likely due to low levels of information in those particular regions. To account for that and to simplify comparisons, I aggregated I aggregated slopes to country level using country means of region slopes, weighted by N. Table 7 shows these results. The mean of the aggregated slopes is 0,445 (compared to 0,311 in the country-level separate models and 0,114-0,122 in preceding models) while SD is extremely large at over 2,2.

	Country slope	Aggregated region slope
Austria	3,14	3,42
Bulgaria	-1,49	-1,83
Czechia	0,21	0,09
Denmark	0,11	0,09
Finland	0,71	0,72
France	0,11	0,13
Germany	0,24	0,24
Great Britain	-0,07	-0,07
Greece	0,39	0,03
Hungary	-0,27	-0,28
Iceland	-2,08	0,54
Ireland	0,68	*NA*
Italy	-0,56	-0,41
Latvia	0,04	0,03
Lithuania	-2,63	-2,60
Netherlands	0,58	0,62
Norway	0,18	0,18
Poland	0,07	-0,54
Portugal	-2,24	-2,20
Romania	-1,18	0,15
Slovakia	2,20	2,58
Slovenia	0,04	0,05
Spain	-0,01	-0,04
Sweden	9,47	9,18
Switzerland	0,51	0,57

Table 7. Estimated slopes in the country- and aggregated region-level models.

The results of the separate models are admittedly noisy in both sets of models, containing extremely widespread values of group level slopes and significantly higher uncertainty, which is most likely due to few available unique values of X within each group. These tests subtly suggest that the relationship between Party System IP and Individual AP in European states generally tends to be positive, but just as importantly, they suggest a degree of heterogeneity in the focal relationship across places not only in terms of degree but also direction. These outputs add to the case for the suitability of a multilevel model for the subsequent analysis as partial pooling accounts for these limitations.

4.2.4 Two-Step Analysis

As the fourth and final step of the preliminary analysis, I ran the two-step analysis. Following Gelman & Hill (2006), the two-step analysis mean fitting a classical regression on the group-level with group predictors, but instead of using the raw outcome variable values as before (Individual AP), it involves taking the estimates from the separate group-level models. Since Y then represents group-level slopes, it contains information of not only Y but the X-Y relationship.

Consequently, the two-step analysis does not include X in the formula as it is already summarised in the slopes, which are then regressed against the group-level predictors. In the context of my analysis, the only such predictor is income inequality. Since I have no predictors on the region-level, I do not fit a two-step analysis model for regions, but focus only on countries. The purpose of this test is to see whether the variation in the estimated focal relationship between countries can be explained away by country-level predictors.

Table 8 presents the findings of this model. With a model p-value of 0,105, the result decisively discards the statistical significance of income inequality in explaining the variation of the focal relationship among countries. This outcome is not unexpected given the instability of the slope estimates in the previous step. Regardless, the insignificance of income inequality in this model may suggest either the lack of a relationship, or the fact that modelling without partial pooling misses these effects.

	Estimate	Std. error	95% CI
(Intercept)	6,443	3,650	-1,11; 13,99
Income inequality	-0,197	0,117	-0,44; 0,04

Table 8. Estimates of the two-step analysis model.

This test concludes the preliminary tests which, albeit oversimplifying the data in different ways, offered distinct insights and justified the need to use multilevel analysis. Complete pooling disregarded within-group variation, found a weak, but significant positive relationship between Party System IP and Individual AP. No-pooling took the other extreme, taking only within-group variation, and found that the focal relationship holds when controlling for country and region indicators and that group-level intercepts vary substantially. Separate group models, albeit with low explanatory power due to few unique X values per group, showed large variation in estimated focal relationship slopes both among countries and regions. The two-step analysis showed that income inequality does not single-handedly explain the variation in the focal relationship between countries. Together, these findings suggest that a positive and significant relationship likely exists between Party System IP and Individual AP; that both baseline level of AP and slopes of the focal relationship vary notably across countries and possibly regions; and that this variance is probably not simply explained away by income inequality.

With the groundwork laid clear, the next section details the core of the analysis: the multilevel models fitted to test my main hypotheses.

4.3 Hypothesis Testing

This section presents the results of the tests for each hypothesis one by one. Afterwards, it overviews other additional findings outside of the hypothesis tests. The analysis overall involved five multilevel models, with three levels each. The first of these, an intercept-only model (M0) with only AP and varying intercepts for testing variance in different levels, is discussed in the subsequent additional findings section as it does not directly test hypotheses. The other models were split by the specification of X to separate between- and within-country trends (Party System IP centred at the global mean for the former and at the country mean for the latter). Accordingly, two models only have the focal variables and group indicators (M1 for between-country and M2 for within-country effect), and two models with controls added (M3 for between-country and M4 for within-country effect). All four models play a role in the testing of each hypothesis and thus are discussed one by one.

4.3.1 Intercept-Only Model

Before the main testing, I ran an intercept-only model with only Individual AP and group IDs ($Y \sim 1 + (1 \mid country{:}region) + (1 \mid country)$) to investigate the extent of variation in AP across levels. With the global mean of AP at 2,36, error standard deviations are 0.21 for the country level, 0.12 for region-level, and 1.08 for the individual level. The values of country intercepts with conditional SD terms

Computing ICCs showed 3,6% of variation clustered between countries and 1,2% clustered between regions within countries. Although the remaining 95% is clustered on the individual level, one takeaway is that both countries and regions-within-countries show non-trivial clustering of individual affective polarisation rates. These results somewhat corroborate the main finding of Betarelli et al. (2023) in that variation of affective polarisation within countries is also significant, albeit in my sample between-country variation is larger. The added value of a disaggregated approach becomes all the more evident given the fact that theirs is the only cross-national study to my knowledge that has investigated AP on the subnational level so far.

