Ideology as Motivated Cultural Cognition

How Culture Translates Personality into Policy Preferences

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Abstract

In different cultures,
the same perceptions make for
different policies.

This paper summarises the results of a quantitative analysis testing the theory that culture acts as an intermediary in the relationship between individual perceptual tendencies and political orientation. Political psychologists have long observed that more "left-wing" individuals tend to be more comfortable than "right-wing" individuals with ambiguity, disorder, and uncertainty, to equivocate more readily between conflicting viewpoints, and to be more willing to change their opinions. These traits are often summarised under the blanket term of "open-mindedness". A recent increase in cross-cultural studies, however, has indicated that these relationships are far less robust, and even reversed, in social contexts outside of North America and Western Europe. The sociological concept of culture may provide an answer to this inconsistency: emergent idea-networks, irreducible to individuals, which nonetheless condition psychological motivations, so that perceptual factors resulting in left-wing preferences in one culture may result in opposing preferences in another. The key is that open-mindedness leads individuals to attack the dominant ideas which they encounter: if prevailing orthodoxies happen to be left-wing, then open minded individuals may become right-wing in protest. Using conditional process analysis of the British Election Study, I find evidence for three specific mechanisms whereby culture interferes with perceptual influences on politics. Conformity to the locally dominant culture mediates these influences, in the sense that open-minded people in Britain are only more left-wing because they are less culturally conformal. This relationship is itself moderated both by cultural group membership and by Philip Converse's notion of "constraint", individual-level connectivity between ideas, such that the strength of perceptual influence differs significantly between cultural groups and between levels of constraint to the idea of the political spectrum. Overall, I find compelling evidence for the importance of culture in shaping perceptions of policy choices.

Key words: *culture, perception, political orientation, motivation, conformity, constraint*

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Table of contents

Word count (from introduction to conclusion): 13,071

List of tables and illustrations

Tables

Figures

Introduction: why study policy preferences?

My aim in this paper is to specify and test a theoretical model which attempts to explain why people are left-wing or right-wing.

This distinction, known variously and often interchangeably as ideology, the political spectrum, or political orientation, is a concept which attempts to summarise differences in political opinion between individuals (Atwan and Roberts, 1996). The definition and scope of these terms are fiercely contested, and as such a precise description of exactly what I am interested in is necessary. I regard left and right, first and foremost, as indicators of policy preferences- individual-level opinions on what a government, or governments in general, ought to do in a given situation (Budge et al, 2001). Policy preferences are predominantly, though not unanimously, arranged into a single-dimension spectrum separating the left, or "liberals", from the right, or "conservatives" (Sidanius, 1993: 205). The question of why different people can be found at different positions along this spectrum is what I wish to investigate.

The question of why people hold certain policy preferences at the expense of others is important for at least two reasons. Firstly, policy preferences are often deeply divisive and controversial. As Aristotle once lamented, although practically all people strive for what is "good", radical differences in specific things considered "good" or "bad" have prevented the human race thus far from agreeing on shared ideals of how to live (Aristotle, 1968: 54, 297-9).

The second, related, reason for the importance of investigating policy preferences is that they are usually highly consequential. In an established democracy, citizens holding policy preferences may use their varying degrees of resources to vote, lobby, and protest to make those preferences a reality (Parsons, 1994). Even in authoritarian dictatorships, which are nominally unresponsive to mass opinion, individuals are able to support or undermine governing authorities in the implementation of policy, up to and including involvement in public uprisings or civil wars (Bunce and Wolchik, 2010). Public policies, once implemented, affect practically every area of human life, from how crops are grown to where roads are built, to when it is acceptable to take a life, to whether nuclear weapons are detonated (Alvarez and Brehm, 2002: 41). In short, policy preferences are important because they are part of the means by which humanity decides what to do with itself.

I begin by surveying an expansive empirical literature concerned with explaining individuals' policy preferences using perceptual measures such as open-mindedness and need for closure. These studies have been convincing in explaining why people of different motivations, and especially with differing approaches to unfamiliar information, tend to develop different political orientations. However, as we shall see, the utility of purely psychological explanations declines sharply when making comparisons across different societies, particularly when studies involve participants from non-Western countries. I propose that sociological and anthropological understandings of the concept of culture- shared belief systems irreducible to their individual adherents- could offer a solution to these apparent inconsistencies.

Therefore, the contribution my study seeks to make is to provide an empirical test of the theory of "motivated cultural cognition", which has been proposed previously but which has hitherto lacked full specification and empirical verification. The theory holds that more "open-minded" individuals- who are more willing to accept new and unfamiliar information and to change their opinions- tend to be more critical of ideas which are predominant and widely accepted in the societies in which they live. That is, open-minded individuals usually have lower cultural conformity. Precisely which policy preferences they hold is thus a product of prevailing social values. In cultures where the balance of opinion is skewed to the right- as it is in most of the Western world- more open-minded people tend to be more left-wing. In traditionally left-wing societies, by contrast, the open-minded become more attracted to right-wing policies.

It is this basic idea which is summed up so well by the Malcolm Evans cartoon on the front cover of this paper (Evans, 2011). Both women in the picture are driven by identical perceptions, in that they are both opposed to inequality- specifically, inequality between men and women. This constitutes the concept of "motivated cognition" identified by political psychologists. Yet their embeddedness in contrasting cultural contexts, which supply them with ideas from beyond their own desires and experiences, serve to flip these motivations on their heads so that they are diametrically opposed when it comes to the concrete question of what clothes women ought to wear. This is the meaning of the "cultural cognition" of the theory: without cultural guidelines, individuals have no way of "knowing" which specific policies are best suited to their perceptual motivations. Policy preferences can only be effectively predicted, I claim, when both perception and culture are considered.

I test this theory using a secondary quantitative analysis of data from the British Election Study. Deriving measures of political orientation, open-mindedness, and cultural considerations, I specify a set of hypotheses to be tested in a "conditional process analysis"- a kind of path analysis which combines mediation and moderation to explore how, and under what cultural conditions, perception affects policy preferences. I discover that, in the contemporary United Kingdom, and in accordance with the theory under investigation, more open-minded people are only more left-wing because they are less attached to British culture, which has a moderately right-wing influence, and that the strength of this influence varies between different cultural groups and between different levels of "constraint" to the political belief system. I conclude by summarising the limitations of my analysis, and briefly propose an agenda for further research into culture as an arbiter of political and psychological motivations.

The theoretical case for a cultural political psychology

Perceptual influences on political orientation

A great number of studies have discovered connections between policy preferences and a wide variety of social, economic and situational factors (Citrin et al, 1997). One of the most fruitful veins of investigation, however, suggests that policy preferences are powerfully influenced by an altogether more basic and fundamental substance: the nature and characteristics of perception and consciousness, human information processing, and sensory stimulation.

A pioneering study in this field was *The Authoritarian Personality*, a study by Theodor Adorno and colleagues partially driven by a need to explain support for the Nazi Party in the mid-20th Century (Adorno et al, 1964). Their key finding was that individuals inclined to political authoritarianism also tend to exhibit "rigidity of thinking", or unwillingness to change existing opinions, and are unusually prone to negative emotions when those opinions are threatened. Subsequently, a considerable number of studies have investigated similar aspects of this relationship. Their findings have been helpfully collated and compared by John Jost and his colleagues in a series of meta-analyses on political conservatism (Jost et al, 2003; Jost, 2017). They find that conservatives are generally characterised by a preference for simple, definite opinions, clearly structured world-views, and long-term stability of existing beliefs.

More recently, this concept has come to be more precisely defined and operationalised as the theoretical construct and survey device known as the need for closure scale (Webster and Kruglanski, 1994). Webster and Kruglanski describe this scale as an opinion-based metric assessing, firstly, how eager individuals are to "seize" upon a precise, certain belief about how the world is or should be, and to "freeze" that belief by refusing to change it in the face of anything less than overwhelming evidence (Roets and Van Hiel, 2011). An equivalent, opposite, tool is the active open-mindedness scale, a measure of how readily individuals claim they change their opinions in response to new information (Stanovich and West, 1997). A very similar concept, conservation, has also been uncovered in the human values literature (Schwartz, 2007; Feldman, 2013; Goren et al, 2016). Conservation is essentially a representation of differing human needs for cognitive parsimony: a preference for simple, clear, stable opinions over complex, ambiguous, ephemeral ones.

Numerous studies have uncovered statistically significant relationships between Need for Closure and right-wing political orientation (e.g. Chirumbolo, 2002; Jost et al, 2003; Golec De Zavala et al, 2010). What's more, Need for Closure has been shown to increase among people recalling threatening situations involving the novel and unfamiliar, whilst both factors are connected with an increase in political conservatism (Matthews et al, 2009; Thórisdóttir and Jost, 2011). In more general terms, those on the conservative right tend to demonstrate greater sensitivity to threat than those of the liberal left (Vigil, 2010).

The claim made by many social psychologists and neuroscientists is that differing political orientations are, to an extent, biologically inherited and physically ingrained in the human brain (Hatemi et al, 2009). As evidence, they cite studies of brain structure and function, which indicate that rightists usually have an increased volume of grey matter, and hence greater information-processing power, in their right amygdalae (Carraro et al, 2011).

The amygdala is a brain sub-organ which regulates responses to novel, and especially threatening, sensory stimuli: because humans tend to perceive the unusual as threatening, threat sensitivity and resistance to new ideas and information go hand in hand (Tritt et al, 2013). Political leftists, by contrast, have greater information-processing power in the brain area known as the anterior cingulate cortex, which manages desire and reward anticipation (Schreiber et al, 2013). Whilst uncertainty and change mean danger for those sensitive to

threats, they might mean the exact opposite for those more conscious of potential future benefit (Taber and Young, 2013). This leads to very different attitudes towards the established, orthodox way of doing things. To use a pastoral metaphor: the right-wing sheep generally prefer the certainty and restriction of the fence, as it keeps wolves at bay, whereas the left-wing sheep wish to break it down, in the hope of finding greener grass on the other side. For this reason, the mainstream argument goes, political leanings reflect perceptual style: the more closed-minded prioritise some ideas over others, and thus favour social hierarchies where some groups are prioritised over others, and they resist changes in belief over time, and thus favour social relations which abide through the ages (Jost et al, 2003).

The "WEIRD" bias and cross-cultural contradictions

If only things were that simple. Recent studies, however, have shown that the relationships reported above are remarkably difficult to replicate in contexts outside of the United States and Western Europe (Van Bavel et al, 2016).

Traditional social scientific studies of political orientation and many other factors have been increasingly criticised for their heavy reliance on the inhabitants of "WEIRD" (White, Educated, Industrialised, Rich, and Democratic) societies as research participants (Henrich et al, 2010). Universalistic claims are often made based merely on smatterings of convenience samples collected from the Global North (Yilmaz and Saribay, 2016). In Jost et al's (2003) meta-analysis, to take one example, 75% of the studies included took place solely within the United States, and the majority of the remainder were conducted in Western Europe (Jost et al, 2003). To many practitioners of social science, it has seemed less than safe to assume that the inhabitants of WEIRD countries- a small and historically atypical minority of the world's population- are representative of "human nature", whatever that is (Ramsay and Pang, 2015).

To rectify this shortcoming, several studies have now been conducted within historically neglected social contexts. Some, such as Yilmaz and Saribay's (2016) study of Turkish nationals, tend to reinforce the finding that those on the right are less willing to scrutinise preconceived opinions (Yilmaz and Saribay, 2016), many other studies appear to throw these findings into doubt.

Kossowska and Van Hiel (2003) compare research subjects from the Netherlands with those from Poland, finding that whilst need for closure is associated with support for free-market policies in the Netherlands, it is in fact associated with state socialism in Poland (Kossowska and Van Hiel, 2003). Similarly, need for closure is related to a confrontational approach to conflict resolution in the United States, but actually predicts a conciliatory approach among citizens of China. Harman (2017) compares general decisiveness of opinion, a measure approximating need for closure, with support for right-wing economic policy across dozens of countries. It appears that, whilst the overall relationship between the two is positive, it is non-significant within many countries, and significantly negative among the inhabitants of Uruguay, Russia and India (Harman, 2017). If policy preferences were innate or universal, as much of established theory implies, then this sort of cross-national variation in the strength, and even direction, of perceptual influences upon political thought would be very difficult to explain.

Culture and its conceptual utility

I wish to suggest, however, that policy preferences are not innate or universal. To support this contention, a turn from psychology to sociology and anthropology will be particularly beneficial. These latter disciplines, unlike the former, possess a credible mechanism by which systematic differences in beliefs and values can coalesce, in a way that is not explicable either by individual idiosyncrasy or by universal human constants: the concept of *culture* (Ellen, 2003). I believe that it is culture to which we must turn to explain the complexities in the interface between individual perception and policy decisions (see Ross, 1997).

The formation of shared identities common to group members is crucial to the study of politics (Huddy, 2013). This has been recognised particularly clearly in studies of foreign policy-making "groupthink", a herd mentality in which opinions within a confined decision-making space become increasingly uniform (Janis, 1973; Badie, 2010). Yet broader, longer-term, and more widespread collective values have often been downplayed by political psychologists.

Social anthropologists, by contrast, have made the study of culture a central aspect of their research. One influential definition of culture is that it is a pattern of beliefs, a repetition of ideas or behaviours across individuals in a way that is too systematic to be explained by individual choice alone, yet too variable to be attributed to biological "human nature" (Benedict, 2005). Anthropologists have used the theory of schemata or "impressions" (Lodge et al, 1989) to advance systematic understandings of culture. A schema is a standardised and simplified model of reality which is used to predict forthcoming events, and to indicate which eventualities are expected and which unexpected (Axelrod, 1973).

What Sperber (2005) suggests is that these schemata, impressions or "representations", coalesce into collective belief systems when they are transmitted epidemiologically across social networks, much like the spread of a disease (Sperber, 2005: 311). Yet the precise content of exactly which ideas become predominant is irreducible to individual psychology: it is an "emergent property" which develops unpredictably out of the complexity of interactions between people (Archer, 1995). A language, for example, is an artefact which transcends individual volition; it is the work of no one individual, and whilst all may contribute in small ways to it, all are likewise required to abide by the majority of its rules if they wish to make themselves understood (Durkheim, 2008). Across repeated iterations, these representations come to be accepted as a "social structure" of interdependent opinions, none of which can be changed without altering the others (Levi-Strauss, 1974).

A similar concept already exists in the writings of the political scientist Philip Converse- that of the belief system (Converse, 1964: 3). According to Converse, political orientation consists of networks of specific policy preferences which are more or less strongly correlated with one another, such that an individual holding a certain opinion- for example, that tax cuts should be encouraged- feels obliged to also hold other, apparently unrelated opinions, such as endorsing military action against other countries, simply because those opinions are perceived to "go together". The sources of information for these interdependencies of opinion are "less logical in the classical sense than they are psychological- and less psychological than social" (Converse,

1964: 5). In other words, people know which opinions are supposed to accompany one another because they observe others who already exhibit these patterns of ideas. As such, "constraint" between policy attitudes is potentially more of a socially emergent property of human groups than an ingrained feature of human physiology (Feldman, 2013).

Motivated cultural cognition: research framework

Jeanne Ho-Ying Fu and her colleagues suggest that culture could play a central role in cross-national differences in perceptual influences upon policy preferences. They claim that qualities such as need for closure, or any other psychological characteristics, are not directly and intrinsically motivations "for" any specific policies (Fu et al, 2007). After all, the sheer volume of potential policies is vast and ever-changing, and it would be hard to see how attitudes so specific could be genetically encoded (Toren, 2003; Gross Stein, 2013). Psychological reactions are driven by brain functions, but these functions are "activated" contextually depending on whether social norms are violated (Schreiber and Iacoboni, 2012). Instead, need for closure predisposes individuals towards "cultural conformity", a tendency to support whichever policies are most favoured in local mainstream culture. Those high in need for closure feel the need to come to quick conclusions on unfamiliar topics, and one of the most abundant sources of ready-made opinions is the surrounding culture (West et al, 2008). Conversely, the "open-minded" are motivated to seek their own, unique opinions as a source of self-expression, and thus regard conventional ideas with suspicion (Xu and Peterson, 2017).

Fu et al describe this theory as "motivated cultural cognition" (Fu et al, 2007). It combines sociological and psychological theories, both of which have been accused of contrasting reductionisms, in an interesting and useful way. Unlike cultural sociology, which often ignores individual differences, motivated cultural cognition holds that some individuals are more likely to accept cultural influence than others. Unlike individualistic psychology, which often assumes that cognitive phenomena are either unique to individuals or universal to all humanity, motivated cultural cognition allows for intermediate-level differences between social groups depending on the content of their emergent beliefs.

Fu et al elaborate the theory of motivated cultural cognition, but they do not fully test it. Their analysis simply compares differences in the influence of need for closure on conflict judgements between the United States of America and China; they do not directly measure any form of cultural conformity or assess whether it is responsible for the relationships observed. What's more, their main focus is on approaches to conflict, not policy preferences in general, and their use of non-probability samples makes statistical inference difficult. My aim is to test their theory of motivated cultural cognition as a predictor of policy preferences, to ascertain whether culture can truly be said to fill the gap between perception and politics. As such, my research question is as follows:

"Can culture explain variations in the relationship between perception and policy preferences?"

Methodological choices: paradigm, data, and analysis

The following sections will outline the rationale behind the research design for my data analysis, before outlining and testing hypotheses to shed light on the role of culture in intermediating between perception and political orientation. Owing to the large volume of statistical data from this analysis, not all results will be fully reported. Instead, they are summarised in detail in the technical appendix to this paper, which contains information on the variables chosen and recoded, selected output from statistical tests, and the code used to generate both these statistics and the various data visualisations.

Research paradigm: quality or quantity?

The domain of research methods is strongly divided between the "qualitative" and "quantitative" paradigms, and perhaps my first methodological task should be to justify my use of quantitative methods (Bryman, 2012). Methodological choices can never be divorced from theory; as such, some theories may be more readily investigated using some methods than others (Gilbert, 2016). In this case, the theory of motivated cultural cognition has been developed by Fu et al (2007) and others within the quantitative paradigm. For my results to be broadly comparable with theirs, it is advisable to employ quantitative methods.

This choice brings with it both advantages and disadvantages. Properly executed quantitative research allows discovered relationships to be reliably extrapolated to a wider population of interest, whereas qualitative methods offer no guarantee that their results exist among anyone other than the research subjects in question (Stoneman and Brunton-Smith, 2016). Yet these benefits are bought at the price of a lack of individual-level depth of measurement. Surveys are largely inimical to open-ended questions- with some exceptions- and their uniform structure prohibits most forms of probing or responsive techniques which could create a dynamic conversation between interviewer and interviewee. This increases the probability that certain results may be mere artefacts of the way a survey has been designed and administered (Zaller, 1992; Alvarez and Brehm, 2002). Consequently, quantitative methods run the risk of producing impressive and sophisticated findings which do not actually *mean* anything.

Data usage: primary or secondary?

I have chosen, in preference to collecting my own quantitative data, to utilise secondary survey data which have already been collected. My reason for making this choice is simple: high-quality survey data are freely available on topics covering almost every aspect of social life (Stoneman and Brunton-Smith, 2016: 90). Effectively executing a representative survey is an expensive and time-consuming task, requiring its own forms of expertise and a considerable collection of resources (Dillman, 2007). Such an investment is outside of the means of most individual researchers, myself included. Furthermore, reusing data that have required such effort to collect is an excellent way to recover additional value from previous work in a timely and cost-effective manner (Economic and Social Research Council, 2015). The chief disadvantage of using secondary data, of course, is lack of autonomy in the design of sampling strategy and question content, wording, and order. In utilising standardised survey questions to answer my research question, I am resigned to using measures which are less than ideal.

The British Election Study: data set, ethics, and limitations

My chosen data set consists of the first nine waves of the 2014-2017 British Election Study internet panel (Fieldhouse et al, 2016), which I analyse using SPSS (IBM Corp, 2016). The British Election Study is the United Kingdom's foremost political survey programme, managed jointly by the universities of Manchester, Oxford, and Nottingham. Its internet panel studies, collected by YouGov, follow the same representative sample of individuals over time- usually a period of two to three years- administering questionnaires repeatedly to them for the duration of the time period. These questionnaires include both unique questions, asked only once to each respondent, and repeated instances of the same question asked multiple times in different "waves" of the study. This multiple-questionnaire structure is the chief advantage of panel data and my principal reason for utilising this data set, even though my analysis is not a longitudinal one. One key aspect of constraint, as Converse understood it, is the extent to which policy preferences remain stable over time or fluctuate, potentially due to random "noise" (Converse, 1964). Asking the same people the same question several times in succession, interspersed with gaps of several months, should help to ascertain the extent to which policy preferences are random or stable in the British electorate. What's more, the practice of dispersing single-use questions across multiple waves has allowed the data set to compile a far broader array of variables than would feasibly fit within a single cross-sectional questionnaire.

It is easy to overlook ethical issues when analysing secondary data, which another agency has already collected and anonymised (Boddy, 2016). After all, crucial decisions about harm to participants, informed consent, invasion of privacy and deception have already been made and independently approved (Bryman, 2012: 135). As a researcher using secondary data, my main ethical duty is twofold: to produce a rigorous and high-quality analysis to ensure that the reputation of social research as a profession is not harmed by association with poor-quality work (Dillman, 2007), and to interpret my results proportionally and impartially, to ensure that individuals of certain political views are not unfairly maligned by misunderstandings of evidence (Haidt, 2013), I shall endeavour to demonstrate both of these considerations by being as transparent about my work as possible, and by including supplementary results and information in the technical appendix.

A total of 30,590 people took part in the first wave of the panel study, starting in February 2014 (British Election Study, 2015). Unfortunately, due to commercial reasons, YouGov does not make details of its response rates publicly available. This makes it difficult to know how many people were originally asked to take part. However, it is possible to ascertain that 10,172 people, 18% of those who answered the first questionnaire, responded to all nine waves represented in the data. This reveals a considerable problem with "attrition", in which panel members contact with the researchers over time (Tarling, 2009). As those respondents who drop out of the study are likely to be different in some meaningful way to those who remain, attrition makes it likely that the remaining sample will be biased and hence unrepresentative in some way. The data set includes a carefully calculated weight variable to correct some of this bias, which I have used, but this can only correct for biases which are directly measured by questions asked in the survey. As there could be any number of potential unmeasured biases, any deviation from the full response of a completely random sample is problematic.

Grasping slippery ideas: operationalising concepts as variables

My research question refers only to the generic abstractions of culture, perception and policy preferences (see Figure 2). These terms on their own are far too vague to use for the formulation of testable hypotheses. As such, my next task was to operationalise these concepts by selecting or constructing variables in the British Election Study data set which can be used to approximate them.

Political orientation: dimensions and underlying forces

If policy preferences are indeed the stuff of which left and right are made, as I have argued above, then it is crucial to understand how a vast array of preferences for specific and heterogeneous policies can result in a simple system of classifying people into broad ideological camps. The unidimensional "political spectrum" model assumes that for every policy area there is a "left" preference and a "right" preference, and none other, apart from perhaps a centrist preference. Yet many scholars have criticised such an approach, insisting that at least two separate dimensions are necessary to understand the complexities of political orientation (Giddens, 1994; Rokeach, 2000; Feldman and Johnston, 2013).

Twenty-six Likert scale variables were available in the data set as measures of respondent attitudes towards specific policy areas, which I recoded so that higher values always represent more left-wing or liberal attitudes. Figure 3 illustrates the interrelations between these policy preferences in the form of a network diagram, where points represent individual policy items and the lines joining them represent Spearman rank correlations between each pair of items (after Azevedo, 2016). The thicker the line joining two preferences, the stronger the correlation between them. Preferences are positioned so that more correlated items are closer together.

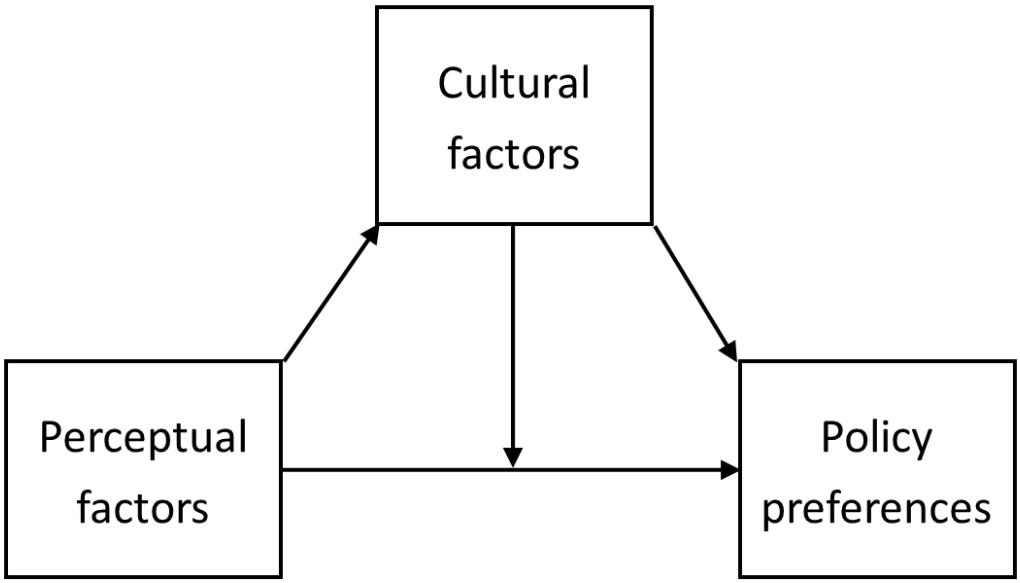


Figure 2. Conceptual diagram indicating the potential ways in which cultural considerations may contribute to perceptual tendencies in the formation of policy preferences. It is possible that cultural factors are directly influenced by individual perception and themselves exert a direct influence on policy preferences. It is also possible that cultural factors influence the strength of other relationships, such as the direct influence of perception on political orientation. Both types of arbitration will be hypothesised using different operationalised variables and tested in the analysis below.

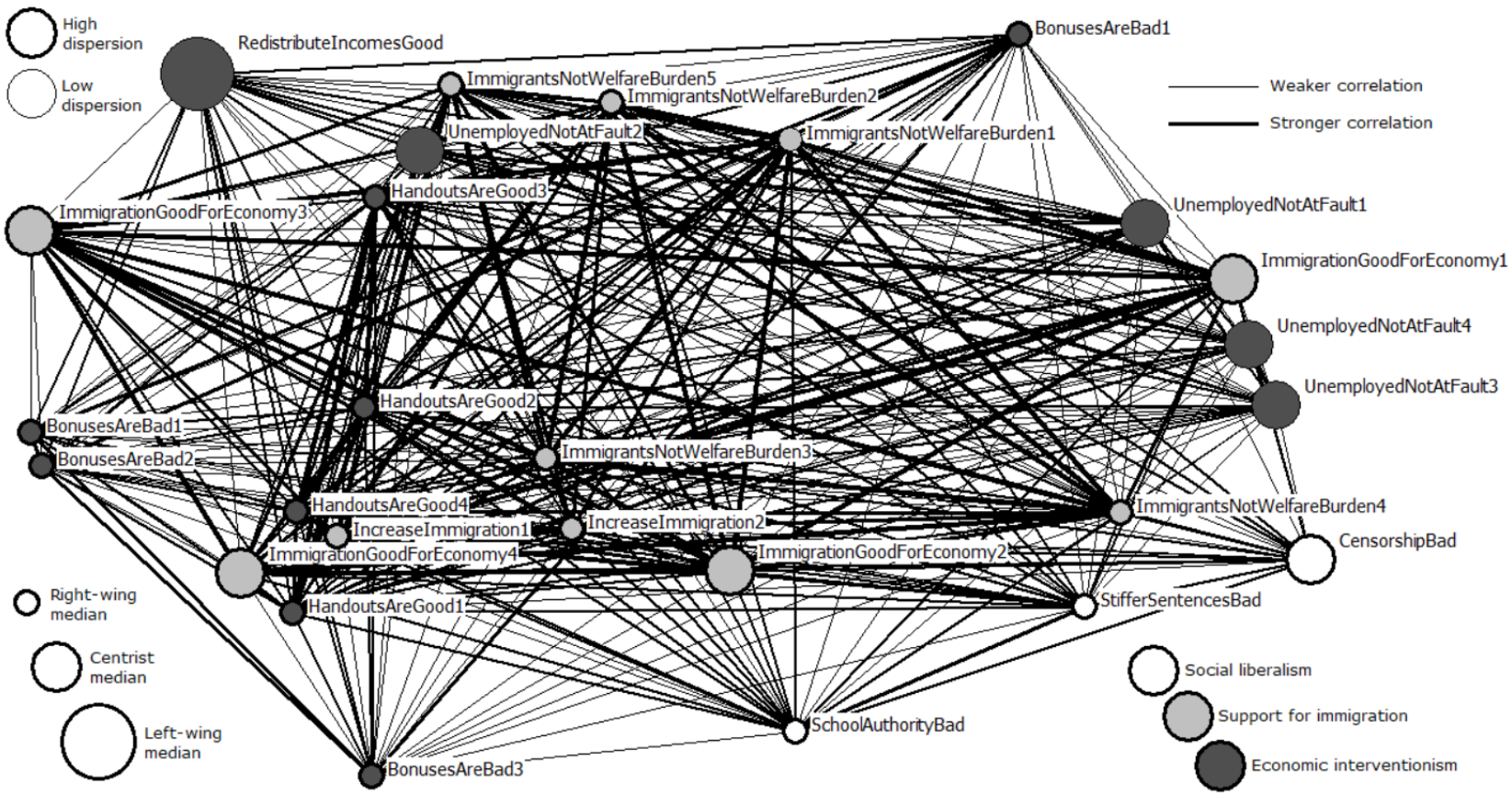


Figure 3. Network diagram illustrating the interconnectedness of policy preference items in the British Election Study panel dataset. Items with the same name but a different number are instances of the same question, asked to the same individuals in multiple different waves of the panel study. The colour of each point represents the broad domain of policy in which its policy preferences fall: law enforcement and regulation of behaviour, immigration and asylum, and the degree to which the state should be active in managing the economy. The size of each point represents how left-wing or liberal, on average, the British Election Study respondents were for that particular item. The larger the point, the more left-wing or liberal the median response. The thickness of the border represents the size of the interquartile range (a measure of heterogeneity or dispersion of responses): the thicker the border, the more diverse responses were to the item in question. The item regarding distribution of incomes, for example, exhibits highly uniform support for state redistribution of incomes, whereas responses to the items on bonuses in business were right-wing (pro-bonus) on average, yet highly diverse around that average. Lines connecting pairs of points are weighted in thickness relative to the Spearman rank correlation coefficient present between the two items, so that thicker lines indicate that policy preferences tend to be more similar to one another than pairs of preferences connected by thinner lines. Non-significant correlations are omitted. In all cases, significant correlations were positive. Points are arranged using multidimensional scaling (MDS) of the correlations between them (Kruskal, 1964), so that policy preferences which are more similar to one another are placed closer to one another. This diagram has been produced using the free software NetDraw (Borgatti, 2002).

As Figure 3 demonstrates, the policy preference items are closely interconnected, indicating some kind of underlying commonality, as is suggested overwhelmingly in the literature. The significant correlations used to produce the diagram varied in strength from a low of 0.02 to a high of 0.78 and were all positive, suggesting that it is conceivable, at least in the United Kingdom, to contrast left-wing liberalism with right-wing conservatism. Nevertheless, there is still an indication of a divide between "economic" and "social" policies.

To investigate how many dimensions of policy may characterise these data, I employed a technique known as principal component factor analysis. This method involves taking a set of intercorrelated variables and attempting to explain variations in them using a smaller number of hypothetical underlying "factors" (Tarling, 2009). These factors are then associated by the researcher with presumed real-life traits which, although not directly observed, can be theoretically imagined to drive observed responses.

I first ran principal components analyses separately on each collection of repeated policy preference questions (see technical appendix). Unsurprisingly, each set of repeated measures could plausibly be explained by a single underlying factor, which I concluded could be taken to represent durable dispositions toward certain specific policies. For example, I reduced the four variables on whether people are unemployed by their own fault to a single factor measuring the same attitude as an enduring disposition over time. This has helped to confirm that policy preferences do generally remain stable and intelligible in the short-term.

The next step is to find out how thematically distinct policy preferences relate to one another. To do this, I incorporated the six repeated-measures factors already saved, and an additional four policy preference items which were only administered to the respondents once, into an additional principal component analysis. This analysis revealed that most of the variations in the ten policy preferences could be explained by three distinct dimensional factors. The first, strongest factor was most closely related to the policy preferences on issues involving immigration, the second to the items on economic management, and the third to the items on social regulation. Whilst the precise number of dimensions found is likely to be an artefact of the range of policy topics in the survey (Azevedo, 2016), it is safe to conclude that policy preferences are, at least sometimes, multidimensional in structure.

