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Relating ‘Science Culture’ and Innovation

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1 Towards subjective indicators of science culture and innovation

The process of modernisation is generally understood as to unleash the productive power of science and technology into society and to fuel economic growth for well-being. Historical narratives position science and technology as the key productive force culminating in a ‘scientific-technological civilisation’ for which notions like the ‘nuclear society’, ‘bio-society’, ‘information’ and ‘knowledge society’ are subordinate and more specific trends. According to this perspective, science, progress and modernity are essentially connected.

19th century economists might have considered growth to be a function of the basic factors of land, labour, capital and entrepreneurship in a system where tastes, technology and institutions are exogenous parameters or historical constants. Later, Kaldor (1957) added technology to the productive factors. Recent historical accounts notice the endogeneity of all these parameters and assumed material output to be dependent on a mix of population, resources, technology and institutions. And for each of these parameters there is a ‘cluster of variables’ (Cameron, 1997, p9ff). Furthermore, historical accounts of long-term developments stress that this variable mix must include indicators of **subjective mentality** in terms of world view, welcoming the everyday use of novel products and care about material efficiency, and of the imagination which enables such welcoming and care (Bloch, 1948; Rosenberg & Birdzell, 1986; Quintanilla, 2012; Aibar & Quintanilla, 2002). Cohen (1994, 282) asked three questions: who are those people who cultivate science as distinct from technology, who supports them and what symbols and images scaffold their support?

The quest for subjective factors of mentality acknowledges that no society dispenses of its cultural environment which can be variously uneasy with, inconsistent with, or simply putting the achievements of science and technology at stake. During the 20th century the environmental and consumer movements raised the stakes for science and technology by setting benchmarks of acceptability for product safety and environmental sustainability. This amounts to the rejection of the equation: STI = PROGRESS. This equation is no longer self-evident; it is tested against benchmarks of variously motivated resistance (see Bauer, 2015a).

Many observers struggle with the ‘**productivity paradox**’ in a world where labour productivity stagnates or declines despite large investments in new technology, particularly in information technology. Hence, science culture may play a role in engaging citizens to STI and maintaining an environment for productivity. One must expect that the “gap” between culture and science may manifest itself differently in the various regions of the world. This is an eminently empirical question for the engagement of citizens into responsible research and innovation. We might happily admit that **science is a global affair, but the culture of science remains bound by local morality** (Bauer, 2015b).

In this paper, we emphasize the need for extending FRASCATI and OSLO Manuals of defining performance indicators of science, technology and innovative capacity, and to include **subjective indicators** of culture of science and innovation. Indicators of science culture are part of the modern quest of harnessing economic productivity for the benefit of society. Our aim is to demonstrate procedures for constructing cultural indicators of STI based on subjective attitude data. For this purpose we rely on data mining of data sources accumulated in Eurobarometer databases since the 1980s. These databases cover information about cognitive, evaluative and affective dimensions on which individuals relate science to

their everyday life. They provide an invaluable data source for studying science literacy; interest and engagement with science events; expectations of utility and welfare arising from science; and worries and concerns, images and representations of science and trust in its institutions.

Our ongoing research concerns the General S&T surveys in the Eurobarometer series collected hitherto in seven waves from 1989 to 2013 (EB 31; EB 38.1; EB 55.2; CCEB 2002.3; EB 63.1 and EB 78.1, EB79.2; N=1000 per country). This data stream initially covered 12 EU members; after 2002 it is extended to 32+ countries, covering European member and candidate states. Similar large datasets of attitudes to science are available in India (2005 and planned 2017), China (2007, 2010 and 2015), and across Latin America and USA (see overview in Bauer & Falade, 2014). The present analysis focuses on EB 55.2_2001; CCEB 2002.3; EB 63.1-2005 and EB 78.1_2010 as they are most comprehensive for our purposes of testing the indicators.

2.1 Defining ‘Science Culture’

To develop the guidelines for a science indicator system, we start with a distinction between ‘scientific’ and ‘science’ culture concepts. STI indicators traditionally focus on ‘scientific’ culture [from Latin ‘scientia facere’], which comprises the material conditions of and the performance of science and innovations in terms of inputs, process and outputs. Innovation indicators use existing S&T information such as R&D investment, scientific publication output and impact, patents and manpower. As such, they are focussed on the innovators, a tiny subsection of the population. However, it is increasingly been recognised that a “science environment” needs to include the wider mentality of public imagination which supports or challenges the material conditions and creates and sustains the career aspirations that staff it. We call the latter ‘science culture’ in contrast to the former ‘scientific system’. While the former is a global affair and lends itself to standardised indicators whose variance is a matter of quantity and rank ordering; the indicators of mentality, however, do not so easily stack up along a single universal model. To use an analogy: the scientific system of innovation is a fish bowl, where effort goes into conditioning the fish for activity. Little attention however is given to the larger environment that maintains the fish bowl in the first place, by acknowledging its existence, loving its displays and supporting its maintenance.

The quest for indicators of science culture is old, however, side-lined by an economic focus (Godin, 2005). Various researchers and agencies have sought in the past to capture the human patterns of diverse practices, world views, and values with sets of indicators of mass media trends (‘world view’ cultivation effect models), of local knowledge of indigenous peoples for agriculture (FAO), of the performance of the culture industry in pop music, opera and other arts (culture indicators of national statistics), of moral values and their change (e.g. World Value Survey), effect of national values on doing business (Hofstede, 1997) or of longitudinal shifts in cultural production (culture trends; for a review of these see Bauer, 2012).

As the concept of ‘culture indicator’ might be controversial, we need to clarify the term ‘**culture**’ here. Even anthropology debates the usefulness of the concept and its right or wrong applications. The ideological critique is pertinent when the concept is used to discursively transform historical variability into ‘natural’ essences of race, ethnic or tribal locality; when

bounded homogeneity, coherence, and stable structures are privileged over a reality that is fluid, inconsistent, and full of conflict, agency and change (Brumann, 1999). However, the term 'culture' remains useful to refer to routines of feeling, thinking and striving in a community, learnt and accumulated, as long as incomplete sharing is part of the concept. Culture in this sense refers to a reality where features are distributed onto individuals with fuzzy boundaries as in statistical cluster sets which become the basis to mobilise collective identities (ibidem, pS7).

Utilitarian-rationalist accounts of human behaviour tend to be sceptical of 'culture' concept, considering it as residual variance for which the exact variable has yet to be defined. Accordingly, culture is an exogenous variable constraining the self-interested rational behaviour of the individuals. Culture seems a remnant of pre-market societies, in modern market societies human interactions are no longer determined by cultural and kinship obligations. Such atomized-individualist accounts of human behaviour are challenged on the grounds that all economic action is embedded in social relationships and persistent cultural values of moral concerns, politics and religion (Polanyi, 1944; Granovetter, 1985; Taylor, 2004). This embeddedness challenges both the view of culture which assumes individuals to be trapped in essentialist identities and the rationalist view which assumes that human behaviour occurs in a vacuum of socially shielded rationality. It emphasizes the role of culture as a context shaping and shaped by the patterns of interactions between individuals.

Equally, innovation indicators tend to ignore culture and focus on competitive performance of innovative activities. **Input** factors such as investment in R&D support **process** activities to convert research into **output** goods, services, and processes for the market. For example, the Innovation Union Scoreboard (IUS), the instrument of the European Commission, focuses on competitiveness as performance of the 'environment' and particular actors. This scoreboard is developed under the Lisbon Strategy for a Knowledge Society and revised after the adoption of the Europe 2020 Strategy to provide a comparative assessment of EU Member States. (see <http://ec.europa.eu/growth/industry/innovation/>).

However, culture is not an exogenous variable to the performance of some target variables. Economics of innovation in heterogeneous populations needs to recognise that all processes of contagion, social influence and social learning of innovations depend on a prior belief space and prior dispositions in the wider population (Young, 2009). Indicators of innovation must consider not only the conditions of supply of innovations but also the generic conditions of their adoption and uses. Hence, we need to broaden the approach and include indicators for mapping people's belief spaces and mentalities.

For this purpose, we will present our ongoing research for generating science culture indicators that make use of existing data from different contexts. Our current project has been curating such data for purposes of reframing and further analyses. Our approach starts with a psychometric model of individual differences on a set of science culture variables; however, we consider the target concept 'culture of science' not as aggregations of a set of variables, but as structural pattern of relations between these variables.

2. Methods, data curation and ‘etic’ / ‘emic’ perspectives

We have two operating principles which distinguish our study from other development efforts: First, we follow an abductive logic for construct development and side-step the more common deductive and inductive approach. Second, we focus on configurative similarity and difference, and not on ranking. We conduct relational analyses between constructs and avoid ranking on aggregate measures to compare the countries and units of analysis.

Traditional subjective indicator development is largely following psychometric attitude research and deductive operationalization of a conceptual framework. However, such a view imposes an “etic” observer perspective on local culture: it generalizes a putatively ‘universal’ parameter model of human experience and behaviour which is then linked to exogenous factors such as economic or ecological conditions. This is reflected in the politics of data collection; over the years there has been much regional reluctance in the research on attitudes to science to replicate simple extensions of ethnocentric standards despite theoretical justification. Hypothetico-deductive reasoning is a top-down approach to scientific inference. It starts with a theory about the subject domain and narrows down with observable hypotheses. Operating principles of psychometric tests are usually built upon deductive reasoning. They start with a theoretical definition of the subject domain, identify its dimensions and determine the items that could be the indicators of these dimensions. On the other hand, inductive reasoning is a bottom-up approach arriving at concepts by means of detecting patterns and regularities in particular observations. While deductive reasoning appears culturally neutral it remains ‘etic’ in outlook, inductive reasoning follows a more ‘emic’, actor-based understanding of cultural elements. However, neither approach is satisfactory for cross-cultural studies. While the former forces a structure on observations, the latter makes comparison impossible. Abductive pattern recognition (Reichertz, 2004; Harman, 1965) offers a more flexible way of rule-governed and replicable production of new and valid constructs. Abductive logic, while considering changing and fragmented cultures, aims to hypothesize tentative structures that possess local validity.