Figure 24 shows all of the country-level intercepts in a caterpillar plot, whereas figure 25 depicts box plots for region intercepts at each country, centred at the global mean AP. Country intercepts show considerable variation, although no obvious pattern stands out at either end. While countries with the highest AP intercepts may seem to be post-communist states in the East with the top five scores including Bulgaria, Hungary, and Poland, the second and third highest values belong to Denmark and Sweden. Further yet, the other Nordic states of Finland and Iceland show up near the opposite end of the list. While such disparities are not out of line in the Nordics per se—Sweden and Denmark have been observed with a notably higher AP than the other states (Ryan, 2023, p. 69) —such a case is harder to make with regards to other parts of Europe without a more in-depth analysis.

Region-level intercepts reveal some more insights. Figure 25 depicts them in the same ordering as the prior chart, although the landscape seems immediately different. Some countries show barely any regional heterogeneity in baseline

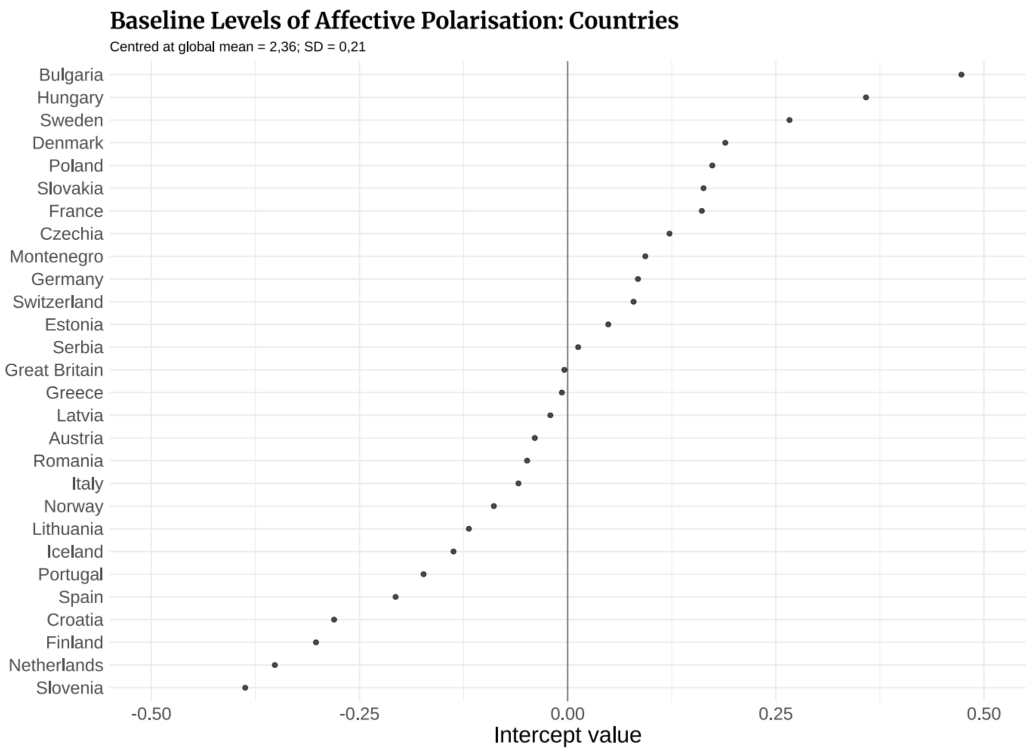

Figure 24. Individual AP intercept values in countries, as per the intercept-only model M0.

Region-level intercepts reveal some more insights into within-country heterogeneity. Figure 25 depicts them in the same ordering as the prior chart, although the landscape seems immediately different. Some countries like Denmark or the Netherlands show barely any regional heterogeneity in baseline affect levels, many others yield extreme variety. More generally, a trend seems to emerge in that countries in East and South Europe tend to have a larger spread in region intercepts, with Bulgaria and Spain as clearest examples. If reordered by the mean of regional intercepts, the rankings would shift somewhat (e.g., Spain would top the list), although this is expected given the generally tight clustering of country AP intercepts around the grand mean.