One further question is whether the distinct dimensions of political orientation are nevertheless driven by a single, unidimensional left-right divide focusing on differing attitudes to equality (Bobbio, 1997; Jost et al, 2003). Most studies are unable to investigate this question because they use a version of factor analysis which assumes that factors derived from the same analysis are totally uncorrelated with one another. This assumption is, to say the least, unreasonable (Jost et al, 2009). By contrast, my factor analyses employ direct oblimin rotation, a technique which allows derived factors to correlate, and thus be included in a further, final factor analysis. On doing this I discovered that all three of the policy dimensions could be explained by a single latent factor, which I dubbed political leftness and determined to use as my dependent variable, the chief variable of interest to be explained in my analysis.

Perception: openness, uncertainty, and ambivalence

The key measure of open-mindedness in the British Election Study panels is the Active open-mindedness scale, a series of seven items asking respondents to broadly indicate how willing they are to change their opinions in the face of new information or evidence. Each item measures a slightly different aspect of active open-mindedness, and the scale was only administered to the respondents on one occasion. The seven items exhibited a high Cronbach's alpha of 0.76, indicating that they are highly intercorrelated. A principal component factor analysis produced a single factor able to explain considerably more variance in these seven items than any other factor. I saved the factor from this analysis for use as my chief independent or explanatory variable, treating it as a measure of cognitive flexibility.

An additional set of variables on levels of comfort with uncertainty and risk may tap into a related aspect of the opposing needs for novelty and security (Roets and Van Hiel, 2011). I recoded the five factors in question so that higher values refer to greater levels of comfort with uncertainty. The five factors highly intercorrelated- with a Cronbach's alpha of 0.72- but factor analysis produced two underlying variables rather than just one. The first factor was related most strongly to tolerance of uncertainty, whereas the second related to propensity to taking risks. I chose to use both factors, treating tolerance of uncertainty as an auxiliary measure of cognitive flexibility, but regarding risk-taking propensity as simply a control variable.

The final measure of perception which I selected is response polarisation, a measure which I introduced in an earlier work (Harman, 2017). This variable was devised by myself as an answer to the absence of usable psychometric variables in most representative social surveys. It essentially measures the same basic quality as the Need for Closure scale: a desire to sort experiences swiftly and decisively into clear categories unclouded by uncertainty or ambiguity. Response polarisation measures this tendency by finding the average extent to which survey respondents provide polarised responses to Likert scale ("agree or disagree?") survey questions. Response polarisation removes the direction- agreement or disagreement- of the response, so that those who "strongly agree" and "strongly disagree" are given the same score. Thus it measures, irrespective of the actual content of their responses, how much on average a given respondent provides strong, decisive responses rather than moderate, equivocal ones.

I selected 100 Likert scales from the variables in the data based on the following criteria: being ordinal rather than nominal, involving subjective, non-concrete distinctions between "strong" and "weak" responses, being symmetrical by having equal number of options on the "agree" and "disagree" sides, and having at least four response options, so that there is at least one choice between "strong" and "weak" responses. The scales do not necessarily need to follow a traditional "agree or disagree" format, so long as subjective differences in strength of opinion on a given topic are allowed to manifest. I duplicated each of these 100 variables and recoded them so that the centremost response, if present, became 0, the two responses either side of the centre became 1, the two responses either side of them became 2, and so on until all the responses had been recoded. These variables were highly intercorrelated, regardless of question content or number of response options (see technical appendix), and factor analysis saved one variable as a generalised indicator of cognitive classification.

Culture: cluster, conformity, and constraint

Culture is perhaps the hardest to operationalise of all the concepts in this study. The concept is somewhat vague, has been underused in quantitative research, and historically has been understood to mean quite different things in different theoretical traditions (Soares et al, 2007). I will specify three distinct aspects of culture, each of which is likely to bear a different statistical relationship to perception and culture to the others. I use the variables available in the British Election Study data to create four variables to represent these three basic concepts.

Perhaps the simplest version of culture as a variable is cultural *cluster*: a categorical variable outlining the cultural group to which each individual belongs (Fearon, 2003). Examples of cultural clusters or categories are the respondent's country of residence, ethnic group, or religious affiliation. Previous quantitative studies have all focused solely on cultural cluster, mostly comparing differences in the relationship between perception and policy preferences by country (Kossowska and Van Hiel, 2003; Fu et al, 2007; Harman, 2017).

The British Election Study takes place solely within a single sovereign state- the United Kingdom- yet clusters of cultural affiliation are nevertheless likely to exist within this context. To identify them, I used a procedure known as two-step cluster analysis. Cluster analysis uses one or more directly measured variables, categorical or continuous, to produce a single variable classifying respondents into a small number of nominal categories, which its algorithms attempt to make as homogeneous and distinct from one another as possible. For this analysis, the constituent variables were all categorical, assessing respondents' ethnicity, country of birth, country of residence within the United Kingdom, whether they have ever lived abroad, and whether at least one of their parents had been born in another country.

The two-step cluster analysis produced three clearly defined groups, reporting a reasonably high score for the "silhouette measure of cohesion and separation" of 0.6 (1.0 is the maximum and 0.5 is considered the minimum for quality clustering). Comparing this new cluster variable with the original, directly measured variables revealed that the first cluster consisted of heterogeneous individuals, including all non-White British respondents, most of whom had lived abroad at some point and some of whom were born outside of the United Kingdom or had one or more foreign parent. The second and third clusters were entirely White British, born and living only within the United Kingdom and with entirely British parents. The second consisted mostly of those born and resident within Scotland and Wales, whereas the third was composed entirely of those native to England. The clusters comprised 30%, 13% and 58% of valid responses in the sample respectively. For convenience, I dubbed them the "External", "Celtic" and "Anglo-Saxon" cultural clusters. In most initial, exploratory, regression models, the "External" and "Celtic" clusters did not differ significantly. For this reason, I recoded the cluster variable to have two values, "Anglo-Saxon" and "Other", for the final analysis.

The implication of the literature- that the relationship between perception and policy preferences differs significantly between cultures- is that cultural cluster acts as a categorical *moderator* of this relationship. Statistical moderation is where the value of one variable- the moderator- influences the strength of the relationship between two others (Hayes, 2013).

Based on this theory, I would expect to find that values for political leftness depend on the multiplicative effect of active open-mindedness and cultural cluster, working together.

An alternative metric which explores levels of individual motivation instead of group membership is cultural conformity (Fu et al, 2007; Siedlecki et al, 2016). According to the theory of motivated cultural cognition, individuals in rightward-leaning societies who are more open-minded are more left-wing, but only because they are less culturally conformal. Similarly, more open-minded individuals in left-leaning societies are more right-wing, again because they attach less value to prevailing cultural norms (Taber and Young, 2013). In statistics, this form of relationship is known as a *mediation*, where some or all of the effect of one variable on another is carried indirectly, through mutual connections with a third, mediating variable (Hayes, 2013). I would expect that cultural conformity mediates the direct and indirect influences of active open-mindedness on political leftness.

To produce a variable for individual cultural conformity, I ran another series of principal component factor analyses, like those used to estimate political leftness. Several variables in the British Election study tap into feelings of cultural allegiance, measuring generic feeling of "Britishness", sense of threat to traditional culture and values, and the extent to which respondents believe British culture and society to be superior to others. I recoded these factors so that higher values refer to greater cultural conformity, and used a short series of factor analyses to generate a single scale measuring this concept.

The above measure of cultural conformity is useful, but should not be exclusively relied upon. Firstly, it is a self-reported measure; respondents may sustain a self-image of being highly attached to British culture, whilst resisting cultural influences and prevailing opinions on many specific topics. Secondly, the measure has much in common with political ideals of nationalism and opposition to immigration and thus may overestimate the strength of the (likely negative) relationship between cultural conformity and political leftness. For these reasons, I devised an alternative measure of cultural conformity based on survey-answering behaviour rather than on specific question topics. For each individual, I calculated the difference between their own score on the political leftness factor and the mean score on this factor for the entire data set. This would, of course, correlate perfectly with political leftness, but I then took the squared square root of this distance, rendering all distances positive and removing any automatic association between the distances and the direction of respondents' political orientations. I reflected these distance values by subtracting each from the highest value present so that higher values came to mean greater conformity to the ideological mean. Finally, I derived a standardised z-score for this variable. I dubbed this variable "ideological conformity", treating it as an auxiliary measure of conformity to the average position in public opinion. The two measures of conformity were positively correlated, with a Pearson coefficient of 0.26 at a 99.9% level of confidence.

My final understanding of culture is inspired by Philip Converse's concept of belief system constraint. Converse found that the political belief patterns of American voters were not all equally constrained; rather, only a small minority were highly constrained or "ideological"

(Converse, 1964). Whilst my principal component factor analyses have found British public opinion to be considerably more stable and systematic than Converse might have predicted, his findings at least suggest that individuals differ markedly in the extent to which their policy preferences are interdependent (Johnston et al, 2017). This is not to say that those with constrained ideologies are likely to be cultural conformists, or at least not conformists to the majority national-ethnic culture: most citizens of most countries have little interest in politics (Alvarez and Brehm, 2002). Constraint is more likely to measure acceptance of the elite cultural understanding of a cohesive and one-dimensional "political spectrum".

I would suggest that ideological constraint functions as a continuous *moderator* of the relationship between open- or closed-mindedness and policy preferences. This is similar to the potential moderating role played by cultural cluster, except that the strength of the aforementioned relationship is different at every point along the constraint scale, being strongest among those with the highest constraint. This is likely to be the case because only individuals with a systematic understanding of political culture should be able to effectively connect their perceptual predispositions with their policy choices (Zaller, 1992; Arzheimer and Schoen, 2016). In this sense, constraint may function as a different and complementary belief system dynamic to cultural conformity and culture group clusters.

As with my measure of ideological conformity, I based my measure of belief system constraint on the policy preference variables, transforming them in such a way as to make the measure of constraint independent of both ideological conformity and political leftness. I recoded the policy preference items so that all followed a uniform five-point ordinal scale structure. These items were already arranged in line with the traditional political spectrum, equating liberal and pro-immigrant policies with left-wing ones, and conservative and nationalist policies with right-wing ones. As such, a person with the same numerical score for every single policy preference item would demonstrate maximal constraint between different areas of policy, and between the same areas of policy across time. I computed a new variable, the standard deviation between the twenty-six policy preference items for each individual. This effectively became an inverse measure of constraint, with higher values indicating less constraint, which I reflected and standardised this statistic to prepare for use in my analysis.

Ruling out the alternatives: control variables

I selected and refined several additional variables to use as statistical controls; consideration of these variables, which have been found to relate to political orientation in studies cited below, ensures that they are not responsible for driving the relationships observed among the variables of interest. They thus represent additional guarantees of statistical validity. The additional control variables selected are as follows:

i) Individual item-level response rate, based on the percentage of questions to which respondents provided a valid answer (Couper and Kreuter, 2011). As this variable was highly negatively skewed, with a small minority of individuals having an extremely low response rate, I reflected the variable, obtained a natural logarithmic transformation

of it, which was approximately normal in distribution, then reflected and standardised the resulting variable to return its original direction and set its mean to zero.

ii) Two standardised scales tallying the number of times a respondent indicated that they feel fear and anger in response to specific political parties, as measures of the role of emotions in respondents' policy decisions (Brader and Marcus, 2013; Burkitt, 2014).

iii) Repeated measures of a question asking respondents how much they feel the economic situation of their household has improved or deteriorated in the twelve months prior to answering the question, recoded so that higher values mean greater perception of personal economic improvement and saved as a single factor (Clarke et al, 2015).

iv) Repeated measures assessing respondents' general trust in Members of Parliament, likewise saved to a single factor (Balliet et al, 2016).

v) Repeated measures assessing respondents' liking of David Cameron and the Conservative Party, condensed into a single factor measuring Conservative partisanship (Allan and Scruggs, 2004).

vi) A series of questions assessing political engagement, including interest in politics, exposure to political information through various media channels, and propensity to vote. Through multiple stages of factor analysis, I condensed these measures into a single variable for political engagement (Flanagan, 2003).

vii) Respondent newspaper readership, recoded into broadsheet readers, tabloid readers, and those who read no newspaper or another sort of newspaper (Gentzkow et al, 2011).

viii) Level of skill required in respondents' employment, recoded into highly skilled, moderately skilled, low skilled jobs, and never worked (Evans and Dirk de Graaf, 2013).

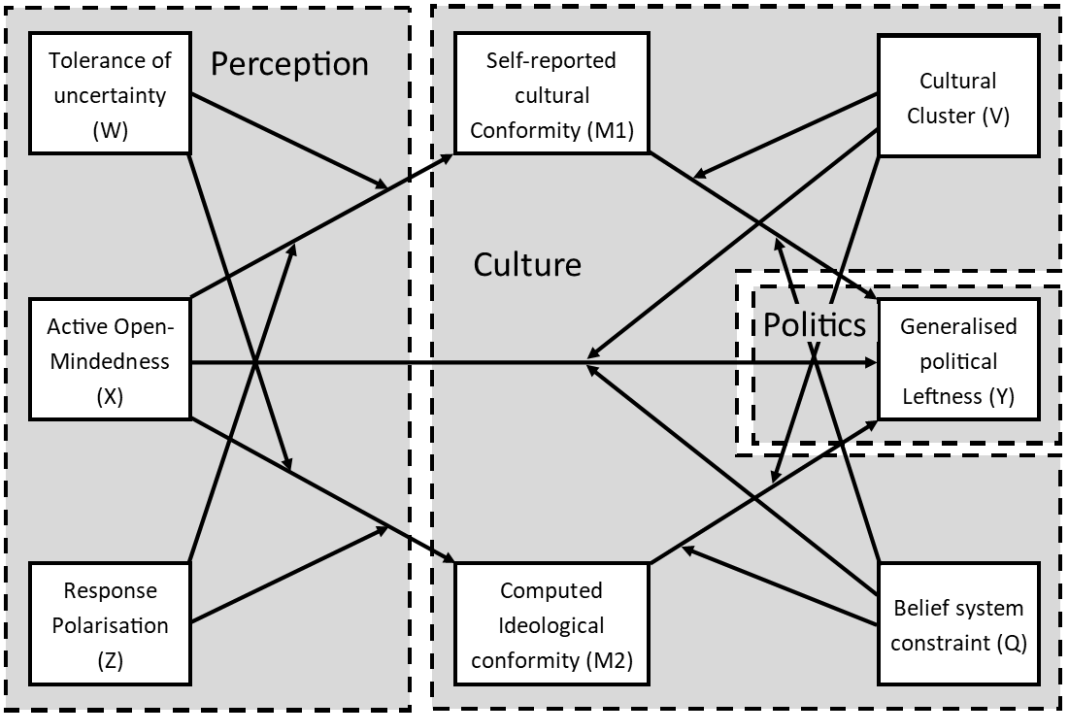
ix) Demographic dummy variables for whether the respondent has been to university (Bobo and Licari, 1989), whether the respondent is disabled (Putnam, 2005), and whether the respondent is female (Sidanius et al, 2000).

x) Respondents' age in whole years on the birthday prior to their completing Wave 7 of the study in April-May 2016, standardised (Hellevik, 2002).

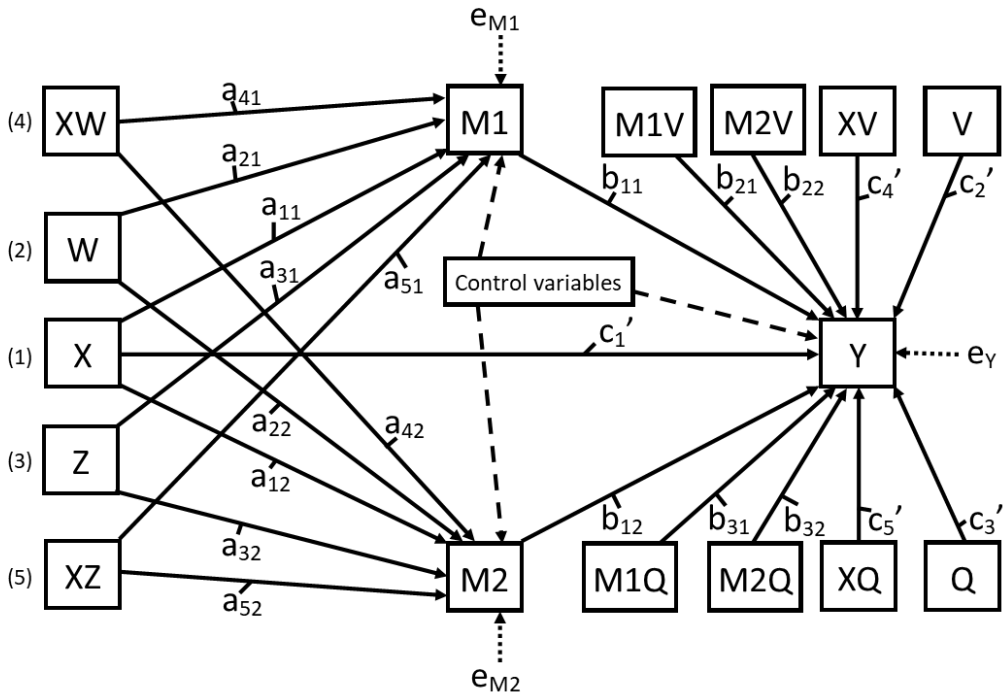
Conditional process analysis: hypotheses and how to test them

Having derived variables to match the concepts discussed in the theoretical literature, I am now able to present a list of hypotheses to be tested in the following analysis. Each hypothesis is accompanied by a theoretical source substantiating it, and by an equation specifying mathematically what the expected significant effects are to be.

Figure 4 illustrates the model proposed by these hypotheses, first as a conceptual diagram developed as a variable-specific version of Figure 2, then as a statistical diagram specifying the actual model to be tested, with annotated relationships representing coefficients which will be produced by the following regression analyses. These are the same letter-codes which are present in the equations underlying each hypothesis. The chief difference between the two diagrams is that in a statistical diagram, arrows cannot point to other arrows, only to variables. As such, moderating relationships are represented by interaction terms, additional variables in the model which consist of the proposed moderator multiplied by the independent variable.



Motivated cultural cognition– conceptual diagram



Motivated cultural cognition– statistical diagram

Figure 4. Conceptual and statistical diagrams representing the model of motivated cultural cognition. Each box is a variable, and each arrow is a relationship between variables. Where an arrow points at another arrow in the conceptual diagram, this represents a moderation and is represented in the statistical diagram as an additional variable consisting of the two influencing variables multiplied together. The influences labelled "e" are error terms, or variations in the three variables to be predicted (the dependent variable and the two mediators) which cannot be explained by any of the variables in the model. It must be noted that the direction of arrows is theoretically informed and cannot be proved by statistical analysis.

The hypotheses are as follows:

H1. That the total effects of active open-mindedness, henceforth X, on political leftness, henceforth Y, are significant and positive (Jost, 2017).

$$c = c_1' + c_4' + c_5' + b_{21} + b_{22} + b_{31} + b_{32} + (a_{11}*b_{11}) + (a_{12}*b_{12}) > 0$$

H2. That the effect of X on Y is significantly mediated by conformity to Britishness and British values, henceforth M1 (Kossowska and Van Hiel, 2013).

$$a_{11}*b_{11} > 0$$

H3. That the effect of X on Y is significantly mediated by similarity to the British ideological average point, henceforth M2 (Van Hiel et al, 2006).

$$a_{12}*b_{12} > 0$$

H4. That the influence of X on M1 is significantly negatively moderated by tolerance of uncertainty, henceforth W (Greenberg and Jonas, 2003).

$$a_{41} < 0$$

H5. That the influence of X on M2 is significantly negatively moderated by W (Haas and Cunningham, 2014).

$$a_{42} < 0$$

H6. That the influence of X on M1 is significantly negatively moderated by response polarisation, henceforth Z (Roets and Van Hiel, 2011).

$$a_{51} < 0$$

H7. That the influence of X on M2 is significantly negatively moderated by Z (Webster and Kruglanski, 1994).

$$a_{52} < 0$$

H8. That the influence of X on Y is significantly negatively moderated by belonging to the Anglo-Saxon as opposed to other cultural clusters, henceforth V (Harman, 2017).

$$c_4' < 0$$

H9. That the influence of M1 on Y is significantly negatively moderated by V (Fu et al, 2007).

$$b_{21} < 0$$

H10. That the influence of M2 on Y is significantly negatively moderated by V (Golec De Zavala et al, 2010).

$$b_{22} < 0$$

H11. That the influence of X on Y is significantly negatively moderated by belief system constraint, henceforth Q (Zaller, 1994).

$$c_5' < 0$$

H12. That the influence of M1 on Y is significantly negatively moderated by Q (Feldman, 2013).

$$b_{31} < 0$$

H13. That the influence of M2 on Y is significantly negatively moderated by Q (Converse, 1964).

$$b_{32} < 0$$

The statistical model used to test my hypotheses will be drawn from the methodological tradition of "conditional process analysis" (Hayes, 2013). Conditional process analysis is an enhanced application of ordinary least squares regression, a technique which intends to explain variation in a key dependent variable using variations in a series of independent variables (Gujarati and Porter, 2008).

One of the greatest criticisms of straightforward regression analysis is that it treats variables and relationships as oversimplified monoliths: effects of independent on dependent variables are assumed to be direct, and not "carried through" intermediary variables, and the strength of the relationship is assumed to apply homogeneously to all individuals in the data. Conditional process analysis is intended to redress these shortcomings: it is "conditional" in the sense that the relationship between X and Y is not universal, but differs between different people in different circumstances. This allows it to explain not only *whether* a relationship exists, but *how* it exists- through mediation analysis- and *when* it exists- through moderation analysis (Hayes, 2013: 5). Conditional process analysis is thus a suitable way to test the plausibility of the theory that cultural forces moderate and mediate the influence of personality on policy preferences.

Professor Andrew Hayes, the chief proponent of conditional process analysis, has developed a useful tool called PROCESS, a macro for IBM SPSS Statistics which allows the data analysis program to readily run integrated moderation, mediation and hybrid analyses (Hayes, 2013). I have used the PROCESS macro to run a moderated mediation analysis of the statistical diagram in Figure 4, the syntax and output for which are available in the technical appendix.

My approach to missing data was to insert mean values for each variable (Downey and King, 1998). This has the advantage of being a simple and readily understandable method of estimating unobserved values which, by definition, will not alter the averages of any of the statistics. I acknowledge that the method known as multiple imputation, which generates multiple estimates of each missing value, is a more authentic approach to this problem, and avoids some of the distortions caused by insertion of means (Brunton-Smith et al, 2014). However, as the PROCESS macro is presently unable to support data sets using multiple imputation, I judged that the substantive advantages of PROCESS outweigh the inferential advantages of multiple imputation for the present analysis.

The results

Overview of results

The results of the conditional process analysis are summarised in Table 1, which reports the results from four regression models: a "total effect model", measuring the complete influence of active open-mindedness on political leftness without controlling for cultural conformity (for testing H1), models measuring the influence of active open-mindedness on both cultural conformity mediators (for testing H2, H3 and H4-H7), and a model measuring the impact of active open-mindedness and the two mediators together on political leftness (for testing H2, H3 and H8-H13). I will explain these results in detail below.

	Total effect model predicting leftness by open-mindedness	Model predicting cultural conformity by open-mindedness	Model predicting ideological conformity by open-mindedness	Final model predicting leftness by open-mindedness and both conformity mediators
R Squared	0.39	0.38	0.21	0.58
F Statistic	293.62***	171.77***	72.14***	301.45***
Constant	0.21*** (0.03)	-0.05 (0.04)	-0.02 (0.05)	-0.02 (0.04)
Cultural conformity (M1)	*n/a*	*n/a*	*n/a*	-0.37*** (0.01) *"b_{11}"*
Ideological conformity (M2)	*n/a*	*n/a*	*n/a*	-0.25*** (0.01) *"b_{12}"*
Active open-mindedness (X)	0.19*** (0.02) *"c"*	-0.12** (0.04) *"a_{11}"*	-0.08 (0.04) *"a_{12}"*	0.01 (0.04)
Anglo-Saxon cultural cluster (V)	-0.10*** (0.02)	*n/a*	*n/a*	0.09*** (0.02)
*X * V interaction*	*n/a*	*n/a*	*n/a*	0.08 (0.06) *"c_4'"*
*M1 * V interaction*	*n/a*	*n/a*	*n/a*	-0.11*** (0.02) *"b_{21}"*
*M2 * V interaction*	*n/a*	*n/a*	*n/a*	0.15*** (0.02) *"b_{22}"*
Belief system constraint (Q)	0.03** (0.01)	*n/a*	*n/a*	0.04*** (0.01)
*X * Q interaction*	*n/a*	*n/a*	*n/a*	0.01 (0.03) *"c_5'"*
*M1 * Q interaction*	*n/a*	*n/a*	*n/a*	-0.11*** (0.01) *"b_{31}"*
*M2 * Q interaction*	*n/a*	*n/a*	*n/a*	-0.02 (0.01) *"b_{32}"*
Tolerance of uncertainty (W)	0.09*** (0.01)	-0.09*** (0.01)	-0.06*** (0.01)	*n/a*
*X * W interaction*	*n/a*	-0.06 (0.03) *"a_{41}"*	-0.08* (0.04) *"a_{42}"*	*n/a*
Response polarisation (Z)	-0.19*** (0.01)	0.16*** (0.01)	-0.37*** (0.02)	*n/a*
*X * Z interaction*	*n/a*	-0.09** (0.03) *"a_{51}"*	-0.13*** (0.04) *"a_{52}"*	*n/a*
Item-level response	0.04*** (0.01)	0.00 (0.02)	-0.01 (0.02)	-0.01 (0.01)
Risk-taking	-0.03*** (0.01)	0.00 (0.01)	0.03* (0.01)	-0.01 (0.01)
Anger at parties	0.16*** (0.01)	-0.13*** (0.01)	-0.09*** (0.01)	0.00 (0.01)
Fear of parties	0.10*** (0.01)	-0.05*** (0.01)	-0.02 (0.01)	0.02 (0.01)
Conservative partisanship	-0.48*** (0.01)	0.52*** (0.01)	0.10*** (0.02)	-0.26*** (0.01)
Trust in MPs	0.19*** (0.01)	-0.10*** (0.01)	-0.08*** (0.01)	0.17*** (0.01)
Positive household economic evaluations	0.00 (0.01)	-0.03* (0.01)	-0.05*** (0.01)	0.01 (0.01)
Political engagement	0.09*** (0.01)	-0.03 (0.01)	-0.02 (0.02)	0.08*** (0.01)
Female	-0.11*** (0.02)	-0.04 (0.02)	-0.08** (0.03)	-0.13*** (0.02)
Age in years	-0.12*** (0.01)	0.24*** (0.02)	0.10*** (0.02)	0.02 (0.01)
Attended university	0.12*** (0.02)	-0.24*** (0.03)	-0.10*** (0.03)	0.15*** (0.02)
Disabled	0.04 (0.02)	0.06* (0.03)	0.06* (0.03)	0.03 (0.02)
Highly-skilled (vs never worked)	-0.03 (0.03)	0.01 (0.04)	0.06 (0.05)	0.02 (0.03)
Moderately skilled (vs never worked)	-0.14*** (0.03)	0.02 (0.04)	0.00 (0.05)	0.00 (0.03)
Lower-skilled (vs never worked)	-0.18*** (0.03)	0.05 (0.05)	0.05 (0.06)	0.02 (0.03)
Broadsheet reader (vs other or no paper)	0.26*** (0.03)	-0.25*** (0.03)	-0.23*** (0.03)	0.09*** (0.02)
Tabloid reader (vs other or no paper)	-0.24*** (0.02)	0.27*** (0.03)	0.21*** (0.03)	-0.19*** (0.02)

*Table 1. Unstandardised regression coefficients and standard errors (in brackets) from the conditional process analysis summarised in the statistical diagram in Figure 4. The R Squared of each model represents the proportion of variance in the dependent variable for each column which can be explained by the independent and control variables listed in column 1. The F statistic is an arbitrary number, but a higher statistic, when significant, demonstrates that one model is a more appropriate description of a population than another, similar model. Where a coefficient is listed as "n/a" the variable in that row was not featured in the model in that column, and hence no coefficient was calculated. Where a coefficient is accompanied by a letter and numbers in inverted commas, e.g. "a_{52}", this represents the arrow in the statistical diagram in Figure 4 which the coefficient represents, and which features in the hypotheses. *=95% confidence. **=99% confidence. ***=99.9% confidence.*

The influence of active open-mindedness on leftness, regardless of culture

The "total effect model" summarised in the second column of Table 1 estimates the total effect of active open-mindedness on political leftness (*c*) when cultural conformity is not controlled for. This model is not produced by PROCESS when a moderated mediation analysis is requested. As such, I ran the total effect model using SPSS's ordinary least squares regression commands. Full diagnostics of the residuals (variations in political leftness which cannot be explained by any of the predictor variables), not reproduced here, showed that the model meets all the assumptions required for the results of linear regression analysis to be relied upon, including absence of strong correlations between predictors, normal distribution of residuals either side of a mean of zero, lack of correlation between the residual values and the predicted values for political leftness, and lack of correlation between the residuals and their potential to seriously skew the results, a quantity known as leverage (Tarling, 2009).

The model explains around 39% of the variation in political leftness- a minority, but nevertheless a reasonably high figure by the standards of the social sciences. What's more, the high and significant F statistic demonstrates that the model's predictor variables make a noteworthy impact in explaining political orientation. The model's constant, 0.21***, represents the expected value for political leftness for an individual with a score of zero on all predictor variables, thus belonging to the reference category- the category which is not assigned its own row- on all the categorical predictors. As all the continuous variables, even age, have been standardised, with the mean value as zero and negative values for all cases below the mean, the constant represents the political orientation of a person who reports the mean values for all continuous variables, does not belong to the Anglo-Saxon cultural cluster, is male, has not attended university, is not disabled, has never worked and does not read a newspaper. The effects of every predictor variable are then to be added to the baseline provided by the constant.

The coefficient of 0.19*** in column 2, row 7 of Table 1 thus represents the full, positive effect of open-mindedness on political leftness, without distinguishing between components of that effect which may be direct, or which may be transmitted via mediating variables. I find, perhaps unsurprisingly given the conclusions of the literature summarised above, that more open-minded people are more left-wing. As this effect is significant and positive, I confirm H1.

The influences of active open-mindedness on conformity

The models in columns 3 and 4 attempt to predict the two hypothesised mediators- cultural conformity and ideological conformity- using active open-mindedness. This is the first step in demonstrating a mediation, and thus in testing the hypotheses H2 and H3. If the independent variable has a significant effect on the mediators, and the mediators have a significant effect on the dependent variable, then part or all of the effect of independent on dependent has been transmitted indirectly via the mediators.

The models explain 38% and 21% of the variance respectively in the measures of conformity, and their lower F statistics suggest that, in general, conformity to belief systems is harder to

effectively predict using the chosen variables than political leftness. As hypothesised, active open-mindedness has a significantly negative effect on cultural conformity. Its negative effect on ideological conformity is not significant. Nevertheless, as will be seen in Figure 6 below, this non-significance is not universal. At many values of the moderators, those who are more open-minded are indeed more distant on average from the mean political position.

The alternative perceptual measures, response polarisation and tolerance of uncertainty, have more consistently significant impacts on the measures of cultural conformity. It should be noted, however, that the strong negative relationship between response polarisation and ideological conformity displayed in column 4, row 18 should not be interpreted, as it is an artefact of the way those two measures have been produced. Those with a tendency to give extreme responses to Likert scales will usually also give extreme, and hence nonconformal, responses to Likert scales regarding political orientation. Response polarisation does, however, have the expected positive effect on cultural conformity (0.16***). Tolerance of uncertainty, in many ways its opposite, has, as expected, a negative effect on both measures of conformity. This provides further evidence that open, flexible perceptual dispositions make individuals more willing to question cultural identities and accepted conventions.

Moderation by tolerance of uncertainty and response polarisation

The models in columns 3 and 4 also test whether the negative influences of active open-mindedness on the two measures of conformity are stronger among respondents who are higher in tolerance of uncertainty and response polarisation. It should be noted that where a negative relationship is concerned, a negative value for the interaction with the moderator indicates that higher values of the moderator make the relationship stronger (Hayes, 2013). As the coefficients in row 17 demonstrate, there is no indication that tolerance of uncertainty enhances the influence of active open-mindedness on cultural conformity, but there is some evidence that it enhances open-mindedness' effect on ideological conformity (-0.08*). The coefficients for the interaction with response polarisation in row 19 show that greater values of response polarisation increase the negative effects of active open-mindedness on both cultural conformity (-0.09**) and ideological conformity (-0.13***). These findings allow me to confirm H5, H6, and H7, although I cannot confirm H4.

The influences of conformity on leftness

The final model in column 5 again turns to predicting values for political leftness, this time including both active open-mindedness *and* the measures of conformity as predictors. As the model shows, once cultural and ideological conformity are taken into account in predicting political leftness (at -0.37*** and -0.25*** respectively), active open-mindedness has no significant effect. This indicates that open-mindedness only positively influences leftness because it negatively influences conformity, which itself negatively influences leftness within the United Kingdom. The overall indirect effects, which are needed to test H2 and H3, are not monolithic, but vary with differing values of the moderators. These will be discussed below.