As for our second principle, while we start from a psychometric approach to individual differences on attitudes, we consider the ‘culture of science’ not as aggregations of particular variables, but as structural features of bundles of such variables, i.e. of the correlations between them. Cultural analysis involves comparing patterns of relations between attitude responses, thus stressing **diversity-in-communality**. The culture of science cannot be assessed by ranking isolated indicators, each of which is subject to semantic diversity and ambiguity despite all precautions of item wording, translations and statistical item analysis. Ranking on any indicator creates a performance index; to achieve a culture index, we must focus on the statistical interaction between bundles of indicators and contexts (see Wagner et al, 2015). Hence, our methodology focuses on similarity and differences of correlations among indicators across units/countries on a tested and fixed regional model. To reach this methodological objective, we used data mining techniques. We fix the cultural model regionally in order to make visible a pattern of relations within that model. We do not assume that this model is universal. In this paper we report our benchmark study of analysing Eurobarometer data and thereby suggest concrete procedures for the development of such a science culture indicator system across the world along similar lines: **clustering unit-based correlation patterns on a regionally fixed parameter model**.

2.1. Data Curating and Data Mining

The increasing availability, encouraged by open access policy, of large scale longitudinal datasets produced for different purposes (WVS, EVS, ESS, EB, NSF etc...) opens up new horizons for indicator development. Cultural meanings are more likely to be endogenous (**emic**) and we must expect that the relations between indicators vary according to contexts to reflect diverse meanings. Data mining and secondary analysis offers procedures for revealing such structures through **inductive pattern detection techniques** followed by **abductive reasoning**, i.e. inference to the most plausible explanation (Harman, 1965). These techniques help us to detect similarities and differences across local patterns. Like any designed product, data once collected and documented enjoys a degree of interpretative flexibility: the use of data is not determined by its initial design. We curate data collected mainly for one purpose, to measure ‘scientific literacy’, to put it to a different purpose, to construct ‘culture of science’ indicators. The abductive move is re-interpreting the past in order to open up new futures.

This chapter reports on our explorations of a science culture indicator system (SCIS) derived from large scale attitude surveys and other data sources. We are currently extending this approach to datasets curated in India (2005 and planned for 2017), China (2007, 2010 and 2015, and planned for 2020) and into South and North America in the context of our international project MACAS (mapping the cultural authority of science; <http://www.macas-project.com/> funded by ESRC, DFG and ISSRC, 2014-2016). We generate indicators using existing nationally representative attitude data taken in different contexts since the 1980s; this database is curated in the MACAS project. Our current analysis will focus on the General S&T surveys in the Eurobarometer series 2001/02, 2005 and 2010 (EB 55.2; CCEB 2002.3; EB 63.1 and EB 78.1; N=1000 per country) as they are most comprehensive for our purposes.

Data mining is following six step phases (Larose & Larose, 2014). We used different R packages (see R, 2008) for examining evaluative attitudes to science, more specifically we used Revelle (2016) for psychometric analyses including exploratory factor analysis (EFA) and item response theory (IRT) and Rosseel (2012) for confirmatory factor analysis (CFA):

1. Project Understanding: the project objectives are determined and formulated to data mining problem definition.
2. Data Understanding: involves familiarizing with the data by exploring it for checking the quality of the data; discovering initial insights and selecting interesting subsets that may contain actionable patterns.
3. Data Preparation: involves cleaning the raw data; preparing the data set and selecting the cases and variables for analysis and performing transformations on certain variables and imputations of missing data if needed.
4. Modelling: requires identifying, applying and calibrating appropriate modelling strategies.
5. Evaluation: compares different models for quality and effectiveness and if the model achieves the objectives defined in phase 1.
6. Deployment: reporting of final model for policy considerations and decisions.

In the following paragraphs, we will explain how we implemented these phases for modelling science culture as a data mining exercise. In terms of **Project understanding** (phase 1) We have started determining project objectives and problem formulation with the definition of science culture, its conceptualization as patterns of indicators as explained above.

For **Data Understanding** (Phase 2) we explored and pre-processed the data to increase the analytical quality; this included missing value analysis. After collating the data from different datasets, work done in the MACAS project, we identified common variables and prepared an integrated codebook for these. We started with EB 78.1 (2010) as benchmark data. We explored the univariate and multivariate distributions for the variables in the codebook for testing parametric assumptions and outliers. Special issues arise for modelling when we have missing data. Listwise and pairwise deletion are the two popular methods for dealing with missing data in basic statistics packages such as SPSS, however these are the worst methods for practical applications. (Wilkinson, 1999). A better practice is to examine if the data is MCAR (missing completely at random; missing values do not show any systematic patterns), MAR (missing at random; missing values on one variable show some systematic patterns depending on other variables) or MNAR (missing not at random; missing values have systematic patterns depending on the variable itself) and follow some imputation strategies accordingly. If the data is MCAR, missing values can be imputed with their means or can be deleted listwise. If the data is MAR, different imputation strategies depending on the values of non-missing variables can be followed. For MNAR, missingness is dependent on the variable itself, hence it is difficult to estimate values for missing cases. To check if the missing values follow systematic patterns on other variables (MAR) we explored the proportion of missing values for the attitude items (for missing pattern visualization on EB 78.1_2010 see Appendix 1). Missing values make about four percent of the data, sometimes exceeding five percent. This suggests that data may not be MCAR. Hence, we checked spinograms if missing values follow any correlation patterns, and we can see patterns with sex, age, education and interest in science: Women, people of lower education, older age and lower interest to science tend to have more missing responses than others.

For **Data Preparation** (Phase 3) we cleaned the raw data from outliers and made necessary imputations to compensate for missing value analysis. In our dataset, attitude responses are collected as 5-point Likert items (1= agree, 5=disagree); data are then recoded in reverse order so that disagreement with the proposition is marked by low scale values (SD=1) and agreement is marked by high scale values (SA=5) on all items; DK-responses recoded as missing. Missing data that occur in more than one variable presents a special challenge. A common approach for imputing such data is known as multivariate imputation by chained equations (MICE). MICE helps imputing missing values with plausible data values. These plausible values are drawn from a distribution specifically designed for each missing datapoint. These data points are determined according to the non-missing values of selected variables (gender, education, age and interest to science in our case).

We explored the **structure of the evaluative attitude space for EB 78.1 data**. First we tested if the attitude space is uni-dimensional (positive-negative attitudes to science) for fifteen Likert items. Cronbach's alpha is low (.57) suggesting that items are not coherently organized in a one-dimensional space. Then, we split the data and conducted exploratory factor analyses (EFA) on the first half to recover the dimensions of the attitude space. We kept the second half for confirmatory factor analysis (CFA) of the structure recovered from exploratory

analysis. We applied different EFA methods, namely minimum residuals, principal components, Omega factor analysis and item cluster analysis, to check the stability of the final structure (see appendix 2). All exploratory analyses recover *three* components with similar items.

Items in Factor1 point to a *critical* view on science consistent with harbouring reservation with reference to non-utilitarian assumption such as action ends or terminal values:

- *The applications of science and technology can threaten human rights.*
- *Science and technology can sometimes damage people's moral sense.*
- ***Because of their knowledge, scientists have a power that makes them dangerous.***
- ***Science makes our ways of life change too fast.***
- *Science and technology could be used by terrorists in the future.*
- ***We depend too much on science and not enough on faith.***

Factor2 points to an *instrumental* view of science consistent with a more pragmatic attitude and expressing a concern with utility and assessing means-to-given ends:

- ***Science and technology make our lives healthier, easier and more comfortable***
- ***Thanks to science and technology, there will be more opportunities for future generations.***
- ***The application of science and new technologies will make people's work more interesting***
- *Scientists should be allowed to do research on animals like mice if it produces new information about human health problems.*

Factor3 suggests a world view element and images of 'science in the world' including of what science is capable of achieving, how important it is personally, and the notion of luck in life:

- *Thanks to scientific and technological advances, the Earth's natural resources will be inexhaustible.*
- *Science and technology can sort out any problem.*
- *In my daily life, it is not important to know about science.*
- *Some numbers are especially lucky for some people.*
- *Science and technology cannot really play a role in improving the environment.*

These findings strongly suggest more than one dimension is required to capture the attitude-evaluation domain of a culture of science across Europe: An instrumental dimension, a value-critical dimension and maybe a world view dimension. We might call this the 3-factor 3F model.

2.2 Validating a 2D evaluation model: accepting the Promise and harbouring Reserve

In the next **Modelling Phase** (4) we identified, applied and calibrated strategies in several steps. This involves identifying the model and testing for measurement invariance across units. Firstly, we applied a confirmatory factor analysis (CFA) on the second half of the EB 78.1_2010 data to check the stability of the aforementioned 3F model. Secondly, we checked for the content validity by grounding the model in the literature. Thirdly, we checked if the final model meets the criteria for measurement invariance.

We performed a CFA to cross-validate if the model emerged from exploratory analysis fits the other half of the pooled data. Fit measures (see table 1) are not satisfactory according to benchmarks. Checking for modification indices, we have noticed that the items ‘*luck*’, ‘*daily life*’ and ‘*cannot save environment*’ have low coefficients and they are ambivalent as they are also loading on other constructs which can be seen from EFA. Removing these items improved the fit values, but not at a satisfactory level. Checking for the modification indices again, we observed that the items in what we named as *world view* factor also load highly with the *value critical* factor. Hence, we excluded those items and decided to settle on a two dimensional structure: a 2D-model of evaluative attitude of science, comprising an **instrumental and critical factor**. For this model, all fit measures are satisfactory (see table 1).