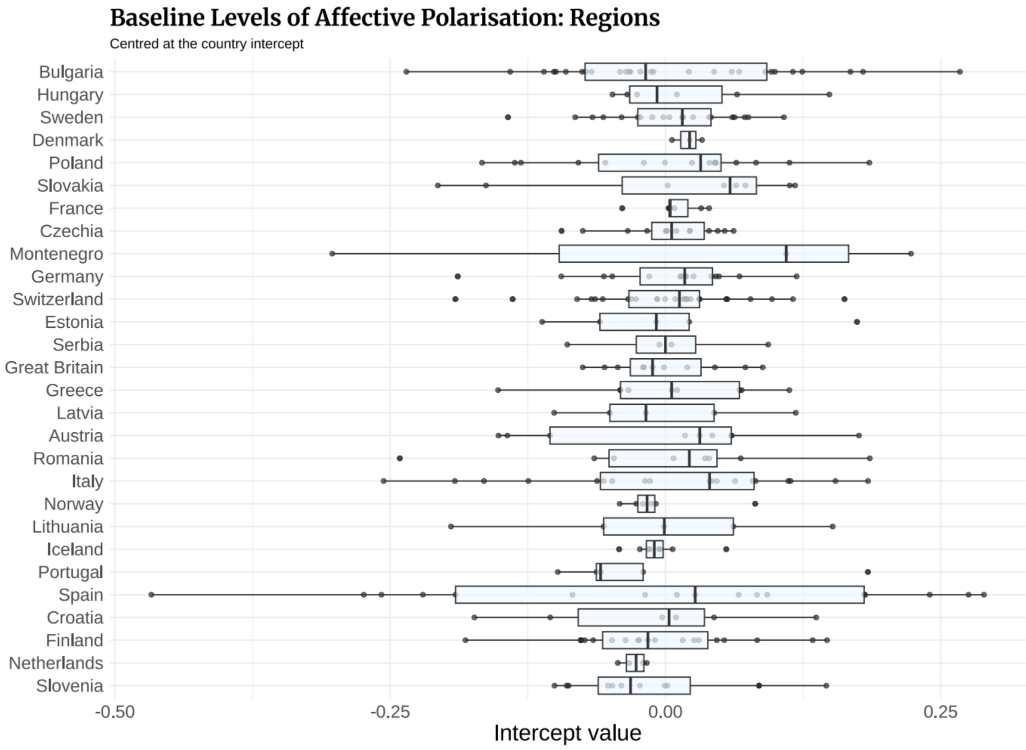

Figure 25. Individual AP intercepts in regions as per M0, centred at and ordered by country intercept, highest to lowest.

With initial AP levels in countries and regions established, the following subsection presents the procedure for specifying whether the subsequent models should use varying slopes ("random effects").

4.3.2 Determining Model Structure

Before the main analysis, I used Analysis of Variance (ANOVA) tests to verify if adding varying slopes improves the fit of either bivariate model. To achieve that, I fit the same two models first with varying intercepts only, then with varying intercepts and varying slopes, and compared both with ANOVA. I ran these tests on the between-country bivariate model (M1), then on the within-country bivariate model (M2). Since Party System IP is aggregated to the entire party system in corpore, i.e., at the country-level, variation does not take place in regions. Accordingly, the suitability of adding varying slopes is only tested for countries.

The below tables present the results of these two ANOVA tests. The first ANOVA test was run on the between-country model M1, as per table 9. Since the more complex model showed slightly higher AIC (+2) and BIC (+21) values than the previous one and the p-value of the test rest far above the threshold of statistical significance, varying slopes do not improve model fit. For this reason, between-country models M1 and M3 hereafter contain varying intercepts but not varying slopes for countries.

	Number of Parameters	AIC	BIC	p-value
M1 (fixed slope)	5	456133	456183	
M1 (varying slope)	7	456135	456204	0,266

Table 9. ANOVA results for M1.

The second ANOVA test on M2 produced the following results, displayed in table 10. Adding varying slopes has notably reduced AIC (-1230) and BIC (-1209) values, and the overall test p-value falls below 0,001. In line with these results, the within-country models employ varying intercepts and varying slopes.

	Number of Parameters	AIC	BIC	p-value
M2 (fixed slope)	5	455518	455567	
M2 (varying slope)	7	454288	454358	< 0,001

Table 10. ANOVA results for M2.

To reiterate, all four models have varying intercepts, and ANOVA indicated that only within-country models benefit from the added complexity of varying slopes. The following formula represents the two most complex models, M3 and M4.

$$AP_{irc} = \gamma_{000} + \gamma_1 * IP_c + \gamma_2 * \mathbf{Z}_{irc} + u_{0c} + v_{0r} + \epsilon_{irc};$$

where AP_{irc} is the Spread-of-Scores index (Y) of the individual *i*, in region *r*, in country *c*; γ_{000} is the global intercept; IP_c is the CPI (X) for the country-year; Z represents controls; γ_1 and γ_2 are regression coefficients for IP and controls respectively; u_{0c} and v_{0r} are the country and region intercepts, respectively; ε_{irc} is the error term.

The analysis consisted of five models in total. M0, the intercept-only model, contained no IP and no Z. Bivariate models M1 and M2 contained every element in the above formula except Z. Expanded models M3 and M4 reflected the formula completely. IP is specified differently in models: M1 and M3 use IP centred at the grand mean to measure between-country effect while M2 and M4 have IP centred at the country mean to measure within-country effects. The latter two models, as per the ANOVA tests, also contain varying country slopes for X.

Before continuing to the discussions of MLM results, the process of generating standard errors deserves clarification. CSES data is clearly clustered in both space and in time. Given the stable character of both of the focal variables over relatively short time span of the study, the hierarchical models only account for clustering in space but not in time, as briefly discussed in section 3.2. Meanwhile, MLM SE generation in *lme4* is by default ignorant of clustering and tends to exaggerate effect estimate accuracy as a result. Several approaches exist for separately computing more accurate values, with bias-corrected estimation of cluster-robust SEs, called *CR2VE* in (Cameron & Miller, 2015, p. 25), as preferable in my case; yet, the extensive hardware requirements compared with the large sample of this study render this option impractical. Additionally, the two-way clustering renders the data structure non-nested (as years/elections do not fall under countries/regions nor vice versa), which further complicates the procedure of estimating more accurate standard errors. As a compromise, I employed the regular Cluster-Robust Variance Estimator (CRVE; ibid.), at times referred to as the *sandwich* algorithm, to compute two additional standard errors for every parameter in the models: one clustered by country (in space) and one clustered by election. (Election ID with country name and full date is preferable over country-years to avoid conflating cases where the same country has more than one election the same year). These estimates are, crucially, still biased in that their functionality is most appropriate for regular OLS models. However, they present a useful benchmark that is closer to the truth than the default model SEs, all the while acting as a robustness checks. Accordingly, model output tables in following subsections present all three SE estimates for each parameter side-by-side.

With the model structure clarified and uncertainty estimation procedures outlined, the following subsections discuss the results of each of the four remaining models.

4.3.3 Bivariate Models

Bivariate models are M1 and M2, which only include the focal variables (Party System IP and Individual AP) and region and country IDs. M1, the bivariate between-country model, uses X as centred at the global mean, namely 3,77. Error term SD varied from 0.21 on the country level to 0.12 in regions, and 1.08 between individuals. The average between-country estimate was statistically insignificant. As a result, the test finds no evidence for an overarching focal relationship. This finding falls in line with literature that claims no evident pan-European AP trend (e.g., Reiljan, 2025) as well as with the preliminary tests of separate country models where the focal relationship was found to vary highly across countries not just in scope but in direction, suggesting no observable cross-country tendency.