Moderation by cultural cluster and constraint

The final model also enables me to assess whether the effects of open-mindedness on leftness, direct and indirect, are different in strength between cultural clusters and between different levels of constraint to the traditional political spectrum. The relevant coefficients are located in rows 9-11 and 13-15 respectively.

Neither of the cultural moderators interacts significantly with active open-mindedness directly in influencing political leftness. I thus cannot confirm H8 or H11. There is, however, an interaction between these moderators and the two conformity-based mediators. Among members of the Anglo-Saxon cultural cluster, the negative influence of cultural conformity on political leftness is stronger than among the members of other clusters. The opposite is true, however, when considering the influence of ideological conformity on political leftness: here, its influence is strongest among those who do not belong to the Anglo-Saxon cluster. Either way, this demonstrates that culture group membership is important in determining the relationships between perception, conformity, and political orientation. However, whilst I confirm H9, I am unable to confirm H10. The reason for this is that although cultural cluster membership interacts significantly with ideological conformity, the direction of this interaction is opposite to the direction hypothesised.

Belief system constraint significantly strengthens the negative effect of cultural conformity on political leftness (-0.11***). This is illustrated in Figure 5, a scatterplot comparing the cultural conformity and political leftness of individual respondents, who I grouped into clusters based on their level of constraint using a univariate two-step cluster analysis. Each of the lines represents the average relationship between cultural conformity and leftness within a cluster of individuals with similar levels of constraint. This demonstrates that the line is steepest- implying the strongest negative relationship- among the respondents with the greatest degree of constraint. I thus confirm H12. I cannot confirm H11 or H13, however, because the relevant coefficients representing interaction terms are not statistically significant.

Direct and indirect effects, at different levels of the four moderators

Finally, in order to fully test H2 and H3, it is necessary to compare the direct and indirect effects of active open-mindedness on political leftness. The direct effect is simply the effect of response polarisation on political leftness, not including any effects which have passed through the mediators. The indirect effect of each mediator is the effect of active open-mindedness on the mediator in question, multiplied by the effect of that mediator on political leftness. A complication arises from the fact that, in a mediation analysis which also involves moderators, direct and indirect effects are not absolute, but conditional upon values of the moderators. As such, PROCESS did not generate a single figure each for direct and indirect effects, but a range of conditional effects. In total, six direct effects and 108 indirect effects- 54 for each mediator- were produced (these can be found in full in the technical appendix). These reveal nuances in the effects which are not shown in table 1. For example, whilst the overall direct effect of open-mindedness on leftness is not significant overall, it does become narrowly significant and positive amongst Anglo-Saxons with average (0.09*) or high (0.10*) levels or constraint.

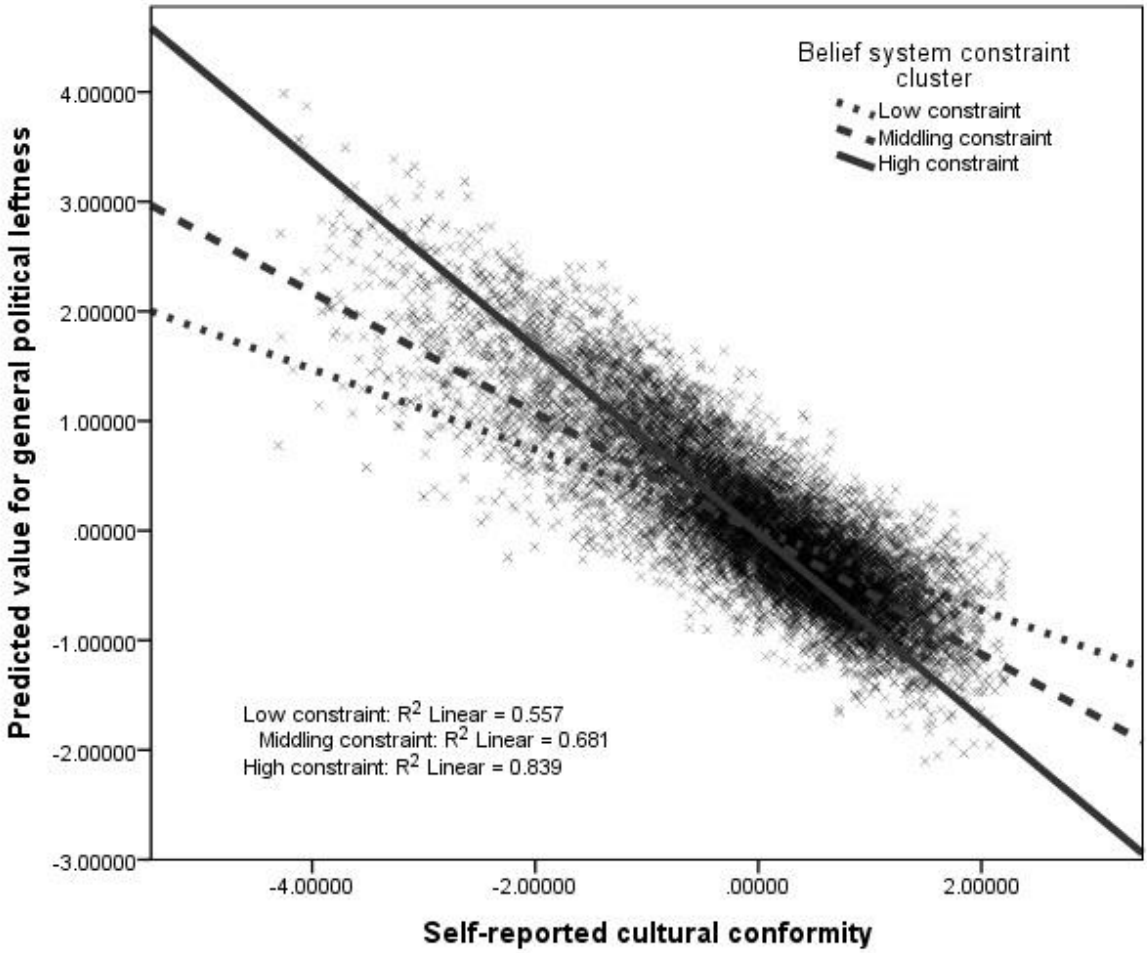


Figure 5. Scatterplot showing the relationship between cultural conformity and political leftness, moderated in strength by belief system constraint. The R Squared statistics represent the proportion of variance in political leftness for each cluster of constraint that can be explained by cultural conformity for each respective line.

The best way to examine the multitude of indirect effects is to observe Figure 6. This diagram displays all 108 effect sizes, with 95% confidence intervals. Crucially, even though it would appear from Table 1 that active open-mindedness does not significantly influence leftness via ideological conformity, against the prediction of H3, it emerges that in many cases it does. In many cases, also, indirect effects transmitted via cultural conformity are not significant. An examination of the tables of effect sizes in the technical appendix reveals that the largest, most significant effects occur in conditions of high constraint, high tolerance of uncertainty and high response polarisation, with differing effects of cultural cluster between the mediators.

To gain a simpler understanding of whether H2 and H3 can be confirmed, I ran a separate mediation analysis in PROCESS, including the moderators as simple control variables without interaction terms. The main results of this analysis are not reported here, but can be found in the technical appendix. In this model, unlike the model in Table 1, the effect of active open-mindedness on ideological conformity is negative and significant (-0.10**). The total effect of open-mindedness on leftness was a highly significant 0.13. The direct effect was 0.05 and was narrowly non-significant. Indirect effects via cultural and ideological conformity were 0.05 and 0.03 respectively, both significant. Indirect effects thus account for 62% of the effect of open-mindedness on leftness. In sum, I found enough evidence to confirm H2 and, narrowly, H3.

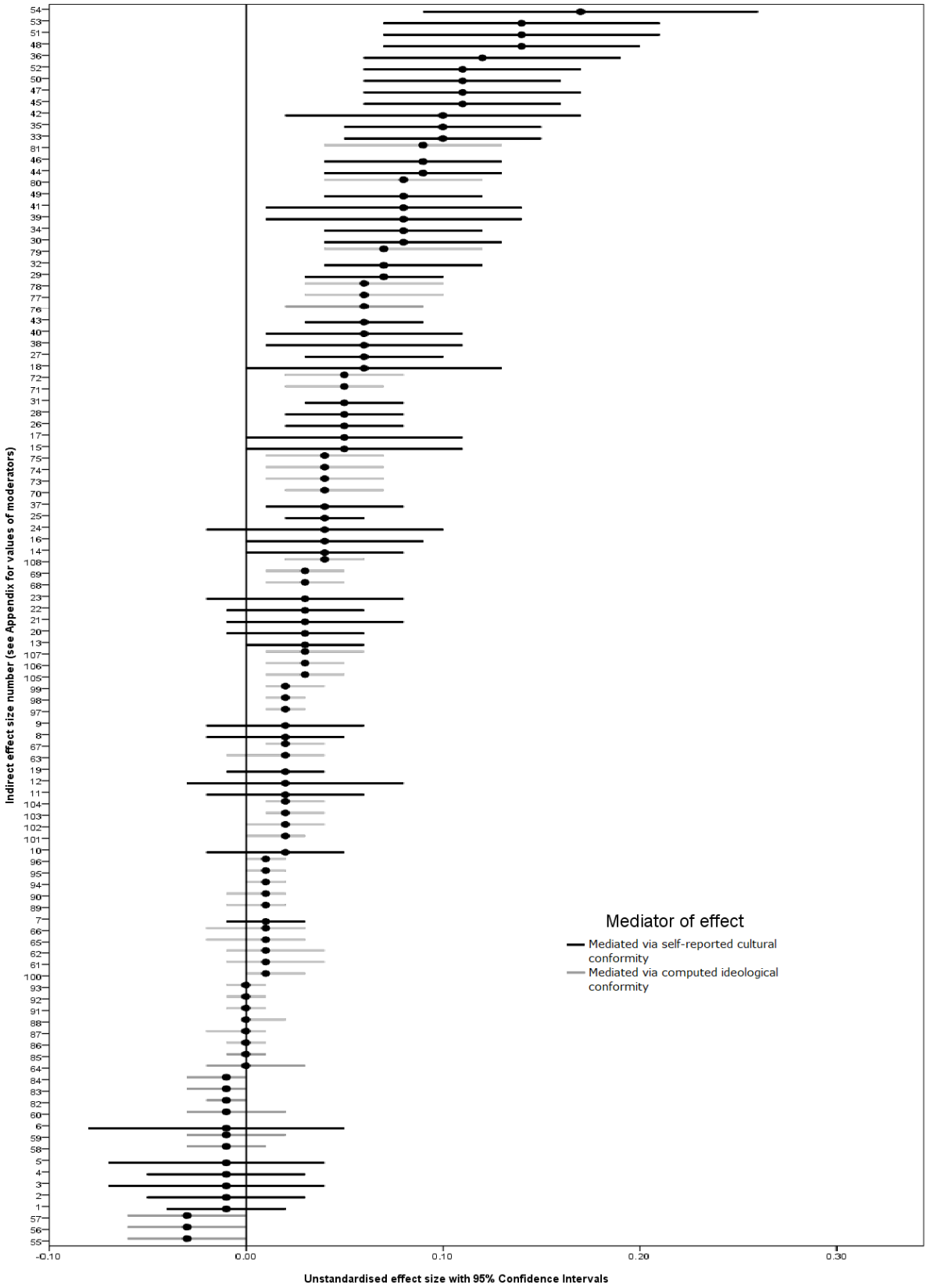


Figure 6. High-low plot showing sizes of the indirect effects of active open-mindedness on political leftness, via both measures of cultural conformity, at different levels of the four moderating variables, arranged in order of size. Dots represent effect sizes, relative to the x axis. Bars represent 95% confidence intervals. Bar colour signifies the mediator through which the effect is transmitted. The vertical line represents an effect size of zero; when a bar touches or crosses this line, the indirect effect is not significant. For information on the levels of each moderator present for each indirect effect, use the reference number for each effect size which can be found on the y axis. Each number corresponds to a row in the effect size tables in the technical appendix.

As such, I confirm eight of the original thirteen hypotheses, the relationships proposed by which are illustrated in Figure 7 below, which is a replica of the conceptual diagram in Figure 4, with significant influences annotated with coefficients from table 1, and with non-significant influences removed. Openness to changing one's beliefs in response to new information appears to weaken commitment to the prevailing local culture, which in turn, within the United Kingdom's social context, leads to their becoming more left-wing. The strength of these relationships is not constant and universal, however, but depends on other psychological quantities concerned with attitudes toward uncertainty and ambiguity, actual cultural group membership, and constraint to the traditional political spectrum between left and right. The inclusion of these mediators and moderators adds considerable predictive power to the final regression model, as compared with the straightforward linear regression model in which culture is not considered, enabling it to explain an additional 19% of the variance in political orientation. Ultimately, I am able to explain 58% of the variance in leftness, a remarkably high proportion by the standards of survey research in the social sciences.

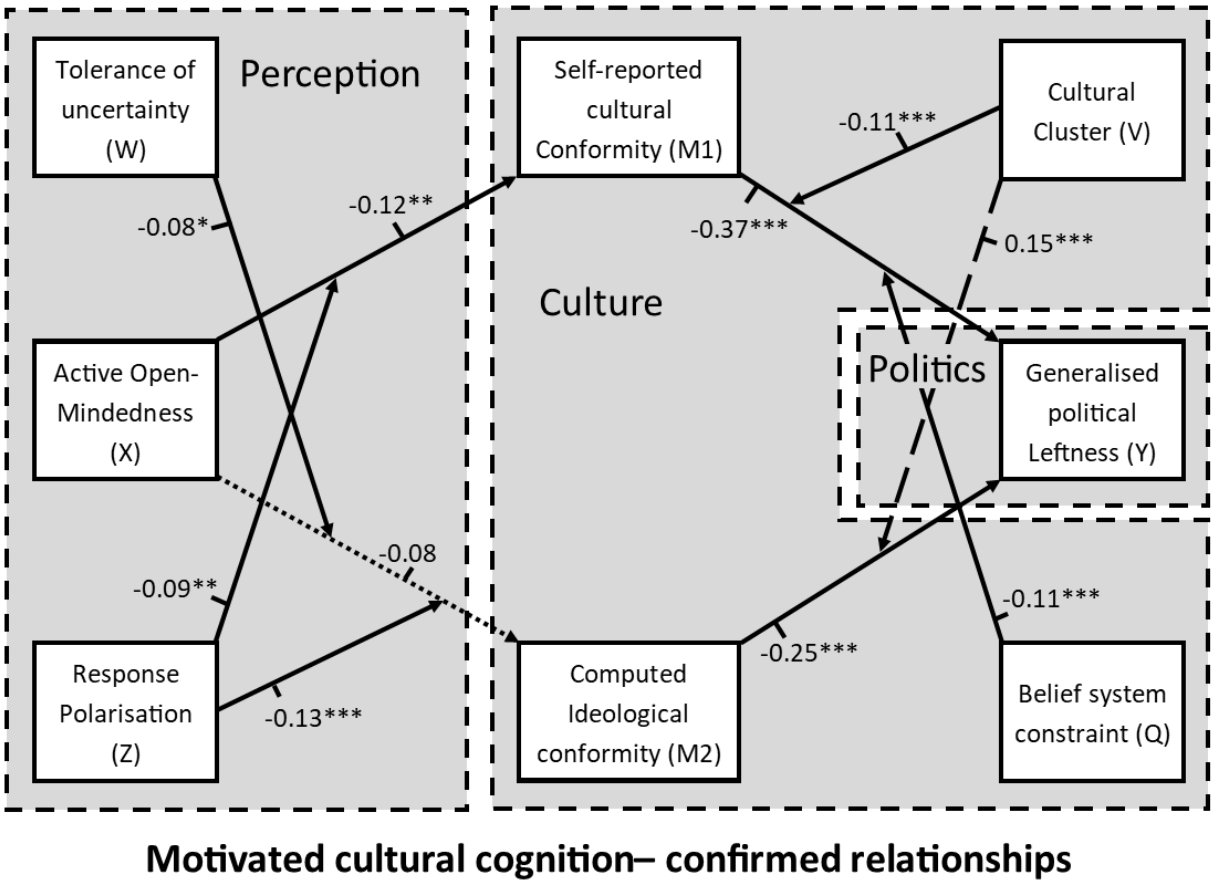


Figure 7. Conceptual diagram showing hypothesised relationships which have been confirmed, annotated with regression coefficients showing the strength, direction, and significance of those relationships. Because active open-mindedness has a negative influence on both measures of conformity, and these measures have a negative influence on political leftness, then active open-mindedness has an indirect positive influence on leftness. The dashed arrow for the role of cultural cluster in moderating the influence of ideological conformity on leftness represents the fact that whilst a significant moderation was found, the hypothesis regarding this moderation cannot be confirmed. This is because the hypothesised relationship was negative, whereas the observed relationship is positive. The dotted line for the influence of open-mindedness on ideological conformity is in recognition of the fact that, although this influence is not positive overall in the model displayed in Table 1, it is significant at higher values of the moderators, and is thus a valid depiction of at least some segments of society, and, additionally, is significantly negative in a mediation model involving both mediators but no moderators.

Discussion: implications for the science of policy preferences

My analysis has recovered evidence to support some theories, challenge others, and add increased layers of nuance to still more.

Policy preferences are the root of my analysis: individuals exhibit measurable differences in levels of support for specific programmes of government action. The question is, where do these differences in support come from? I have demonstrated the usefulness of Converse's (1964) conception of "belief systems": networks of logically distinct policy preferences which are bound together by ties of socially arbitrary "constraint" (Converse, 1964). This concept appears to be, if anything, even more useful than Converse originally thought; whilst he argued that only the opinions of the most sophisticated are highly constrained, my research suggests that constraint between policy opinions is, in fact, widespread within mass publics.

The question then emerges, can these structures in policy preferences be accurately summarised using the terms "left" and "right"? To an extent, I confirm criticisms of a simple, one-dimensional political spectrum, uncovering a clear divide between economic and non-economic policies, as claimed by Rokeach and many others (Rokeach, 2000; Bryson and McDill, 1968; Mitchell, 2006). Indeed, rather than applying an arbitrary limit of two ideological axes, I find evidence that the precise number of dimensions produced by constraint between policy preferences is both dependent on measurement techniques and situationally contingent, as suggested by Alvarez and Brehm (Alvarez and Brehm, 2002). Nevertheless, the existence of distinct policy dimensions is not the same as the idea of *independent* policy dimensions, as implied by the idea of the political compass. I find that the dimensions of political orientation not only correlate, they can ultimately be explained by a single underlying factor which can be thought of as a generalised attitude towards social equality combining economic regulation with social freedom, as argued by Norberto Bobbio (Bobbio, 1997). This suggests that "left" and "right" are indeed meaningful as catch-all political terms summarising meaningful differences in the human population.

My research question aimed to explain why these differences exist. I find, in line with the theories of John Jost and much of mainstream political psychology, that those on the "left" do indeed score more highly on measures of open-mindedness, willingness to accept ambiguity, and tolerance of uncertainty, and less highly on measures of commitment to one's beliefs, decisiveness, and preference for predictability (Jost et al, 2003; Jost, 2017). As anticipated by the long theoretical tradition originated by Theodor Adorno, political views appear to be anchored in psychological antecedents representing general firmness, or flexibility, of opinion (Adorno et al, 1964). Strict classification of ideas into "right" or "wrong" appears to accompany the strict classification of people into "worthy" and "unworthy".

Yet my findings challenge any supposition that a single, monolithic "natural" or "inherent" relationship between psychology and politics exists for all people, or even for all people within a specific society. I present cultural variation as both a problem in the field of the social sciences (after Van Bavel et al, 2016) and a solution to some of its inconsistencies (Fu et al, 2007).

I find evidence to support the proposal of Kossowska and Van Hiel (2003), Harman (2017) and others, which holds that the relationship between openness or closure and public opinion differs in strength between cultural groups (Kossowska and Van Hiel, 2003; Harman, 2017). In this sense, perceptual influences on politics are *moderated by*, and thus conditional on, cultural identities.

I have also substantiated the claim made by Fu et al (2007) that at least part of the reason why open- or closed-mindedness can have such different political implications across societies is that closed perceptual dispositions encourage cultural conformity, whereas open ones encourage cultural cynicism (Fu et al, 2007). Depending on cultural content, these tendencies to support or attack the dominant idea-system can result in support for very different policies. In a right-wing culture, the counterculture is left-wing, and vice versa. Deriving two measures approximating conformity, I find that more open-minded individuals generally express less attachment to British culture and society, which would otherwise have had a right-wing political influence over them. I find weaker, though non-negligible, evidence to support the case that more open-minded people tend to prefer policies which are more unusual or unconventional by the standards of their host society, and that, in a generally rightward-leaning society, these policies tend to be more left-wing. When these two conformal influences are taken into account in predicting political leftness, active open-mindedness no longer has any significant direct effect upon the latter. To underscore the importance of cultural identity in determining the precise influence of cultural conformity on policy preferences, I discover that the influences of both measures of conformity on political leftness are also significantly moderated by cultural cluster membership. I thus reveal a wide selection of evidence that perceptual influences on politics are *mediated by*, and thus dependent on, cultural conformity and anti-conformity (Siedlecki et al, 2016).

Finally, I find evidence that Conversian belief system constraint, itself a metric of cultural origin, interacts with conformity to strengthen the indirect influence of perception on political orientation. Individuals who accept both dominant British values and the dominant assumptions of political culture regarding which policies "go together" tend to be the most right-wing. Conversely, those who are highly opposed to British culture and yet most attuned to patterns of constraint tend to be the most left-wing. This supports the theory articulated by John Zaller and others, holding that understanding of the dominant factions and dimensions within political belief systems enables individuals to more effectively connect their general values and dispositions with support for specific programmes of state action (Zaller, 1992).

In sum, I have further specified and largely substantiated the model of "motivated cultural cognition" first elaborated by Jeanne Fu and her colleagues (Fu et al, 2007). Cognition is indeed motivated by differing psychological dispositions, as John Jost and others claim (Jost et al, 2003), but these motivations do not influence attitudes towards policies directly. Instead, perceptual motivations target socially shared belief systems. The more "open-minded" become more disposed to hold their own, unique view on a given topic, and thus develop an inbuilt suspicion toward whichever ideas are most popularly accepted. These effects are dependent on individual cultural identity and alignment to the dominant political belief system.

Conclusion: limits of the study and needs for further research

This study has provided some interesting empirical evidence to suggest that policy preferences originate from an interplay between individual perceptual dispositions and collective cultural systems of integrated beliefs and values. Both the promise of this theory, and the limitations of my own approach to test it, suggest a rich vein of avenues for further research.

The chief flaw of my analytical method is its inability to demonstrate causal relationships. An association between variables is necessary to prove causality, but not sufficient. To demonstrate that open-mindedness causes reduced cultural conformity, which in turn causes reduced political leftness, it is necessary to demonstrate that the causing variables precede the caused variables in time. For this purpose, a longitudinal study of a similar nature is valuable. The data which I have used, of course, have been collected on several consecutive occasions, but their two-year time span is not long enough to measure systematic changes in attitudes within individuals. A longitudinal study taking place over a significant number of years- say, at least four or five- would considerably aid causal inference.

Having used only secondary data, I have been limited in my choice of variables and have been unable to design questionnaire content to minimise error and plan appropriate question ordering. A representative survey targeted to this topic of research, where funds allow, would be highly advantageous.

As noted above, the structure and dimensionality of policy preferences are, to a great extent, a function of the number and content of preferences measured in a survey. The policy preferences selected were fewer in number than would ideally be desired. What's more, they were skewed in content, including far more items on immigration than any other policy area. Many additional policy preference items are available in the British Election Study, but most of these could not be used because a considerable number of responses were missing. A future study aiming to analyse a fuller, more comprehensive selection of policy preferences might employ a different data set with less missing data, a more sophisticated approach to the imputation of missing values, or both.

The restrictions and limitations of the PROCESS macro partly account for some of the shortcomings in my analysis. PROCESS is not compatible with multiple imputation of missing values; will accommodate multiple mediators, but assumes that, in models involving moderators, they are not causally associated; and provides a fixed selection of models to test which, although large, cannot be customised by the user. Structural equation modelling, which integrates the testing of flexible path-based relationships with factor analysis, could be used to help build more sophisticated models of belief system dynamics.

It is easy to confuse "left" and "right" with "right" and "wrong"- whichever side one identifies with. Psychological motivations and cultural influences are fundamental to the arbitrary subjectivity inherent in the human condition. Only by understanding these forces can we hope to unwrap the age-old mystery that is human public opinion.

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Technical Appendix

Section 1: question wording, coding and recoding of selected variables

Variable name(s)	Question wording	Original coding	Response labels	Recoding
Country	Respondent country- coded, not asked	1	England	Reference category
[theme: culture]		2	Scotland	Scot = 1
		3	Wales	Wales = 1
turnoutUKGeneralW1 turnoutUKGeneralW2 turnoutUKGeneralW3 turnoutUKGeneralW4	"Many people don't vote in elections these days. If there were a UK General Election tomorrow, how likely is it that you would vote?"	1	Very unlikely that I would vote	Same
[theme: engagement]		2	Fairly unlikely	Same
		3	Neither likely nor unlikely	Same
		4	Fairly likely	Same
		5	Very likely that I would vote	Same
		9999	Don't know	MISSING
polAttentionW1 polAttentionW2 polAttentionW3 polAttentionW4 polAttentionW6 polAttentionW7 polAttentionW8	"How much attention do you generally pay to politics?"	0	Pay no attention	Same
[theme: engagement]		1	1	Same
		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	7	Same
		8	8	Same
		9	9	Same
		10	Pay a great deal of attention	Same
		9999	Don't know	MISSING
trustMPsW1 trustMPsW2 trustMPsW3 trustMPsW4 trustMPsW6 trustMPsW7 trustMPsW9	"How much trust do you have in Members of Parliament in general?"	1	No trust	Same
[theme: general politics]		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	A great deal of trust	Same
		9999	Don't know	MISSING
likeCameronW1 likeCameronW2 likeCameronW3 likeCameronW4 likeCameronW5 likeCameronW6 likeCameronW7 likeCameronW8 likeCameronW9	"How much do you like or dislike each of the following party leaders? [David Cameron]"	0	Strongly dislike	Same
[theme: partisanship]		1	1	Same
		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	7	Same
		8	8	Same
		9	9	Same
		10	Strongly like	Same
		9999	Don't know	MISSING
econPersonalRetroW1 econPersonalRetroW2 econPersonalRetroW3 econPersonalRetroW4 econPersonalRetroW7	"How does the financial situation of your household now compare with what it was 12 months ago? Has it:"	1	Got a lot worse	Same

[theme: general politics]		2	Got a little worse	Same
		3	Stayed the same	Same
		4	Got a little better	Same
		5	Got a lot better	Same
		9999	Don't know	MISSING
likeConW7 likeConW8 likeConW9	"How much do you like or dislike each of the following parties? [Conservatives]"	0	Strongly dislike	Same
[theme: partisanship]		1	1	Same
		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	7	Same
		8	8	Same
		9	9	Same
		10	Strongly like	Same
		9999	Don't know	MISSING
ptvConW9	"How likely is it that you would ever vote for each of the following parties? [Conservatives]"	0	Very unlikely	Same
[theme: partisanship]		1	1	Same
		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	7	Same
		8	8	Same
		9	9	Same
		10	Very likely	Same
		9999	Don't know	MISSING
immigEconW1 immigEconW2 immigEconW3 immigEconW4	"Do you think immigration is good or bad for Britain's economy?"	1	Bad for economy	1
[theme: policies]		2	2	1.67
		3	3	2.33
		4	4	3
		5	5	3.67
		6	6	4.33
		7	Good for economy	5
		9999	Don't know	MISSING
immigCulturalW1 immigCulturalW2 immigCulturalW3 immigCulturalW4 immigCulturalW6 immigCulturalW8	"And do you think that immigration undermines or enriches Britain's cultural life?"	1	Undermines cultural life	7
[theme: culture]		2	2	6
		3	3	5
		4	4	4
		5	5	3
		6	6	2
		7	Enriches cultural life	1
		9999	Don't know	MISSING
britishnessW1 britishnessW2 britishnessW3 britishnessW4 britishnessW7 britishnessW8 britishnessW9	"Where would you place yourself on these scales? [Britishness]"	1	Not at all British	Same
[theme: culture]		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	Very strongly British	Same
		9999	Don't know	MISSING

reasonForUnemploymentW1 reasonForUnemploymentW2 reasonForUnemploymentW3 reasonForUnemploymentW4 reasonForUnemploymentW7	"How much do you agree or disagree with the following statements? [When someone is unemployed, it's usually through no fault of their own]"	1	Strongly disagree	Same
[theme: policies]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
immigrantsWelfareStateW1 immigrantsWelfareStateW2 immigrantsWelfareStateW3 immigrantsWelfareStateW4 immigrantsWelfareStateW7	"How much do you agree or disagree with the following statements? [Immigrants are a burden on the welfare state]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1ss
		9999	Don't know	MISSING
govtHandoutsW1 govtHandoutsW2 govtHandoutsW3 govtHandoutsW4 govtHandoutsW7	"How much do you agree or disagree with the following statements? [Too many people these days like to rely on government handouts]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
businessBonusW1 businessBonusW2 businessBonusW3 businessBonusW4 businessBonusW7	"How much do you agree or disagree with the following statements? [In business, bonuses are a fair way to reward hard work]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
countryOfBirth	"Where were you born?"	1	England	
[theme: culture]		2	Scotland	
		3	Wales	
		4	Northern Ireland	
		5	Republic of Ireland	
		6	Commonwealth member country	
		7	European Union member country	
		8	Rest of world	
		998	Skipped	
		999	Not asked	
		9999	Prefer not to answer	MISSING
discussPolDaysW2 discussPolDaysW4 discussPolDaysW5 discussPolDaysW6 discussPolDaysW7	"During the last week, roughly on how many days did you talk about politics with other people?"	0	0 days	Same
[theme: engagement]		1	1 day	Same
		2	2 days	Same
		3	3 days	Same
		4	4 days	Same
		5	5 days	Same
		6	6 days	Same
		7	7 days	Same
		9999	Don't know	MISSING
immigrationLevelW4 immigrationLevelW6	"Do you think the number of immigrants from foreign countries who are permitted to come to the	1	Decreased a lot	Same

	United Kingdom to live should be increased, decreased, or left the same as it is now?"			
[theme: policies]		2	Decreased a little	Same
		3	Left the same as it is now	Same
		4	Increased a little	Same
		5	Increased a lot	Same
		99	Don't know	MISSING
		998	Skipped	MISSING
		999	Not asked	MISSING
		9999	Don't know	MISSING
conAngryW4 conAngryW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Conservatives] [Angry]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
labAngryW4 labAngryW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Labour] [Angry]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
ldAngryW4 ldAngryW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Liberal Democrats] [Angry]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
ukipAngryW4 ukipAngryW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [UKIP] [Angry]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
grnAngryW4 grnAngryW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Green] [Angry]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
conFearW4 conFearW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Conservatives] [Afraid]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
labFearW4 labFearW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Labour] [Afraid]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING

ldFearW4 ldFearW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Liberal Democrats] [Afraid]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
ukipFearW4 ukipFearW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [UKIP] [Afraid]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
grnFearW4 grnFearW6	"Now we would like to know something about the feelings you have towards each of the parties. Which of these emotions do you feel about each of the parties? Tick all that apply [Green] [Afraid]"	0	No	Same
[theme: psychology]		1	Yes	Same
		9999	Don't know	MISSING
electionInterestW4 electionInterestW5	"How interested are you in the General Election that will be held on May 7th this year?"	1	Not at all interested	Same
[theme: engagement]		2	Not very interested	Same
		3	Somewhat interested	Same
		4	Very interested	Same
		9999	Don't know	MISSING
electionInterestW6	"How interested were you in the General Election that was held on May 7th this year?"	1	Not at all interested	Same
[theme: engagement]		2	Not very interested	Same
		3	Somewhat interested	Same
		4	Very interested	Same
		9999	Don't know	MISSING
infoSourceTVW4 infoSourceTVW5 infoSourceTVW6 infoSourceTVW7 infoSourceTVW8	"During the last seven days, on average how much time (if any) have you spent per day following news about politics or current affairs from each of these sources? [Television]"	1	None, no time at all	Same
[theme: engagement]		2	Less than half an hour	Same
		3	Half an hour to an hour	Same
		4	One to two hours	Same
		5	More than two hours	Same
		9999	Don't know	MISSING
infoSourcePaperW4 infoSourcePaperW5 infoSourcePaperW6 infoSourcePaperW7 infoSourcePaperW8	"During the last seven days, on average how much time (if any) have you spent per day following news about politics or current affairs from each of these sources? [Newspaper (including online)]"	1	None, no time at all	Same
[theme: engagement]		2	Less than half an hour	Same
		3	Half an hour to an hour	Same
		4	One to two hours	Same
		5	More than two hours	Same
		9999	Don't know	MISSING
infoSourceRadioW4 infoSourceRadioW5 infoSourceRadioW6 infoSourceRadioW7 infoSourceRadioW8	"During the last seven days, on average how much time (if any) have you spent per day following news about politics or current affairs from each of these sources? [Radio]"	1	None, no time at all	Same
[theme: engagement]		2	Less than half an hour	Same
		3	Half an hour to an hour	Same