Table 1: CFA fit indices for evaluative attitude models on EB 2010 data

	Chisq	df	cfi	rmsea	tli
3D model	11248.5	74	0.798	0.070	0.751
3D model, modified	3705.4	41	0.919	0.054	0.891
2D model	350.8	13	0.984	0.029	0.973

The literature on attitudes to science is edging towards a global consensus on two-dimensions of evaluation, the naming of which remains something to be discussed. Miller & Pardo (2000) reported a two-dimensional space for the evaluation of science based on an overlapping and not identical set of items in US, German, Japanese and Canadian data collected in the 1980s and early 1990s. Their CFA refers to these dimensions as **Promise and Reservations**. Crettaz (in press for 2017) examines the six waves of the World Value Survey (1981-2014) across Sweden, US, Japan, India, Chile, Spain and South Africa. On the items pertaining to the evaluation of science, she again finds a two dimensional space being the best fit using CFA, which she identifies as Promise and Reservation, following Miller & Pardo’s earlier analyses. Todorov et al. (2009) examined 18 Likert-type attitude items included in Eurobarometer survey 224 (EB 63.1_2005, split-ballot A only) using principal component exploratory analysis (EFA). They find three factors which they name ‘**evaluation**’, ‘**efficacy**’ and ‘**control**’ of science following Osgood’s universal semantic space of ‘associative meaning’ (Osgood, Suci & Tannenbaum, 1957). ‘Evaluation’ includes items that celebrate the achievements of science and its promises; ‘efficacy’ refers to the limitations of science including statements of what science cannot achieve. The third factor, ‘control’ refers to the need to regulate science under public oversight and within the boundaries of ethics. It is not surprising, that their 1st and 2nd factors are close to what others have called ‘promise’ and ‘reservation’ about science, and which we have confirmed on the same 2005 data. Finally, Bauer & Howard (2013) in their analysis of Eurobarometer time-series data for Spain

explored a 3D-model of attitudes to science - **Attention, Enculturation and Progressivism** - by examining the associations of items on interest, knowledge, engagement and evaluation over time; the model remains descriptive, but it shows that these three dimensions have different time trajectories for age cohorts and educational groups.

More generally, American political science, taking a new look at **polity mood** over past 60 years, suggests that the belief space of US citizens, long expected to be exhausted by the left-right continuum, does require a second dimension to represent the flow of issues. The first dimension is the 'economic' assessment of government policy delivery; while the second dimension captures 'cultural' issues on which people take positions (Stimson, 2014). Despite different naming, this does not seem too far from the distinction between promise and reserve. We might expect at least similar degrees of complexity elsewhere. And on an even more abstract note, we consider Rokeach (1973) who distinguishes between **'instrumental' and 'terminal' values** which can be mobilised for the evaluation of attitude objects. Terminal values are the goals that a person would like to achieve during his or her lifetime; they refer to desirable end-states of human existence. Instrumental values refer to preferable modes of behaviour or means of achieving these terminal values. It might well be that we rediscover this means-end distinction also in the evaluation of science, 'means' being the very down-to-earth evaluation of the good of science in utilitarian terms, and 'ends' as the assessment of more 'transcendental' orientations towards science less bound up with the empirical reality of experience and giving rise to a more critical evaluation.

The distinction between **'instrumental' and 'critical'** criteria for the evaluation of public goods is also resonant of Horkheimer's (1947) statement in the first chapter of *'Eclipse of Reason'* entitled *'Means and Ends'*. Horkheimer demarcates between two different types of rationality which form the basis of enlightenment philosophy: Instrumental reason is interested in determining the means to a goal, without reasoning about ends; while critical reason is concerned with more transcendent ends in themselves and their relation to the progress of civilization. According to Horkheimer, Enlightenment turns against itself as it largely equates Progress with the advancement of instrumental reason. *"Enlightenment, understood in the widest sense as the advance of thought, has always aimed at liberating human beings from fear and installing them as masters. Yet the wholly enlightened earth is radiant with triumphant calamity"* (Horkheimer, 1947, p.1).

Hence, we suggest that a first factor of evaluating science is consistent with a drive to make nature calculable, and calculability is assimilated to usefulness of science. This scientific picture is further reproduced through activities which seek to dominate nature, thus instrumental-scientific activity creates a reality to fit this picture and evaluates states-of-affairs in these terms. On a second factor, the critical reasoning seeks to root truth and meaning, the proper ends of thought, within a more comprehensive totality than means-to-given-ends. Critical reasoning is oriented towards examining and elaborating ends, while instrumental reason remains fixated on means to given ends. The identification of historical 'Progress' with the rise of instrumental reasoning has given rise to Horkheimer & Adorno's (2002) later analysis of modernity and its discontents dominated by instrumental reasoning.

We thus expect to find resonance of both features of modern sentiment, instrumental and critical, economic and cultural, means and ends reasoning in the public perceptions of science of most contexts. And our examination of the data on evaluative attitudes towards science

seems consistent with these analyses. After examining the structure of evaluation of science globally, and struggling over the naming of this structure, we proceed with checking if the 2D-hypothesis fits across all of Europe, and we call it ‘promise’ and ‘reserve’ (see box 1).

Box 1: Measuring Promise and Reserve vis-à-vis Science and Technology

The factor ‘**Promise**’ (**P**) combines those items across various Eurobarometer surveys which allude to the utility of science; they therefore represent an instrumental, means-focused orientation towards science. We include here the following items for further analysis of response patterns:

- *Science and technology make our lives healthier, easier and more comfortable [welfare]*
- *Thanks to science and technology, there will be more opportunities for future generations [opportunities]*
- *The application of science and new technologies will make people’s work more interesting [work interesting]*
- *Scientists should be allowed to do research on animals like mice if it produces new information about human health problems [animal experiments].*

The factor ‘**Reserve**’ (**R**) we call the set of items in Eurobarometer surveys which express some discontent with the course of science. This discontent refers to the power of scientists that deserves our mistrust, the undue acceleration of life and the excessive secularism of modern society. In all these aspects Reserve allude to underlying values or desirable end-states (accountable science, slow down of life, and to a certain competition between science and religion. They therefore allude to a critical-terminal orientation towards science in the Horkheimer-Rokeach sense:

- *Because of their knowledge, scientists have a power that makes them dangerous [dangerously powerful].*
- *Science makes our ways of life change too fast [accelerate life].*
- *We depend too much on science and not enough on faith [faith not secularism].*
- *S&T cannot really play a role in improving the environment [environ worry]*

We conclude that attitudes to science are well represented by a two factorial belief space of **Promise**, involving utility expectations and instrumental reasoning about science, **and Reserve**, involving critical examination of science on values. These attitudes represent coherently organized belief systems and potentially follow universally the global science system. Belief systems simplify everyday decision processes; people aggregate a multiplicity of issues into a small number of considerations on which they can reasonably position themselves (Converse, 1964).

After settling the model this way, we then tested **measurement invariance** to check if the model measures the same model constructs and is stable across all EU countries.

Measurement invariance involves the degree to which the psychometric properties of the observed indicators can be generalized across units and over time. This ensures that the latent

construct has the same correlative meaning across (EU) countries, allowing for cross-country comparisons of their configuration. We first tested for **configural invariance**, that is the fit of the same 2-factor structure is imposed on all countries (same factor structure in each country, but factor loadings can vary). And fits indices are good (see table xxx). Then, we tested for weak invariance, i.e. fixing the factor structure and the factor loadings. The fit measures are not perfect but satisfactory (see table 2).

Table 2: CFA fit indices for measurement invariance

	<i>chisq</i>	<i>df</i>	<i>cfi</i>	<i>rmsea</i>	<i>tli</i>
<i>Configural invariance</i>	1267.8	442	0.962	0.045	0.939
<i>Weak invariance</i>	1684.1	469	0.927	0.053	0.889

Bulgaria, Ireland and Romania are ‘Heywood cases’ (i.e. units with dubious fit as indicated by negative estimates of variances or standardized regression coefficients > 1 in absolute value for some of the variables), where the regression assumptions are violated with too few latent variable indicators (Kolenikov & Bollen, 2012). While for some countries parametric assumptions of linearity and multivariate normality are violated, the overall distribution of the data is close to multivariate normal for the pooled data. Increasing the number of indicators could improve this situation. Hence, we must interpret results for these countries with Heywood cases cautiously. As we are working with secondary data, the design is not under our control. But this suggests a consideration for future research: designs on attitude to science need increase the number of items and pilot those items locally.

For a cultural analysis of subjective data, we seek out the relations between these two dimensions Reserve and Promise, which gives us an idea about the organization of belief space in different contexts. While checking for measurement invariance to ensure that the ‘same construct’ is being measured across different countries, we relaxed the orthogonality assumption and allowed the correlation between the factors to vary to reflect the science culture in different contexts.

As we can observe from Choropleth map in figure 1, Turkey (and Bulgaria, Cyprus, Greece, Portugal, Italy and Romania to a lesser degree) aligns Promise and Reserve, the utilitarian come together with the critical dimensions: those who see much utility in science have also much reservation; and those who do not see any utility in science have also few reservations. One can have critical thoughts about science but this does not prevent the Turks from accepting its utility. On the other hand, in Germany and Scandinavian countries Promise and Reservation are negatively correlated: if one is critical of science one has few utilitarian or instrumental expectations, and if one has high expectations of science, one is not critical of it. In many other countries, there is no correlation between Promise and Reservation, as they are independent criteria on which to evaluate science; scoring on one has not implications on scoring on the other, all combinations are possible. We conclude that the way these two dimensions stack up constitutes an important feature of the belief spaces across Europe, and to evaluate science one needs two dimensions, a one-dimensional valence ‘good-bad’ does not suffice for the evaluation of science. We will come back to this observation later.

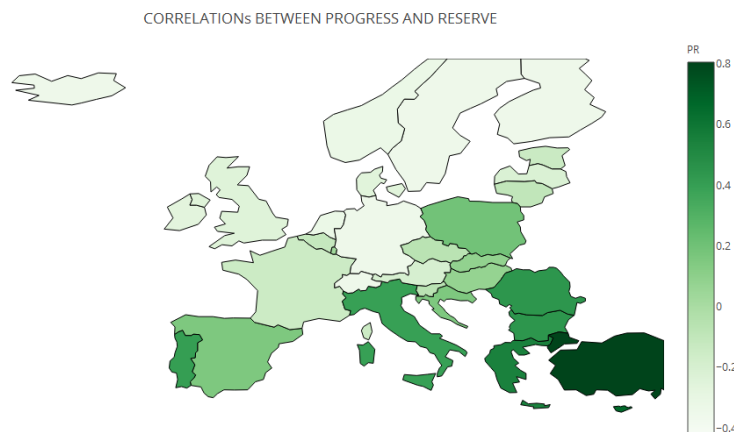


Figure 1: The choropleth Map shows the correlation between accepting the Promise and harbouring Reserve about science; the darker the territory, the more positive is this correlation for EB2010.