	Fixed effects estimate	Std. Error (model) *(clustered – country)* ***(clustered-election)***	95% CI (min; max)
(Intercept)	2,366	0,041 *< 0,001* ***0,019***	2,23; 2,45
Party System IP	0,055	0,044 *< 0,001* ***0,024***	-0,03; 0,14

Table 11. Estimates of the between-country model without controls, M1.

M2 ran the same test as M1, except centering X at the corresponding country mean so as to capture within-country variation. Error SD amounted to 0,22 on the country-level, 0,12 on the region level, and 1,07. Here, likewise, the focal relationship appears slightly positive but statistically indistinguishable from the global mean, as the effect estimate is eclipsed by all of the three estimated standard errors. The intercept/slope correlation is negative at -0,08, showing countries with higher baseline AP tending to have a marginally weaker focal relationship estimate.

	Fixed effects estimate	Std. Error (model) *(clustered – country)* **(clustered-election)**	95% CI (min; max)
(Intercept)	2,366	0,042 *< 0,001* **0,019**	2,28; 2,45
Party System IP	0,085	0,181 *0,012* **0,011**	-0,28; 0,45

Table 12. Estimates of the within-country model without controls, M2.

Figures 25 depicts the random effects, i.e. deviations of each country slopes from the fixed effects estimate of the preceding table 12, with bars at 2 conditional SD. Naturally, the four countries with only one election each show extremely large conditional SD, although Lithuania and Slovakia also hold rather high standard deviations, likely due to rather small samples at around three thousand individuals in each, while also representing the two most distant points from the overall estimate. Other countries, except for Bulgaria, largely fall close to the fixed effects estimate. Nine countries have a slope higher than 0.

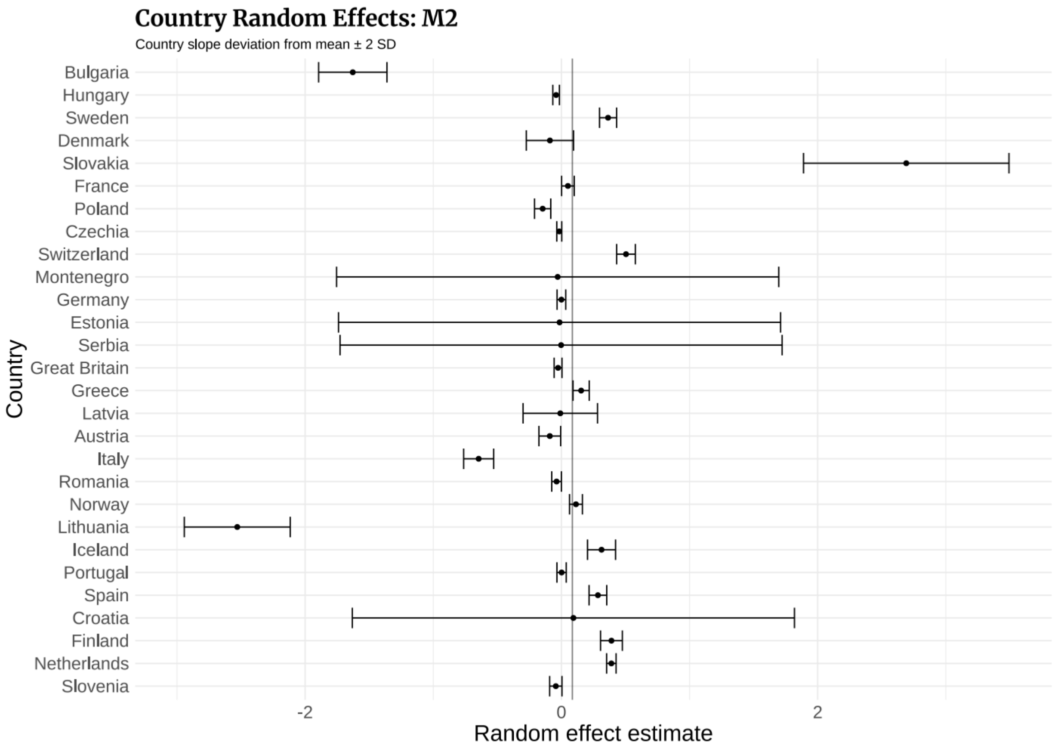

Figure 26. Varying slopes by country in the bivariate within-country model, M2.

Both bivariate models find no statistically significant link between Party System IP and Individual AP. These results lead to the conclusion that no meaningful relationship between the focal variables remains that is not explained away by accounting for country- and region-level contextual differences in the sampled states. The ways that the interplay between Party System IP and Individual AP manifests itself seems highly context-dependent, and so much so that the degree of heterogeneity argues against trends between countries as well as within. One way or another, concluding the discussion of the bivariate models, **H1** – that Individual AP is positively affected by Party System IP within countries – is clearly **rejected.**

The following subsection describe M3 and M4 that test the remaining two hypotheses.

4.3.4 Expanded Models

Models M3 and M4 correspond to the previous two models, but include controls. Due to the removal of missing values for the controls, the resulting N is significantly lower at 91 941 individuals in 300 regions within 28 countries. Missingness does not follow any clear spatial nor temporal patterns, aside from Gini index data being missing for all entries from 1999. Both models have varying intercepts while M4 employs varying slopes as well, in line with ANOVA tests described above.