		4	One to two hours	Same
		5	More than two hours	Same
		9999	Don't know	MISSING
infoSourceInternetW4 infoSourceInternetW5 infoSourceInternetW6 infoSourceInternetW7 infoSourceInternetW8	"During the last seven days, on average how much time (if any) have you spent per day following news about politics or current affairs from each of these sources? [Internet (not including online newspapers)]"	1	None, no time at all	Same
[theme: engagement]		2	Less than half an hour	Same
		3	Half an hour to an hour	Same
		4	One to two hours	Same
		5	More than two hours	Same
		9999	Don't know	MISSING
infoSourcePeopleW4 infoSourcePeopleW5 infoSourcePeopleW6 infoSourcePeopleW7 infoSourcePeopleW8	"During the last seven days, on average how much time (if any) have you spent per day following news about politics or current affairs from each of these sources? [Talking to other people]"	1	None, no time at all	Same
[theme: engagement]		2	Less than half an hour	Same
		3	Half an hour to an hour	Same
		4	One to two hours	Same
		5	More than two hours	Same
		9999	Don't know	MISSING
conGovTrustW5	"How much would you expect each of the following political parties to do a good job or a bad job if they are in government after the General Election (either by themselves or as part of a coalition)? [Conservatives]"	1	Would do a bad job	Same
[theme: partisanship]		2	2	Same
		3	3	Same
		4	4	Same
		5	5	Same
		6	6	Same
		7	Would do a good job	Same
		9999	Don't know	MISSING
lr1W6	"How much do you agree or disagree with the following statements? [Government should redistribute income from the better off to those who are less well off]"	1	Strongly disagree	Same
[theme: policies]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
al1W6	"How much do you agree or disagree with the following statements? [Young people today don't have enough respect for traditional British values]"	1	Strongly disagree	Same
[theme: culture]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
al3W6	"How much do you agree or disagree with the following statements? [Schools should teach children to obey authority]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING

al4W6	"How much do you agree or disagree with the following statements? [Censorship of films and magazines is necessary to uphold moral standards]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
al5W6	"How much do you agree or disagree with the following statements? [People who break the law should be given stiffer sentences]"	1	Strongly disagree	5
[theme: policies]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
disabilityW6	"Do you have any long-term illness, health problem or disability which limits your daily activities or the work you can do? *Include problems which are due to old age*"	0	No	Same
[theme: demographics]		1	Yes	Same
		9999	Don't know	MISSING
euRefTurnoutW7	"Many people don't vote in elections these days. How likely is it that you will vote in the referendum on Britain's membership of the European Union on June 23rd?"	1	Very unlikely that I would vote	Same
[theme: engagement]		2	Fairly unlikely	Same
		3	Neither likely nor unlikely	Same
		4	Fairly likely	Same
		5	Very likely that I would vote	Same
		9999	Don't know	MISSING
euRefInterestW7	"How interested are you in the EU referendum that will be held on June 23rd?"	1	Not at all interested	Same
[theme: engagement]		2	Not very interested	Same
		3	Somewhat interested	Same
		4	Very interested	Same
		9999	Don't know	MISSING
ethno1W7	"How much do you agree or disagree with the following statements? [Britain has a lot to learn from other countries in running its affairs]"	1	Strongly disagree	5
[theme: culture]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
ethno2W7	"How much do you agree or disagree with the following statements? [I would rather be a citizen of Britain than of any other country in the world]"	1	Strongly disagree	Same
[theme: culture]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
ethno3W7	"How much do you agree or disagree with the following statements? [There are some things about Britain today that make me ashamed to be British]"	1	Strongly disagree	5

[theme: culture]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
ethno4W7	"How much do you agree or disagree with the following statements? [People in Britain are too ready to criticise their country]"	1	Strongly disagree	Same
[theme: culture]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
ethno5W7	"How much do you agree or disagree with the following statements? [The world would be a better place if people from other countries were more like the British]"	1	Strongly disagree	Same
[theme: culture]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
ethno6W7	"How much do you agree or disagree with the following statements? [I am often less proud of Britain than I would like to be]"	1	Strongly disagree	5
[theme: culture]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
radicalW7	"How much do you agree or disagree with the following statements? [We need to fundamentally change the way society works in Britain]"	1	Strongly disagree	5
[theme: culture]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
riskTakingW7 risktakingW8	"Generally speaking, how willing are you to take risks?"	1	Very unwilling to take risks	Same
[theme: psychology]		2	Somewhat unwilling to take risks	Same
		3	Somewhat willing to take risks	Same
		4	Very willing to take risks	Same
		9999	Don't know	MISSING
aom1W7	"Do you agree or disagree with the following statements? [Allowing oneself to be convinced by an opposing argument is a sign of good character]"	1	Strongly disagree	Same
[theme: psychology]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
aom2W7	"Do you agree or disagree with the following statements? [People should take into consideration evidence that goes against their beliefs]"	1	Strongly disagree	Same
[theme: psychology]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same

		9999	Don't know	MISSING
aom3W7	"Do you agree or disagree with the following statements? [People should revise their beliefs in response to new information or evidence]"	1	Strongly disagree	Same
[theme: psychology]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
aom4W7	"Do you agree or disagree with the following statements? [Changing your mind is a sign of weakness]"	1	Strongly disagree	5
[theme: psychology]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
aom5W7	"Do you agree or disagree with the following statements? [Changing your mind is a sign of weakness]"	1	Strongly disagree	5
[theme: psychology]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
aom6W7	"Do you agree or disagree with the following statements? [It is important to persevere in your beliefs even when evidence is brought to bear against them]"	1	Strongly disagree	5
[theme: psychology]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
aom7W7	"Do you agree or disagree with the following statements? [One should disregard evidence that conflicts with one's established beliefs]"	1	Strongly disagree	5
[theme: psychology]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
anyUniW7	"Have you ever attended a University or other higher education institution?"	0	No, I have never attended higher education	0
[theme: demographics]		1	Yes, I am currently enrolled in higher education	1
		2	Yes, but I didn't complete higher education	1
		3	Yes, I graduated from higher education	1
		9999	Don't know	MISSING
ageW7	"What is your age?" [asked April-May 2016]	Any whole no.	Age last birthday shown by whole no.	Same
[theme: demographics]		-9	Not asked	MISSING
		-8	Skipped	MISSING
profile_work_typeW7	[work type as recorded independently by YouGov]	1	Professional or higher technical work / higher managerial - work that requires at least degree-level qualifications	Upskilled dummy = 1
[theme: demographics]		2	Manager or Senior Administrator / intermediate managerial / professional	Upskilled dummy = 1

		3	Clerical/junior managerial/ professional/ administrator	Midskilled dummy = 1
		4	Sales or Services	Midskilled dummy = 1
		5	Foreman or Supervisor of Other Workers	Midskilled dummy = 1
		6	Skilled Manual Work	Midskilled dummy = 1
		7	Semi-Skilled or Unskilled Manual Work	Unskilled dummy = 1
		8	Other	MISSING
		9	Have never worked	Reference category
		98	Skipped	MISSING
		99	Not asked	MISSING
tolUncertain1W8	"To what extent do you agree or disagree with the following statement? [I hate not knowing what the future holds]"	1	Strongly disagree	5
[theme: psychology]		2	Disagree	4
		3	Neither agree nor disagree	3
		4	Agree	2
		5	Strongly agree	1
		9999	Don't know	MISSING
tolUncertain2W8	"To what extent do you agree or disagree with the following statement? [I strongly prefer to be certain about the outcome before making a decision]"	1	Strongly disagree	Same
[theme: psychology]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
tolUncertain3W8	"To what extent do you agree or disagree with the following statement? [I hate uncertainty]"	1	Strongly disagree	Same
[theme: psychology]		2	Disagree	Same
		3	Neither agree nor disagree	Same
		4	Agree	Same
		5	Strongly agree	Same
		9999	Don't know	MISSING
livedAbroadW8	"Have you ever lived in a country other than the UK?"	0	No	Same
[theme: culture]		1	Yes	Same
		9999	Don't know	MISSING
parentsForeignW8	"Were either of your parents born outside the United Kingdom?"	0	No	Same
[theme: culture]		1	Yes	Same
		9999	Don't know	MISSING
gender	[gender as recorded independently by YouGov]	1	Male	0
[theme: demographics]		2	Female	1
profile_ethnicity	[Ethnicity as recorded independently by YouGov]	1	White British	1
[theme: culture]		2	Any other white background	0
		3	White and Black Caribbean	0
		4	White and Black African	0
		5	White and Asian	0
		6	Any other mixed background	0
		7	Indian	0
		8	Pakistani	0
		9	Bangladeshi	0
		10	Any other Asian background	0
		11	Black Caribbean	0
		12	Black African	0
		13	Any other black background	0
		14	Chinese	0
		15	Other ethnic group	0
		16	Prefer not to say	MISSING

profile_newspaper_readership_201	[daily newspaper readership as recorded independently by YouGov]	1	The Express	Tabloid dummy = 1
[theme: demographics]		2	The Daily Mail / The Scottish Daily Mail	Tabloid dummy = 1
		3	The Mirror / Daily Record	Tabloid dummy = 1
		4	The Daily Star / The Daily Star of Scotland	Tabloid dummy = 1
		5	The Sun	Tabloid dummy = 1
		6	The Daily Telegraph	Broadsheet dummy = 1
		7	The Financial Times	Broadsheet dummy = 1
		8	The Guardian	Broadsheet dummy = 1
		9	The Independent	Broadsheet dummy = 1
		10	The Times	Broadsheet dummy = 1
		11	The Scotsman	Broadsheet dummy = 1
		12	The Herald (Glasgow)	Broadsheet dummy = 1
		13	The Western Mail	Broadsheet dummy = 1
		14	Other local daily morning newspaper	Reference category
		15	Other Newspaper	Reference category
		16	None	Reference category

Table 2. Summary of all variables from the British Election Study selected for use in the analysis, including variable names, question wording, response options, response coding, and response recoding by the author for analytical purposes.

Section 2: annotated summary of key statistical results

Cronbach's alphas for related items grouped into scales

Cronbach's alpha is a measure of how closely intercorrelated several separate variables are when a researcher wishes to treat them as multiple measures of the same underlying concept, and thus to group them into a scale and reduce them to one variable. The statistic varies between zero and one, with higher values indicating greater similarity between the selected variables, and thus a greater probability that they measure the same thing. Unsurprisingly, those variables which consist of the same question asked at multiple points in time are the most highly intercorrelated, and can be collated most validly into single measures.

List of variables in each proposed scale	Cronbach's alpha for scale
britishnessW1 britishnessW2 britishnessW3 britishnessW4 britishnessW7 britishnessW8 britishnessW9	0.94
immigCulturalW1 immigCulturalW2 immigCulturalW3 immigCulturalW4 immigCulturalW6 immigCulturalW8	0.95
ethno1W7 ethno2W7 ethno3W7 ethno4W7 ethno5W7 ethno6W7 radicalW7	0.65
polAttentionW1 polAttentionW2 polAttentionW3 polAttentionW4 polAttentionW6 polAttentionW7 polAttentionW8	0.97
discussPolDaysW2 discussPolDaysW4 discussPolDaysW5 discussPolDaysW6 discussPolDaysW7	0.87
infoSourcePeopleW4 infoSourcePeopleW5 infoSourcePeopleW6 infoSourcePeopleW7 infoSourcePeopleW8	0.80
infoSourceInternetW4 infoSourceInternetW5 infoSourceInternetW6 infoSourceInternetW7 infoSourceInternetW8	0.84
infoSourcePaperW4 infoSourcePaperW5 infoSourcePaperW6 infoSourcePaperW7 infoSourcePaperW8	0.88
infoSourceRadioW4 infoSourceRadioW5 infoSourceRadioW6 infoSourceRadioW7 infoSourceRadioW8	0.90
infoSourceTVW4 infoSourceTVW5 infoSourceTVW6 infoSourceTVW7 infoSourceTVW8	0.84
electionInterestW4 electionInterestW5 electionInterestW6	0.88
turnoutUKGeneralW1 turnoutUKGeneralW2 turnoutUKGeneralW3 turnoutUKGeneralW4	0.93
trustMPsW1 trustMPsW2 trustMPsW3 trustMPsW4 trustMPsW6 trustMPsW7 trustMPsW9	0.93

econPersonalRetroW1 econPersonalRetroW2 econPersonalRetroW3 econPersonalRetroW4 econPersonalRetroW7	0.85
likeCameronW1 likeCameronW2 likeCameronW3 likeCameronW4 likeCameronW5 likeCameronW6 likeCameronW7 likeCameronW8 likeCameronW9	0.98
likeConW7 likeConW8 likeConW9	0.97
aom1W7 aom2W7 aom3W7 aom4W7 aom5W7 aom6W7 aom7W7	0.76
tolUncertain1W8 tolUncertain2W8 tolUncertain3W8 riskTakingW7 risktakingW8	0.72
conAngryW4 conAngryW6 labAngryW4 labAngryW6 ldAngryW4 ldAngryW6 ukipAngryW4 ukipAngryW6 grnAngryW4 grnAngryW6	0.59
conFearW4 conFearW6 labFearW4 labFearW6 ldFearW4 ldFearW6 ukipFearW4 ukipFearW6 grnFearW4 grnFearW6	0.49
businessBonusW1 businessBonusW2 businessBonusW3 businessBonusW4 businessBonusW7	0.84
govtHandoutsW1 govtHandoutsW2 govtHandoutsW3 govtHandoutsW4 govtHandoutsW7	0.91
immigEconW1 immigEconW2 immigEconW3 immigEconW4	0.94
immigrationLevelW4 immigrationLevelW6	0.75
immigrantsWelfareStateW1 immigrantsWelfareStateW2 immigrantsWelfareStateW3 immigrantsWelfareStateW4 immigrantsWelfareStateW7	0.93
reasonForUnemploymentW1 reasonForUnemploymentW2 reasonForUnemploymentW3 reasonForUnemploymentW4 reasonForUnemploymentW7	0.74
[6 four-point Likert scales with directions removed, as indicators of response polarisation]	0.66
[51 five-point Likert scales with directions removed, as indicators of response polarisation]	0.86

[23 seven-point Likert scales with directions removed, as indicators of response polarisation]	0.86
[20 eleven-point Likert scales with directions removed, as indicators of response polarisation]	0.93
[20 cultural conformity-related Likert scales with directions removed, as indicators of response polarisation]	0.83
[6 political, non-policy-related Likert scales with directions removed, as indicators of response polarisation]	0.86
[21 political engagement-related Likert scales with directions removed, as indicators of response polarisation]	0.86
[14 political partisanship-related Likert scales with directions removed, as indicators of response polarisation]	0.95
[27 policy preference-related Likert scales with directions removed, as indicators of response polarisation]	0.86
[12 psychology-related Likert scales with directions removed, as indicators of response polarisation]	0.75
[the complete 100 Likert scales with directions removed, as indicators of response polarisation]	0.93
Table 3. Cronbach's alphas for related items grouped into scales.	

Factor analyses for reducing numbers of variables

Factor analysis takes a set of intercorrelated variables, such as any of those identified immediately above, and attempts to explain variations in those variables using a smaller number of hypothetical "factors" assumed to cause the intercorrelations between different items identified by Cronbach's alpha. These factors can then be saved as continuous scale variables, have substantive meanings attributed to them, and used in analyses, thus condensing several different highly correlated variables into a single measure, or a smaller number of measures. Factors with an "eigenvalue" of greater than 1 are considered to represent something real which can be reliably measured. The greater the percentage of variance in the scale items which can be explained by a factor, the more that factor accurately represents the content of the items in question. In second and other higher-order factor analyses, several of which are below, one or more factors which have been generated by a previous factor analysis (for example, FAC1_1, which represents feeling of "Britishness" throughout the panel study) are themselves included as items in a subsequent factor analyses, to reduce the number of variables still further. This is useful as a technique for both acknowledging the particular validity of certain dimensions of variables- for example, the highly intercorrelated repeat questions, or economic policy items as opposed to social or immigration ones- whilst at the same time situating these dimensions as aspects of still deeper factors- for example, general cultural conformity, political engagement, or political leftness.

List of items in each analysis	Eigenvalue(s) of saved factor(s)	Percentage of variance in items explained by saved factor(s)	Name of saved factor(s)	Interpretation and label of saved factor(s)
britishnessW1 britishnessW2 britishnessW3 britishnessW4 britishnessW7 britishnessW8 britishnessW9	5.12	73.17%	FAC1_1	Feeling of Britishness
immigCulturalW1 immigCulturalW2 immigCulturalW3 immigCulturalW4 immigCulturalW6 immigCulturalW8	4.01	80.19%	FAC1_2	Immigration undermines cultural life
Fac1_2 al1W6 (young people have no respect for traditional British values)	1.48	74.20%	FAC1_14	Cultural threat perception
ethno1W7 ethno2W7 ethno3W7 ethno4W7 ethno5W7 ethno6W7 radicalW7	2.24	32.04%	FAC1_22	Intolerance of criticism of British society
	1.40	19.94%	FAC2_22	Feelings of shame at being British
FAC1_1 FAC1_14 FAC1_22	1.77	58.94	Conform	General cultural conformity
polAttentionW1 polAttentionW2 polAttentionW3 polAttentionW4 polAttentionW6 polAttentionW7 polAttentionW8	5.70	81.47%	FAC1_3	Attention to politics

discussPolDaysW2 discussPolDaysW4 discussPolDaysW5 discussPolDaysW6 discussPolDaysW7	2.77	69.30%	FAC1_4	Frequency discussing politics
infoSourcePeopleW4 infoSourcePeopleW5 infoSourcePeopleW6 infoSourcePeopleW7 infoSourcePeopleW8	2.67	53.34%	FAC1_5	Time talking about politics to other people
infoSourceInternetW4 infoSourceInternetW5 infoSourceInternetW6 infoSourceInternetW7 infoSourceInternetW8	2.98	59.58%	FAC1_6	Time following politics on the internet
infoSourcePaperW4 infoSourcePaperW5 infoSourcePaperW6 infoSourcePaperW7 infoSourcePaperW8	3.26	65.11%	FAC1_7	Time following politics in newspapers
infoSourceRadioW4 infoSourceRadioW5 infoSourceRadioW6 infoSourceRadioW7 infoSourceRadioW8	3.52	70.35%	FAC1_8	Time following politics on the radio
infoSourceTVW4 infoSourceTVW5 infoSourceTVW6 infoSourceTVW7 infoSourceTVW8	2.95	58.91%	FAC1_9	Time following politics on TV
electionInterestW4 electionInterestW5 electionInterestW6	2.36	78.73%	FAC1_10	Interest in 2015 general election
turnoutUKGeneralW1 turnoutUKGeneralW2 turnoutUKGeneralW3 turnoutUKGeneralW4	3.16	79.06%	FAC1_12	Likelihood to vote in 2015 GE
FAC1_3 FAC1_4 FAC1_5 FAC1_6 FAC1_7 FAC1_8 FAC1_9 FAC1_10 FAC1_12 euRefInterestW7 (interest in EU referendum) euRefTurnoutW7 (likelihood to vote in EU referendum)	4.87	44.22%	FAC1_11	Interest in politics
	1.69	15.36%	FAC2_11	Likelihood to vote in elections
trustMPsW1 trustMPsW2 trustMPsW3 trustMPsW4 trustMPsW6 trustMPsW7 trustMPsW9	4.30	71.73%	TrustMPs	Trusting MPs in general
econPersonalRetroW1 econPersonalRetroW2 econPersonalRetroW3 econPersonalRetroW4 econPersonalRetroW7	3.10	62.02%	Econom	Thinking personal household situation has improved in year
likeCameronW1 likeCameronW2 likeCameronW3 likeCameronW4 likeCameronW5 likeCameronW6 likeCameronW7 likeCameronW8 likeCameronW9	7.46	82.94%	FAC1_17	Liking David Cameron
likeConW7 likeConW8 likeConW9	2.78	92.65%	FAC1_18	Liking the Conservatives
FAC1_17 FAC1_18	2.73	90.83%	ConPart	Conservative Partisanship

ptvConW9 (probability of voting for the Conservatives) conGovTrustW5 (trusting the Conservatives to do a good job in government)				
aom1W7 aom2W7 aom3W7 aom4W7 aom5W7 aom6W7 aom7W7	2.85	40.65%	Aom	Active open-mindedness
tolUncertain1W8 tolUncertain2W8 tolUncertain3W8 riskTakingW7 risktakingW8	2.34	46.73%	TolUncer	Tolerance of uncertainty
	1.33	73.26%	Willrisk	Risk willingness
businessBonusW1 businessBonusW2 businessBonusW3 businessBonusW4 businessBonusW7	2.68	67.04%	FAC1_25	Hostility toward business bonuses
govtHandoutsW1 govtHandoutsW2 govtHandoutsW3 govtHandoutsW4 govtHandoutsW7	3.07	76.77%	FAC1_26	Defensiveness of welfare claimants
immigEconW1 immigEconW2 immigEconW3 immigEconW4	3.29	82.19%	FAC1_27	Immigration helps economy
immigrationLevelW4 immigrationLevelW6	1.58	79.16%	FAC1_28	Would increase immigration
immigrantsWelfareStateW1 immigrantsWelfareStateW2 immigrantsWelfareStateW3 immigrantsWelfareStateW4 immigrantsWelfareStateW7	3.82	76.35%	FAC1_29	Immigration not a burden on the welfare state
reasonForUnemploymentW1 reasonForUnemploymentW2 reasonForUnemploymentW3 reasonForUnemploymentW4 reasonForUnemploymentW7	2.22	55.48%	FAC1_30	Sympathy for the unemployed
FAC1_25 FAC1_26 FAC1_27 FAC1_28 FAC1_29 FAC1_30 lr1W6 (favours redistribution) al3W6 (disfavours authority in schools) al4W6 (disfavours censorship) al5W6 (disfavours stiffer sentences for law breakers)	3.63	36.31%	Immig	Support for immigration
	1.55	15.53%	Interv	Government economic interventionism
	1.14	11.39%	Social	Social liberalism
Immig Interv Social	1.55	51.65%	Leftness	General political leftness
[the 100 Likert scales with directions removed, as indicators of response polarisation; factor analysis set to save factors with eigenvalues of 10 or above, rather than 1 or above, due to the extremely large number of items included]	11.95	11.95%	ResPol	Polarisation of Likert scale responses (cognitive classification)

Table 4. Principal component factor analysis results including details of factors saved

Constituent variables	Factor 1 Loadings	Factor 2 Loadings	Factor 3 Loadings
	FAC1_22 (intolerance of criticism of British society)	FAC2_22 (feelings of shame at being British)	---
ethno1W7 (Britain does not have a lot to learn from other countries)	0.51	0.21	---
ethno2W7 (often as proud of Britain as would like to be)	0.66	-0.46	---
ethno3W7 (would rather be citizen of Britain than of any other country)	0.62	0.42	---
ethno4W7 (people in Britain are too ready to criticise their country)	0.42	0.49	---
ethno5W7 (other countries should be more like Britain)	0.56	0.50	---
ethno6W7 (some things make me ashamed to be British)	0.65	-0.47	---
radicalW7 (do not need to fundamentally change the way society works in Britain)	0.51	-0.49	---
	FAC1_11 (interest in politics)	FAC2_11 (likelihood to vote in elections)	---
FAC1_3 (attention to politics)	0.72	0.71	---
FAC1_4 (days in a week discussing politics)	0.78	0.41	---
FAC1_5 (talking about politics to other people)	0.83	0.23	---
FAC1_6 (following politics on the internet)	0.76	0.15	---
FAC1_7 (following politics in the papers)	0.71	0.30	---
FAC1_8 (following politics on the radio)	0.58	0.14	---
FAC1_9 (following politics on TV)	0.70	0.37	---
FAC1_10 (interest in the 2015 general election)	0.56	0.81	---
FAC1_12 (likelihood to vote in the 2015 general election)	0.22	0.82	---
euRefInterestW7 (interest in EU referendum)	0.37	0.70	---
euRefTurnoutW7 (likelihood to vote in EU referendum)	0.13	0.78	---
	TolUncer (tolerance of uncertainty)	Willrisk (risk willingness)	---
tolUncertain1W8 (comfortable not knowing what the future holds)	0.82	0.12	---
tolUncertain2W8 (comfortable with uncertainty)	0.83	0.29	---
tolUncertain3W8 (does not feel the need to be certain about the outcome before making a decision)	0.75	0.24	---
riskTakingW7 (willingness to take risks in wave 7)	0.23	0.93	---
risktakingW8 (willingness to take risks in wave 8)	0.27	0.93	---
	Immig (support for immigration)	Interv (government economic interventionism)	Social (social liberalism)
FAC1_25 (anti-bonuses)	0.07	0.60	0.03
FAC1_26 (pro-handouts)	0.56	0.70	0.38
FAC1_27 (immigration good for economy)	0.91	0.17	0.35
FAC1_28 (wants to increase immigration)	0.81	0.16	0.33
FAC1_29 (immigrants not burden on the welfare state)	0.92	0.27	0.46
FAC1_30 (unemployed not at fault)	0.19	0.76	0.21
lr1W6 (favours redistribution)	0.12	0.71	0.02
al3W6 (disfavours authority in schools)	0.37	0.15	0.81
al4W6 (disfavours censorship)	0.22	0.04	0.74
al5W6 (disfavours stiffer sentences for law breakers)	0.41	0.18	0.77

Table 5. Rotated factor loadings for principal components analyses which saved more than one factor. The closer the factor loading number is to 1, the more strongly associated the relevant item is to the relevant factor.

Cluster analysis for grouping individuals into categories

Two-step cluster analysis classifies a set of individual cases into a discrete number of categories, or "clusters", based on similar responses to a certain number of selected variables, which can be either categorical or continuous. The clustering algorithm attempts to makes differences in these variables within a category as small as possible, whilst making differences in the same variables between categories as large as possible. These metrics are jointly assessed in the form of the "silhouette measure of cohesion and separation, a statistic which ranges from -1 to 1. The larger the value of the statistic, the greater are the between-group differences and the lesser the within-group differences on the selected variables. A silhouette measure of 0.5 or greater is generally considered necessary to conclude that the cluster analysis has identified groups which are sufficiently distinguished from one another. Cluster analysis can be used to save a new nominal variable signifying which of the identified clusters each individual case belongs to.

Input Variables	Silhouette measure	Clustering variable	Number of clusters	Populations of clusters	Composition of clusters	Names of clusters
country countryOfBirth livedAbroadW8 parentsForeignW8 profile_ethnicity	0.60	TSC_4171	3	2850	Mixed ethnicity; live across UK; born across the world; many lived abroad; many foreign parents;	"External"
				1241	White British; live in Scotland and Wales; born in UK; few lived abroad; no foreign parents;	"Celtic"
				5530	White British; live in England; born in UK; none lived abroad; no foreign parents;	"Anglo-Saxon"
Cnstrnt	0.65	TSC_5725	3	1677	Low average level of constraint	"Low"
				4375	Moderate average level of constraint	"Medium"
				3894	High average level of constraint	"High"

Table 6. Cluster analysis results for cultural cluster and level of constraint cluster.

Descriptive statistics for continuous variables

Variable	Mean	Standard deviation	Skewness
Political leftness	0.00	1.00	0.71
Cultural conformity	0.00	1.00	-0.80
Ideological conformity	0.00	1.00	-1.35
Active open-mindedness	0.00	0.48	0.64
Anglo-Saxon cultural cluster membership * cultural conformity interaction term	0.11	0.65	-0.35
Anglo-Saxon cultural cluster membership * ideological conformity interaction term	0.03	0.69	-1.39
Anglo-Saxon cultural cluster membership * active open-mindedness interaction term	-0.01	0.35	-0.25
Belief system constraint	0.00	1.00	-0.40
Constraint * cultural conformity interaction term	-0.13	1.05	-0.64
Constraint * ideological conformity interaction term	-0.14	1.06	-2.48
Constraint * active open-mindedness interaction term	0.01	0.50	-0.50
Tolerance of uncertainty	0.00	1.00	0.31
Active open-mindedness * tolerance of uncertainty interaction term	0.00	0.48	0.47
Response polarisation	0.00	1.00	0.16
Active open-mindedness * response polarisation interaction term	0.00	0.53	-0.45

Table 7. Descriptive statistics for continuous variables used in the analysis. The interaction terms are simply pairs of other variables multiplied together, used to assess whether they are required to work together to produce an outcome.

Frequency tables for categorical variables

Variable	Response categories	Frequencies	Valid percentages
Cultural cluster membership	Anglo-Saxon	4807	48.4%
	Not Anglo-Saxon	5128	51.6%
Level of education	Has not attended higher education	4176	42.0%
	Is enrolled at, has been enrolled at, or has completed higher education	5775	58.0%
Disability	Is not disabled	7114	71.2%
	Is disabled	2872	28.8%
Gender	Male	5583	54.9%
	Female	4589	45.1%
Newspaper readership	Broadsheet	2301	22.6%
	Tabloid	3532	34.7%
	Other or none	4339	42.7%
Level of skill in work	Highly-skilled	4014	39.5%
	Moderately skilled	4098	40.3%
	Lower-skilled	1005	9.9%
	Never worked	1055	10.3%

Table 8. Frequency tables for all categorical variables used in the analysis. "Valid percentages" refers to the percentage of non-missing responses which fall within each response category.

Bivariate comparisons with key variables

Bivariate analysis involves comparing pairs of variables to see whether and how variations in one variable accompany variations in the other. The following tables summarise a series of comparisons between each of the key political, cultural and psychological variables (all of which are continuous) and each of the other variables selected or created for the analysis. Where two continuous variables are compared, the comparison consists of a Pearson correlation, a regression coefficient which varies between -1 (a perfect negative correlation) and 1 (a perfect positive correlation). The stars following these are indicative of the statistical significance of the relationship: * indicates that the likelihood of there being no true relationship between the two variables is 5% or less but greater than 1%; ** indicates that this likelihood is 1% or less but greater than 0.1%; *** indicates that the likelihood is 0.1% or less. As such, the more stars a correlation coefficient has, the more confident one can be that the coefficient represents a meaningful real-world relationship. Where a continuous variable is compared with a categorical one, a t-test to assess differences of means has been carried out. This compares mean values of the continuous variable between categories of the categorical variable, with a difference in means being considered significant if the probability of the mean values being the same in the real-world population is 5% or less. The full t-tests have not been reported here; they can be replicated using the syntax below and the essential results have been described in the following tables. Only statistically significant differences in means have been reported. For example, the results of the first t-test, listed as External = Celtic > Anglo-Saxon, can be translated thus: members of the "External" cultural cluster do not have a significantly different mean level of immigration support to members of the "Celtic" cluster, but both have significantly greater mean immigration support than members of the "Anglo-Saxon" cluster. When a mean difference is only marginal- that is, one group has a significantly higher or lower mean than another but the probably of it being spurious is very nearly 5%- a ≥ or ≤ symbol is used.

	Pro-immigration	Pro-economic interventionism	Pro-social liberalism	General leftness
Pro-immigration	---	0.23***	0.42***	0.81***
Pro-economic interventionism	---	---	0.15***	0.55***
Pro-social liberalism	---	---	---	0.77***
Cultural cluster	External = Celtic > Anglo-Saxon	Celtic > Anglo-Saxon = External	External = Celtic > Anglo-Saxon	External = Celtic > Anglo-Saxon
Self-reported cultural conformity	-0.51***	-0.24***	-0.56***	-0.63***
Computed ideological conformity	-0.21***	-0.17***	-0.25***	-0.30***
Belief system constraint	0.18***	-0.28***	0.15***	0.07***
Newspaper readership	Broadsheet > other or none > tabloid	No significant differences by newspaper readership	Broadsheet > other or none > tabloid	Broadsheet > other or none > tabloid
Work type	Highly skilled > never worked > middling skilled > low skilled	Low skilled > never worked = middling skilled > highly skilled	Highly skilled > never worked > middling skilled > low skilled	Highly skilled > never worked > middling = low skilled
Age	-0.21***	0.10***	-0.25***	-0.20***
Education	Graduates > non-graduates	Non-graduates ≥ graduates	Graduates > non-graduates	Graduates > non-graduates
Disability	Not disabled > disabled	Disabled > not disabled	Not disabled > disabled	No significant differences by disability
Gender	Male > female	No significant differences by gender	Male > female	Male > female
Political engagement	0.16***	0.12***	0.11***	0.18***
Positive household economic evaluations	0.08***	-0.33***	0.09***	-0.03**

Trust in MPs	0.18***	-0.16**	0.06***	0.07***
Conservative partisanship	-0.14***	-0.53***	-0.20***	-0.36***
Active open-mindedness	0.13***	0.02*	0.20***	0.17***
Anger at parties	0.12***	0.29***	0.18***	0.25***
Fear of parties	0.12***	0.04***	0.09***	0.12***
Tolerance of uncertainty	0.09***	-0.04***	0.18***	0.13***
Risk-taking	0.06***	-0.08***	0.08***	0.04***
Item-level response rate	-0.01	0.06***	-0.02	0.01
Response polarisation	-0.20***	0.28***	-0.10***	-0.06***

Table 9. Bivariate comparisons between the political orientation factors and other selected variables.