In the **Evaluation Phase (5)** we comparing different models for quality and effectiveness and if the model achieves the objectives set in phase 1. After deciding the final model for summarizing attitude data, to check if the model achieves the objectives and test the quality and effectiveness of different models we applied the model to other datasets and we added new constructs. We add two more constructs to the attitude model in line with theory of attitudes: cognitive familiarity with science as indicated by science literacy measures and cultural engagement of paying attention and participation in science events such as news reporting and expository science in museums. This model amounts to a trilogy model of cognitive, affective and conative intentionality towards an otherwise ‘obscure object of experience’ in modern society. The idea that humans entertain relations to objects on three dimensions is a very old and potentially universal intuition (Hilgard, 1980; Bauer & Suerdem, in press for 2017). We tested the four dimensional model (4Ds of Promise; Reserve; Science Literacy and Engagement) on the datasets EB2005 and EB2001/02.

‘Science literacy’ as familiarity with science

A core feature of past efforts to measure public understanding of science has been the indicators of ‘literacy’. Most generally, the term ‘literacy’ marks a threshold target of educational activities. For the purposes of constructing indicators of science culture, literacy is however not the target variable, but one of the elements to consider. Although we use the science ‘literacy items’ in Eurobarometers, we re-frame these as indicators of familiarity with and cultural distance from science. This allows us to make use of the existing corpus of items without buying into its conceptualisation as ‘objective knowledge’ or universal literacy. Science knowledge of science is measured by classical items used all world-wide since the 1980s (see Bauer & Falade, 2015). Literacy items are traditionally quiz items: respondents are asked to state whether a statement is ‘true’ or ‘false’; the respondents gets a point weighted by difficulty, depending on how many other people answer correctly. The latent trait model assumes that a particular set of items are taken from a hypothetical pool of many such

items, which jointly indicate a latent construct ‘science literacy’. Items are not equally difficult and thus not equally useful to discriminate the population on ‘science literacy’.

For testing the quality of the test and selecting the items for science literacy questions, we relied on Item Response Theory (IRT). IRT is a method for assessing psychometric quality by providing information about a scale’s items and of the entire scale. According to IRT, a person’s response to an item is affected by the quality of the person and the item. IRT provides us with two important indicators showing the quality of a test and its items: difficulty and discrimination. An item’s **difficulty** shows the probability of responding in a specific way to an item, positive values indicating more difficulty. An item’s **discrimination** is the degree to which the item differentiates people with low levels of the underlying construct from people with high levels. In a sense, it reflects the degree to which the item reflects the underlying psychological construct; in this way, it is conceptually similar to an item-total correlation or an item’s factor loading. Discrimination values usually range from zero to 3.0 or more, with large values reflecting better psychometric quality.

According to our analysis, the results suggest that difficulties and discriminatory power of the items is stable over the years, implying that the test has the quality to test science literacy. Testing the psychometric qualities of 12 available quiz items in the data led us to select the six items with the highest power of discrimination (see table 3). The six items are as follows:

- **Radioact:** *All radioactivity is man-made [false=correct]*
- **Laser:** *Laser words by focusing soundwaves [false=correct]*
- **Contin:** *The continents on which we live have been moving for millions of years and will continue to move in the future [true=correct]*
- **Radmilk:** *Radioactive milk can be made safe by boiling [false=correct]*
- **Dinosaur:** *The earliest humans lived at the same time as the dinosaurs [false=correct]*
- **Antibio:** *antibiotics kills viruses as well as bacteria [false=correct]*

	2001-2002		2005		Diff ²
	difficulty	discrim	difficulty	discrim	
radi oact	0.006	1.831	-0.209	1.888	0.046
l aser	0.591	1.673	0.290	1.573	0.091
radmi lk	-0.532	1.330	-0.782	1.550	0.062
cont i n	-1.221	1.353	-1.563	1.370	0.117
di nosaur	-0.200	1.306	-0.500	1.362	0.090
anti bi o	0.706	1.214	0.265	1.319	0.195
sunt ime	-0.447	1.135	-0.701	1.219	0.064
earth	-1.669	1.249	-1.832	1.103	0.026
sexgene	0.733	0.307	-0.602	0.937	1.781
electron	0.419	0.916	0.358	0.806	0.004
evol uti on	-0.839	0.525	-1.251	0.476	0.169
oxygen	-3.004	0.533	-4.788	0.335	3.183

Table 3: Item response theory IRT results for all literacy items; the first six are the ones selected for the model

Engagement with expository science

The fourth dimension of our model of cognitive, evaluative and conative relations with science is ‘engagement’. Here we consider items that ask about people’s interest in new scientific discoveries (very interested, moderately interested, or not at all), how much they feel informed about new scientific discoveries and whether they have visited science and nature in museums or zoos in the past 12 months. Being interested, informed and making visits all point to science on display that require attention, an older term here is ‘expository science’ (Shinn & Whitley, 1985). All three indicators combine well to form the indicator of engagement, interest or attention to science; we call it ‘engagement’ from the point of view of the public. There is a different meaning of ‘engagement’ in the activity of setting up opportunities for public contacts and displays from the point of view of scientific actors, which is a whole other data stream for indicators of science culture (Entradas & Bauer, 2016).

2.3 Measurement Invariance and Fit of a Parametrised 4D-Model of Science Culture

Having now refined our model to include four dimensions we test this model for weak invariance across years and across countries to determine its parameters, i.e. fixed loadings and varying correlations between constructs across countries. However, when testing this model on EB 2005 data we encountered a small difficulty: attitude-evaluation items were split into A and B versions. Hence we conducted our analysis separately on these two parts, by matching the corresponding items to the relevant latent dimension of Promise and Reserve.

From split A, we retained for dimension *Promise* the items of ‘makes work more interesting’ and ‘more future opportunities’. For *Reserve* we retained ‘makes life change too fast’ and ‘scientists have power making them dangerous’. CFA fit measures for weak invariance are satisfactory (see table 4), however, this model needs some caution for Greece, Cyprus, Spain, France, Germany, N. Ireland, Bulgaria, Estonia, Latvia and Switzerland as they are Heywood cases. For split B, we retained on *Promise* the items ‘more comfort and health’ and ‘allow animal experiments’. For *Reserve* we retained ‘not enough faith’ and ‘S&T cannot improve environment’. The weak invariance CFA modelling shows Heywood cases for Belgium, Italy, Luxembourg, Austria, Bulgaria, Cyprus, Latvia, Malta, Slovakia and Slovenia. By examining both version A and B, we finally created a synthetic model using either A or B, depending on the quality of the data when considering the Heywood cases. Fit measures are good for both splits. For 2001-2002 we find the four dimensional model with good overall fit. We retained for Promise the items ‘welfare’, ‘work interesting’ and ‘opportunities’, but excluded animals experiments to improve the fit. For Reserve we included ‘not enough faith’, ‘life change too fast’ and ‘scientists are dangerous’. Again the overall fit is satisfactory.

Table 4: CFA fit indices for measurement invariance

	chisq	df	cfi	rmsea	tli
2005 A	4447.5	2435	0.957	0.042	0.938
2005 B	4679.4	2435	0.954	0.043	0.931
2001/2	4394.9	2506	0.981	0.028	0.980

This overall procedure for developing the regional parameter model allows us to be flexible with the choices of the exact items, while keeping the underlying dimensions as the communality: Literacy, Promise, Reserve and Engagement. For each of the survey waves, the linear combination is slightly different, both in the items included. Whether an item is included or not depends on availability and on model fit. For each survey wave the item weights are also slightly different reflecting the optimal fit to the latent dimension. Table 5 below shows the fixed weights for the regional parameter model, a linear combination of each wave of survey. We assume that on a regional model with variable parameters we are comparing functional equivalences, the basic indicators for our cultural analysis: Promise, Reserve, Engagement and Literacy.

	2001-2002	2005A	2005B	2010
Promise =~com	0.618	0.719		0.349
Promise=~opp	0.767		0.738	0.759
Promise=~interest	0.726		0.522	0.678
Promise=~mice		0.299		0.606
Reserve=~res_dang	0.476		0.318	0.390
Reserve=~fast	0.688		0.884	0.820
Reserve=~faith	0.583	0.412		0.525
Reserve=~envi		0.574		
engage=~int	0.692	0.905	0.874	
engage=~info	0.690	0.786	0.805	
engage=~sci.muse	0.548	0.495	0.489	
knowledge=~radmilk	0.612	0.639	0.640	
knowledge=~radioact	0.730	0.723	0.720	
knowledge=~laser	0.696	0.668	0.635	
knowledge=~antibio	0.567	0.596	0.582	
knowledge=~dinosaur	0.580	0.554	0.558	
knowledge=~contin	0.530	0.537	0.530	

$$\begin{aligned}
 \textit{Promise} & \quad P = a_1 P_1 + \dots a_k P_k \quad [k=3 \text{ or } 4] \\
 \textit{Reserve} & \quad R = b_1 R_1 + \dots b_k R_k \quad [k=3 \text{ or } 4] \\
 \textit{Engagement} & \quad E = c_1 E_1 + \dots c_k E_k \quad [k=3] \\
 \textit{Knowledge} & \quad K = d_1 K_1 + \dots d_k K_k \quad [k=6]
 \end{aligned}$$

Table 5: The regional fixed parameter model for Europe at different years

3 Results: Characterising Four Science Cultures across EU32+

As we have tested the robustness of the model across countries and through time, we can proceed with the cross-cultural comparison of the organization of the science culture space across Europe. Taking a structural approach, we will concentrate on the correlations between the constructs rather than the level differences. The structure of the correlation matrix reflects the organization of the cross-cultural space of attitudes to science.

3.1 *Clustering the EU32+ countries*

We amalgamated matrices by averaging the 2001/02 and 2005 correlations and draw the cluster from the average matrix. We assume that cultural structures do not change so fast, and indeed when we compared the shifts between 2001/02 and 2005 correlation matrices, we observed that squared differences across waves are very small (mean $<.03$; see appendix, table A1). For the 2005 data, we combined the split data by taking into consideration the Heywood cases. If a country was a Heywood case in any of the split, we opted for the value in the other split.