Table 13 presents the results of M3, the expanded between-country model with fixed slopes, centred around the global mean IP at 1,73 which is notably lower than that of the prior bivariate models. Error SD remains similar to prior models at 0,21 for the country level and 0,12 on the region level, although drops to 0,97 on the individual level. The effects of Party System IP remains statistically indistinguishable from zero, alongside those of income inequality, as per respective confidence intervals. Gender and education show estimates that may seem significant upon first glance, but clustered standard errors effectively cancel out the tiny effect estimates. Age and income quintile show slight, but significant positive influences on AP, although by far the strongest and the most decisive estimate is that of individual extremism which exceeds that of all other variables combined at over 0,2-point increase in AP for each 1-point increase in extremism.

	Fixed effects estimate	Std. Error (model) *(clustered – country)* ***(clustered-election)***	95% CI (min; max)
(Intercept)	1,731	0,083 *0,093* ***0,138***	1,57; 1,89
Party System IP	0,602	0,045 *0,006* ***0,027***	-0,03; 0,15
Age	0,004	< 0,001 *< 0,001* ***< 0,001***	0,004; 0,005
Gender: Female	0,007	0,006 *0,010* ***0,009***	0,05; 0,08
Education	0,007	0,003 *0,009* ***0,010***	0,001; 0,014
Income quintile	0,010	0,003 *0,005* ***0,005***	0,005; 0,015
Individual extremism	0,213	0,002 *0,012* ***0,007***	0,21; 0,22
Income inequality	< 0,001	0,220 *0,003* ***0,004***	-0,003; 0,005

Table 13. Average estimates for the between-country model with controls, M3.

The next and final model, M4, has a slightly lower global mean intercept of 1,638. Error SD remains at 0,23 on the country level and 0,12 on the region level, nearly identical to the bivariate models, although individual-level error SD is at 0,97. Average effects of Party System IP are, likewise, statistically indistinguishable from the global mean, as is the case for education and income inequality. Older individual with higher income and women are more likely to show higher Individual AP, but by an exceedingly thin margin. Individual extremism, however, stands out as a comparably strong predictor with a distinctly strong and significant positive correlation to affect.

	Fixed effects estimate	Std. Error (model) *(clustered – country)* **(clustered-election)**	95% CI (min; max)
(Intercept)	1,638	0,010 *0,053* ***0,075***	1,45; 1,83
Party System IP	0,129	0,148 *0,002* ***0,015***	-0,16; 0,43
Age	0,004	< 0,001 *< 0,001* ***< 0,001***	0,004; 0,005
Gender: Female	0,068	0,006 *0,010* ***0,009***	0,06; 0,08
Education	< 0,001	0,003 *0,008* ***0,008***	-0,006; 0,006
Income quintile	0,012	0,003 *0,005* ***0,005***	0,007; 0,017
Individual extremism	0,211	0,002 *0,011* ***0,007***	0,207; 0,216
Income inequality	0,004	0,003 *0,001* ***0,002***	-0,001; 0,009

Table 14. Average estimates of the within-country model with controls, M4.

Figure 26 depicts the deviations of each country slope from the average effects laid out in table 14. Compared to the results before adding controls, the picture seems rather similar with Lithuania and Bulgaria still at the opposite extremes, with Bulgaria further away from the mean towards the negatives, and the Netherlands drifting slightly further towards the positive direction. Only seven countries have a positive slope. A notable negative correlation between slopes and intercepts at -0.25 shows that countries with higher general AP levels tend to show a weaker effect of Party System IP on Individual AP.

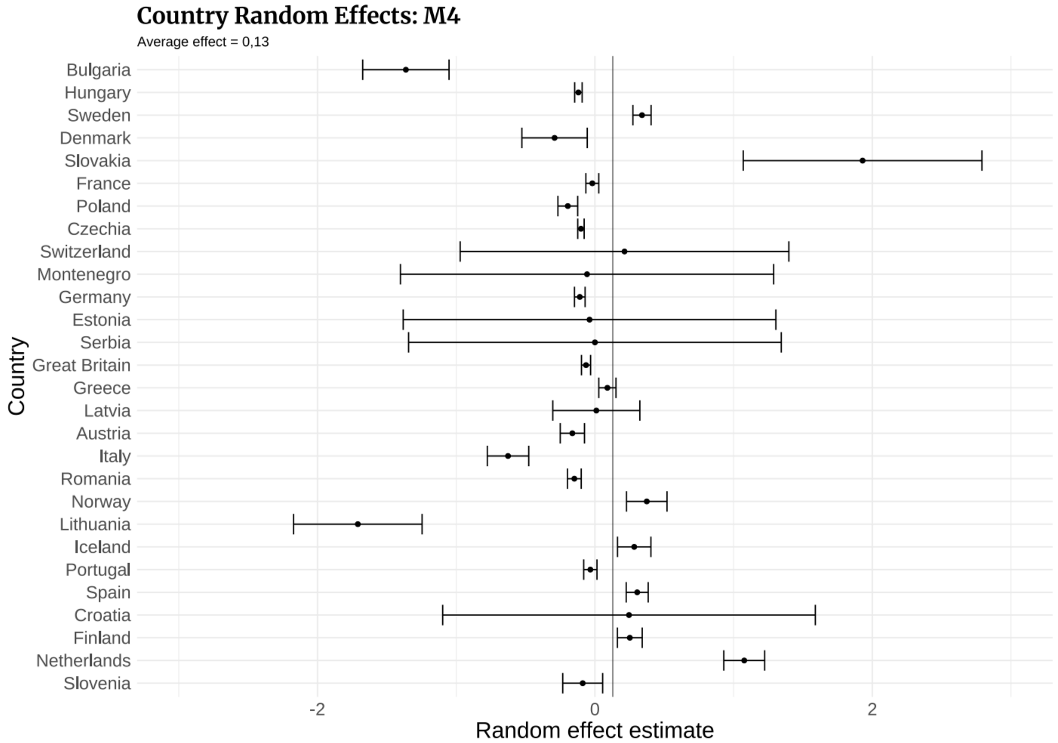

Figure 27. Varying slopes of each country in the expanded within-country model, M4.