	Active open-mindedness	Tolerance of uncertainty	Response polarisation
Cultural cluster	External = Celtic > Anglo-Saxon	External > Anglo-Saxon (both = Celtic)	Celtic > Anglo-Saxon = External
Self-reported cultural conformity	-0.18***	-0.09***	0.09***
Computed ideological conformity	-0.10***	-0.06***	-0.33***
Belief system constraint	0.01	0.09***	-0.48***
Newspaper readership	Broadsheet > Other or none > Tabloid	Broadsheet > Other or none > Tabloid	Tabloid > Other or none > Broadsheet
Work type	Highly skilled > never worked = middling skilled > low skilled	Highly skilled > never worked > middling skilled = low skilled	Low skilled > never worked = middling skilled > highly skilled
Age	-0.08***	0.07***	0.13***
Education	Graduates > non-graduates	No significant differences	Non-graduates > Graduates
Disability	Not disabled ≥ disabled	Not disabled > disabled	Disabled > not disabled
Gender	Male > female	Male > female	No significant differences
Political engagement	0.08***	0.06***	0.18***
Positive household economic evaluations	0.04***	0.07***	-0.26***
Trust in MPs	0.00	0.09***	-0.28***
Conservative partisanship	-0.04***	0.05***	-0.37***

Table 10. Bivariate comparisons between the perceptual factors and other selected variables.

	Self-reported cultural conformity	Computed ideological conformity	Belief system constraint
Cultural cluster	Anglo-Saxon > Celtic = External	Anglo-Saxon = External > Celtic	Celtic = Anglo-Saxon > External
Newspaper readership	Tabloid > other or none > broadsheet	Tabloid > other or none > broadsheet	Broadsheet > other or none > tabloid
Work type	Low skilled = middling skilled > never worked > highly skilled	Low skilled > middling skilled > never worked > highly skilled	All others > low skilled, other differences not significant
Age	0.35***	0.03*	-0.11***
Education	Non-graduates > graduates	Non-graduates > graduates	Graduates > non-graduates
Disability	Disabled > not disabled	No significant differences	Not disabled > disabled
Gender	No significant differences	No significant differences	Female > male
Political engagement	-0.03**	-0.16***	-0.09***
Positive household economic evaluations	-0.03**	0.00	0.18***
Trust in MPs	0.04***	0.05***	0.14***
Conservative partisanship	0.32***	0.14***	0.17***-

Table 11. Bivariate comparisons between the continuous cultural variables and other selected variables.

Section 3: complete PROCESS output for the mediation and moderated mediation models

Note: the indirect effect sizes for the moderated mediation analysis have been assigned numbers from 1-108 to correspond to the effect sizes displayed in Figure 6.

Mediation analysis

Run MATRIX procedure:

```
************** PROCESS Procedure for SPSS Release 2.16.3 *****************

        Written by Andrew F. Hayes, Ph.D.       www.afhayes.com

**************************************************************************
Model = 4
   Y = Leftness
   X = Aom
  M1 = Conform
  M2 = Compform

Statistical Controls:
Columns   1 -  14
CONTROL= TolUncer ResPol   Cnstrnt  Anglo    Celtic   ResRate  Willrisk AngerPty FearPty  ConPart  TrustMPs Econom   Engage
Columns  15 -  22
CONTROL= Zage     Graduate Disabled Upskill  Midskill Unskill  Bdsheet  Tbloid

Sample size
      6108

**************************************************************************
Outcome: Conform

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6387      .4080      .7458   182.2824    23.0000  6084.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.2050      .0471    -4.3536      .0000      -.2974      -.1127
Aom          -.1326      .0349    -3.7952      .0001      -.2011      -.0641
TolUncer     -.0911      .0116    -7.8578      .0000      -.1139      -.0684
ResPol        .1043      .0153     6.8086      .0000       .0743       .1343
Cnstrnt      -.1242      .0136    -9.1348      .0000      -.1508      -.0975
Anglo         .3046      .0265    11.4856      .0000       .2526       .3566
Celtic        .0111      .0309     .3584      .7201      -.0495       .0717
ResRate      -.0084      .0174     -.4827      .6293      -.0425       .0257
Willrisk      .0070      .0128     .5459      .5852      -.0181       .0321
AngerPty     -.1140      .0128    -8.8870      .0000      -.1391      -.0888
FearPty      -.0478      .0113    -4.2450      .0000      -.0699      -.0257
ConPart       .5031      .0142    35.5275      .0000       .4753       .5308
TrustMPs     -.0985      .0133    -7.4153      .0000      -.1245      -.0725
Econom       -.0234      .0127    -1.8386      .0660      -.0483       .0015
Engage       -.0202      .0141    -1.4307      .1526      -.0480       .0075
Gender       -.0255      .0233    -1.0921      .2748      -.0712       .0203
Zage          .2348      .0147    15.9177      .0000       .2059       .2637
Graduate     -.2200      .0263    -8.3567      .0000      -.2717      -.1684
Disabled      .0629      .0260     2.4198      .0156       .0119       .1138
Upskill       .0017      .0411      .0424      .9661      -.0788       .0823
Midskill      .0007      .0399      .0170      .9864      -.0776       .0789
Unskill       .0324      .0516      .6269      .5308      -.0688       .1336
Bdsheet      -.2105      .0298    -7.0609      .0000      -.2689      -.1521
Tbloid        .2540      .0270     9.4245      .0000       .2012       .3069

**************************************************************************
Outcome: Compform

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5738      .3292      .8013   129.8236    23.0000  6084.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     -.0197      .0488     -.4043      .6860      -.1154       .0760
Aom          -.1042      .0362    -2.8785      .0040      -.1752      -.0332
TolUncer     -.0555      .0120    -4.6181      .0000      -.0791      -.0320
ResPol       -.5822      .0159   -36.6710      .0000      -.6133      -.5511
Cnstrnt      -.4706      .0141   -33.3933      .0000      -.4982      -.4430
Anglo         .0359      .0275     1.3055      .1918      -.0180       .0898
Celtic       -.0314      .0320     -.9801      .3271      -.0942       .0314
ResRate      -.0237      .0180    -1.3126      .1894      -.0590       .0117
Willrisk      .0218      .0133     1.6417      .1007      -.0042       .0478
AngerPty     -.0564      .0133    -4.2394      .0000      -.0824      -.0303
```

FearPty	-.0157	.0117	-1.3480	.1777	-.0387	.0072
ConPart	.0718	.0147	4.8883	.0000	.0430	.1005
TrustMPs	-.0581	.0138	-4.2204	.0000	-.0851	-.0311
Econom	-.0249	.0132	-1.8941	.0583	-.0508	.0009
Engage	-.0100	.0147	-.6853	.4932	-.0388	.0187
Gender	-.0231	.0242	-.9539	.3402	-.0705	.0243
Zage	.0856	.0153	5.5969	.0000	.0556	.1155
Graduate	-.1062	.0273	-3.8908	.0001	-.1597	-.0527
Disabled	.0383	.0269	1.4213	.1553	-.0145	.0910
Upskill	-.0613	.0426	-1.4384	.1504	-.1447	.0222
Midskill	-.0287	.0414	-.6933	.4881	-.1098	.0524
Unskill	.0072	.0535	.1355	.8922	-.0977	.1121
Bdsheet	-.1799	.0309	-5.8222	.0000	-.2405	-.1193
Tbloid	.1175	.0279	4.2055	.0000	.0627	.1723

****
Outcome: Leftness

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7659	.5866	.5025	345.1409	25.0000	6082.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.0210	.0387	.5411	.5884	-.0550	.0969
Conform	-.3491	.0109	-32.0183	.0000	-.3704	-.3277
Compform	-.3005	.0105	-28.5715	.0000	-.3211	-.2799
Aom	.0522	.0287	1.8188	.0690	-.0041	.1085
TolUncer	.0375	.0096	3.9172	.0001	.0187	.0563
ResPol	-.2658	.0142	-18.7743	.0000	-.2936	-.2381
Cnstrnt	-.0584	.0121	-4.8133	.0000	-.0822	-.0346
Anglo	.0547	.0220	2.4849	.0130	.0115	.0978
Celtic	-.0064	.0254	-.2539	.7996	-.0562	.0433
ResRate	-.0121	.0143	-.8490	.3959	-.0401	.0159
Willrisk	-.0175	.0105	-1.6636	.0962	-.0381	.0031
AngerPty	.0477	.0106	4.5028	.0000	.0269	.0685
FearPty	.0236	.0093	2.5485	.0108	.0054	.0418
ConPart	-.3472	.0128	-27.1437	.0000	-.3722	-.3221
TrustMPs	.1418	.0110	12.9432	.0000	.1203	.1633
Econom	-.0041	.0104	-.3901	.6965	-.0245	.0164
Engage	.1236	.0116	10.6477	.0000	.1009	.1464
Gender	-.1283	.0192	-6.6970	.0000	-.1658	-.0907
Zage	.0053	.0124	.4302	.6670	-.0189	.0295
Graduate	.1201	.0217	5.5221	.0000	.0774	.1627
Disabled	.0577	.0213	2.7066	.0068	.0159	.0996
Upskill	-.0038	.0337	-.1138	.9094	-.0700	.0623
Midskill	-.0190	.0328	-.5784	.5630	-.0832	.0453
Unskill	.0177	.0424	.4172	.6765	-.0654	.1008
Bdsheet	.0871	.0246	3.5409	.0004	.0389	.1354
Tbloid	-.1717	.0223	-7.7043	.0000	-.2154	-.1280

********** TOTAL EFFECT MODEL **********
Outcome: Leftness

Model Summary

R	R-sq	MSE	F	df1	df2	p
.6460	.4174	.7079	189.4910	23.0000	6084.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.0985	.0459	2.1457	.0319	.0085	.1884
Aom	.1298	.0340	3.8147	.0001	.0631	.1965
TolUncer	.0860	.0113	7.6106	.0000	.0638	.1081
ResPol	-.1273	.0149	-8.5298	.0000	-.1565	-.0980
Cnstrnt	.1263	.0132	9.5374	.0000	.1004	.1523
Anglo	-.0624	.0258	-2.4157	.0157	-.1131	-.0118
Celtic	-.0009	.0301	-.0290	.9769	-.0599	.0582
ResRate	-.0021	.0169	-.1228	.9022	-.0353	.0311
Willrisk	-.0265	.0125	-2.1224	.0338	-.0510	-.0020
AngerPty	.1044	.0125	8.3589	.0000	.0799	.1289
FearPty	.0450	.0110	4.1022	.0000	.0235	.0666
ConPart	-.5443	.0138	-39.4566	.0000	-.5714	-.5173
TrustMPs	.1937	.0129	14.9652	.0000	.1683	.2190
Econom	.0116	.0124	.9355	.3496	-.0127	.0359
Engage	.1337	.0138	9.7042	.0000	.1067	.1607
Gender	-.1125	.0227	-4.9470	.0000	-.1570	-.0679
Zage	-.1023	.0144	-7.1223	.0000	-.1305	-.0742
Graduate	.2288	.0257	8.9182	.0000	.1785	.2791
Disabled	.0243	.0253	.9602	.3370	-.0253	.0739
Upskill	.0140	.0400	.3487	.7273	-.0645	.0924
Midskill	-.0106	.0389	-.2718	.7858	-.0868	.0657

```
Unskill      .0042     .0503     .0836     .9334    -.0944     .1028
Bdsheet      .2147     .0290    7.3908     .0000     .1577     .2716
Tbloid      -.2957     .0263  -11.2611     .0000    -.3472    -.2442

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************
Total effect of X on Y
    Effect         SE          t          p       LLCI       ULCI
     .1298      .0340     3.8147      .0001      .0631      .1965
Direct effect of X on Y
    Effect         SE          t          p       LLCI       ULCI
     .0522      .0287     1.8188      .0690     -.0041      .1085
Indirect effect of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
TOTAL       .0776      .0194      .0412      .1170
Conform     .0463      .0133      .0214      .0738
Compform    .0313      .0111      .0102      .0539
Partially standardized indirect effect of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
TOTAL       .0921      .0231      .0487      .1390
Conform     .0549      .0158      .0253      .0874
Compform    .0372      .0132      .0120      .0641
Completely standardized indirect effect of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
TOTAL       .0292      .0073      .0155      .0442
Conform     .0174      .0050      .0080      .0276
Compform    .0118      .0042      .0038      .0202
Ratio of indirect to total effect of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
TOTAL       .5977      .2644      .3210     1.1304
Conform     .3564      .1713      .1616      .7312
Compform    .2412      .1268      .0859      .4907
Ratio of indirect to direct effect of X on Y
           Effect    Boot SE   BootLLCI   BootULCI
TOTAL      1.4857    59.9040    -2.9861    21.6596
Conform     .8860    35.6705    -1.9728    12.8463
Compform    .5997    24.6272    -1.1596     8.1679

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
   10000

Level of confidence for all confidence intervals in output:
   95.00

NOTE: Some cases were deleted due to missing data.  The number of such cases was:
  4064

------ END MATRIX -----
```

Moderated mediation analysis

```
Run MATRIX procedure:

************** PROCESS Procedure for SPSS Release 2.16.3 *****************

        Written by Andrew F. Hayes, Ph.D.       www.afhayes.com

**************************************************************************
Model = 50
   Y = Leftness
   X = Aom
  M1 = Conform
  M2 = Compform
   W = ResPol
   Z = TolUncer
   V = AngloCul
   Q = Cnstrnt

Statistical Controls:
Columns   1 -  14
CONTROL= ResRate  Willrisk AngerPty FearPty  ConPart  TrustMPs Econom   Engage   Gender   Zage     Graduate Disabled Upskill
Columns  15 -  17
CONTROL= Unskill  Bdsheet  Tbloid

Sample size
      6108
```

****
Outcome: Conform

Model Summary

R	R-sq	MSE	F	df1	df2	p
.6190	.3831	.7769	171.7722	22.0000	6085.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	-.0509	.0446	-1.1405	.2541	-.1383	.0366
Aom	-.1154	.0369	-3.1278	.0018	-.1877	-.0431
ResPol	.1585	.0143	11.0685	.0000	.1304	.1866
int_1	-.0937	.0332	-2.8202	.0048	-.1588	-.0286
TolUncer	-.0923	.0119	-7.7641	.0000	-.1156	-.0690
int_2	-.0638	.0335	-1.9066	.0566	-.1294	.0018
ResRate	.0049	.0178	.2743	.7839	-.0301	.0398
Willrisk	-.0004	.0130	-.0320	.9745	-.0260	.0251
AngerPty	-.1263	.0131	-9.6771	.0000	-.1519	-.1007
FearPty	-.0452	.0115	-3.9328	.0001	-.0677	-.0227
ConPart	.5158	.0144	35.8536	.0000	.4876	.5440
TrustMPs	-.1026	.0135	-7.5836	.0000	-.1292	-.0761
Econom	-.0313	.0130	-2.4153	.0158	-.0567	-.0059
Engage	-.0282	.0144	-1.9522	.0510	-.0564	.0001
Gender	-.0377	.0237	-1.5886	.1122	-.0842	.0088
Zage	.2389	.0150	15.8740	.0000	.2094	.2684
Graduate	-.2434	.0268	-9.0775	.0000	-.2959	-.1908
Disabled	.0635	.0265	2.3971	.0166	.0116	.1155
Upskill	.0061	.0419	.1451	.8846	-.0761	.0883
Midskill	.0166	.0407	.4076	.6836	-.0632	.0964
Unskill	.0476	.0527	.9038	.3662	-.0556	.1508
Bdsheet	-.2503	.0303	-8.2499	.0000	-.3097	-.1908
Tbloid	.2682	.0275	9.7564	.0000	.2143	.3221

Product terms key:

int_1	Aom	X	ResPol
int_2	Aom	X	TolUncer

****
Outcome: Compform

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4548	.2069	.9473	72.1439	22.0000	6085.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	-.0175	.0492	-.3557	.7221	-.1140	.0790
Aom	-.0774	.0407	-1.8989	.0576	-.1572	.0025
ResPol	-.3696	.0158	-23.3754	.0000	-.4006	-.3386
int_1	-.1326	.0367	-3.6142	.0003	-.2045	-.0607
TolUncer	-.0641	.0131	-4.8862	.0000	-.0898	-.0384
int_2	-.0824	.0370	-2.2294	.0258	-.1549	-.0099
ResRate	-.0079	.0197	-.4020	.6877	-.0465	.0307
Willrisk	.0294	.0144	2.0459	.0408	.0012	.0576
AngerPty	-.0876	.0144	-6.0752	.0000	-.1158	-.0593
FearPty	-.0226	.0127	-1.7837	.0745	-.0475	.0022
ConPart	.1043	.0159	6.5653	.0000	.0732	.1354
TrustMPs	-.0824	.0149	-5.5164	.0000	-.1117	-.0531
Econom	-.0498	.0143	-3.4813	.0005	-.0778	-.0218
Engage	-.0212	.0159	-1.3280	.1842	-.0524	.0101
Gender	-.0828	.0262	-3.1607	.0016	-.1342	-.0315
Zage	.0999	.0166	6.0141	.0000	.0674	.1325
Graduate	-.1046	.0296	-3.5330	.0004	-.1626	-.0466
Disabled	.0636	.0293	2.1728	.0298	.0062	.1210
Upskill	-.0611	.0463	-1.3197	.1870	-.1519	.0297
Midskill	-.0040	.0450	-.0884	.9296	-.0921	.0842
Unskill	.0525	.0581	.9025	.3668	-.0615	.1664
Bdsheet	-.2309	.0335	-6.8920	.0000	-.2965	-.1652
Tbloid	.1175	.0304	3.8721	.0001	.0580	.1770

Product terms key:

int_1	Aom	X	ResPol
int_2	Aom	X	TolUncer

****
Outcome: Leftness

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7624	.5813	.5091	301.4505	28.0000	6079.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	-.0197	.0374	-.5271	.5981	-.0931	.0536
Conform	-.3716	.0127	-29.1841	.0000	-.3966	-.3467
Compform	-.2489	.0127	-19.6582	.0000	-.2737	-.2241
Aom	.0107	.0412	.2598	.7950	-.0701	.0916
AngloCul	.0914	.0191	4.7972	.0000	.0541	.1288
Cnstrnt	.0367	.0107	3.4258	.0006	.0157	.0577
int_3	-.1114	.0187	-5.9456	.0000	-.1481	-.0747
int_4	-.1141	.0091	-12.4690	.0000	-.1320	-.0962
int_5	.1498	.0184	8.1316	.0000	.1137	.1859
int_6	-.0171	.0098	-1.7453	.0810	-.0363	.0021
int_7	.0799	.0575	1.3892	.1648	-.0328	.1926
int_8	.0096	.0296	.3238	.7461	-.0485	.0676
ResRate	-.0111	.0144	-.7687	.4421	-.0393	.0172
Willrisk	-.0065	.0101	-.6466	.5179	-.0264	.0133
AngerPty	.0026	.0104	.2491	.8033	-.0178	.0230
FearPty	.0179	.0093	1.9250	.0543	-.0003	.0362
ConPart	-.2635	.0126	-20.9697	.0000	-.2881	-.2388
TrustMPs	.1670	.0110	15.2481	.0000	.1455	.1885
Econom	.0121	.0105	1.1565	.2475	-.0084	.0326
Engage	.0813	.0115	7.0655	.0000	.0588	.1039
Gender	-.1282	.0193	-6.6404	.0000	-.1660	-.0903
Zage	.0151	.0123	1.2212	.2220	-.0091	.0393
Graduate	.1482	.0218	6.7852	.0000	.1054	.1910
Disabled	.0304	.0214	1.4189	.1560	-.0116	.0724
Upskill	.0211	.0340	.6213	.5344	-.0455	.0877
Midskill	-.0027	.0330	-.0831	.9338	-.0674	.0619
Unskill	.0142	.0426	.3339	.7385	-.0694	.0978
Bdsheet	.0905	.0248	3.6538	.0003	.0420	.1391
Tbloid	-.1914	.0224	-8.5436	.0000	-.2353	-.1475

Product terms key:

int_3	Conform	X	AngloCul
int_4	Conform	X	Cnstrnt
int_5	Compform	X	AngloCul
int_6	Compform	X	Cnstrnt
int_7	Aom	X	AngloCul
int_8	Aom	X	Cnstrnt

********** DIRECT AND INDIRECT EFFECTS **********

Conditional direct effect(s) of X on Y at values of the moderator(s):

AngloCul	Cnstrnt	Effect	SE	t	p	LLCI	ULCI
.0000	-.9426	.0017	.0488	.0344	.9726	-.0939	.0973
.0000	-.0072	.0106	.0412	.2582	.7963	-.0702	.0915
.0000	.9282	.0196	.0506	.3880	.6981	-.0795	.1187
1.0000	-.9426	.0816	.0474	1.7226	.0850	-.0113	.1744
1.0000	-.0072	.0905	.0404	2.2388	.0252	.0113	.1698
1.0000	.9282	.0995	.0506	1.9657	.0494	.0003	.1987

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator

	ResPol	TolUncer	AngloCul	Cnstrnt	Effect	Boot SE	BootLLCI	BootULCI	Effect size number featured in Figure 6
Conform	-.9006	-.8453	.0000	-.9426	-.0061	.0151	-.0369	.0221	1
Conform	-.9006	-.8453	.0000	-.0072	-.0085	.0211	-.0515	.0311	2
Conform	-.9006	-.8453	.0000	.9282	-.0109	.0272	-.0662	.0400	3
Conform	-.9006	-.8453	1.0000	-.9426	-.0086	.0214	-.0520	.0317	4
Conform	-.9006	-.8453	1.0000	-.0072	-.0110	.0274	-.0666	.0407	5
Conform	-.9006	-.8453	1.0000	.9282	-.0135	.0335	-.0816	.0497	6
Conform	-.9006	.1755	.0000	-.9426	.0112	.0118	-.0119	.0347	7
Conform	-.9006	.1755	.0000	-.0072	.0157	.0166	-.0167	.0490	8
Conform	-.9006	.1755	.0000	.9282	.0202	.0214	-.0216	.0631	9
Conform	-.9006	.1755	1.0000	-.9426	.0159	.0168	-.0169	.0499	10
Conform	-.9006	.1755	1.0000	-.0072	.0204	.0216	-.0216	.0641	11
Conform	-.9006	.1755	1.0000	.9282	.0249	.0264	-.0265	.0779	12
Conform	-.9006	1.1962	.0000	-.9426	.0284	.0156	-.0013	.0603	13

Conform	-.9006	1.1962	.0000	-.0072	.0398	.0219	-.0021	.0842	14
Conform	-.9006	1.1962	.0000	.9282	.0513	.0282	-.0023	.1086	15
Conform	-.9006	1.1962	1.0000	-.9426	.0403	.0221	-.0017	.0859	16
Conform	-.9006	1.1962	1.0000	-.0072	.0518	.0284	-.0023	.1096	17
Conform	-.9006	1.1962	1.0000	.9282	.0632	.0348	-.0026	.1341	18
Conform	.0982	-.8453	.0000	-.9426	.0187	.0132	-.0085	.0436	19
Conform	.0982	-.8453	.0000	-.0072	.0262	.0185	-.0116	.0610	20
Conform	.0982	-.8453	.0000	.9282	.0337	.0238	-.0147	.0789	21
Conform	.0982	-.8453	1.0000	-.9426	.0265	.0189	-.0117	.0623	22
Conform	.0982	-.8453	1.0000	-.0072	.0341	.0242	-.0151	.0797	23
Conform	.0982	-.8453	1.0000	.9282	.0416	.0295	-.0184	.0972	24
Conform	.0982	.1755	.0000	-.9426	.0359	.0100	.0174	.0563	25
Conform	.0982	.1755	.0000	-.0072	.0504	.0139	.0244	.0785	26
Conform	.0982	.1755	.0000	.9282	.0648	.0179	.0314	.1011	27
Conform	.0982	.1755	1.0000	-.9426	.0510	.0143	.0244	.0806	28
Conform	.0982	.1755	1.0000	-.0072	.0655	.0182	.0315	.1028	29
Conform	.0982	.1755	1.0000	.9282	.0800	.0222	.0381	.1250	30
Conform	.0982	1.1962	.0000	-.9426	.0531	.0147	.0256	.0839	31
Conform	.0982	1.1962	.0000	-.0072	.0745	.0204	.0356	.1166	32
Conform	.0982	1.1962	.0000	.9282	.0960	.0264	.0460	.1512	33
Conform	.0982	1.1962	1.0000	-.9426	.0754	.0208	.0365	.1189	34
Conform	.0982	1.1962	1.0000	-.0072	.0969	.0265	.0469	.1521	35
Conform	.0982	1.1962	1.0000	.9282	.1183	.0325	.0573	.1860	36
Conform	1.0970	-.8453	.0000	-.9426	.0434	.0176	.0085	.0774	37
Conform	1.0970	-.8453	.0000	-.0072	.0609	.0245	.0118	.1082	38
Conform	1.0970	-.8453	.0000	.9282	.0784	.0316	.0149	.1393	39
Conform	1.0970	-.8453	1.0000	-.9426	.0617	.0252	.0120	.1106	40
Conform	1.0970	-.8453	1.0000	-.0072	.0792	.0321	.0149	.1409	41
Conform	1.0970	-.8453	1.0000	.9282	.0967	.0392	.0180	.1716	42
Conform	1.0970	.1755	.0000	-.9426	.0606	.0156	.0308	.0923	43
Conform	1.0970	.1755	.0000	-.0072	.0850	.0218	.0430	.1280	44
Conform	1.0970	.1755	.0000	.9282	.1095	.0281	.0554	.1649	45
Conform	1.0970	.1755	1.0000	-.9426	.0861	.0224	.0437	.1311	46
Conform	1.0970	.1755	1.0000	-.0072	.1106	.0285	.0560	.1670	47
Conform	1.0970	.1755	1.0000	.9282	.1351	.0348	.0682	.2047	48
Conform	1.0970	1.1962	.0000	-.9426	.0778	.0193	.0412	.1169	49
Conform	1.0970	1.1962	.0000	-.0072	.1092	.0268	.0576	.1631	50
Conform	1.0970	1.1962	.0000	.9282	.1406	.0347	.0743	.2105	51
Conform	1.0970	1.1962	1.0000	-.9426	.1106	.0274	.0580	.1652	52
Conform	1.0970	1.1962	1.0000	-.0072	.1420	.0349	.0749	.2115	53
Conform	1.0970	1.1962	1.0000	.9282	.1734	.0427	.0915	.2593	54

Mediator

ResPol	TolUncer	AngloCul	Cnstrnt	Effect	Boot SE	BootLLCI	BootULCI	Effect size number featured in Figure 7
Compform	-.9006	-.8453	.0000	-.9426	-.0260	.0153	-.0571	.0026	55
Compform	-.9006	-.8453	.0000	-.0072	-.0278	.0163	-.0607	.0030	56
Compform	-.9006	-.8453	.0000	.9282	-.0296	.0174	-.0647	.0034	57
Compform	-.9006	-.8453	1.0000	-.9426	-.0093	.0061	-.0247	.0000	58
Compform	-.9006	-.8453	1.0000	-.0072	-.0111	.0069	-.0264	.0007	59
Compform	-.9006	-.8453	1.0000	.9282	-.0128	.0079	-.0308	.0009	60
Compform	-.9006	.1755	.0000	-.9426	-.0064	.0112	-.0296	.0146	61
Compform	-.9006	.1755	.0000	-.0072	-.0069	.0120	-.0318	.0156	62
Compform	-.9006	.1755	.0000	.9282	-.0073	.0128	-.0342	.0166	63
Compform	-.9006	.1755	1.0000	-.9426	-.0023	.0042	-.0120	.0050	64
Compform	-.9006	.1755	1.0000	-.0072	-.0027	.0049	-.0135	.0062	65
Compform	-.9006	.1755	1.0000	.9282	-.0032	.0057	-.0156	.0071	66
Compform	-.9006	1.1962	.0000	-.9426	.0132	.0133	-.0125	.0394	67
Compform	-.9006	1.1962	.0000	-.0072	.0141	.0142	-.0134	.0413	68
Compform	-.9006	1.1962	.0000	.9282	.0150	.0151	-.0143	.0443	69
Compform	-.9006	1.1962	1.0000	-.9426	.0047	.0050	-.0037	.0165	70
Compform	-.9006	1.1962	1.0000	-.0072	.0056	.0058	-.0050	.0178	71
Compform	-.9006	1.1962	1.0000	.9282	.0065	.0067	-.0058	.0205	72
Compform	.0982	-.8453	.0000	-.9426	.0048	.0114	-.0172	.0280	73
Compform	.0982	-.8453	.0000	-.0072	.0052	.0122	-.0183	.0296	74
Compform	.0982	-.8453	.0000	.9282	.0055	.0130	-.0193	.0316	75
Compform	.0982	-.8453	1.0000	-.9426	.0017	.0043	-.0060	.0113	76
Compform	.0982	-.8453	1.0000	-.0072	.0021	.0050	-.0073	.0126	77
Compform	.0982	-.8453	1.0000	.9282	.0024	.0057	-.0084	.0144	78
Compform	.0982	.1755	.0000	-.9426	.0244	.0093	.0069	.0434	79
Compform	.0982	.1755	.0000	-.0072	.0261	.0098	.0073	.0460	80
Compform	.0982	.1755	.0000	.9282	.0278	.0105	.0077	.0488	81
Compform	.0982	.1755	1.0000	-.9426	.0087	.0041	.0025	.0192	82
Compform	.0982	.1755	1.0000	-.0072	.0104	.0044	.0032	.0206	83
Compform	.0982	.1755	1.0000	.9282	.0121	.0051	.0035	.0234	84
Compform	.0982	1.1962	.0000	-.9426	.0440	.0142	.0182	.0737	85

Compform	.0982	1.1962	.0000	-.0072	.0470	.0149	.0194	.0773	86
Compform	.0982	1.1962	.0000	.9282	.0500	.0160	.0202	.0823	87
Compform	.0982	1.1962	1.0000	-.9426	.0157	.0066	.0053	.0317	88
Compform	.0982	1.1962	1.0000	-.0072	.0187	.0068	.0074	.0344	89
Compform	.0982	1.1962	1.0000	.9282	.0217	.0079	.0086	.0396	90
Compform	1.0970	-.8453	.0000	-.9426	.0356	.0161	.0056	.0684	91
Compform	1.0970	-.8453	.0000	-.0072	.0381	.0171	.0056	.0724	92
Compform	1.0970	-.8453	.0000	.9282	.0405	.0182	.0059	.0772	93
Compform	1.0970	-.8453	1.0000	-.9426	.0127	.0068	.0025	.0302	94
Compform	1.0970	-.8453	1.0000	-.0072	.0152	.0075	.0029	.0324	95
Compform	1.0970	-.8453	1.0000	.9282	.0176	.0087	.0031	.0371	96
Compform	1.0970	.1755	.0000	-.9426	.0552	.0167	.0236	.0887	97
Compform	1.0970	.1755	.0000	-.0072	.0590	.0175	.0250	.0938	98
Compform	1.0970	.1755	.0000	.9282	.0628	.0189	.0262	.1003	99
Compform	1.0970	.1755	1.0000	-.9426	.0197	.0080	.0073	.0391	100
Compform	1.0970	.1755	1.0000	-.0072	.0235	.0083	.0098	.0423	101
Compform	1.0970	.1755	1.0000	.9282	.0273	.0096	.0109	.0480	102
Compform	1.0970	1.1962	.0000	-.9426	.0748	.0214	.0350	.1185	103
Compform	1.0970	1.1962	.0000	-.0072	.0799	.0224	.0364	.1236	104
Compform	1.0970	1.1962	.0000	.9282	.0851	.0241	.0386	.1326	105
Compform	1.0970	1.1962	1.0000	-.9426	.0267	.0104	.0100	.0513	106
Compform	1.0970	1.1962	1.0000	-.0072	.0318	.0107	.0140	.0559	107
Compform	1.0970	1.1962	1.0000	.9282	.0369	.0123	.0161	.0638	108

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

********** ANALYSIS NOTES AND WARNINGS **********
Number of bootstrap samples for bias corrected bootstrap confidence intervals:
10000
Level of confidence for all confidence intervals in output:
95.00

NOTE: Some cases were deleted due to missing data. The number of such cases was:
4064