This correlation matrix is our **core rendered data**; it gives us a raw idea but is too complex to draw conclusions. We need to reduce the information in the correlation matrix by detecting patterns to understand how science culture is mapped. Cluster analysis is a pattern detection technique which groups objects (observations, cases) based on the information found in the data describing the objects or their relationships. The goal is that the objects in a group will be similar (or related) to one other and different from (or unrelated to) the objects in other groups. The definition of what constitutes a cluster is imprecise, and the best definition depends on the type of data and the desired results.

Cluster analysis is an exploratory technique and findings may change depending on the method used. Two most common methods are **Hierarchical and K-means**. In hierarchical clustering the goal is to produce a hierarchical series of nested clusters, ranging from clusters of individual points at the bottom to an all-inclusive cluster at the top. A diagram called 'dendrogram' graphically represents this emerging hierarchy. Hierarchical techniques do not assume any particular number of clusters. On the other hand, k-means classifies a given data set through a pre-determined number of clusters a priori by defining k centroids, one for each cluster and associating each point in the data to the nearest centroid. Hence, hierarchical methods are commonly used for exploring and determining the number of clusters, k-means is used for understanding the typical characteristics of the clusters. There are a variety of hierarchical clustering methods, their use depending on the purpose and data. After experimenting with different methods, we have decided on WARD's method because other methods tend to count outliers as clusters. Besides, it overlaps reasonably with k-means clusters. Basically, WARD looks at cluster analysis as an analysis of variance problem as it aims to minimize within cluster variance and maximize between clusters variance. This method is most appropriate for quantitative variables, which is our case, and less so for binary variables. Ward's Method has a tendency to split data into groups of roughly equal size. This means that when the "natural" clusters differ much in size, then the big ones will be split in smaller parts roughly equal in size to the smaller "natural" clusters. The advantage of WARD's Method is that it doesn't leave any outliers. All data is grouped in bite size chunks, which can be examined further quite easily.

When examining the patterns of correlations across countries, we examined various indices for determining the optimal number of clusters: for WARD’s method, 7 indices proposed 4 as the optimal number of clusters and for k-means 6 indices suggested 2 or 3 clusters (see appendix, Figure A2). Silhouette analysis helps us to visually examine cluster membership; it shows how far they are away from the neighbouring members in their clusters, and whether a country is a core or a marginal member of the cluster (see appendix, Figure A3). After checking for various options, we decided on a four cluster solution; both Ward’s and k-means methods produce similar results. EU countries are thus mapped into one of **four Science Cultures** as shown in figure 2 below in the form of a listing and profiles of overall and relative correlation patterns.

The overall science culture model across Europe suggests little or no correlation between Promise and Reserve and between Knowledge and Promise ($r < 0.10$); positive correlations between Interest and Promise, and between Knowledge and Interest ($r > 0.25$); negative correlations between Interest and Reserve and between Knowledge and Reserve ($r < -0.20$). All clusters show the strongest relation between being interested in and being familiar with science ($r > 0.50$). Our profile chart shows how each of the four groups deviates from the average overall ‘standard’ profile in terms of z-values.

	EU countries in the cluster	Relationship to science
Cluster_1 (15)	BE, CH, DE-E, DE-W, DK, FI , FR, GB-GBN , GB-NIR, EIRE , IS, IT, NL , NO, SE	Either love it or hate it [scientific literacy model]
Cluster_2 (4)	AT, BG, PT , RO	Love it and worry , or be indifferent and ignorant
Cluster_3 (3)	CY , GR, TR [most contrasting to C1]	Love and hate , knowledge makes little difference
Cluster_4 (12)	CZ , EE , ES, HR , HU, LT, LU, LV, MT, PL, SI, S K [least constraint]	Anything goes : worries or optimism or knowledge-interest

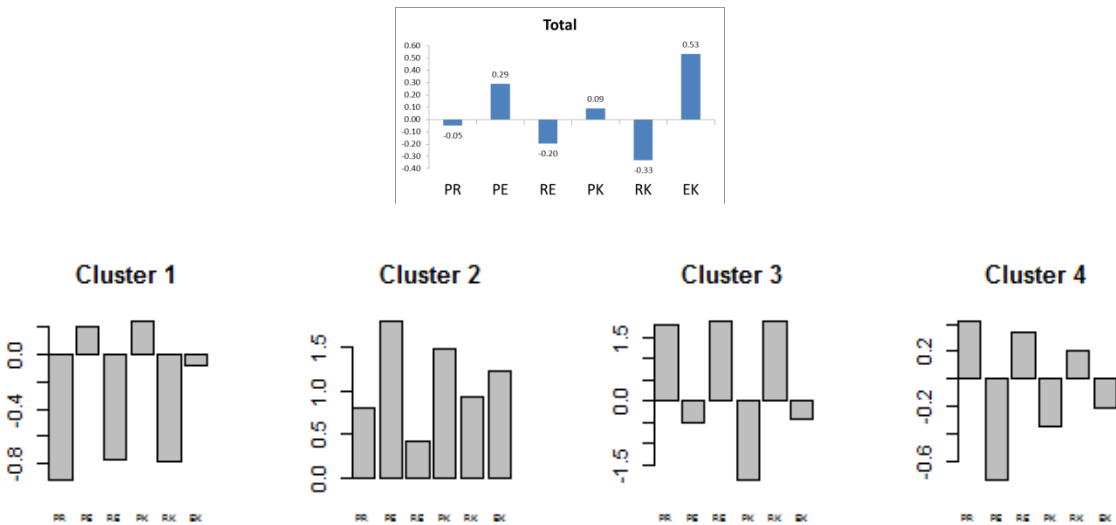


Figure 2: Listing the countries in the four clusters; the overall ‘standard’ profile of absolute correlations ($n=34$), and profiling the clusters on z-values for PR, PE, RE, PK, RK, and EK (see also appendix, figures A6 for absolute profiles).

In the following, we are characterising these four Science Cultures by giving them meaningful names and by examining the meanings of the indicated correlations. The naming of these cultures might deserve further work.

Cluster 1: Either you love or worry, but operate on the ‘scientific literacy model’

Cluster_1 is the largest group comprising 15 units, mainly Old Europe, and consistent with the ‘deficit model’ of the more you know, the more you love it. Ireland, Finland, Britain, Sweden, Belgium, France and Netherlands are the typical members in this group. Their cluster profile shows accentuated negative correlations for PR, RE and RK. Those who harbouring reservation, do not accept the promise of science ($r = -0.27$), are less interest in science and tend to be less familiar with it. Those who harbour few reservations also accept its promises and tend to be more familiar with science and also more interested. And those familiar with science also show are certain indifference as they seem to take science rather for granted in life. In these contexts, citizens are casting utilitarian judgements or they are fundamentally critical. We recognise here the operation of the **classical model of scientific literacy** on both sides: ‘the more you know it, the more you love it’ and ‘the more you know, the less you worry’ (see Miller, 1983: being scientifically literate means being familiar and interested in science, and showing positive appreciation), you either love it or hate it depending on how familiar you. Familiarity with science comes with a moderate, but positive correlation with accepting its utilitarian outcomes. This observation is often invoked to remind observers of the empirically reality of a ‘deficit model’ of the public (Allum et al., 2008). While our results are consistent with this argument, we also show that its validity is specific to a subset of European countries.

Cluster 2: Love it and be worried; the more so, the more you know

Cluster_2 groups a small set of countries, namely Portugal, Rumania, Bulgaria and Austria, where all correlations are accentuated compared to the rest, particularly high for those involving knowledge and familiarity with science as in PE, PK, and EK. Basic knowledge of science makes a difference here, and our all dimensions are highly constraint. But more importantly, these four countries embody a **love-hate relationship** with science. Accepting the promise and harbouring reservations about science go hand in hand ($r=0.14$). Being interested in science and accepting its promise, being knowledgeable and accepting the promise, and knowledge and interest are all highly correlated. Those who are familiar with science are more likely to accept its promises, but they also hold more reservations. Those who accept the promise of science also harbour more reservations. Here citizens both **‘love and hate’ the sciences**, and this in proportion to their interest and familiarity. Those who have utility expectations also harbour reservation; those who have no utility expectation do not think badly of science; they have rather no evaluation at all. These countries seem to be internally polarised between those who are interested, familiar and opinionated and those who are indifferent towards science.

Cluster 3: Love it and hate it, and knowledge does hardly matter

Cluster_3 comprises the three countries of Cyprus, Greece, and Turkey in the Eastern Mediterranean of the old Levant. Here the pattern is the most dissimilar to Cluster_1, as they display higher than expected correlations on PR, RE and RK. The key feature is here as in Cluster_2 that reservation and accepting the promise is strongly correlated, and interest comes with reservations, and knowledge discourages accepting the promise. Interest in science fuels both reservations and accepting the promise, while more knowledge brings little endorsement of its promises but much reservation. Those who know about science are more sceptical as to its outcomes. Those who accept the promise, do so more likely from a position of being unfamiliar with it. However, acceptance of the promise and reservations are strongly correlated ($r = 0.39$), which suggests either the love-hate relationship with science or otherwise being indifferent; this is the region of **stark ambivalence towards science**. In these places, citizens **love and hate** science or otherwise they are indifferent, and lack of interest means indifference and, contrary to cluster_2 knowledge has little impact on how people feel as if cognition and judgement are unconnected. Maybe here still resonates the feeling expressed by old Roman poet Catullus who, exiled to the Black Sea, is known for his clamour of ‘*Odi et amo .. nescio, sed fieri sentio...*’ (I love and hate, I don’t know why, but I feel it strongly). The passion is felt with or without a clear notion of the object.