Overall, within-country models corroborate the findings of the between-country models (M1 and M2) in that the effect of Party System IP on Individual AP, when controlling for countries and regions, is statistically insignificant. Further, they also reinforce the findings regarding other hypotheses. Individual extremism, however, has been highly significant and shows an unwavering positive effect on individual affect in both expanded models. It stays a consistent predictor of higher IP both within- and between countries, unlike the effects of the focal relationship. The overall picture suggests that although the effects of party system ideological shifts on individual affect are highly contingent on local contextual factors to the point of no observable noteworthy transnational tendency, higher individual-level extremism amplifies one's sentiments towards political parties—even when controlling for country and region. In other words, when it comes to predicting an individual's extent of affect towards parties, the extremity of his or her own ideological beliefs is a significantly more reliable and consistent metric than the divergence of party opinions either between states or within one over time. Ideology thus seems to drive affect, as anticipated; yet, contrary to expectations, the role of party ideology seems decisively context-dependent, while that of individual extremism stays relevant between- and within-countries even when accounting for controls. **H2**, as a result, **is supported.**

The average effects of income inequality on affect are consistently designated as statistically insignificant in both expanded models. As prior comparative work found income inequality to be a strong predictor which might come down to how it changes exceedingly slowly in the relatively stable economic climate of Europe, thus the time frame of 25 years in my analysis might not be sufficient to capture the presence of an effect in general. One way or another, following these results, **H3 is rejected.**

Having discussed the hypothesis tests, the next subsection presents other findings of the study.

4.4 Additional Findings

Two other findings, in addition to the hypothesis tests, seem nonetheless worthy of note. First, I present the outcome variance reduction rates across the four models compared to M0. Second, I overview two more ANOVA tests that measured how the addition of party system IP in M1 and M2 changed the fit of the intercept-only model.

The first of these tests, presented in table 15, concerns the change in explained variance for every model, compared to the intercept-only model M0. Variance of Y on the region- and country-levels stayed almost identical in all models, which is reasonable given that no predictors on the region-level were part of the model and that the only predictor for countries (income inequality) was absent in bivariate models and had a null average effect in both expanded models. Residual variance, however, was lower than that that of M0 with all models, and was further notably reduced in both expanded models. This result signifies that adding Party System IP explained a fraction variation in affect on the individual level, especially between-countries with over 7 percent reduction in variance. Yet, the other controls, once added, accomplished significantly more in that same regard, with nearly the same amount of variance reduction in both within- and between-country expanded models. In line with prior literature, party system ideology reduces variation in affect, but only marginally so: inclusion of sociodemographics, individual extremism, and income inequality accomplishes significantly more in this regard.

Model	Country variance	Region variance	Residual variance
M0	***0,045***	***0,014***	***1,159***
M1	0,043	0,014	1,076
	(-4,4%)	*(+0)*	*(-7,2%)*
M2	0,047	0,014	1,143
	(+4,4%)	*(+0)*	*(-1,4%)*
M3	0,045	0,015	0,943
	(+0%)	*(+7,1%)*	*(-18,6%)*
M4	0,054	0,014	0,933
	(+20%)	*(+0)*	*(-19,5%)*

Table 15. Variance by level in each model, with percentage of variance reduction compared to M0 in parentheses (positive values mean the more complex model has higher variance than M0).

The second finding came from two additional ANOVA tests on M0-M1 (table 16) and M0-M2 (table 17) to estimate how does the mere inclusion of Party System IP affected model fit, compared to the intercept-only model. ANOVA on M0 and M1 showed poorer fit in M1—adding X worsened the model fit, with AIC identical in both models but BIC growing by +10 and the p-value far outside the threshold of significance at 0,203. A key likely contributor to this result is the statistical insignificance of the average effect of the focal relationship in M1 itself, which renders the overall model fit rather poor as the only predictor shows no association with the outcome. As such, adding only the grand mean-centred Party System IP does not explain away variance in between-country affect.

	Number of Parameters	AIC	BIC	p-value
M0	4	456133	456179	
M1	5	456133	456183	0,203

Table 16. ANOVA results for M0-M1.

Running the second ANOVA test on M0 and M2 painted a different and more informative picture. In this case, adding X notably improved model fit with AIC reduction by -1845 and BIC by -1815 points, and the test p-value at less than 0,001. This test shows that simply adding country-mean centred Party System IP with varying slopes improves the fit of the model. In fact, the improvement turned out so pronounced that it remained significant despite the statistical significance of the average effect in M2. Even though the average effect of the focal relationship turned out null in both between- and within-country bivariate models, the reduction of model fit due to this insignificance was overshadowed by the improvements following the inclusion of within-country X. While M1 and M2 are not directly comparable given their different specifications of X, these tests solidify the case cross-country heterogeneity is far more relevant to the data compared to seeking for pan-European trends.

	Number of Parameters	AIC	BIC	p-value
M0	4	456133	456173	
M2	7	454288	454358	< 0,001

Table 17. ANOVA results for M0-M2.

Having overviewed the results, the thesis moves on to the fifth and final chapter, conclusions.