------ END MATRIX -----

Section 4: VNA file for visualising correlations between policy preferences

The following data represent Spearman rank correlations between every policy preference variable and every other policy preference variable. Spearman correlations are similar to Pearson correlations, varying between -1 and 1, except that they are more appropriate when comparing ordinal variables, which all of the policy preference items are. These data were used to create the network diagram shown in Figure 2, where points represent policy preference variables and lines represent correlations between them. Only significant correlations are featured; non-significant correlations are valued as zero. To be reproduced, the following text should be copied into Notepad and saved as a .vna file, then opened in Netdraw.

```
ode data
ID name theme median iqr
bonusw1 bonusnotfairwave1
economy 2 2
bonusw2 bonusnotfairwave2
economy 2 2
bonusw3 bonusnotfairwave3
economy 2 2
bonusw4 bonusnotfairwave4
economy 2 2
handoutsw1
handoutsjustifiedwave1
economy 2 2
handoutsw2
handoutsjustifiedwave2
economy 2 2
handoutsw3
handoutsjustifiedwave3
economy 2 2
handoutsw4
handoutsjustifiedwave4
economy 2 2
immigeconw1
immigrationgoodeconomywav
e1 immigration 3 2
immigeconw2
immigrationgoodeconomywav
e2 immigration 3 2
immigeconw3
immigrationgoodeconomywav
e3 immigration 3 2
immigeconw4
immigrationgoodeconomywav
e4 immigration 3 2
immlevelw4
increaseimmigrationW4
immigration 2 2
immlevelw6
increaseimmigrationW6
immigration 2 2
immwelfarew1
immigrantsnotwelfareburden
wave1 immigration 2 1
immwelfarew2
immigrantsnotwelfareburden
wave2 immigration 2 2
immwelfarew3
immigrantsnotwelfareburden
wave3 immigration 2 2
immwelfarew4
immigrantsnotwelfareburden
wave4 immigration 2 2
immwelfarew8
immigrantsnotwelfareburden
wave8 immigration 2 2
unempw1
unemployednotatfaultwave1
economy 3 1
unempw2
unemployednotatfaultwave2
economy 3 1
unempw3
unemployednotatfaultwave3
economy 3 1
unempw4
unemployednotatfaultwave1
economy 3 1
censor
censorshipnotnecessary social
3 2
redist
govshouldredistributeincomes
economy 4 1
sentence
lawbreakersnotgetstiffersente
ncces social 2 2
schoolauth
schoolsnotteachobeyauthorit
y social 2 2
*node properties
ID color size shape shortlabel
bonusw1 0 10 1
BonusesAreBad1
bonusw2 0 10 1
BonusesAreBad2
bonusw3 0 10 1
BonusesAreBad3
bonusw4 0 10 1
BonusesAreBad4
handoutsw1 0 10 1
HandoutsAreGood1
handoutsw2 0 10 1
HandoutsAreGood2
handoutsw3 0 10 1
HandoutsAreGood3
handoutsw4 0 10 1
HandoutsAreGood4
immigeconw1 127 20 1
ImmigrationGoodForEconomy
1
immigeconw2 127 20 1
ImmigrationGoodForEconomy
2
immigeconw3 127 20 1
ImmigrationGoodForEconomy
3
immigeconw4 127 20 1
ImmigrationGoodForEconomy
4
immlevelw4 127 10 1
IncreaseImmigration1
immlevelw6 127 10 1
IncreaseImmigration2
immwelfarew1 127 10 2
ImmigrantsNotWelfareBurden
1
immwelfarew2 127 10 1
ImmigrantsNotWelfareBurden
2
immwelfarew3 127 10 1
ImmigrantsNotWelfareBurden
3
immwelfarew4 127 10 1
ImmigrantsNotWelfareBurden
4
immwelfarew8 127 10 1
ImmigrantsNotWelfareBurden
5
unempw1 0 20 2
UnemployedNotAtFault1
unempw2 0 20 2
UnemployedNotAtFault2
unempw3 0 20 2
UnemployedNotAtFault3
unempw4 0 20 2
UnemployedNotAtFault4
censor 255 20 1
CensorshipBad
redist 0 30 2
RedistributeIncomesGood
sentence 255 10 1
StifferSentencesBad
schoolauth 255 10 1
SchoolAuthorityBad
*tie data
from to strength
bonusw1 bonusw2 0.54
bonusw2 bonusw1 0.54
bonusw1 bonusw3 0.55
bonusw3 bonusw1 0.55
bonusw1 bonusw4 0.54
bonusw4 bonusw1 0.54
bonusw1 handoutsw1 0.25
handoutsw1 bonusw1 0.25
bonusw1 handoutsw2 0.21
handoutsw2 bonusw1 0.21
bonusw1 handoutsw3 0.21
handoutsw3 bonusw1 0.21
bonusw1 handoutsw4 0.20
handoutsw4 bonusw1 0.20
bonusw1 immigeconw1 0.05
immigeconw1 bonusw1 0.05
bonusw1 immigeconw2 0.05
immigeconw2 bonusw1 0.05
bonusw1 immigeconw3 0.05
immigeconw3 bonusw1 0.05
bonusw1 immigeconw4 0.05
immigeconw4 bonusw1 0.05
bonusw1 immlevelw4 0.05
immlevelw4 bonusw1 0.05
bonusw1 immlevelw6 0.05
immlevelw6 bonusw1 0.05
bonusw1 immwelfarew1 0.10
immwelfarew1 bonusw1 0.10
bonusw1 immwelfarew2 0.10
immwelfarew2 bonusw1 0.10
bonusw1 immwelfarew3 0.10
immwelfarew3 bonusw1 0.10
bonusw1 immwelfarew4 0.11
immwelfarew4 bonusw1 0.11
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immwelfarew8 bonusw1 0.11
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unempw4 bonusw1 0.13
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censor bonusw1 0
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redist bonusw1 0.19
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sentence bonusw1 0.05
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schoolauth bonusw1 0.06
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handoutsw3 bonusw3 0.22
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handoutsw4 bonusw3 0.22
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censor immlevelw6 0.17
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schoolauth immlevelw6 0.29
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schoolauth immwelfarew1 0.30

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schoolauth immwelfarew2
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unempw2 immwelfarew8
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schoolauth immwelfarew8
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unempw3 unempw1 0.40
unempw1 unempw4 0.40
unempw4 unempw1 0.40
unempw1 censor 0.05
censor unempw1 0.05
unempw1 redist 0.26
redist unempw1 0.26
unempw1 sentence 0.10
sentence unempw1 0.10
unempw1 schoolauth 0.09
schoolauth unempw1 0.09
unempw2 unempw3 0.40
unempw3 unempw2 0.40
unempw2 unempw4 0.37
unempw4 unempw2 0.37
unempw2 censor 0.06
censor unempw2 0.06
unempw2 redist 0.25
redist unempw2 0.25
unempw2 sentence 0.08
sentence unempw2 0.08
unempw2 schoolauth 0.07
schoolauth unempw2 0.07
unempw3 unempw4 0.48
unempw4 unempw3 0.48
unempw3 censor 0.06
censor unempw3 0.06
unempw3 redist 0.35
redist unempw3 0.35
unempw3 sentence 0.13
sentence unempw3 0.13
unempw3 schoolauth 0.11
schoolauth unempw3 0.11
unempw4 censor 0.09
censor unempw4 0.09
unempw4 redist 0.29
redist unempw4 0.29
unempw4 sentence 0.15
sentence unempw4 0.15
unempw4 schoolauth 0.15
schoolauth unempw4 0.15
censor redist 0
redist censor 0
censor sentence 0.32
sentence censor 0.32
censor schoolauth 0.36
schoolauth censor 0.36
censor sentence 0.05
sentence censor 0.05
censor schoolauth 0.37
schoolauth censor 0.37
sentence schoolauth 0.53
schoolauth sentence 0.53

Section 5: complete SPSS syntax used in the analysis

```
* Encoding: UTF-8.

DATA SET ACTIVATE Data
set3.
FREQUENCIES
VARIABLES=wt_full_W1W2W
3W4W5W6W7W8W9
  /FORMAT=NOTABLE
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
  /ORDER=ANALYSIS.

GRAPH
/HISTOGRAM(NORMAL)=wt_f
ull_W1W2W3W4W5W6W7W
8W9.

RECODE
wt_full_W1W2W3W4W5W6
W7W8W9 (20 thru
Highest=20).
EXECUTE.

GRAPH
/HISTOGRAM(NORMAL)=wt_f
ull_W1W2W3W4W5W6W7W
8W9.

FILTER OFF.
USE ALL.
SELECT IF
(MISSING(wt_full_W1W2W3
W4W5W6W7W8W9)=0).
EXECUTE.

DATA SET ACTIVATE Data
set1.
SORT VARIABLES BY NAME
(A).

SORT VARIABLES BY LABEL (A).

MVA VARIABLES=id
wt_full_W1W2W3W4W5W6
W7W8W9 country
countryOfBirth
profile_ethnicity gor
   livedAbroadW8
profile_religion
parentsForeignW8
britishnessW1 britishnessW2
britishnessW3
   britishnessW4
britishnessW7 britishnessW8
britishnessW9 ethno1W7
ethno6W7 ethno2W7
ethno4W7
   ethno5W7 ethno3W7
radicalW7 immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
   immigCulturalW8 al1W6
ageW7
profile_newspaper_readershi
p_201 disabilityW6 gender
anyUniW7
   profile_work_typeW7
polAttentionW1
polAttentionW2
polAttentionW3
polAttentionW4
polAttentionW6
   polAttentionW7
polAttentionW8
discussPolDaysW2
discussPolDaysW4
discussPolDaysW5
discussPolDaysW6
   infoSourcePeopleW4
infoSourcePeopleW5
infoSourcePeopleW6
infoSourcePeopleW7
infoSourcePeopleW8
   infoSourceInternetW4
infoSourceInternetW5
infoSourceInternetW6
infoSourceInternetW7
   infoSourceInternetW8
infoSourcePaperW4
infoSourcePaperW5
infoSourcePaperW6
infoSourcePaperW7
   infoSourcePaperW8
infoSourceRadioW4
infoSourceRadioW5
infoSourceRadioW6
infoSourceRadioW7
   infoSourceRadioW8
infoSourceTVW4
infoSourceTVW5
infoSourceTVW6
infoSourceTVW7
infoSourceTVW8
   electionInterestW4
electionInterestW5
electionInterestW6
euRefInterestW7
registeredW3 registeredW4
   registeredW6 registeredW7
registeredW8
euRefTurnoutW7
turnoutUKGeneralW1
turnoutUKGeneralW2
   turnoutUKGeneralW3
turnoutUKGeneralW4
genElecTurnoutRetroW6
genElecTurnoutRetroW7
   euroTurnoutRetroW2
partyMemberW6
econPersonalRetroW1
econPersonalRetroW2
econPersonalRetroW3
   econPersonalRetroW4
econPersonalRetroW7
trustMPsW1 trustMPsW2
trustMPsW3 trustMPsW4
trustMPsW6
   trustMPsW7
generalElectionVoteW5
likeCameronW1
likeCameronW2
likeCameronW3
likeCameronW4
   likeCameronW5
likeCameronW6
likeCameronW7
likeCameronW8
likeCameronW9 likeConW7
likeConW8 likeConW9
   ptvConW9 conGovTrustW5
businessBonusW1
businessBonusW2
businessBonusW3
businessBonusW4
   govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
immigEconW1 immigEconW2
immigEconW3
   immigEconW4
immigrationLevelW4
immigrationLevelW6
immigrantsWelfareStateW1
immigrantsWelfareStateW2
   immigrantsWelfareStateW3
immigrantsWelfareStateW4
immigrantsWelfareStateW8
reasonForUnemploymentW1

reasonForUnemploymentW2
reasonForUnemploymentW3
reasonForUnemploymentW4
al4W6 lr1W6 al5W6 al3W6
   aom1W7 aom4W7
aom5W7 aom6W7 aom7W7
aom3W7 aom2W7
conAngryW4 conAngryW6
grnAngryW4 grnAngryW6
   labAngryW4 labAngryW6
ldAngryW4 ldAngryW6
ukipAngryW4 ukipAngryW6
conFearW4 conFearW6
grnFearW4
   grnFearW6 labFearW4
labFearW6 ldFearW4
ldFearW6 ukipFearW4
ukipFearW6
personality_agreeableness

personality_conscientiousness
personality_extraversion
personality_neuroticism
personality_openness
   riskTakingW7 riskTakingW8
tolUncertain1W8
tolUncertain3W8
tolUncertain2W8 .

RECODE gender (1=0) (2=1).
EXECUTE.

RECODE anyUniW7 (0=0)
(1=1) (2=1) (3=1).
EXECUTE.

RECODE country (2=1)
(MISSING=SYSMIS) (ELSE=0)
INTO Scot.
VARIABLE LABELS  Scot
'[theme: culture] [cluster]
Country is Scotland as
opposed to England'.
EXECUTE.

RECODE country
(MISSING=SYSMIS) (3=1)
(ELSE=0) INTO Wales.
VARIABLE LABELS  Wales
'[theme: culture] [cluster]
Country is Wales as opposed
to England'.
EXECUTE.

RECODE profile_ethnicity
(1=1) (MISSING=SYSMIS)
(ELSE=0).
EXECUTE.

RECODE
profile_work_typeW7
(MISSING=SYSMIS) (1=1) (2=1)
(ELSE=0) INTO Upskilled.
VARIABLE LABELS  Upskilled
'[theme: demographics] Work
type highly skilled as opposed
to never '+
   'worked'.
EXECUTE.

RECODE
profile_work_typeW7
(MISSING=SYSMIS) (3=1) (4=1)
(5=1) (6=1) (ELSE=0) INTO
Midskilled.
VARIABLE LABELS  Midskilled
'[theme: demographics] Work
type middling skilled as
opposed to '+
   'never worked'.
EXECUTE.

RECODE
profile_work_typeW7
(MISSING=SYSMIS) (7=1)
(ELSE=0) INTO Unskilled.
VARIABLE LABELS  Unskilled
'[theme: demographics] Work
type low skilled or unskilled as
opposed '+
   'to never worked'.
EXECUTE.

COMPUTE
policy1=businessBonusW1f.
VARIABLE LABELS  policy1
'[theme: policies] [bonus] In
business, bonuses are a fair
way to '+
   'reward hard work W1'.
EXECUTE.

RECODE ageW7
(MISSING=SYSMIS) (Lowest
thru 49=0) (50 thru
Highest=1) INTO ageGroup.
VARIABLE LABELS  ageGroup
'Under 50 or 50 or over?'.
EXECUTE.

COMPUTE demogCleave=0.
VARIABLE LABELS
demogCleave '[theme:
demographics] eight-way
demographic cleavage
between age, '+
   'gender and education'.
EXECUTE.

DO IF (ageGroup = 1 & gender
= 1 & anyUniW7 = 1).
RECODE demogCleave (0=1).
END IF.
EXECUTE.

DO IF (ageGroup = 1 & gender
= 1 & anyUniW7 = 0).
RECODE demogCleave (0=2).
END IF.
EXECUTE.

DO IF (ageGroup = 1 & gender
= 0 & anyUniW7 = 0).
RECODE demogCleave (0=3).
END IF.
EXECUTE.

DO IF (ageGroup = 1 & gender
= 0 & anyUniW7 = 1).
RECODE demogCleave (0=4).
END IF.
EXECUTE.

DO IF (ageGroup = 0 & gender
= 1 & anyUniW7 = 1).
RECODE demogCleave (0=5).
END IF.
EXECUTE.

DO IF (ageGroup = 0 & gender
= 1 & anyUniW7 = 0).
RECODE demogCleave (0=6).
END IF.
EXECUTE.

DO IF (ageGroup = 0 & gender
= 0 & anyUniW7 = 0).
RECODE demogCleave (0=7).
END IF.
EXECUTE.

DO IF (ageGroup = 0 & gender
= 0 & anyUniW7 = 1).
```

```
RECODE demogCleave (0=8).
END IF.
EXECUTE.

SORT CASES  BY demogCleave.
SPLIT FILE LAYERED BY
demogCleave.

FREQUENCIES
VARIABLES=businessBonusW1
f businessBonusW2f
businessBonusW3f
businessBonusW4f
   govtHandoutsW1f
govtHandoutsW2f
govtHandoutsW3f
govtHandoutsW4f
immigEconW1f
immigEconW2f
   immigEconW3f
immigEconW4f
immigrationLevelW4f
immigrationLevelW6f
immigrantsWelfareStateW1f

immigrantsWelfareStateW2f
immigrantsWelfareStateW3f
immigrantsWelfareStateW4f

immigrantsWelfareStateW8f
reasonForUnemploymentW1f
reasonForUnemploymentW2f

reasonForUnemploymentW3f
reasonForUnemploymentW4f
al4W6f lr1W6f al5W6f al3W6f
  /FORMAT=NOTABLE
  /STATISTICS=MEDIAN
  /ORDER=ANALYSIS.

DO IF (ageGroup = 0 & gender
= 0 & anyUniW7 = 1).
RECODE gor
(MISSING=SYSMIS) (7=3)
(10=5) (11=6) (12=7) (1 thru
3=1) (4 thru 6=2) (8 thru 9=4).
END IF.
EXECUTE.

SPLIT FILE OFF.

RECODE ethno1W7 (1=5)
(2=4) (3=3) (4=2) (5=1).
EXECUTE.

RECODE ethno6W7 (1=5)
(2=4) (3=3) (4=2) (5=1).
EXECUTE.

RECODE ethno3W7 radicalW7
(1=5) (2=4) (3=3) (4=2) (5=1).
EXECUTE.

RELIABILITY
  /VARIABLES=britishnessW1
britishnessW2 britishnessW3
britishnessW4 britishnessW7
britishnessW8
   britishnessW9
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES britishnessW1
britishnessW2 britishnessW3
britishnessW4 britishnessW7
britishnessW8
   britishnessW9
  /MISSING MEANSUB
  /ANALYSIS britishnessW1
britishnessW2 britishnessW3
britishnessW4 britishnessW7
britishnessW8
   britishnessW9
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
immigCulturalW8 (1=7) (2=6)
   (3=5) (4=4) (5=3) (6=2)
(7=1).
EXECUTE.

RELIABILITY
/VARIABLES=immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
immigCulturalW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
immigCulturalW8
  /MISSING MEANSUB
  /ANALYSIS immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
immigCulturalW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=polAttentionW1
polAttentionW2
polAttentionW3
polAttentionW4
polAttentionW6
   polAttentionW7
polAttentionW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES polAttentionW1
polAttentionW2
polAttentionW3
polAttentionW4
polAttentionW6
   polAttentionW7
polAttentionW8
  /MISSING MEANSUB
  /ANALYSIS polAttentionW1
polAttentionW2
polAttentionW3
polAttentionW4
polAttentionW6
   polAttentionW7
polAttentionW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=discussPolDaysW
2 discussPolDaysW4
discussPolDaysW5
discussPolDaysW6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
discussPolDaysW2
discussPolDaysW4
discussPolDaysW5
discussPolDaysW6
  /MISSING MEANSUB
  /ANALYSIS discussPolDaysW2
discussPolDaysW4
discussPolDaysW5
discussPolDaysW6
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=infoSourcePeopl
eW4 infoSourcePeopleW5
infoSourcePeopleW6
infoSourcePeopleW7
   infoSourcePeopleW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
infoSourcePeopleW4
infoSourcePeopleW5
infoSourcePeopleW6
infoSourcePeopleW7
   infoSourcePeopleW8
  /MISSING MEANSUB
  /ANALYSIS
infoSourcePeopleW4
infoSourcePeopleW5
infoSourcePeopleW6
infoSourcePeopleW7
   infoSourcePeopleW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=infoSourceIntern
etW4 infoSourceInternetW5
infoSourceInternetW6
infoSourceInternetW7
   infoSourceInternetW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
infoSourceInternetW4
infoSourceInternetW5
infoSourceInternetW6
infoSourceInternetW7
   infoSourceInternetW8
  /MISSING MEANSUB
  /ANALYSIS
infoSourceInternetW4
infoSourceInternetW5
infoSourceInternetW6
infoSourceInternetW7
   infoSourceInternetW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=infoSourcePaper
W4 infoSourcePaperW5
infoSourcePaperW6
infoSourcePaperW7
   infoSourcePaperW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
infoSourcePaperW4
infoSourcePaperW5
infoSourcePaperW6
infoSourcePaperW7
   infoSourcePaperW8
  /MISSING MEANSUB
  /ANALYSIS
infoSourcePaperW4
infoSourcePaperW5
infoSourcePaperW6
infoSourcePaperW7
   infoSourcePaperW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
```

```
/VARIABLES=infoSourceRadio
W4 infoSourceRadioW5
infoSourceRadioW6
infoSourceRadioW7
   infoSourceRadioW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
infoSourceRadioW4
infoSourceRadioW5
infoSourceRadioW6
infoSourceRadioW7
   infoSourceRadioW8
  /MISSING MEANSUB
  /ANALYSIS
infoSourceRadioW4
infoSourceRadioW5
infoSourceRadioW6
infoSourceRadioW7
   infoSourceRadioW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=infoSourceTVW4
infoSourceTVW5
infoSourceTVW6
infoSourceTVW7
infoSourceTVW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES infoSourceTVW4
infoSourceTVW5
infoSourceTVW6
infoSourceTVW7
infoSourceTVW8
  /MISSING MEANSUB
  /ANALYSIS infoSourceTVW4
infoSourceTVW5
infoSourceTVW6
infoSourceTVW7
infoSourceTVW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=electionInterest
W4 electionInterestW5
electionInterestW6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
electionInterestW4
electionInterestW5
electionInterestW6
  /MISSING MEANSUB
  /ANALYSIS
electionInterestW4
electionInterestW5
electionInterestW6
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=turnoutUKGener
alW1 turnoutUKGeneralW2
turnoutUKGeneralW3
turnoutUKGeneralW4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
turnoutUKGeneralW1
turnoutUKGeneralW2
turnoutUKGeneralW3
turnoutUKGeneralW4
  /MISSING MEANSUB
  /ANALYSIS
turnoutUKGeneralW1
turnoutUKGeneralW2
turnoutUKGeneralW3
turnoutUKGeneralW4
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=FAC1_3 FAC1_4
FAC1_5 FAC1_6 FAC1_7
FAC1_8 FAC1_9 FAC1_10
FAC1_12 euRefInterestW7
   euRefTurnoutW7
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES FAC1_3 FAC1_4
FAC1_5 FAC1_6 FAC1_7
FAC1_8 FAC1_9 FAC1_10
FAC1_12 euRefInterestW7
   euRefTurnoutW7
  /MISSING MEANSUB
  /ANALYSIS FAC1_3 FAC1_4
FAC1_5 FAC1_6 FAC1_7
FAC1_8 FAC1_9 FAC1_10
FAC1_12 euRefInterestW7
   euRefTurnoutW7
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

CORRELATIONS
  /VARIABLES=FAC1_11
FAC2_11
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

FACTOR
  /VARIABLES FAC1_11
FAC2_11
  /MISSING MEANSUB
  /ANALYSIS FAC1_11 FAC2_11
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

GRAPH
/HISTOGRAM(NORMAL)=FAC1
_13.

CORRELATIONS
  /VARIABLES=FAC1_1 FAC1_2
al1W6
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_1 al1W6
FAC1_2
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

FACTOR
  /VARIABLES FAC1_2 al1W6
  /MISSING MEANSUB
  /ANALYSIS FAC1_2 al1W6
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

CORRELATIONS
  /VARIABLES=FAC1_1
FAC1_14
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RELIABILIT
/VARIABLES=econPersonalRet
roW1 econPersonalRetroW2
econPersonalRetroW3
econPersonalRetroW4
   econPersonalRetroW7
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
econPersonalRetroW1
econPersonalRetroW2
econPersonalRetroW3
econPersonalRetroW4
   econPersonalRetroW7
  /MISSING MEANSUB
  /ANALYSIS
econPersonalRetroW1
econPersonalRetroW2
econPersonalRetroW3
econPersonalRetroW4
   econPersonalRetroW7
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=trustMPsW1
trustMPsW2 trustMPsW3
trustMPsW4 trustMPsW6
trustMPsW7
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES trustMPsW1
trustMPsW2 trustMPsW3
trustMPsW4 trustMPsW6
trustMPsW7
  /MISSING MEANSUB
  /ANALYSIS trustMPsW1
trustMPsW2 trustMPsW3
trustMPsW4 trustMPsW6
trustMPsW7
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=likeCameronW1
likeCameronW2
likeCameronW3
likeCameronW4
likeCameronW5
likeCameronW6
   likeCameronW7
likeCameronW8
likeCameronW9
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES likeCameronW1
likeCameronW2
likeCameronW3
likeCameronW4
likeCameronW5
likeCameronW6
   likeCameronW7
likeCameronW8
likeCameronW9
  /MISSING MEANSUB
  /ANALYSIS likeCameronW1
likeCameronW2
likeCameronW3
```

```
likeCameronW4
likeCameronW5
likeCameronW6
   likeCameronW7
likeCameronW8
likeCameronW9
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=likeConW7
likeConW8 likeConW9
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES likeConW7
likeConW8 likeConW9
  /MISSING MEANSUB
  /ANALYSIS likeConW7
likeConW8 likeConW9
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=FAC1_17
FAC1_18 ptvConW9
conGovTrustW5
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES FAC1_17
FAC1_18 conGovTrustW5
  /MISSING MEANSUB
  /ANALYSIS FAC1_17 FAC1_18
conGovTrustW5
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE aom4W7 aom5W7
aom6W7 aom7W7 (1=5) (2=4)
(3=3) (4=2) (5=1).
EXECUTE.

RELIABILITY
  /VARIABLES=aom1W7
aom4W7 aom5W7 aom6W7
aom7W7 aom3W7 aom2W7
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES aom1W7
aom4W7 aom5W7 aom6W7
aom7W7 aom3W7 aom2W7
  /MISSING MEANSUB
  /ANALYSIS aom1W7
aom4W7 aom5W7 aom6W7
aom7W7 aom3W7 aom2W7
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE tolUncertain1W8
tolUncertain3W8
tolUncertain2W8 (1=5) (2=4)
(3=3) (4=2) (5=1).
EXECUTE.

RELIABILITY
  /VARIABLES=riskTakingW7
riskTakingW8
tolUncertain1W8
tolUncertain3W8
tolUncertain2W8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES riskTakingW7
riskTakingW8
tolUncertain1W8
tolUncertain3W8
tolUncertain2W8
  /MISSING MEANSUB
  /ANALYSIS riskTakingW7
riskTakingW8
tolUncertain1W8
tolUncertain3W8
tolUncertain2W8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

CORRELATIONS
  /VARIABLES=FAC1_21
FAC2_21
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_20
FAC1_21 FAC2_21
personality_agreeableness
personality_conscientiousness
   personality_extraversion
personality_neuroticism
personality_openness
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RELIABILITY
  /VARIABLES=conFearW4
conFearW6 grnFearW4
grnFearW6 labFearW4
labFearW6 ldFearW4
ldFearW6
   ukipFearW4 ukipFearW6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=conAngryW4
conAngryW6 grnAngryW4
grnAngryW6 labAngryW4
labAngryW6 ldAngryW4
ldAngryW6
   ukipAngryW4 ukipAngryW6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

COMPUTE
angerScale=(conAngryW4 +
conAngryW6 + grnAngryW4 +
grnAngryW6 + labAngryW4 +
labAngryW6 +
   ldAngryW4 + ldAngryW6 +
ukipAngryW4 +
ukipAngryW6)/10.
VARIABLE LABELS  angerScale
'[theme: psychology]
[emotion] Proportional
additive scale for '+
   'feeling anger when
thinking about political
parties'.
EXECUTE.

FREQUENCIES
VARIABLES=angerScale
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
fearScale=(conFearW4 +
conFearW6 + grnFearW4 +
grnFearW6 + labFearW4 +
labFearW6 + ldFearW4
   + ldFearW6 + ukipFearW4 +
ukipFearW6)/10.
VARIABLE LABELS  fearScale
'[theme: psychology]
[emotion] Proportional
additive scale for '+
   'feeling fear when thinking
about political parties'.
EXECUTE.

FREQUENCIES
VARIABLES=fearScale
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

RELIABILITY
  /VARIABLES=ethno1W7
ethno6W7 ethno2W7
ethno4W7 ethno5W7
ethno3W7 radicalW7
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES ethno1W7
ethno6W7 ethno2W7
ethno4W7 ethno5W7
ethno3W7 radicalW7
  /MISSING MEANSUB
  /ANALYSIS ethno1W7
ethno6W7 ethno2W7
ethno4W7 ethno5W7
ethno3W7 radicalW7
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

CORRELATIONS
  /VARIABLES=ethno1W7
ethno6W7 ethno2W7
ethno4W7 ethno5W7
ethno3W7 radicalW7
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_22
FAC2_22
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=FAC2_22
ethno3W7
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

COMPUTE
EthnoProud=FAC2_22 *  - 1.
VARIABLE LABELS  EthnoProud
'[theme: culture] [ethno]
Ethno factor for pride in
British identity '+
   'created by inverting
FAC2_22 by multiplying it by -
1'.
EXECUTE.

RELIABILITY
  /VARIABLES=FAC1_1
FAC1_22 EthnoProud
FAC1_14
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES FAC1_1
FAC1_22 FAC1_14
  /MISSING MEANSUB
  /ANALYSIS FAC1_1 FAC1_22
FAC1_14
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

COMPUTE
ItemResponseNumber=NVALI
```

```
D(profile_ethnicity, gor,
livedAbroadW8,
profile_religion,
   parentsForeignW8,
britishnessW1, britishnessW2,
britishnessW3, britishnessW4,
britishnessW7,
   britishnessW8,
britishnessW9, ethno1W7,
ethno6W7, ethno2W7,
ethno4W7, ethno5W7,
ethno3W7,
   radicalW7,
immigCulturalW1,
immigCulturalW2,
immigCulturalW3,
immigCulturalW4,
immigCulturalW8,
   al1W6, ageW7,
profile_newspaper_readershi
p_201, disabilityW6,
anyUniW7,
profile_work_typeW7,
   polAttentionW1,
polAttentionW2,
polAttentionW3,
polAttentionW4,
polAttentionW6,
polAttentionW7,
   polAttentionW8,
discussPolDaysW2,
discussPolDaysW4,
discussPolDaysW5,
discussPolDaysW6,
   infoSourcePeopleW4,
infoSourcePeopleW5,
infoSourcePeopleW6,
infoSourcePeopleW7,
infoSourcePeopleW8,
   infoSourceInternetW4,
infoSourceInternetW5,
infoSourceInternetW6,
infoSourceInternetW7,
   infoSourceInternetW8,
infoSourcePaperW4,
infoSourcePaperW5,
infoSourcePaperW6,
infoSourcePaperW7,
   infoSourcePaperW8,
infoSourceRadioW4,
infoSourceRadioW5,
infoSourceRadioW6,
infoSourceRadioW7,
   infoSourceRadioW8,
infoSourceTVW4,
infoSourceTVW5,
infoSourceTVW6,
infoSourceTVW7,
infoSourceTVW8,
   electionInterestW4,
electionInterestW5,
electionInterestW6,
euRefInterestW7,
euRefTurnoutW7,
   turnoutUKGeneralW1,
turnoutUKGeneralW2,
turnoutUKGeneralW3,
turnoutUKGeneralW4,
   econPersonalRetroW1,
econPersonalRetroW2,
econPersonalRetroW3,
econPersonalRetroW4,
   econPersonalRetroW7,
trustMPsW1, trustMPsW2,
trustMPsW3, trustMPsW4,
trustMPsW6, trustMPsW7,
   generalElectionVoteW5,
likeCameronW1,
likeCameronW2,
likeCameronW3,
likeCameronW4,
likeCameronW5,
   likeCameronW6,
likeCameronW7,
likeCameronW8,
likeCameronW9, likeConW7,
likeConW8, likeConW9,
   ptvConW9,
conGovTrustW5,
businessBonusW1,
businessBonusW2,
businessBonusW3,
businessBonusW4,
   govtHandoutsW1,
govtHandoutsW2,
govtHandoutsW3,
govtHandoutsW4,
immigEconW1,
immigEconW2,
   immigEconW3,
immigEconW4,
immigrationLevelW4,
immigrationLevelW6,
immigrantsWelfareStateW1,

immigrantsWelfareStateW2,
immigrantsWelfareStateW3,
immigrantsWelfareStateW4,

immigrantsWelfareStateW8,
reasonForUnemploymentW1,
reasonForUnemploymentW2,

reasonForUnemploymentW3,
reasonForUnemploymentW4,
al4W6, lr1W6, al5W6, al3W6,
aom1W7, aom4W7,
   aom5W7, aom6W7,
aom7W7, aom3W7, aom2W7,
conAngryW4, conAngryW6,
grnAngryW4, grnAngryW6,
labAngryW4,
   labAngryW6, ldAngryW4,
ldAngryW6, ukipAngryW4,
ukipAngryW6, conFearW4,
conFearW6, grnFearW4,
   grnFearW6, labFearW4,
labFearW6, ldFearW4,
ldFearW6, ukipFearW4,
ukipFearW6, riskTakingW7,
   riskTakingW8,
tolUncertain1W8,
tolUncertain3W8,
tolUncertain2W8).
VARIABLE LABELS
ItemResponseNumber
'Number of items with valid
responses, out of 160'.
EXECUTE.

COMPUTE
ItemResponseRate=(ItemResp
onseNumber / 160)*100.
VARIABLE LABELS
ItemResponseRate '[theme:
psychology] Item-level
response rate'.
EXECUTE.