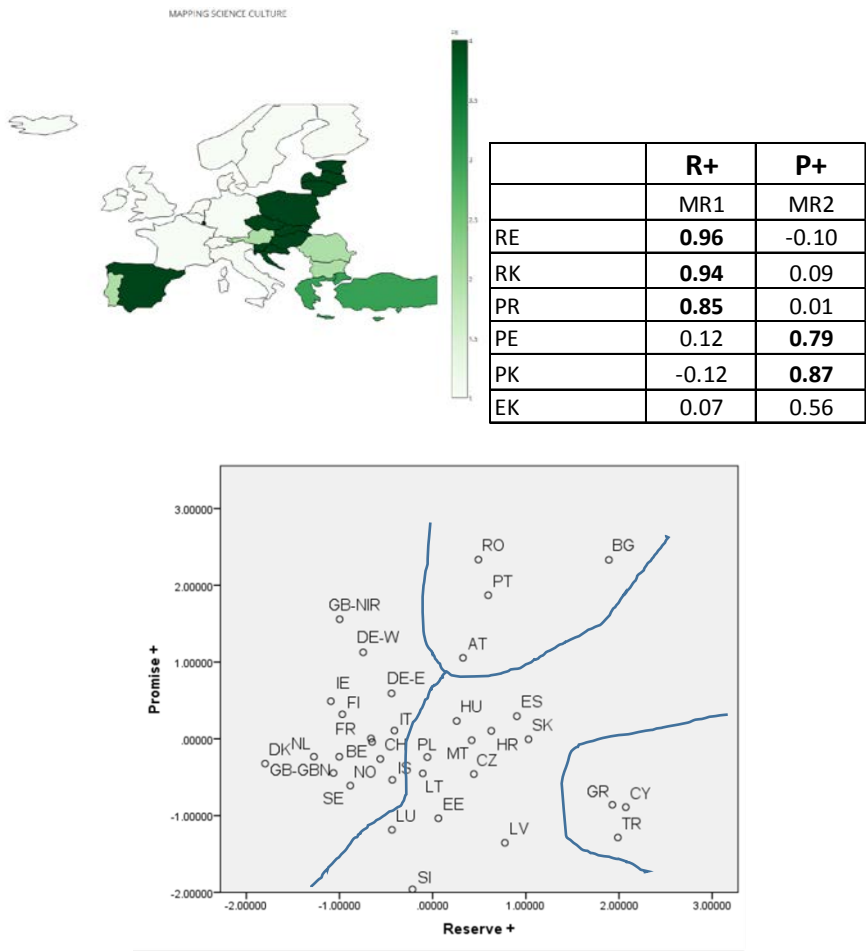


Figure 3: Choropleth Map of four Cultures of Science across Europe (EB2005) on the dimension PR; component scores of four relational indicators produces a visualisation of 32+ European countries into a 2D Euclidean space.

Cluster 4: Anything goes: utilitarian or critical, knowledgeable or interested.

Cluster_4 groups again a larger set of countries, mainly New Europe of the former East, but also including Spain, Malta, and Luxembourg. Czech Republic, Estonia and Croatia are the prototypical members here. Their profile is overall similar to Cluster 1, but correlations are regressing towards the mean on all dimensions; none of the dimensions of the model seem to combine as elsewhere. Admittedly, interest in science comes with less reservations and more acceptance of the promise; and familiarity brings acceptance of the welfare promise with less reservation and vice-versa. But this is all a more mooted affair with less constraint than elsewhere. The key contrast to Old Europe of cluster_1 is the **no-correlation** between promise and reservations ($r = 0.05$) and between knowledge and promise in this group ($r = 0.05$): whether you accept the promise of science has little bearing on whether you also harbour reservations or not; **some love it and also hate it, some love it or worry, others are entirely indifferent and neither love nor worry.** Interest in science plays a role in this, but does so less than elsewhere. The old literacy model only works one-sided: ‘the more you know, the less you worry’ in New Europe. Overall, we are as likely to encounter there the informed optimist and naïve pessimist as we find the naïve utilitarian and the informed sceptic. It seems that citizens in the New Europe make good use of all four dimensions in sorting out their relationship with science.

Mapping the countries on principal component weightings is another way of visualising the cluster characteristics. When we reduce to two dimensions, we observe a first dimension loading high on RP and RK; we call this Reserve R+. The second dimension shows high loadings PE and PK; we call this Promise P+. The first component R+ points to an association between being both critical and utilitarian and being scientifically literate when worrying or not about science. The second component P+ refers to a pattern of being utilitarian and engaged and being interested and familiar with science when accepting its promises, or being unengaged, unfamiliar and without expectations. If we plot the principal component scores for 34 units on all six correlations into a two-dimensional space, we come to one visualisation of the cultural space of science (see figure 3). Of all our relational indicators, PR has the largest range ($-.40 < r < .59$) and this indicator orders all EU32+ countries on a gradient as shown in the Choropleth map in figure 3.

3.2 Validating the four clusters of Science Culture

In the final **Deployment Phase (6)** of data mining we validated our four clusters with other indicators of socio-economic and cultural affairs. People develop long-term socialized value predispositions which they cultivate through institutions and cultural values. They acquire basic beliefs and attitudes about science through formal and informal, primary and secondary socialisation processes. While basic attitudes towards science are acquired through education and family, the institutional environment of political culture and social values usually updates this knowledge by focusing on specific topics in public controversies and debates (see Brossard & Shanahan 2003; Brossard & Nisbet 2007 for such debates in the USA). In this part of the study, we will investigate the relations of institutional and value variables and our four European science cultures.

Figure 4 shows two indicators, The Human Development Index (HDI) and Hofstede's Uncertainty Avoidance Index (uai) which show significant co-variation with our four science cultures. HDI differentiates Cluster_1 from all others; uai distinguishes Cluster_2 and Cluster_3 from the others two.

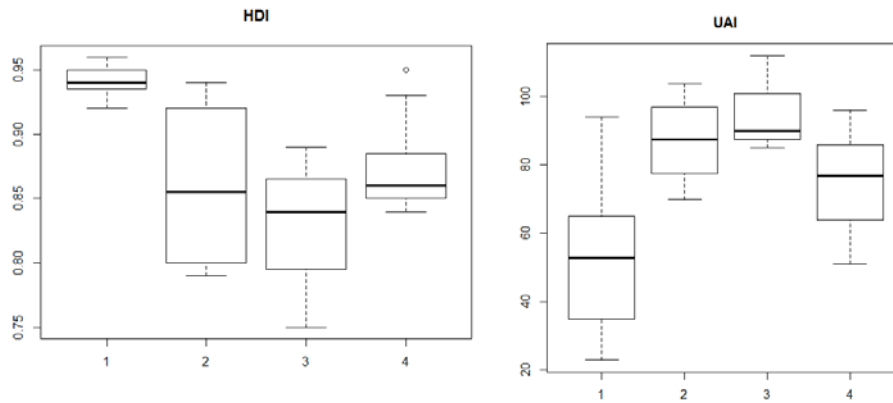


Figure 4: Box Plots for Human Development Index (HDI; $\eta^2=0.54$) and Hofstede's uncertainty avoidance index (UAI; $\eta^2=0.43$) for four science cultures across Europe 32+.

The UN's **HDI** is an index emphasizing the capabilities of the people for having a long and healthy life, being knowledgeable and having a decent standard of living as criterion for level of development of a country. It is widely reported and comprises indicators of life expectancy at birth, adult basic literacy rates, gross school enrolment, and GDP per capita. We are using data for 2003, close to our attitude data 2005. The HDI is an important policy indicator as it helps us to detect human development outcomes controlling for per capita income and thus contrast government policy priorities. (<http://hdr.undp.org/en/content/human-development-index-hdi>). HDI is an important candidate to understand the shaping of science culture as it includes information on schooling and life expectancy. Countries in cluster_1 tend to be higher on HDI compared to the other three clusters (see figure 4; $\eta^2 = 0.54$); the difference among those three clusters is not significant. Cluster 1 indeed groups most of Old Europe, which is highly development in economic and human development.

Cultural dimensions are prominent in comparative psychology which maps society and subsections of it into aggregate value profiles of individuals and shows how these values relate to organisational-productive behaviour (Hofstede, 1997). The **Uncertainty Avoidance Index (UAI)** represents one of several dimensions in this profile: individualism-collectivism; uncertainty avoidance; power distance (i.e. strength of social hierarchy) and masculinity-femininity (i.e. task orientation versus person-orientation). UAI reflects the extent to which a typical person feels uncomfortable with experiencing uncertainty and ambiguity. High UAI cultures maintain rigid mental codes and are intolerant towards unorthodox behaviour and unusual, unconventional ideas. We consider tolerance of uncertainty, low UAI scores, to indicate a disposition of openness for innovation. According to Merton (1973) organized scepticism is one of the institutional norms that define the ethos of modern science. Sometimes, expansion of scientific research may challenge established attitudes and values and the authority of established institutions. Low UAI enables such scepticism as the individuals tend to be more open and inclined to challenge traditional dogmas. UAI makes a difference for the smaller clusters 2 and 3 as compared to clusters 1 and 4 (see figure 4; $\eta^2 =$

0.43). What we identified as the love-and-hate ambivalence cultures, the utility-and-critical judgement of science is correlated with a tendency towards uncertainty avoidance and intolerance. People feel the love-hate relationship and seem to suffer from it at the same time. Further analyses of the data in these contexts might reveal a strong polarisation between opinionated and indifferent publics; this is not something we can demonstrate here.

F2: Regressing dimension PR on various predictor combinations (beta values)

$$\begin{array}{ll}
 PR = a - 0.61 * zHDI + 0.38 * zUAI & [adjR^2 = 0.73; n=34] \\
 PR = a - 0.59 * zIUS + 0.36 * zUAI & [adjR^2 = 0.69; n=34] \\
 PR = a - 0.52 * zPol_Cul + 0.43 * zUAI & [adjR^2 = 0.65; n=34]
 \end{array}$$

If we consider only the correlation of our model with the largest variability, the relational indicator PR, we find that the partial correlation with HDI is negative ($r = -0.73$) and with UAI it is positive ($r = 0.55$; $n=34$) on a regression model. Other predictors are not making any independent contribution due to multi-collinearity; they are strongly correlated to HDI, but their individual contribution can be compared as in F2 below, which shows that HDI and UAI are indeed the best predictors of promise and worry correlations.

We also examined the European Innovation Union index (IUS) and an index of political culture (Pol_Cul) in relation to our four science cultures (see appendix, figure A7). The pattern is similar to that of HDI: they distinguish cluster_1 from all other cultures of science.

Innovation Union Scoreboard (IUS) is a measure of innovation performance in EU Member States, other European countries, and regional neighbours. It assesses the relative strengths and weaknesses of innovation systems and helps countries identify areas they could address to improve innovation performance (<http://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards/>). Innovation must be related to people's attitudes toward science. Attitudes signal an environment of mentality that supports innovative activities in general and mostly likely also the investment in research and development (R&D). However, this impact is not very specific as yet as IUS and HDI are highly correlated for our 32+ countries. One might consider moving outlier countries Italy and Norway to cluster_4, and Luxembourg to cluster_1 to increase the fit on this criterion.