5 Concluding Remarks

5.1 Conclusions

As acts of political violence make headlines worldwide time and time again, questions emerge on how understanding political polarisation might contribute to explaining such concerning trends. Polarisation on ideological grounds (ideological polarisation, or IP) is to some extent a healthy and necessary part of life in democratic societies as disagreements enable contestation and party competition. Meanwhile affective polarisation (AP) – the animosity one might feels towards politically other-minded individuals – may easily become a detriment to democracy. However, the concept of affective polarisation is relatively new. Most prior studies come from the US in whose two-party system measuring partisan affect is straightforward, but cross-national studies are sparse and consensus on the optimal measurements of affect in other, mostly multiparty systems, are absent. Europe is a region of particular interest in this regard, least because of the rise of right-wing parties and subsequent restructuring of the party systems (Dalton, 2018; Kriesi et al., 2008). This thesis attempted to contribute to these discussions by looking into whether party systems drifting apart by ideology might be a potential driver of individual affective polarisation in Europe.

Some prior scholarship in social identity theory argued for ideological disparities as the root of affect towards political opponents. In this view, disagreements over ideological beliefs fosters affect between opponents in two ways simultaneously: by igniting the somewhat tribal in-group and out-group identity mechanisms with attached corresponding sentiments, but also by virtue of being disagreements in that opponents represent an ideas that is opposed to one's own and therefore stand as enemies (Turkenburg & van Erkel, 2025). The latter trend is exemplified by the rise of cultural cleavages in the recent decades whereas areas of party competition (and thus of ideological disagreement) tend to shift from economic to cultural cleavages (Dalton, 2018) and thus often concern deeply divisive and personal topics that invite stronger emotional reactions, such as national identity or moral values (views on abortion, migration, etc.). While earlier studies found no pan-European trends in affective polarisation (Reiljan, 2025), these findings led me to assume that when parties in a state diverge on policy stances, so do their voters; and consequently, this lack of common ground sparks affect towards opponents. Literature identified income inequality and individual extremism as other potential contributors to individual affect.

This study Employed data from the Comparative Studies of Electoral Systems waves 1 through 5. I tested the hypotheses via multilevel regression analysis on a sample of around 170 thousand individuals from 300 regions in 29 countries, structured around 115 elections from 1996 to 2021. Following several stages of preliminary tests for establishing whether the data structure supports a multilevel design, the analysis was run on a total of five models computed using the *lme4* package of R on three levels: individual, region, and country levels. The focal variables were party system ideological polarisation (X) and individual-level affective polarisation (Y); alternative predictors were individual extremism and income inequality, and sociodemographic indicators were used as controls. The CSES Polarisation Index by (Dalton, 2008) was used as a proxy for party system ideological polarisation whereas individual affective polarisation was operationalised as the Spread-of-Scores Index by (Wagner, 2021) due to its suitability for measuring affect at the individual level and its inclusion of non-partisans into the equation.

Following four stages of preliminary testing, five multilevel models formed the core of the analysis. One model (M0) was constructed with only Y and the group IDs to compute the country intercepts. Two models used X centred at the grand mean to test between-country effects (M1 and M3) and two models were centred at the country mean to test within-country estimates (M2 and M4). The average effect of X was statistically indistinguishable from zero in all models, arguing that the relationship of party ideology and individual affect in Europe follows no observable trends cross-nationally but rather depends heavily on local context. Cross-national heterogeneity thus becomes a defining feature not only of the distribution of affect (Reiljan, 2025), but also of the extent to which party system ideology affects individual affective sentiments. Preliminary tests corroborated this trend: complete pooling with no separation of groups pointed towards a subtle, but significant and positive effect between the focal variable in the entire sample; no-pooling showed that this effect remains almost identical in scale and direction when controlling for region and country, as well as the notable heterogeneity of group intercepts; separate country models, while unstable due to few distinct values of X in each group, pointed to noteworthy differences in country slopes as well; and regressing the estimated slopes against the group-level predictor suggested that income inequality does not explain away these distinct patterns single-handedly. Null results of the main tests may negate the presence of an average pan-European relationship between party system ideology and individual affect, but the added complexity of varying intercepts and slopes describe a landscape where countries follow trends in unique ways. Both within-country models showed a prevalent negative intercept-slope correlation which suggests that countries with higher baseline AP levels tend to have a weaker or (more) negative relationship between party IP and individual AP. Baseline AP level differs somewhat in countries, but the distribution does not seem to follow self-evident spatial or temporal patterns. Yet, somewhat consistently with (Bettarelli et al., 2023), AP shows small but non-trivial variance on the regional level, and countries vary exceedingly in how widespread are baseline affect levels across their regions. The latter finding corroborates the arguments in favour of disaggregated approaches to researching affect going forward: a Europe-wide sample may be a narrower option than the census of all surveyed countries as per some prior studies, but apparently is still too wide to capture overarching trends between party ideology and individual affect.

Income inequality on the country-level was also found to be statistically insignificant. As this finding runs contrary to expectations set forth by prior research, rejecting the potential causal relationship straight away seems unwarranted. One explanation might be that income inequality generally remains stable and changes extremely slowly, in which case the 25-year sample time frame might be insufficient to capture the effect it has on affect; alternatively, the reasoning might follow that I proposed on party system IP, namely in that the effects may manifest themselves in a manner so contingent on national or sub-national European political contexts so that no one trend is common to the entire sample. Individual extremism, however, had a consistent positive effect on affective polarisation in both within- and between-country models. The overall picture suggests that ideological distance between parties in one's country does not reliably predict individual affect in a cross-national setting; yet, one's own ideological convictions – or rather, their extremity – demonstrably foster stronger sentiments towards parties, even when controlling for country and region, both within and between states. This evidence points that ideology, be it in how one perceives one's own beliefs or beliefs of political parties, has an influence on affect, but that influence occurs distinctly. While party ideology effects are dominated by heterogeneity between states, the positive relationship between affect and individual extremism transcends borders. Regarding additional findings, the level of variance in affect in regions was lower than in countries, but not to the point of insignificance, which supports the case for more sub-national inquiries in studies of affect.