FREQUENCIES
VARIABLES=ItemResponseRat
e
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

FREQUENCIES
VARIABLES=ItemResponseRat
e
  /FORMAT=NOTABLE
  /STATISTICS=MAXIMUM
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
ReflectItemResponseRate=10
0 - ItemResponseRate.
VARIABLE LABELS
ReflectItemResponseRate
'[theme: psychology]
Reflected item-level response
rate'.
EXECUTE.

FREQUENCIES
VARIABLES=ReflectItemRespo
nseRate
  /FORMAT=NOTABLE
  /STATISTICS=MAXIMUM
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
LnReflectedItemResponseRat
e=LN(ReflectItemResponseRat
e).
VARIABLE LABELS
LnReflectedItemResponseRat
e '[theme: psychology]
Natural logarithm of reflected
'+
   'item-level response rate'.
EXECUTE.

FREQUENCIES
VARIABLES=LnReflectedItemR
esponseRate
  /FORMAT=NOTABLE
  /STATISTICS=MAXIMUM
SKEWNESS SESKEW KURTOSIS
SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

NONPAR CORR
/VARIABLES=LnReflectedItem
ResponseRate
ItemResponseRate
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

COMPUTE
ReflectedLnReflectedItemRes
ponseRate=4.56 -
LnReflectedItemResponseRat
e.
VARIABLE LABELS
ReflectedLnReflectedItemRes
ponseRate '[theme:
psychology] Reflected natural
'+
   'logarithm of reflected
item-level response rate'.
EXECUTE.

FREQUENCIES
VARIABLES=ReflectedLnReflec
tedItemResponseRate
  /FORMAT=NOTABLE
  /STATISTICS=MAXIMUM
SKEWNESS SESKEW KURTOSIS
SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

RECODE britishnessW1
britishnessW2 britishnessW3
britishnessW4 britishnessW7
britishnessW8
   britishnessW9
immigCulturalW1
immigCulturalW2
immigCulturalW3
immigCulturalW4
immigCulturalW8
   trustMPsW1 trustMPsW2
trustMPsW3 trustMPsW4
trustMPsW6 trustMPsW7
conGovTrustW5
immigEconW1
   immigEconW2
immigEconW3 immigEconW4
(4=0) (3=1) (5=1) (2=2) (6=2)
(1=3) (7=3) (MISSING=SYSMIS)
INTO
   Likert1 Likert2 Likert3
Likert4 Likert5 Likert7 Likert8
Likert9 Likert10 Likert11
Likert12 Likert13
   Likert14 Likert15 Likert16
Likert17 Likert18 Likert19
Likert20 Likert21 Likert22
Likert23 Likert24.
VARIABLE LABELS  Likert9 '7-
point, culture' /Likert10 '7-
point, culture' /Likert11 '7-
point, '+
   'culture' /Likert12 '7-point,
culture' /Likert13 '7-point,
culture' /Likert14 '7-point, '+
   'general politics' /Likert15
'7-point, general politics'
/Likert16 '7-point, general
politics'
   /Likert17 '7-point, general
politics' /Likert18 '7-point,
general politics' /Likert19 '7-
point, '+
   'general politics' /Likert20
'7-point, partisanship'
/Likert21 '7-point, policy'
/Likert22
   '7-point, policy' /Likert23 '7-
point, policy' /Likert24 '7-
point, policy'.
EXECUTE.

RECODE ethno1W7
ethno6W7 ethno2W7
ethno4W7 ethno5W7
ethno3W7 radicalW7 al1W6
euRefTurnoutW7
   turnoutUKGeneralW1
turnoutUKGeneralW2
turnoutUKGeneralW3
turnoutUKGeneralW4
econPersonalRetroW1
   econPersonalRetroW2
econPersonalRetroW3
econPersonalRetroW4
econPersonalRetroW7
businessBonusW1
   businessBonusW2
businessBonusW3
businessBonusW4
govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
   govtHandoutsW4
immigrationLevelW4
immigrationLevelW6
immigrantsWelfareStateW1
   immigrantsWelfareStateW2
immigrantsWelfareStateW3
immigrantsWelfareStateW4
immigrantsWelfareStateW8
```

```
reasonForUnemploymentW1
reasonForUnemploymentW2
reasonForUnemploymentW3
reasonForUnemploymentW4
   al4W6 lr1W6 al5W6 al3W6
aom1W7 aom4W7 aom5W7
aom6W7 aom7W7 aom3W7
aom2W7 tolUncertain1W8
   tolUncertain3W8
tolUncertain2W8 (3=0) (2=1)
(4=1) (1=2) (5=2)
(MISSING=SYSMIS) INTO
Likert25
   Likert26 Likert27 Likert28
Likert29 Likert30 Likert31
Likert32 Likert33 Likert34
Likert35 Likert36
   Likert37 Likert38 Likert39
Likert40 Likert41 Likert42
Likert43 Likert44 Likert45
Likert46 Likert47
   Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55 Likert56
Likert57 Likert58
   Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65 Likert66 Likert67
Likert68 Likert69
   Likert70 Likert71 Likert72
Likert73 Likert74 Likert75.
VARIABLE LABELS  Likert25 '5-
point, culture' /Likert26 '5-
point, culture' /Likert27 '5-
point, '+
   'culture' /Likert28 '5-point,
culture' /Likert31 '5-point,
culture' /Likert32 '5-point,
culture'
   /Likert33 '5-point,
engagement' /Likert34 '5-
point, engagement' /Likert35
'5-point, engagement'
   /Likert36 '5-point,
engagement' /Likert37 '5-
point, engagement' /Likert38
'5-point, engagement'
   /Likert39 '5-point,
engagement' /Likert40 '5-
point, engagement' /Likert41
'5-point, engagement'
   /Likert42 '5-point,
engagement' /Likert43 '5-
point, policy' /Likert44 '5-
point, policy'
   /Likert45 '5-point, policy'
/Likert46 '5-point, policy'
/Likert47 '5-point, policy'
/Likert48
   '5-point, policy' /Likert49 '5-
point, policy' /Likert50 '5-
point, policy' /Likert51 '5-
point, '+
   'policy' /Likert52 '5-point,
policy' /Likert53 '5-point,
policy' /Likert54 '5-point,
policy'
   /Likert55 '5-point, policy'
/Likert56 '5-point, policy'
/Likert57 '5-point, policy'
/Likert58
   '5-point, policy' /Likert59 '5-
point, policy' /Likert60 '5-
point, policy' /Likert61 '5-
point, '+
   'policy' /Likert62 '5-point,
policy' /Likert63 '5-point,
policy' /Likert64 '5-point,
policy'
   /Likert65 '5-point, policy'
/Likert66 '5-point, psychology'
/Likert67 '5-point, psychology'
   /Likert68 '5-point,
psychology' /Likert69 '5-point,
psychology' /Likert70 '5-point,
psychology'
   /Likert71 '5-point,
psychology' /Likert72 '5-point,
psychology' /Likert73 '5-point,
psychology'
   /Likert74 '5-point,
psychology' /Likert75 '5-point,
psychology'.
EXECUTE.

RECODE polAttentionW1
polAttentionW2
polAttentionW3
polAttentionW4
polAttentionW6
polAttentionW7
   polAttentionW8
likeCameronW1
likeCameronW2
likeCameronW3
likeCameronW4
likeCameronW5
likeCameronW6
   likeCameronW7
likeCameronW8
likeCameronW9 likeConW7
likeConW8 likeConW9
ptvConW9 (5=0) (4=1) (6=1)
   (3=2) (7=2) (2=3) (8=3)
(1=4) (9=4) (0=5) (10=5)
(MISSING=SYSMIS) INTO
Likert76 Likert77 Likert78
   Likert79 Likert80 Likert81
Likert82 Likert83 Likert84
Likert85 Likert86 Likert87
Likert88 Likert89
   Likert90 Likert91 Likert92
Likert93 Likert94 Likert95.
VARIABLE LABELS  Likert76
'11-point, engagement'
/Likert77 '11-point,
engagement' /Likert78
   '11-point, engagement'
/Likert79 '11-point,
engagement' /Likert80 '11-
point, engagement'
   /Likert81 '11-point,
engagement' /Likert82 '11-
point, engagement' /Likert83
'11-point, '+
   'partisanship' /Likert84 '11-
point, partisanship' /Likert85
'11-point, partisanship'
/Likert86
   '11-point, partisanship'
/Likert87 '11-point,
partisanship' /Likert88 '11-
point, partisanship'
   /Likert89 '11-point,
partisanship' /Likert90 '11-
point, partisanship' /Likert91
'11-point, '+
   'partisanship' /Likert92 '11-
point, partisanship' /Likert93
'11-point, partisanship'
/Likert94
   '11-point, partisanship'
/Likert95 '11-point,
partisanship'.
EXECUTE.

RECODE electionInterestW4
electionInterestW5
electionInterestW6
euRefInterestW7
riskTakingW7
   riskTakingW8 (2=1) (3=1)
(1=2) (4=1) (MISSING=SYSMIS)
INTO Likert96 Likert97
Likert98 Likert99
   Likert100 Likert101.
VARIABLE LABELS  Likert96 '4-
point, engagement' /Likert97
'4-point, engagement'
/Likert98
   '4-point, engagement'
/Likert99 '4-point,
engagement' /Likert100 '4-
point, psychology'
   /Likert101 '4-point,
psychology'.
EXECUTE.

RELIABILITY
  /VARIABLES=Likert96
Likert97 Likert98 Likert99
Likert100 Likert101
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert25
Likert26 Likert27 Likert28
Likert29 Likert30 Likert31
Likert32 Likert33
   Likert34 Likert35 Likert36
Likert37 Likert38 Likert39
Likert40 Likert41 Likert42
Likert43 Likert44
   Likert45 Likert46 Likert47
Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55
   Likert56 Likert57 Likert58
Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65 Likert66
   Likert67 Likert68 Likert69
Likert70 Likert71 Likert72
Likert73 Likert74 Likert75
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert1 Likert2
Likert3 Likert4 Likert5 Likert7
Likert8 Likert9 Likert10
Likert11
   Likert12 Likert13 Likert14
Likert15 Likert16 Likert17
Likert18 Likert19 Likert20
Likert21 Likert22
   Likert23 Likert24
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert76
Likert77 Likert78 Likert79
Likert80 Likert81 Likert82
Likert83 Likert84
   Likert85 Likert86 Likert87
Likert88 Likert89 Likert90
Likert91 Likert92 Likert93
Likert94 Likert95
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert1 Likert2
Likert3 Likert4 Likert5 Likert7
Likert8 Likert9 Likert10
Likert11
   Likert12 Likert13 Likert25
Likert26 Likert27 Likert28
Likert29 Likert30 Likert31
Likert32
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert14
Likert15 Likert16 Likert17
Likert18 Likert19
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert33
Likert34 Likert35 Likert36
Likert37 Likert38 Likert39
Likert40 Likert41
   Likert42 Likert76 Likert77
Likert78 Likert79 Likert80
Likert81 Likert82 Likert96
Likert97 Likert98
   Likert99
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert20
Likert83 Likert84 Likert85
Likert86 Likert87 Likert88
Likert89 Likert90
   Likert91 Likert92 Likert93
Likert94 Likert95
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert21
Likert22 Likert23 Likert24
Likert43 Likert44 Likert45
Likert46 Likert47
   Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55 Likert56
Likert57 Likert58
   Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert66
Likert67 Likert68 Likert69
Likert70 Likert71 Likert72
Likert73 Likert74
   Likert75 Likert100 Likert101
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

RELIABILITY
  /VARIABLES=Likert1 Likert2
Likert3 Likert4 Likert5 Likert7
Likert8 Likert9 Likert10
Likert11
   Likert12 Likert13 Likert14
Likert15 Likert16 Likert17
Likert18 Likert19 Likert20
Likert21 Likert22
   Likert23 Likert24 Likert25
Likert26 Likert27 Likert28
```

```
Likert29 Likert30 Likert31
Likert32 Likert33
   Likert34 Likert35 Likert36
Likert37 Likert38 Likert39
Likert40 Likert41 Likert42
Likert43 Likert44
   Likert45 Likert46 Likert47
Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55
   Likert56 Likert57 Likert58
Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65 Likert66
   Likert67 Likert68 Likert69
Likert70 Likert71 Likert72
Likert73 Likert74 Likert75
Likert76 Likert77
   Likert78 Likert79 Likert80
Likert81 Likert82 Likert83
Likert84 Likert85 Likert86
Likert87 Likert88
   Likert89 Likert90 Likert91
Likert92 Likert93 Likert94
Likert95 Likert96 Likert97
Likert98 Likert99
   Likert100 Likert101
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES Likert96 Likert97
Likert98 Likert99 Likert100
Likert101
  /MISSING MEANSUB
  /ANALYSIS Likert96 Likert97
Likert98 Likert99 Likert100
Likert101
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

FACTOR
  /VARIABLES Likert1 Likert2
Likert3 Likert4 Likert5 Likert7
Likert8 Likert9 Likert10
Likert11
   Likert12 Likert13 Likert14
Likert15 Likert16 Likert17
Likert18 Likert19 Likert20
Likert21 Likert22
   Likert23 Likert24 Likert25
Likert26 Likert27 Likert28
Likert29 Likert30 Likert31
Likert32 Likert33
   Likert34 Likert35 Likert36
Likert37 Likert38 Likert39
Likert40 Likert41 Likert42
Likert43 Likert44
   Likert45 Likert46 Likert47
Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55
   Likert56 Likert57 Likert58
Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65 Likert66
   Likert67 Likert68 Likert69
Likert70 Likert71 Likert72
Likert73 Likert74 Likert75
Likert76 Likert77
   Likert78 Likert79 Likert80
Likert81 Likert82 Likert83
Likert84 Likert85 Likert86
Likert87 Likert88
   Likert89 Likert90 Likert91
Likert92 Likert93 Likert94
Likert95 Likert96 Likert97
Likert98 Likert99
   Likert100 Likert101
  /MISSING MEANSUB
  /ANALYSIS Likert1 Likert2
Likert3 Likert4 Likert5 Likert7
Likert8 Likert9 Likert10
Likert11
   Likert12 Likert13 Likert14
Likert15 Likert16 Likert17
Likert18 Likert19 Likert20
Likert21 Likert22
   Likert23 Likert24 Likert25
Likert26 Likert27 Likert28
Likert29 Likert30 Likert31
Likert32 Likert33
   Likert34 Likert35 Likert36
Likert37 Likert38 Likert39
Likert40 Likert41 Likert42
Likert43 Likert44
   Likert45 Likert46 Likert47
Likert48 Likert49 Likert50
Likert51 Likert52 Likert53
Likert54 Likert55
   Likert56 Likert57 Likert58
Likert59 Likert60 Likert61
Likert62 Likert63 Likert64
Likert65 Likert66
   Likert67 Likert68 Likert69
Likert70 Likert71 Likert72
Likert73 Likert74 Likert75
Likert76 Likert77
   Likert78 Likert79 Likert80
Likert81 Likert82 Likert83
Likert84 Likert85 Likert86
Likert87 Likert88
   Likert89 Likert90 Likert91
Likert92 Likert93 Likert94
Likert95 Likert96 Likert97
Likert98 Likert99
   Likert100 Likert101
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

NONPAR CORR
  /VARIABLES=FAC1_24
FAC1_20
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=FAC1_24
angerScale fearScale
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=FAC1_24
FAC1_21 FAC2_21
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
  /VARIABLES=FAC1_24
ReflectedLnReflectedItemRes
ponseRate
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
/VARIABLES=ReflectedLnRefle
ctedItemResponseRate
FAC1_20
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
/VARIABLES=ReflectedLnRefle
ctedItemResponseRate
angerScale fearScale
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

NONPAR CORR
/VARIABLES=ReflectedLnRefle
ctedItemResponseRate
FAC1_21 FAC2_21
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_20
angerScale fearScale FAC1_21
FAC2_21
ReflectedLnReflectedItemRes
ponseRate
   FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC1_24
  /METHOD=ENTER FAC1_20
angerScale fearScale FAC1_21
FAC2_21
ReflectedLnReflectedItemRes
ponseRate.

CORRELATIONS
/VARIABLES=ReflectedLnRefle
ctedItemResponseRate
FAC1_24
personality_agreeableness

personality_conscientiousness
personality_extraversion
personality_neuroticism
personality_openness
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RECODE Likert76 Likert77
Likert78 Likert79 Likert80
Likert81 Likert82 Likert83
Likert84 Likert85
   Likert86 Likert87 Likert88
Likert89 Likert90 Likert91
Likert92 Likert93 Likert94
Likert95 (0=0)
   (1=20) (2=40) (3=60) (4=80)
(5=100).
EXECUTE.

RECODE Likert96 Likert97
Likert98 Likert99 Likert100
Likert101 (1=50) (2=100).
EXECUTE.

RECODE Likert25 Likert26
Likert27 Likert28 Likert29
Likert30 Likert31 Likert32
Likert33 Likert34
   Likert35 Likert36 Likert37
Likert38 Likert39 Likert40
Likert41 Likert42 Likert43
Likert44 Likert45
   Likert46 Likert47 Likert48
Likert49 Likert50 Likert51
Likert52 Likert53 Likert54
Likert55 Likert56
   Likert57 Likert58 Likert59
Likert60 Likert61 Likert62
Likert63 Likert64 Likert65
Likert66 Likert67
   Likert68 Likert69 Likert70
Likert71 Likert72 Likert73
Likert74 Likert75 (0=0) (1=50)
(2=100).
EXECUTE.

RECODE Likert1 Likert2 Likert3
Likert4 Likert5 Likert7 Likert8
Likert9 Likert10 Likert11
Likert12
   Likert13 Likert14 Likert15
Likert16 Likert17 Likert18
Likert19 Likert20 Likert21
Likert22 Likert23
   Likert24 (0=0) (1=33) (2=67)
(3=100).
EXECUTE.

COMPUTE
ResponsePolarisation=MEAN(
Likert76, Likert77, Likert78,
Likert79, Likert80, Likert81,
   Likert82, Likert83, Likert84,
Likert85, Likert86, Likert87,
Likert88, Likert89, Likert90,
Likert91,
   Likert92, Likert93, Likert94,
Likert95, Likert96, Likert97,
Likert98, Likert99, Likert100,
   Likert101, Likert25,
Likert26, Likert27, Likert28,
Likert29, Likert30, Likert31,
Likert32,
   Likert33, Likert34, Likert35,
Likert36, Likert37, Likert38,
Likert39, Likert40, Likert41,
Likert42,
   Likert43, Likert44, Likert45,
Likert46, Likert47, Likert48,
Likert49, Likert50, Likert51,
Likert52,
   Likert53, Likert54, Likert55,
Likert56, Likert57, Likert58,
Likert59, Likert60, Likert61,
Likert62,
   Likert63, Likert64, Likert65,
Likert66, Likert67, Likert68,
Likert69, Likert70, Likert71,
Likert72,
   Likert73, Likert74, Likert75,
Likert1, Likert2, Likert3,
Likert4, Likert5, Likert7,
Likert8,
   Likert9, Likert10, Likert11,
Likert12, Likert13, Likert14,
Likert15, Likert16, Likert17,
Likert18,
   Likert19, Likert20, Likert21,
Likert22, Likert23, Likert24).
```

```
VARIABLE LABELS
ResponsePolarisation '[theme:
psychology] Percentage
polarisation of Likert '+
   'scale survey responses'.
EXECUTE.

CORRELATIONS
/VARIABLES=ResponsePolarisa
tion FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RECODE businessBonusW1
businessBonusW2
businessBonusW3
businessBonusW4 (1=5) (2=4)
(3=3) (4=2)
   (5=1).
EXECUTE.

RELIABILITY
/VARIABLES=businessBonusW
1 businessBonusW2
businessBonusW3
businessBonusW4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
businessBonusW1
businessBonusW2
businessBonusW3
businessBonusW4
  /MISSING MEANSUB
  /ANALYSIS businessBonusW1
businessBonusW2
businessBonusW3
businessBonusW4
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4 (1=5) (2=4)
(3=3) (4=2) (5=1).
EXECUTE.

RELIABILITY
/VARIABLES=govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
 /VARIABLES govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
  /MISSING MEANSUB
  /ANALYSIS govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=immigEconW1
immigEconW2 immigEconW3
immigEconW4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES immigEconW1
immigEconW2 immigEconW3
immigEconW4
  /MISSING MEANSUB
  /ANALYSIS immigEconW1
immigEconW2 immigEconW3
immigEconW4
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=immigrationLevel
W4 immigrationLevelW6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
immigrationLevelW4
immigrationLevelW6
  /MISSING MEANSUB
  /ANALYSIS
immigrationLevelW4
immigrationLevelW6
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE
immigrantsWelfareStateW1
immigrantsWelfareStateW2
immigrantsWelfareStateW3
   immigrantsWelfareStateW4
immigrantsWelfareStateW8
(1=5) (2=4) (3=3) (4=2) (5=1).
EXECUTE.

RELIABILITY
/VARIABLES=immigrantsWelfa
reStateW1
immigrantsWelfareStateW2
immigrantsWelfareStateW3
   immigrantsWelfareStateW4
immigrantsWelfareStateW8
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
immigrantsWelfareStateW1
immigrantsWelfareStateW2
immigrantsWelfareStateW3
   immigrantsWelfareStateW4
immigrantsWelfareStateW8
  /MISSING MEANSUB
  /ANALYSIS
immigrantsWelfareStateW1
immigrantsWelfareStateW2
immigrantsWelfareStateW3
   immigrantsWelfareStateW4
immigrantsWelfareStateW8
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
/VARIABLES=reasonForUnemp
loymentW1
reasonForUnemploymentW2
reasonForUnemploymentW3

reasonForUnemploymentW4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES
reasonForUnemploymentW1
reasonForUnemploymentW2
reasonForUnemploymentW3

reasonForUnemploymentW4
  /MISSING MEANSUB
  /ANALYSIS
reasonForUnemploymentW1
reasonForUnemploymentW2
reasonForUnemploymentW3

reasonForUnemploymentW4
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA FACTORS(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RECODE al4W6 al5W6 al3W6
(1=5) (2=4) (3=3) (4=2) (5=1).
EXECUTE.

FACTOR
  /VARIABLES FAC1_25
FAC1_26 FAC1_27 FAC1_28
FAC1_29 FAC1_30 al4W6
lr1W6 al5W6 al3W6
  /MISSING MEANSUB
  /ANALYSIS FAC1_25 FAC1_26
FAC1_27 FAC1_28 FAC1_29
FAC1_30 al4W6 lr1W6 al5W6
al3W6
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

RELIABILITY
  /VARIABLES=FAC1_25
FAC1_26 FAC1_27 FAC1_28
FAC1_29 FAC1_30 al4W6
lr1W6 al5W6 al3W6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

CORRELATIONS
  /VARIABLES=FAC1_32
FAC2_32 FAC3_32
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RELIABILITY
  /VARIABLES=FAC1_32
FAC2_32 FAC3_32
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /SUMMARY=TOTAL.

FACTOR
  /VARIABLES FAC1_32
FAC2_32 FAC3_32
  /MISSING MEANSUB
  /ANALYSIS FAC1_32 FAC2_32
FAC3_32
  /PRINT INITIAL EXTRACTION
ROTATION
  /PLOT EIGEN ROTATION
  /CRITERIA MINEIGEN(1)
ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
DELTA(0)
  /ROTATION OBLIMIN
  /SAVE REG(ALL)
  /METHOD=CORRELATION.

CORRELATIONS
  /VARIABLES=FAC1_31
FAC1_32 FAC2_32 FAC3_32
FAC1_25 FAC1_26 FAC1_27
FAC1_28 FAC1_29 FAC1_30
al4W6
   lr1W6 al5W6 al3W6
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

RECODE
profile_newspaper_readershi
p_201 (MISSING=SYSMIS) (1
thru 5=1) (ELSE=0) INTO
Tabloid.
VARIABLE LABELS  Tabloid
'[ANALYSE] Tabloid
newspaper readership as
opposed to other or none'.
EXECUTE.

RECODE
profile_newspaper_readershi
p_201 (MISSING=SYSMIS) (6
thru 13=1) (ELSE=0) INTO
Broadsheet.
VARIABLE LABELS  Broadsheet
'[ANALYSE] Broadsheet
```

```
newspaper readership as
opposed to other or none'.
EXECUTE.

RECODE immigEconW1
immigEconW2 immigEconW3
immigEconW4 (1=1) (2=1.67)
(3=2.33) (4=3) (5=3.67)
   (6=4.33) (7=5).
EXECUTE.

COMPUTE
SDPolicyPreferences=SD(busin
essBonusW1,
businessBonusW2,
businessBonusW3,
businessBonusW4,
   govtHandoutsW1,
govtHandoutsW2,
govtHandoutsW3,
govtHandoutsW4,
immigEconW1,
immigEconW2,
   immigEconW3,
immigEconW4,
immigrationLevelW4,
immigrationLevelW6,
immigrantsWelfareStateW1,

immigrantsWelfareStateW2,
immigrantsWelfareStateW3,
immigrantsWelfareStateW4,

immigrantsWelfareStateW8,
reasonForUnemploymentW1,
reasonForUnemploymentW2,

reasonForUnemploymentW3,
reasonForUnemploymentW4,
al4W6, lr1W6, al5W6, al3W6).
VARIABLE LABELS
SDPolicyPreferences '[theme:
culture] Individual-level
standard deviation of '+
   'policy preference items, as
an inverse measure of
constraint'.
EXECUTE.

FREQUENCIES
VARIABLES=SDPolicyPreferenc
es
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
BeliefSystemConstraint=2.12-
SDPolicyPreferences.
VARIABLE LABELS
BeliefSystemConstraint
'[ANALYSE] [theme: culture]
Reflected standard deviation
'+
   'of policy preferences, as a
measure of belief system
constraint'.
EXECUTE.

DESCRIPTIVES
VARIABLES=FAC1_31
  /STATISTICS=MEAN.

COMPUTE
PoliticalOrientationDifference
Overall=SQRT(FAC1_31 *
FAC1_31).
VARIABLE LABELS
PoliticalOrientationDifference
Overall '[theme: culture]
Individual difference '+
   'in general political leftness
from mean political leftness
for the overall data'.
EXECUTE.

FREQUENCIES
VARIABLES=PoliticalOrientatio
nDifferenceOverall
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
OverallCulturalPoliticalConfor
mity=4.07-
PoliticalOrientationDifference
Overall.
VARIABLE LABELS
OverallCulturalPoliticalConfor
mity '[theme: culture]
individual conformity to '+
   'overall mean political
orientation'.
EXECUTE.

FREQUENCIES
VARIABLES=OverallCulturalPol
iticalConformity
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

SORT CASES  BY TSC_5887.
SPLIT FILE LAYERED BY
TSC_5887.

DESCRIPTIVES
VARIABLES=FAC1_31
  /STATISTICS=MEAN.

SPLIT FILE OFF.

COMPUTE
MeanOrientationofCulturalClu
ster=0.
VARIABLE LABELS
MeanOrientationofCulturalClu
ster "[theme: culture] mean
general political "+
   "leftness of individual's
cultural cluster".
EXECUTE.

DO IF
(MISSING(TSC_5887)=1).
RECODE
MeanOrientationofCulturalClu
ster (0=SYSMIS).
END IF.
EXECUTE.

DO IF (TSC_5887 = 0).
RECODE
MeanOrientationofCulturalClu
ster (0=0.13).
END IF.
EXECUTE.

DO IF (TSC_5887 = 1).
RECODE
MeanOrientationofCulturalClu
ster (0=0.57).
END IF.
EXECUTE.

DO IF (TSC_5887 = 2).
RECODE
MeanOrientationofCulturalClu
ster (0=-0.20).
END IF.
EXECUTE.

DO IF (TSC_5887 = 3).
RECODE
MeanOrientationofCulturalClu
ster (0=-0.32).
END IF.
EXECUTE.

DO IF (TSC_5887 = 4).
RECODE
MeanOrientationofCulturalClu
ster (0=0.10).
END IF.
EXECUTE.

FREQUENCIES
VARIABLES=MeanOrientation
ofCulturalCluster
  /ORDER=ANALYSIS.

COMPUTE
DistanceFromMeanOfCultural
Cluster=MeanOrientationofCu
lturalCluster - FAC1_31.
VARIABLE LABELS
DistanceFromMeanOfCultural
Cluster "[theme: culture]
distance between individual
"+
   "political leftness and mean
political leftness for
individual's culcluster".
EXECUTE.

COMPUTE
NoDirDistanceFromMeanOfCu
lturalCluster=SQRT(DistanceFr
omMeanOfCulturalCluster*

DistanceFromMeanOfCultural
Cluster).
VARIABLE LABELS
NoDirDistanceFromMeanOfCu
lturalCluster "[theme: culture]
distance between "+
   "political leftness and mean
political leftness for
individual's culcluster no +-".
EXECUTE.

FREQUENCIES
VARIABLES=NoDirDistanceFro
mMeanOfCulturalCluster
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

COMPUTE
ClusterCulturalPoliticalConfor
mity=3.94 -
NoDirDistanceFromMeanOfCu
lturalCluster.
VARIABLE LABELS
ClusterCulturalPoliticalConfor
mity '[theme: culture]
Individual conformity to '+
   'mean cluster political
orientation'.
EXECUTE.

FREQUENCIES
VARIABLES=ClusterCulturalPol
iticalConformity
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

CORRELATIONS

/VARIABLES=OverallCulturalPo
liticalConformity
ClusterCulturalPoliticalConfor
mity
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

GRAPH

/SCATTERPLOT(BIVAR)=Overal
lCulturalPoliticalConformity
WITH
ClusterCulturalPoliticalConfor
mity
  /MISSING=LISTWISE.

SORT VARIABLES BY LABEL (A).

CORRELATIONS
  /VARIABLES=FAC1_31
FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7 FAC1_13 FAC1_15
FAC1_16 FAC1_19 FAC1_20
angerScale fearScale FAC1_21
FAC2_21
ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC3_32
FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7
   FAC1_13 FAC1_15 FAC1_16
FAC1_19 FAC1_20 angerScale
fearScale FAC1_21 FAC2_21

ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC2_32
FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7
   FAC1_13 FAC1_15 FAC1_16
FAC1_19 FAC1_20 angerScale
fearScale FAC1_21 FAC2_21
```

```
ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_32
FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7
    FAC1_13 FAC1_15 FAC1_16
FAC1_19 FAC1_20 angerScale
fearScale FAC1_21 FAC2_21

ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
```

```
VARIABLES=Tabloid
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
```

```
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
```

```
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
```

```
VARIABLES=anyUniW7
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC2_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_31,
95)[name="MEAN_FAC1_31"

LOW="MEAN_FAC1_31_LOW
"
HIGH="MEAN_FAC1_31_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_31=col(source(s)
, name("MEAN_FAC1_31"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_31_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_31_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] General
Political Leftness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_31),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
```

```
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC3_32,
95)[name="MEAN_FAC3_32"

LOW="MEAN_FAC3_32_LOW
"
HIGH="MEAN_FAC3_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC3_32=col(source(s)
, name("MEAN_FAC3_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC3_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC3_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 3 pro-social
freedom regression ",
    "factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC3_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(FAC1_32,
95)[name="MEAN_FAC1_32"

LOW="MEAN_FAC1_32_LOW
"
HIGH="MEAN_FAC1_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_FAC1_32=col(source(s)
, name("MEAN_FAC1_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 1 pro-
immigration regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_FAC1_32),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC2_32,
95)[name="MEAN_FAC2_32"

LOW="MEAN_FAC2_32_LOW
"
HIGH="MEAN_FAC2_32_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC2_32=col(source(s)
, name("MEAN_FAC2_32"))
  DATA: LOW=col(source(s),
name("MEAN_FAC2_32_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC2_32_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: policy] 2 pro-
government involvement in ",
    "economy regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC2_32),
shape.interior(shape.square))
```

```
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

FREQUENCIES
VARIABLES=FAC1_23
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

FREQUENCIES
VARIABLES=OverallCulturalPol
iticalConformity
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

FREQUENCIES
VARIABLES=BeliefSystemCons
traint
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

FREQUENCIES
VARIABLES=ageW7
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

FREQUENCIES
VARIABLES=FAC1_13 FAC1_15
FAC1_16 FAC1_19 FAC1_32
FAC2_32 FAC3_32 FAC1_31
FAC1_20
    angerScale fearScale
FAC1_21 FAC2_21
ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /FORMAT=NOTABLE
  /NTILES=4
  /STATISTICS=STDDEV
MINIMUM MAXIMUM MEAN
MEDIAN SKEWNESS SESKEW
KURTOSIS SEKURT
  /HISTOGRAM NORMAL
  /ORDER=ANALYSIS.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
23 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=Overal
lCulturalPoliticalConformity
WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=BeliefS
ystemConstraint WITH
FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=BeliefS
ystemConstraint WITH
FAC1_32
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=BeliefS
ystemConstraint WITH
FAC2_32
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=BeliefS
ystemConstraint WITH
FAC3_32
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=ageW
7 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
13 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
15 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
16 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
19 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
20 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=angerS
cale WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
21 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC2_
21 WITH FAC1_31
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=Reflec
tedLnReflectedItemResponse
Rate WITH FAC2_32
  /MISSING=LISTWISE.