The democracy Indicators are compiled by the Economist Intelligence Unit and Freedom House measuring the state of democracy in 167 countries. The index is based on 60 indicators grouped in five different categories including pluralism, civil liberties, and political culture. Political culture (Pol_Cul) measures the level of anomie and the strength of democratic practice and is an indicator of the sustainability of democracy. Passivity and apathy, an obedient and docile citizenry do not go together with a democratic political culture (see <http://graphics.eiu.com/PDF/Democracy%20Index%202008.pdf>). Political culture refers to the process by which values are mobilised, made explicit and brought into public decision-making (Purcel et al. 2000). Complexity of scientific issues should not impede citizens from expressing their voice on moral concerns, questions of equity and access, and transparency and procedures in decision making. Therefore, people's attitudes towards science maybe related to a democratic political culture; we would assume that a wider culture of science reflects elements of the 'republic of science' where freedom of expression and evidence-based

argumentation, and tolerance for deviant opinion are core norms (Merton, 1973). And again, political culture as indicated here is highly correlated with HDI.

This co-variance analysis shows that our four classes of science culture is meaningful across Europe in terms of concurrent validation. The four cultures co-vary with indicators of socio-economic development on the one hand (HDI or IUS or Pol_Cul), and independently with the cultural disposition for uncertainty avoidance (UAI) on the other. Both types of predictors contribute independently to the core dimensions of science culture, namely the endorsement of utility and the critical assessment of science. Whether you love or worry about science, whether you love and worry, or whether you are indifferent, and whether familiarity and interest with science make any difference, is bound up with socio-economic development and with a general culture of uncertainty avoidance. As our classification of science cultures across Europe co-varies with these existing indicators, we have substantiated the claim for concurrent validity for our procedure.

4 Conclusions: the Subjective Levers of Performance

In this chapter we made the case for including subjective indicators of science culture as part of the drive to **broaden indicators of STI** in the context of global comparisons. Understanding culture requires grasping the material and mental conditions of performance. If relevant attitudes and its correlates can be measured and shown to be related to STI input and output activities, then the formation of subjective dispositions becomes another lever to potentially enhance the innovative performance of a country. The historical literature suggests that the relation between scientific performance and culture is not straight forward. Equally, we have shown that science culture indicators do not easily form a singular linear composite index but reflect associations that are potentially changing in time and space. This has important implications for developing an indicator systems for science culture concepts.

We developed a **rule-based abductive procedure** of data mining to construct indicators of mentality on the basis of existing streams of attitude to science data. To develop this procedures our focus was the Eurobarometer series between 2001 and 2010. Through several steps of examining items, missing values, exploratory and confirmatory factor analyses, we reached a refined 4D-model that includes **Promise, Reserve, Engagement and Knowledge** of science. Our operating principle states that the effective comparison of cultures of science does not reside in aggregate levels on these indicators, but in the relations between them. A **culture indicator ultimately relates relations**. Clustering these correlations across all units yields four Science Cultures across Europe, mainly grouping Old and New Europe, and two specifically characterised smaller groups of countries.

Our efforts show that **the old science literacy model** – the more you know, the more you appreciate it – is a special case and far from being universal, not even across Europe. Like with any model, the issue is less whether it is true or false, but what are the boundary conditions of its validity; overstepping that boundary is likely to lead to confusion and to misguided interventions. The basic scientific literacy model seems to make sense mainly in Old Europe which operates on either-love-it-or-hate-it in function of familiarity and interest in science. In this context, citizens cast either utilitarian judgements or are more fundamentally worried and critical. Our analysis puts this model into perspective, and at the same time specifies alternative configurations of indicators. In addition, we identified two versions of a

culture of science where an ambivalent **love-hate relationship** (odi et amo ...) is the characteristic feature. In one type of these, knowledge drives acceptance of the promise of science and at the same time the harbouring of reservations. In the other type, knowledge is much less of a driver; judgements seem to be ambivalent sui-generis. Finally, we identified a fourth culture, mainly but not exclusively in New Europe, where the literacy model is evident, but flat and less constraint, tending towards **anything goes**. Worries or optimism about science combine freely with familiarity and interest, ignorance and indifference; the anything goes mentality seems to be the prevailing mentality, where all four dimensions of our model are independently used to position oneself vis-à-vis science.

Validating this four-fold classification of cultures of science shows that the UN's HDI and Hofstede's uncertainty avoidance index are independent correlates of this diversity. HDI separates the 'literacy type' from all other types, while uncertainty avoidance is a characteristic of the 'love-hate' type in contrast to either-love-it-or-hate-it or anything goes. The difference between the constraint literacy model of Old Europe and the weaker 'anything goes' model of New Europe could be a additional third gradient on cultural 'Masculinity' (according to Hofstede), however, this correlation needs further examination.

We have undertaken this exploration of science cultures with European data, and in the effort we developed a model of regionally fixed parameters to capture the diversity-in-unity of science. This reflects our starting point that science is a global affair, but science culture remains bound by morality and local common sense. Future work within our immediate reach will extend these analytic procedures to data curated on the Indian subcontinent, in mainland China and across North and Latin America (project MACAS <http://www.macas-project.com/>). Guidelines for an indicator system of science culture need to define, beyond the collection of data through questionnaires and representative sampling designs, also the analytic procedure for detecting science cultures on the operating **principles of 'relating relations' and 'diversity-in-communality'**. We see two immediate implications of this argument. First, it will help policy makers to understand better the contextual features of science cultures between and within their country, and help them to concentrate on targeted policy rather than assuming a one-dimensional and universal policy space called 'scientific literacy'. Culture indicators will enhance the fine-tuning of interventions beyond any self-defeating logic of 'one shoe fits all'. Subjective science culture is most likely a 'mediator' between input and output of innovation. Future work will have to concentrate on an input-output mediator models to guide policy intervention. Secondly, the explicit statement of our analytic operating principle of 'relating relations' and 'diversity-in-communality' will avoid the difficulties which have hampered earlier attempts to globalise indicators of science culture. Previous attempts to 'globalise' a local, mainly US-EU model through premature standardisation have over the past 30 years created much resistance and difficulties for collaborations in collecting and analysing data on attitudes to science. A culturally circumspect and context sensitive approach is required for making progress in understanding the innovation process.

This study is a good beginning but has limits in so far as we have not yet concentrated our efforts on the analysis of mediating model between 'hard' traditional STI performance indicators and 'soft' cultural indicators of attitudes. Future studies will have to focus on the associations between these different classes of indicators to examine and explain the differences in contexts. Work on this complex task remains piecemeal and unfinished, but with large amounts of data at hand, and the right approach in mind, we might well have real progress within reach.

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Appendices

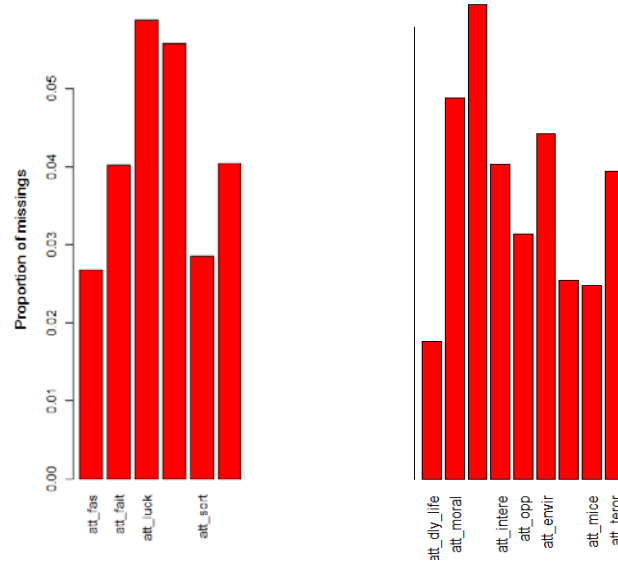


Figure A1: ratios of missing values for different evaluation-attitude items in EB2010

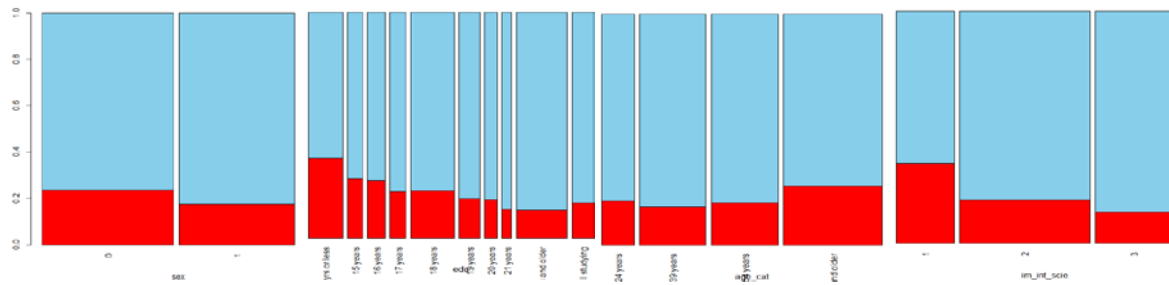
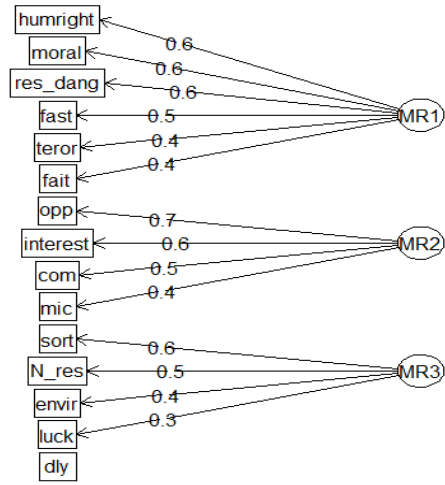
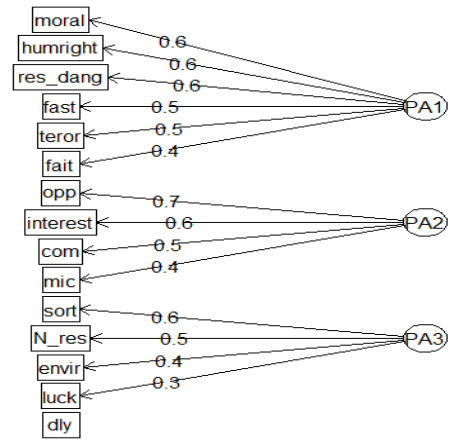