5.2 Limitations and Recommendations

Polarisation is a notoriously complex and multifaceted concept. Empirical analyses, especially on the international scale like this one, always run the risk of oversimplifying the phenomenon in the efforts towards tangible and sufficiently parsimonious measurement, and such trade-offs inevitably lead to limitations. For one, although the data structure in this study strongly pointed to variation of the focal variables in both space and time, my tests only accounted for variation in space – i.e., in countries and regions-within-countries. This choice was mostly meant to take into account the findings of (Bettarelli et al., 2023) who found that within-country AP variation was about as prominent as that between countries, especially as no study since has taken a disaggregated approach; as a result, I included the region IDs but not election IDs as a proxy for time. This way I could avoid an overcomplicated non-nested four-level structure, partly for complexity in interpretation, partly for parsimony sake, partly due to hardware limitations that hinder calculating bias-corrected clustered standard errors for mixed-effects in a large N model, let alone five such models. While not ideal, this arrangement was a reasonable compromise because both party ideology and individual affect remain fairly stable over time, as the descriptive data confirms purports. Any notable shifts generally should take a longer time span than the two and a half decades covered by this study—essentially rendering spatial variation more decisive than temporal variation. Besides, as a partial mitigation and a robustness check, the tables with model results present 3 estimates of standard errors every time: the non-clustered model SE, and the CRVE country- and election-clustered SEs.

As polarisation is a difficult concept, so is multilevel modeling as a research method. Despite its power in dealing with hierarchical data structures growing popularity in social sciences, many experienced researchers in social sciences voice concerns over the lack of established reporting practices and their own knowledge gaps. Summarising the results of a survey of social scientists, (Meteyard & Davies, 2020) write about mixed effects as ”a method of analysis that the community feels is not well understood, not clearly reported and not robustly reviewed” (p. 12). Since I have never worked with this method before starting this thesis, the odds of human error are naturally higher. To minimise this, I have followed through with the checklist of best practices compiled in the above-mentioned study (p. 16).

As with any quantitative study, the central issue is data availability. CSES, while vast and widely used, has a rather sporadic coverage of elections over time and space, and questions from wave to wave were not always identical. Political knowledge and interest, two variables of notable theoretical interest, may not be reliably captured using this dataset or any other dataset of comparable scale to this day. Further, measuring AP as sentiment towards parties may obscure whether respondents mean party elites or party voters (Druckman & Levendusky, 2019, p. 122)—however, partisan affect towards both, while not the same, shows a correlation (Tichelbaecker et al., 2023, p. 812). The question of whether or not this extends to non-partisans may be another venue for research.

Continuing on recommendations, future researchers may target the robustness of these tests by employing other measures of polarisation, either of affect (e.g., Reiljan's (2020) API) or of ideology (e. g., expert estimates by Chapel Hill Expert Survey, rather than perceived values of individuals). Reversing the causation might be of interest as well, to offer an overview for how the top-down effect of party polarisation on individual affect compares to the bottom-up effect of individual affect steering party competition, especially along cleavage lines. Alternative model specifications could also offer worthwhile insights, such as switching out the region-level for election IDs to account for variation in both space and time, although further analysing AP from a regional perspective would also benefit the field. Finally, the clear heteregeneity in how party ideology impacts affect along with a lack of any general cross-national trend suggest that future studies of affect in Europe should focus on a smaller sample of states and analyse them on a lower level to shed light on precisely what aspects of the political contexts mediate these relationships.

6 References

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Appendix

X = CSES Polarisation Index;
dalton_cpi_between = centred at the global mean;
dalton_cpi_within = centred at the group (country) mean.

Y = spread_like_wgt = individual AP, using the weighted Spread-of-Scores Index by Wagner (2021).

Null and between-country models

	M0	M1	M3
(Intercept)	2.361	2.366	1.731
	(0.041)	(0.041)	(0.083)
dalton_cpi_between		0.055	0.060
		(0.044)	(0.045)
respondent_age			0.004
			(0.000)
respondent_genderFemale			0.066
			(0.006)
respondent_education			0.007
			(0.003)
respondent_income			0.010
			(0.003)
respondent_extremism			0.213
			(0.002)
gini			0.001
			(0.002)
SD (Intercept region)	0.120	0.120	0.121
SD (Intercept country)	0.212	0.208	0.213
SD (Observations)	1.076	1.076	0.971
Num.Obs.	152612	152612	91941
R2 Marg.	0.000	0.001	0.108
R2 Cond.	0.049	0.049	0.162
AIC	456137.6	456142.5	256159.3
BIC	456177.3	456192.1	256263.1
ICC	0.0	0.0	0.1

RMSE	1.08	1.08	0.97

Null and within-country models

	M0	M2	M4
(Intercept)	2.361	2.366	1.638
	(0.041)	(0.042)	(0.096)
dalton_cpi_within		0.085	0.129
		(0.181)	(0.148)
respondent_age			0.004
			(0.000)
respondent_genderFemale			0.068
			(0.006)
respondent_education			0.000
			(0.003)
respondent_income			0.012
			(0.003)
respondent_extremism			0.211
			(0.002)
gini			0.004
			(0.003)
SD (Intercept countryregion)	0.120	0.118	0.117
SD (Intercept country)	0.212	0.217	0.233
SD (dalton_cpi_within country)		0.883	0.707
Cor (Intercept~dalton_cpi_within country)		-0.080	-0.253
SD (Observations)	1.076	1.069	0.966
Num.Obs.	152612	152612	91941
R2 Marg.	0.000	0.002	0.096
R2 Cond.	0.049	0.227	0.280
AIC	456137.6	454294.4	255287.0
BIC	456177.3	454364.0	255409.6
ICC	0.0	0.2	0.2
RMSE	1.08	1.07	0.96