GRAPH

/SCATTERPLOT(BIVAR)=FAC1_
24 WITH FAC2_32
  /MISSING=LISTWISE.

CORRELATIONS
  /VARIABLES=FAC1_20
angerScale fearScale FAC1_21
FAC2_21
ReflectedLnReflectedItemRes
ponseRate
    FAC1_24
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

GRAPH

/BAR(SIMPLE)=MEAN(FAC1_2
3) BY TSC_5887
  /INTERVAL CI(95.0).

GRAPH

/BAR(SIMPLE)=MEAN(Overall
CulturalPoliticalConformity)
BY TSC_5887
  /INTERVAL CI(95.0).

GRAPH

/BAR(SIMPLE)=MEAN(BeliefSy
stemConstraint) BY TSC_5887
  /INTERVAL CI(95.0).

CORRELATIONS
  /VARIABLES=FAC1_20
FAC1_21 FAC1_24 FAC1_23
OverallCulturalPoliticalConfor
mity
    BeliefSystemConstraint
ageW7 FAC1_13 FAC1_15
FAC1_16 FAC1_19
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

CORRELATIONS
  /VARIABLES=FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7 FAC1_13
    FAC1_15 FAC1_16 FAC1_19
  /PRINT=TWOTAIL NOSIG
  /MISSING=PAIRWISE.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
```

```
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
    "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
```

```
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
    "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
    "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
    "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
```

```
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
    "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
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demographics] Attended
university as opposed to ",
   "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
   "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
   "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
   "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_24,
95)[name="MEAN_FAC1_24"

LOW="MEAN_FAC1_24_LOW
"
HIGH="MEAN_FAC1_24_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_24=col(source(s)
, name("MEAN_FAC1_24"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_24_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_24_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] Response
polarisation chief ",
   "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_24),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(FAC1_21,
95)[name="MEAN_FAC1_21"

LOW="MEAN_FAC1_21_LOW
"
HIGH="MEAN_FAC1_21_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_FAC1_21=col(source(s)
, name("MEAN_FAC1_21"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_21_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_21_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [risk] 1
Tolerance of ",
   "uncertainty regression
factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_FAC1_21),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
```

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),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(FAC1_20,
95)[name="MEAN_FAC1_20"

LOW="MEAN_FAC1_20_LOW
"
HIGH="MEAN_FAC1_20_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_FAC1_20=col(source(s)
, name("MEAN_FAC1_20"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_20_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_20_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: psychology] [aom]
Active open-mindedness ",
    "regression factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_FAC1_20),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
    "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_OverallCulturalPoliticalConf
ormity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
    "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_OverallCulturalPolitical
Conformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
```

```
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Broadsheet
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Broadsheet=col(source(s),
name("Broadsheet"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Broadsheet newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Broadsheet*
MEAN_BeliefSystemConstrain
t),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Broadsheet*(LOW+HI
GH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Tabloid
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Tabloid=col(source(s),
name("Tabloid"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [readership]
Tabloid newspaper ",
    "readership as opposed to
other or none"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Tabloid*MEA
N_BeliefSystemConstraint),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Tabloid*(LOW+HIGH)
)),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
    "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_BeliefSystemConstraint),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_BeliefSystemConstrain
t),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
```

```
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_BeliefSystemConstraint),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
   "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
   "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_OverallCulturalPoliticalC
onformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
   "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
   "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_OverallCulturalPolitical
Conformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Upskilled
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
   "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
   "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_OverallCulturalPoliticalC
onformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Upskilled=col(source(s),
name("Upskilled"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type highly skilled as ",
   "opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
   "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Upskilled*M
EAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Upskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Midskilled
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Midskilled=col(source(s),
name("Midskilled"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
```

```
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type middling skilled ",
    "as opposed to never
worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Midskilled*
MEAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Midskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Unskilled
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Unskilled=col(source(s),
name("Unskilled"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] [work] Work
type low skilled or ",
    "unskilled as opposed to
never worked"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(Unskilled*M
EAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(Unskilled*(LOW+HIG
H))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(OverallCulturalPolitic
alConformity,
95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
    "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_OverallCulturalPolitical
Conformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=anyUniW7
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
anyUniW7=col(source(s),
name("anyUniW7"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Attended
university as opposed to ",
    "not attended university"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(anyUniW7*
MEAN_BeliefSystemConstrain
t),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(anyUniW7*(LOW+HI
GH))),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
```

```
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_BeliefSystemConstrai
nt),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6

MEANCI(OverallCulturalPolitic
alConformity,
95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
    "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_OverallCulturalPolitic
alConformity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=disabilityW6
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
disabilityW6=col(source(s),
name("disabilityW6"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Disabled as
opposed to not disabled"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(disabilityW6
*MEAN_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(disabilityW6*(LOW+H
IGH))),

shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(FAC1_23,
95)[name="MEAN_FAC1_23"

LOW="MEAN_FAC1_23_LOW
"
HIGH="MEAN_FAC1_23_HIGH
"] MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_FAC1_23=col(source(s)
, name("MEAN_FAC1_23"))
  DATA: LOW=col(source(s),
name("MEAN_FAC1_23_LOW
"))
  DATA: HIGH=col(source(s),
name("MEAN_FAC1_23_HIGH
"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_FAC1_23),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(OverallCulturalPolitic
alConformity,

95)[name="MEAN_OverallCult
uralPoliticalConformity"

LOW="MEAN_OverallCultural
PoliticalConformity_LOW"

HIGH="MEAN_OverallCultural
PoliticalConformity_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_OverallCulturalPolitical
Conformity=col(source(s),

name("MEAN_OverallCultural
PoliticalConformity"))
  DATA: LOW=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_OverallCultural
PoliticalConformity_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] individual
conformity to overall ",
    "mean political
orientation"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_OverallCulturalPoliticalConf
ormity),

shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=gender
MEANCI(BeliefSystemConstrai
nt,

95)[name="MEAN_BeliefSyste
mConstraint"
LOW="MEAN_BeliefSystemCo
nstraint_LOW"

HIGH="MEAN_BeliefSystemCo
nstraint_HIGH"]
MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
```

```
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: gender=col(source(s),
name("gender"),
unit.category())
  DATA:
MEAN_BeliefSystemConstrain
t=col(source(s),
name("MEAN_BeliefSystemCo
nstraint"))
  DATA: LOW=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_LOW"))
  DATA: HIGH=col(source(s),
name("MEAN_BeliefSystemCo
nstraint_HIGH"))
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
demographics] Gender female
as opposed to male"))
  GUIDE: axis(dim(2),
label("Mean [ANALYSE]
[theme: culture] Reflected
standard deviation of ",
    "policy preferences, as a
measure of belief system
constraint"))
  GUIDE:
text.footnote(label("Error
Bars: 95% CI"))
  SCALE: cat(dim(1),
include("0", "1"))
  SCALE: linear(dim(2),
include(0))
  ELEMENT:
interval(position(gender*MEA
N_BeliefSystemConstraint),
shape.interior(shape.square))
  ELEMENT:
interval(position(region.sprea
d.range(gender*(LOW+HIGH))
),
shape.interior(shape.ibeam))
END GPL.

TWOSTEP CLUSTER
  /CATEGORICAL
VARIABLES=country
countryOfBirth
profile_ethnicity gor
livedAbroadW8
parentsForeignW8
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES.

TWOSTEP CLUSTER
  /CATEGORICAL
VARIABLES=country
countryOfBirth
profile_ethnicity
livedAbroadW8
parentsForeignW8
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES.

TWOSTEP CLUSTER
  /CATEGORICAL
VARIABLES=country
countryOfBirth
profile_ethnicity
livedAbroadW8
parentsForeignW8
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES
  /SAVE VARIABLE=TSC_3694.

FREQUENCIES
VARIABLES=TSC_4171
  /ORDER=ANALYSIS.

CROSSTABS
  /TABLES=TSC_4171 BY
profile_ethnicity
countryOfBirth country
livedAbroadW8
parentsForeignW8
  /FORMAT=AVALUE TABLES
  /STATISTICS=CHISQ
  /CELLS=COUNT ROW
COLUMN
  /COUNT ROUND CELL
  /BARCHART.

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_3
2) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC2_3
2) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC3_3
2) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_3
1) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_2
0) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_2
1) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_2
4) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(FAC1_2
3) BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(Overall
CulturalPoliticalConformity)
BY TSC_4171
  /INTERVAL CI(95.0).

GRAPH
/BAR(SIMPLE)=MEAN(BeliefSy
stemConstraint) BY TSC_4171
  /INTERVAL CI(95.0).

RECODE TSC_4171 (2=1)
(MISSING=SYSMIS) (ELSE=0)
INTO Celtic.
VARIABLE LABELS  Celtic
'Celtic cultural cluster as
opposed to External cluster'.
EXECUTE.

RECODE TSC_4171 (3=1)
(MISSING=SYSMIS) (ELSE=0)
INTO AngloSaxon.
VARIABLE LABELS  Celtic
'Anglo-Saxon cultural cluster
as opposed to External
cluster'.
EXECUTE.
DESCRIPTIVES
VARIABLES=FAC1_23
OverallCulturalPoliticalConfor
mity BeliefSystemConstraint
ageW7
    FAC1_13 FAC1_15 FAC1_16
FAC1_19 FAC1_32 FAC2_32
FAC3_32 FAC1_31 FAC1_20
angerScale fearScale
    FAC1_21 FAC2_21
ReflectedLnReflectedItemRes
ponseRate FAC1_24
  /STATISTICS=MEAN STDDEV
MIN MAX.

DESCRIPTIVES
VARIABLES=OverallCulturalPol
iticalConformity
BeliefSystemConstraint
ageW7 angerScale
    fearScale
ReflectedLnReflectedItemRes
ponseRate
  /SAVE
  /STATISTICS=MEAN STDDEV
MIN MAX.

DESCRIPTIVES
VARIABLES=ZOverallCulturalP
oliticalConformity
ZBeliefSystemConstraint
ZageW7
    ZangerScale ZfearScale
ZReflectedLnReflectedItemRe
sponseRate
  /STATISTICS=MEAN STDDEV
MIN MAX.

* Curve Estimation.
TSET NEWVAR=NONE.
CURVEFIT
  /VARIABLES=FAC1_31
FAC1_32 FAC2_32 FAC3_32
FAC1_23
ZOverallCulturalPoliticalConfo
rmity
    ZBeliefSystemConstraint
WITH FAC1_20
  /CONSTANT
  /MODEL=LINEAR
QUADRATIC CUBIC
  /PLOT FIT.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC1_31
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24 FAC1_23
ZOverallCulturalPoliticalConfo
rmity
    ZBeliefSystemConstraint
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate FAC2_21
ZangerScale
    ZfearScale FAC1_19
FAC1_16 FAC1_15 FAC1_13
gender ZageW7 anyUniW7
disabilityW6 Upskilled
Midskilled
    Unskilled Broadsheet
Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC1_32
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24 FAC1_23
ZOverallCulturalPoliticalConfo
rmity
    ZBeliefSystemConstraint
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate FAC2_21
ZangerScale
    ZfearScale FAC1_19
FAC1_16 FAC1_15 FAC1_13
gender ZageW7 anyUniW7
disabilityW6 Upskilled
Midskilled
    Unskilled Broadsheet
Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC2_32
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24 FAC1_23
ZOverallCulturalPoliticalConfo
rmity
    ZBeliefSystemConstraint
AngloSaxon Celtic
```

```
ZReflectedLnReflectedItemRe
sponseRate FAC2_21
ZangerScale
   ZfearScale FAC1_19
FAC1_16 FAC1_15 FAC1_13
gender ZageW7 anyUniW7
disabilityW6 Upskilled
Midskilled
   Unskilled Broadsheet
Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC3_32
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24 FAC1_23
ZOverallCulturalPoliticalConfo
rmity
   ZBeliefSystemConstraint
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate FAC2_21
ZangerScale
   ZfearScale FAC1_19
FAC1_16 FAC1_15 FAC1_13
gender ZageW7 anyUniW7
disabilityW6 Upskilled
Midskilled
   Unskilled Broadsheet
Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

DATA SET ACTIVATE Data
set1.
REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT FAC1_23
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate
   FAC2_21 ZangerScale
ZfearScale FAC1_19 FAC1_16
FAC1_15 FAC1_13 gender
ZageW7 anyUniW7
disabilityW6
   Upskilled Midskilled
Unskilled Broadsheet Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT
ZOverallCulturalPoliticalConfo
rmity
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate
   FAC2_21 ZangerScale
ZfearScale FAC1_19 FAC1_16
FAC1_15 FAC1_13 gender
ZageW7 anyUniW7
disabilityW6
   Upskilled Midskilled
Unskilled Broadsheet Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT
ZBeliefSystemConstraint
  /METHOD=ENTER FAC1_20
FAC1_21 FAC1_24
AngloSaxon Celtic
ZReflectedLnReflectedItemRe
sponseRate
   FAC2_21 ZangerScale
ZfearScale FAC1_19 FAC1_16
FAC1_15 FAC1_13 gender
ZageW7 anyUniW7
disabilityW6
   Upskilled Midskilled
Unskilled Broadsheet Tabloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

COMPUTE
AngloAom=AngloSaxon *
Aom.
VARIABLE LABELS  AngloAom
'Anglo*Aom interaction'.
EXECUTE.

COMPUTE CeltAom=Celtic *
Aom.
VARIABLE LABELS  CeltAom
'Celt*Aom interaction'.
EXECUTE.

COMPUTE
AngloRP=AngloSaxon *
ResPol.
VARIABLE LABELS  AngloRP
'Anglo*Response Polarisation
interaction'.
EXECUTE.

COMPUTE CeltRP=Celtic *
ResPol.
VARIABLE LABELS  CeltRP
'Celt*Response Polarisation
interaction'.
EXECUTE.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ResPol Anglo Celtic
AngloAom CeltAom ResRate
   Willrisk AngerPty FearPty
ConPart TrustMPs Econom
Engage Gender Zage
Graduate Disabled Upskill
   Midskill Unskill Bdsheet
Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Aom PRE_1
TSC_4171 MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Aom=col(source(s),
name("Aom"))
  DATA: PRE_1=col(source(s),
name("PRE_1"))
  DATA:
TSC_4171=col(source(s),
name("TSC_4171"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] [aom] Active
open-mindedness ",
   "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number [CULTURAL ",
   "CLUSTER!]"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Aom*PRE_1),
color.exterior(TSC_4171))
END GPL.

COMPUTE CstAom=Cnstrnt *
Aom.
VARIABLE LABELS  CstAom
'Constraint*aom interaction'.
EXECUTE.

COMPUTE CstRP=Cnstrnt *
ResPol.
VARIABLE LABELS  CstRP
'Constraint*response
polarisation interaction'.
EXECUTE.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ResPol Anglo Celtic
AngloRP CeltRP ResRate
   Willrisk AngerPty FearPty
ConPart TrustMPs Econom
Engage Gender Zage
Graduate Disabled Upskill
   Midskill Unskill Bdsheet
Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Aom
PRE_1RpCluster TSC_4171
MISSING=LISTWISE
   REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Aom=col(source(s),
name("Aom"))
  DATA:
PRE_1RpCluster=col(source(s)
, name("PRE_1RpCluster"))
  DATA:
TSC_4171=col(source(s),
name("TSC_4171"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] [aom] Active
open-mindedness ",
   "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for Rp*cluster
regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number [CULTURAL ",
   "CLUSTER!]"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Aom*PRE_1Rp
Cluster),
color.exterior(TSC_4171))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
```

```
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt CstAom ResPol Anglo
Celtic ResRate Willrisk
    AngerPty FearPty ConPart
TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
    Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

TWOSTEP CLUSTER
  /CONTINUOUS
VARIABLES=Cnstrnt
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES
  /SAVE VARIABLE=TSC_2997.

GRAPH
/BAR(SIMPLE)=MEAN(Cnstrnt)
BY TSC_5725.

FREQUENCIES
VARIABLES=TSC_5725
  /ORDER=ANALYSIS.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Aom
PRE_1AomCst
TSC_5725Constraint
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Aom=col(source(s),
name("Aom"))
  DATA:
PRE_1AomCst=col(source(s),
name("PRE_1AomCst"))
  DATA:
TSC_5725Constraint=col(sour
ce(s),
name("TSC_5725Constraint"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] [aom] Active
open-mindedness ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
Aom*constraint regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for
Constraint"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Aom*PRE_1Ao
mCst),
color.exterior(TSC_5725Const
raint))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ResPol CstRP Anglo
Celtic ResRate Willrisk
    AngerPty FearPty ConPart
TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
    Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Aom PRE_1RpCst
TSC_5725Constraint
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: Aom=col(source(s),
name("Aom"))
  DATA:
PRE_1RpCst=col(source(s),
name("PRE_1RpCst"))
  DATA:
TSC_5725Constraint=col(sour
ce(s),
name("TSC_5725Constraint"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] [aom] Active
open-mindedness ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
Rp*constraint regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for
Constraint"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Aom*PRE_1Rp
Cst),
color.exterior(TSC_5725Const
raint))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=ResPol
PRE_1RpCluster TSC_4171
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: ResPol=col(source(s),
name("ResPol"))
  DATA:
PRE_1RpCluster=col(source(s)
, name("PRE_1RpCluster"))
  DATA:
TSC_4171=col(source(s),
name("TSC_4171"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for Rp*cluster
regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number [CULTURAL ",
    "CLUSTER!]"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(ResPol*PRE_1R
pCluster),
color.exterior(TSC_4171))
END GPL.

COMPUTE AngloCnf=Anglo *
Conform.
VARIABLE LABELS  AngloCnf
'Anglo*conformity
interaction'.
EXECUTE.

COMPUTE CeltCnf=Celtic *
Conform.
VARIABLE LABELS  CeltCnf
'Celt*conformity interaction'.
EXECUTE.

COMPUTE ConstCnf=Cnstrnt *
Conform.
VARIABLE LABELS  ConstCnf
'Constraint*conformity
interaction'.
EXECUTE.

COMPUTE AngloCmp=Anglo *
Compform.
VARIABLE LABELS  AngloCmp
'Anglo*computed conformity
interaction'.
EXECUTE.

COMPUTE CeltCmp=Celtic *
Compform.
VARIABLE LABELS  CeltCmp
'Celt*computed conformity
interaction'.
EXECUTE.

COMPUTE ConstCmp=Cnstrnt
* Compform.
VARIABLE LABELS  ConstCmp
'Constraint*computed
conformity interaction'.
EXECUTE.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ResPol Anglo Celtic
AngloCnf CeltCnf ResRate
    Willrisk AngerPty FearPty
ConPart TrustMPs Econom
Engage Gender Zage
Graduate Disabled Upskill
    Midskill Unskill Bdsheet
Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ConstCnf ResPol Anglo
Celtic ResRate Willrisk
    AngerPty FearPty ConPart
TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
    Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Conform
PRE_2CnfCst
TSC_5725Constraint
    MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Conform=col(source(s),
name("Conform"))
  DATA:
PRE_2CnfCst=col(source(s),
name("PRE_2CnfCst"))
  DATA:
TSC_5725Constraint=col(sour
ce(s),
```

```
name("TSC_5725Constraint"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
culture] [conformity]
Generalised (British) ",
    "Cultural Conformity
Regression Factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
conformity*constraint
regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for
Constraint"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Conform*PRE_
2CnfCst),
color.exterior(TSC_5725Const
raint))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer Conform Compform
Cnstrnt ResPol Anglo Celtic
AngloCmp CeltCmp ResRate
    Willrisk AngerPty FearPty
ConPart TrustMPs Econom
Engage Gender Zage
Graduate Disabled Upskill
    Midskill Unskill Bdsheet
Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Compform
PRE_1CmpCluster TSC_4171
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Compform=col(source(s),
name("Compform"))
  DATA:
PRE_1CmpCluster=col(source(
s),
name("PRE_1CmpCluster"))
  DATA:
TSC_4171=col(source(s),
name("TSC_4171"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
culture] Z individual
conformity to overall mean ",
    "political orientation"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for computed
conformity*cluster ",
    "regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number [CULTURAL ",
    "CLUSTER!]"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Compform*PR
E_1CmpCluster),
color.exterior(TSC_4171))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
TolUncer ResPol Conform
Compform Cnstrnt ConstCmp
Anglo Celtic ResRate Willrisk
    AngerPty FearPty ConPart
TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
    Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=Compform
PRE_1CmpCst
TSC_5725Constraint
    MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
Compform=col(source(s),
name("Compform"))
  DATA:
PRE_1CmpCst=col(source(s),
name("PRE_1CmpCst"))
  DATA:
TSC_5725Constraint=col(sour
ce(s),
name("TSC_5725Constraint"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
culture] Z individual
conformity to overall mean ",
    "political orientation"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for computed
conformity*constraint ",
    "regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for
Constraint"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(Compform*PR
E_1CmpCst),
color.exterior(TSC_5725Const
raint))
END GPL.

COMPUTE AomRP=Aom *
ResPol.
VARIABLE LABELS  AomRP
'Aom*response polarisation
interaction'.
EXECUTE.

COMPUTE AomTlunc=Aom *
TolUncer.
VARIABLE LABELS  AomTlunc
'Aom*tolerance of
uncertainty interaction'.
EXECUTE.

COMPUTE RPTlunc=ResPol *
TolUncer.
VARIABLE LABELS  RPTlunc
'Response
polarisation*tolerance of
uncertainty interaction'.
EXECUTE.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Conform
  /METHOD=ENTER Aom
TolUncer ResPol AomRP
Compform Cnstrnt Anglo
Celtic ResRate Willrisk
AngerPty
    FearPty ConPart TrustMPs
Econom Engage Gender Zage
Graduate Disabled Upskill
Midskill Unskill
    Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

TWOSTEP CLUSTER
  /CONTINUOUS
VARIABLES=Aom
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES
  /SAVE VARIABLE=TSC_7109.

FREQUENCIES
VARIABLES=TSC_5075
  /ORDER=ANALYSIS.

GRAPH
  /BAR(SIMPLE)=MEAN(Aom)
BY TSC_5075.

RECODE TSC_5075 (3=1) (1=2)
(2=3).
EXECUTE.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=ResPol
PRE_1AomRP TSC_5075
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: ResPol=col(source(s),
name("ResPol"))
  DATA:
PRE_1AomRP=col(source(s),
name("PRE_1AomRP"))
  DATA:
TSC_5075=col(source(s),
name("TSC_5075"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
aom*response polarisation ",
    "regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for active ",
    "open-mindedness"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(ResPol*PRE_1A
omRP),
color.exterior(TSC_5075))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Compform
  /METHOD=ENTER Aom
TolUncer ResPol Conform
AomRP Cnstrnt Anglo Celtic
ResRate Willrisk AngerPty
    FearPty ConPart TrustMPs
Econom Engage Gender Zage
Graduate Disabled Upskill
Midskill Unskill
    Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.
```

```
* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=ResPol
PRE_1AomRPCmp TSC_5075
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: ResPol=col(source(s),
name("ResPol"))
  DATA:
PRE_1AomRPCmp=col(source(
s),
name("PRE_1AomRPCmp"))
  DATA:
TSC_5075=col(source(s),
name("TSC_5075"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
aom*response polarisation on
",
    "compformity regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for active ",
    "open-mindedness"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(ResPol*PRE_1A
omRPCmp),
color.exterior(TSC_5075))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Conform
  /METHOD=ENTER Aom
TolUncer ResPol AomTlunc
Compform Cnstrnt Anglo
Celtic ResRate Willrisk
    AngerPty FearPty ConPart
TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
    Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Conform
  /METHOD=ENTER Aom
TolUncer ResPol AomTlunc
Conform Cnstrnt Anglo Celtic
ResRate Willrisk AngerPty
    FearPty ConPart TrustMPs
Econom Engage Gender Zage
Graduate Disabled Upskill
Midskill Unskill
    Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=TolUncer
PRE_1AomTluncCmp
TSC_5075 MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA:
TolUncer=col(source(s),
name("TolUncer"))
  DATA:
PRE_1AomTluncCmp=col(sour
ce(s),
name("PRE_1AomTluncCmp")
)
  DATA:
TSC_5075=col(source(s),
name("TSC_5075"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] [risk] 1 Tolerance
of uncertainty ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for
aom*tolerance of uncertainty
on ",
    "compformity regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for active ",
    "open-mindedness"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2", "3"))
  ELEMENT:
point(position(TolUncer*PRE_
1AomTluncCmp),
color.exterior(TSC_5075))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Conform
  /METHOD=ENTER Aom
TolUncer ResPol RPTlunc
Compform Cnstrnt Anglo
Celtic ResRate Willrisk
AngerPty
    FearPty ConPart TrustMPs
Econom Engage Gender Zage
Graduate Disabled Upskill
Midskill Unskill
    Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

TWOSTEP CLUSTER
  /CONTINUOUS
VARIABLES=TolUncer
  /DISTANCE LIKELIHOOD
  /NUMCLUSTERS AUTO 15
BIC
  /HANDLENOISE 0
  /MEMALLOCATE 64
  /CRITERIA INITHRESHOLD(0)
MXBRANCH(8) MXLEVEL(3)
  /VIEWMODEL DISPLAY=YES
  /SAVE VARIABLE=TSC_1139.

FREQUENCIES
VARIABLES=TSC_8103
  /ORDER=ANALYSIS.

GRAPH
/BAR(SIMPLE)=MEAN(TolUnce
r) BY TSC_8103.

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=ResPol
PRE_1RPTluncCnf TSC_8103
MISSING=LISTWISE
    REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: ResPol=col(source(s),
name("ResPol"))
  DATA:
PRE_1RPTluncCnf=col(source(
s), name("PRE_1RPTluncCnf"))
  DATA:
TSC_8103=col(source(s),
name("TSC_8103"),
unit.category())
  GUIDE: axis(dim(1),
label("[ANALYSE] [theme:
psychology] Response
polarisation chief ",
    "regression factor"))
  GUIDE: axis(dim(2),
label("Unstandardized
Predicted Value for response
polarisation*tolerance ",
    "of uncertainty on
conformity regression"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.exterior), label("TwoStep
Cluster Number for tolerance
",
    "of uncertainty"))
  SCALE:
cat(aesthetic(aesthetic.color.e
xterior), include("1", "2"))
  ELEMENT:
point(position(ResPol*PRE_1R
PTluncCnf),
color.exterior(TSC_8103))
END GPL.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Compform
  /METHOD=ENTER Aom
TolUncer ResPol RPTlunc
Conform Cnstrnt Anglo Celtic
ResRate Willrisk AngerPty
    FearPty ConPart TrustMPs
Econom Engage Gender Zage
Graduate Disabled Upskill
Midskill Unskill
    Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID)
  /SAVE PRED.

process vars=Leftness
Conform Aom TolUncer
ResPol Compform Cnstrnt
    Anglo Celtic ResRate
Willrisk AngerPty FearPty
ConPart TrustMPs
    Econom Engage Gender
Zage Graduate Disabled
Upskill Midskill Unskill
    Bdsheet
Tbloid/y=Leftness/x=Aom/m=
Conform
Compform/model=4/total=1/
effsize=1/boot=10000.

RECODE TSC_4171 (3=1)
(MISSING=SYSMIS) (ELSE=0)
INTO AngloCulture.
VARIABLE LABELS
AngloCulture 'Belongs to the
Anglo-Saxon cultural cluster?'.
EXECUTE.

FREQUENCIES
VARIABLES=AngloCul
  /ORDER=ANALYSIS.

SORT VARIABLES BY LABEL (A).

process vars=Leftness
Conform Aom TolUncer
ResPol Compform Cnstrnt
    AngloCul ResRate Willrisk
AngerPty FearPty ConPart
TrustMPs
    Econom Engage Gender
Zage Graduate Disabled
Upskill Midskill Unskill
    Bdsheet
Tbloid/y=Leftness/x=Aom/m=
Conform
Compform/w=ResPol/z=TolUn
cer/v=AngloCul/q=Cnstrnt/mo
del=50/boot=10000.

REGRESSION
  /MISSING
MEANSUBSTITUTION
  /STATISTICS COEFF OUTS R
ANOVA COLLIN TOL
```

```
  /CRITERIA=PIN(.05)
POUT(.10)
  /NOORIGIN
  /DEPENDENT Leftness
  /METHOD=ENTER Aom
AngloCul Cnstrnt TolUncer
ResPol ResRate Willrisk
AngerPty FearPty ConPart
    TrustMPs Econom Engage
Gender Zage Graduate
Disabled Upskill Midskill
Unskill Bdsheet Tbloid
  /SCATTERPLOT=(*ZRESID
,*ZPRED)
  /RESIDUALS
HISTOGRAM(ZRESID)
NORMPROB(ZRESID).

*The following commands
were performed on a data set
of indirect effect sizes for
both mediators at a series of
values of the four moderator.
N = 108

* Chart Builder.
GGRAPH
  /GRAPHDATA SET
NAME="graphdata set"
VARIABLES=effno
MAXIMUM(highCI)[name="M
AXIMUM_highCI"]

MINIMUM(lowCI)[name="MI
NIMUM_lowCI"]
MEAN(indeffect)[name="MEA
N_indeffect"] whichmed
    MISSING=LISTWISE
REPORTMISSING=NO
  /GRAPHSPEC
SOURCE=INLINE.
BEGIN GPL
  SOURCE:
s=userSource(id("graphdata
set"))
  DATA: effno=col(source(s),
name("effno"),
unit.category())
  DATA:
MAXIMUM_highCI=col(source
(s),
name("MAXIMUM_highCI"))
  DATA:
MINIMUM_lowCI=col(source(
s), name("MINIMUM_lowCI"))
  DATA:
MEAN_indeffect=col(source(s
), name("MEAN_indeffect"))
  DATA:
whichmed=col(source(s),
name("whichmed"),
unit.category())
  COORD: rect(dim(1,2),
cluster(3,0))
  GUIDE: axis(dim(3),
label("effno"))
  GUIDE: axis(dim(2),
label("Maximum(highCI),
Minimum(lowCI),
Mean(indeffect)"))
  GUIDE:
legend(aesthetic(aesthetic.col
or.interior),
label("whichmed"))
  SCALE: linear(dim(2),
include(0))
  SCALE:
cat(aesthetic(aesthetic.color.i
nterior), include("1.00",
"2.00"))
  SCALE: cat(dim(1),
include("1.00", "2.00"))
  ELEMENT:
interval(position(region.sprea
d.range(whichmed*(MINIMU
M_lowCI+MAXIMUM_highCI)
*effno)),
    shape(shape.ibeam),
color.interior(whichmed))
  ELEMENT:
point(position(whichmed*ME
AN_indeffect*effno),
shape(shape.circle))
END GPL.

GRAPH
 /HILO(SIMPLE)=MEAN(highCI)
MEAN(lowCI)
MEAN(indeffect) BY rp
  /MISSING=LISTWISE.

GRAPH
 /HILO(SIMPLE)=MEAN(highCI)
MEAN(lowCI)
MEAN(indeffect) BY tlunc
  /MISSING=LISTWISE.

GRAPH
/HILO(SIMPLE)=MEAN(highCI)
MEAN(lowCI)
MEAN(indeffect) BY constraint
  /MISSING=LISTWISE.

GRAPH
 /HILO(SIMPLE)=MEAN(highCI)
MEAN(lowCI)
MEAN(indeffect) BY culclust
  /MISSING=LISTWISE.

DATA SET ACTIVATE Data
set1.
RELIABILITY
  /VARIABLES=FAC1_2 al1W6
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA.

DATA SET ACTIVATE Data
set1.
FREQUENCIES
VARIABLES=businessBonusW1
businessBonusW2
businessBonusW3
businessBonusW4
    govtHandoutsW1
govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
immigEconW1 immigEconW2
immigEconW3
    immigEconW4
immigrationLevelW4
immigrationLevelW6
immigrantsWelfareStateW1
immigrantsWelfareStateW2
    immigrantsWelfareStateW3
immigrantsWelfareStateW4
immigrantsWelfareStateW8
reasonForUnemploymentW1

reasonForUnemploymentW2
reasonForUnemploymentW3
reasonForUnemploymentW4
al4W6 lr1W6 al5W6 al3W6
  /FORMAT=NOTABLE
  /NTILES=4
  /ORDER=ANALYSIS.

NONPAR CORR
/VARIABLES=businessBonusW
1 businessBonusW2
businessBonusW3
businessBonusW4
govtHandoutsW1
    govtHandoutsW2
govtHandoutsW3
govtHandoutsW4
immigEconW1 immigEconW2
immigEconW3 immigEconW4
    immigrationLevelW4
immigrationLevelW6
immigrantsWelfareStateW1
immigrantsWelfareStateW2
    immigrantsWelfareStateW3
immigrantsWelfareStateW4
immigrantsWelfareStateW8
reasonForUnemploymentW1
  reasonForUnemploymentW2
reasonForUnemploymentW3
reasonForUnemploymentW4
al4W6 lr1W6 al5W6 al3W6
  /PRINT=SPEARMAN
TWOTAIL NOSIG
  /MISSING=PAIRWISE
```