Figure A2: Spinogram: sex, education, age, interest in science (EB 2010)

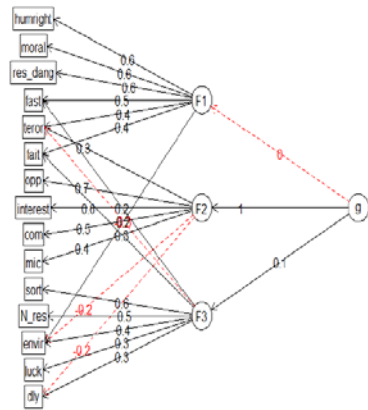
Minimum residuals



Principal components



Omega



ICluster

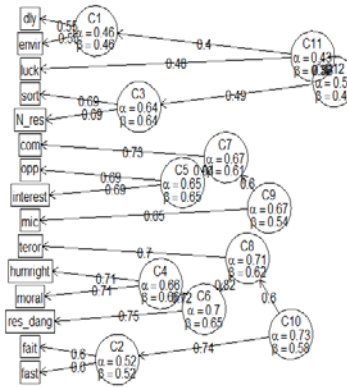


Figure A3: different structural solutions for evaluation-attitude items (data EB 2010)

	2001/02						2005						Squared differences						Average
	PR	PE	RE	PK	RK	EK	PR	PE	RE	PK	RK	EK	PR	PE	RE	PK	RK	EK	
AT	0.05	0.34	-0.33	0.28	-0.19	0.83	-0.01	0.47	-0.14	0.22	-0.22	0.41		0.02	0.04			0.17	0.04
BE	-0.22	0.68	-0.25	0.29	-0.43	0.70	-0.17	0.29	-0.20	0.05	-0.39	0.42		0.15		0.06		0.07	0.05
BG	0.13	0.38	0.06	0.13	-0.08	0.78	0.47	0.48	0.13	0.34	0.10	0.74	0.11	0.01	0.01	0.04	0.03		0.03
CH							-0.24	0.32	-0.25	0.05	-0.24	0.39							
CY	0.18	0.09	0.00	-0.06	-0.06	0.73	0.52	0.26	0.23	-0.12	0.12	0.53	0.11	0.03	0.05		0.03	0.04	0.05
CZ	0.22	0.29	-0.11	0.21	-0.35	0.38	0.05	0.22	-0.05	0.10	-0.21	0.41	0.03			0.01	0.02		0.01
DE-E	-0.01	0.10	-0.35	0.04	-0.34	0.63	-0.09	0.53	-0.18	0.14	-0.35	0.43	0.01	0.19	0.03	0.01		0.04	0.05
DE-W	-0.30	0.27	-0.20	0.13	-0.35	0.74	-0.15	0.39	-0.23	0.16	-0.37	0.61	0.02	0.01				0.02	0.01
DK	-0.44	0.27	-0.91	0.02	-0.75	0.77	-0.28	0.17	-0.37	0.10	-0.44	0.55	0.03	0.01	0.29	0.01	0.1	0.05	0.08
EE	-0.08	0.19	-0.14	0.02	-0.33	0.45	-0.02	0.10	-0.15	-0.03	-0.18	0.49		0.01			0.02		0.01
ES	0.26	0.42	0.02	0.15	-0.25	0.56	0.23	0.29	-0.07	0.13	-0.14	0.48		0.02	0.01		0.01	0.01	0.01
FI	-0.20	0.40	-0.42	0.29	-0.47	0.81	-0.24	0.30	-0.35	0.10	-0.37	0.53		0.01		0.04	0.01	0.08	0.02
FR	-0.33	0.49	-0.34	0.17	-0.45	0.66	-0.17	0.22	-0.18	-0.06	-0.39	0.50	0.03	0.07	0.03	0.05	0	0.03	0.03
GB-GBN	-0.44	0.32	-0.59	0.13	-0.58	0.90	-0.17	0.19	-0.23	-0.06	-0.38	0.49	0.07	0.02	0.13	0.04	0.04	0.17	0.08
GB-NIR	-0.11	0.55	-0.59	0.43	-0.56	0.92	-0.10	0.30	-0.30	0.14	-0.35	0.55		0.06	0.08	0.09	0.04	0.14	0.07
GR	0.38	0.20	0.07	-0.14	-0.05	0.46	0.43	0.23	0.15	-0.05	-0.02	0.50			0.01	0.01			0.00
HR							0.29	0.38	-0.05	-0.02	-0.23	0.65							
HU	0.05	0.16	-0.25	0.01	-0.52	0.77	0.16	0.22	-0.12	0.07	-0.19	0.66	0.01		0.02		0.1	0.01	0.03
IE	-0.21	0.41	-0.57	0.00	-0.51	0.73	-0.29	0.32	-0.29	0.13	-0.40	0.52	0.01	0.01	0.07	0.02	0.01	0.04	0.03
IS							-0.22	0.25	-0.12	0.06	-0.33	0.41							
IT	-0.03	0.31	-0.44	-0.06	-0.59	0.72	0.21	0.26	-0.17	0.10	-0.32	0.55	0.06		0.08	0.03	0.07	0.03	0.04
LT	-0.04	0.19	-0.34	0.06	-0.45	0.50	0.06	0.20	-0.18	0.16	-0.20	0.43	0.01		0.03	0.01	0.06		0.02
LU	-0.03	0.14	-0.50	-0.02	-0.55	0.61	0.17	0.23	-0.25	-0.10	-0.49	0.37	0.04	0.01	0.06	0.01		0.06	0.03
LV	0.05	0.23	0.01	0.04	-0.21	0.43	0.35	0.13	-0.01	-0.01	-0.20	0.32	0.09	0.01				0.01	0.02
MT	0.01	0.09	-0.32	-0.09	-0.41	0.59	0.18	0.18	0.00	-0.04	-0.11	0.73	0.03	0.01	0.1		0.08	0.02	0.04
NL	-0.36	0.27	-0.45	0.08	-0.46	0.76	-0.15	0.23	-0.35	0.10	-0.50	0.51	0.04		0.01			0.06	0.02
NO							-0.20	0.17	-0.25	0.04	-0.30	0.42							
PL	0.12	0.21	-0.17	0.02	-0.34	0.48	0.21	0.16	-0.17	0.16	-0.19	0.56	0.01			0.02	0.02	0.01	0.01
PT	0.19	0.34	-0.22	0.08	-0.21	0.72	0.16	0.52	-0.08	0.31	-0.14	0.70		0.03	0.02	0.05	0.01		0.02
RO	0.07	0.15	-0.19	0.07	-0.35	0.76	0.28	0.60	0.01	0.39	-0.15	0.75	0.04	0.2	0.04	0.1	0.04		0.07
SE	-0.34	0.24	-0.53	0.02	-0.49	0.65	-0.31	0.25	-0.29	0.04	-0.32	0.47			0.05		0.03	0.03	0.02
SI	-0.13	0.18	-0.15	-0.14	-0.42	0.62	-0.08	0.22	-0.06	-0.13	-0.40	0.25			0.01			0.13	0.02
SK	0.25	0.43	0.01	0.09	-0.27	0.53	0.30	0.27	0.03	0.12	-0.10	0.46		0.03			0.03	0.01	0.01
TR	0.29	0.08	-0.01	-0.14	-0.16	0.32	0.80	0.35	0.16	-0.14	-0.14	0.49	0.26	0.07	0.03			0.03	0.06
Total	-0.03	0.28	-0.27	0.07	-0.37	0.65	0.06	0.29	-0.13	0.07	-0.25	0.51	0.03	0.03	0.04	0.02	0.03	0.04	0.03

Table A1: the correlation matrix among basic indicators for each country 2001/02 and 2005

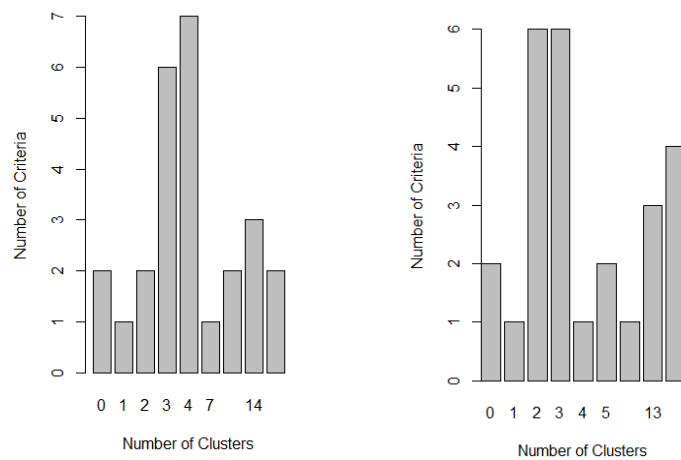


Figure A4: Optimal cluster numbers

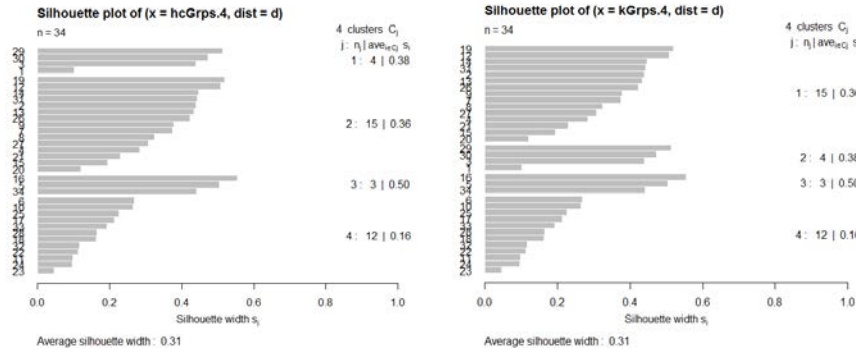


Figure A5: two overlapping cluster solutions: silhouette plots of hierarchical analysis on the left, k-means analysis on the right

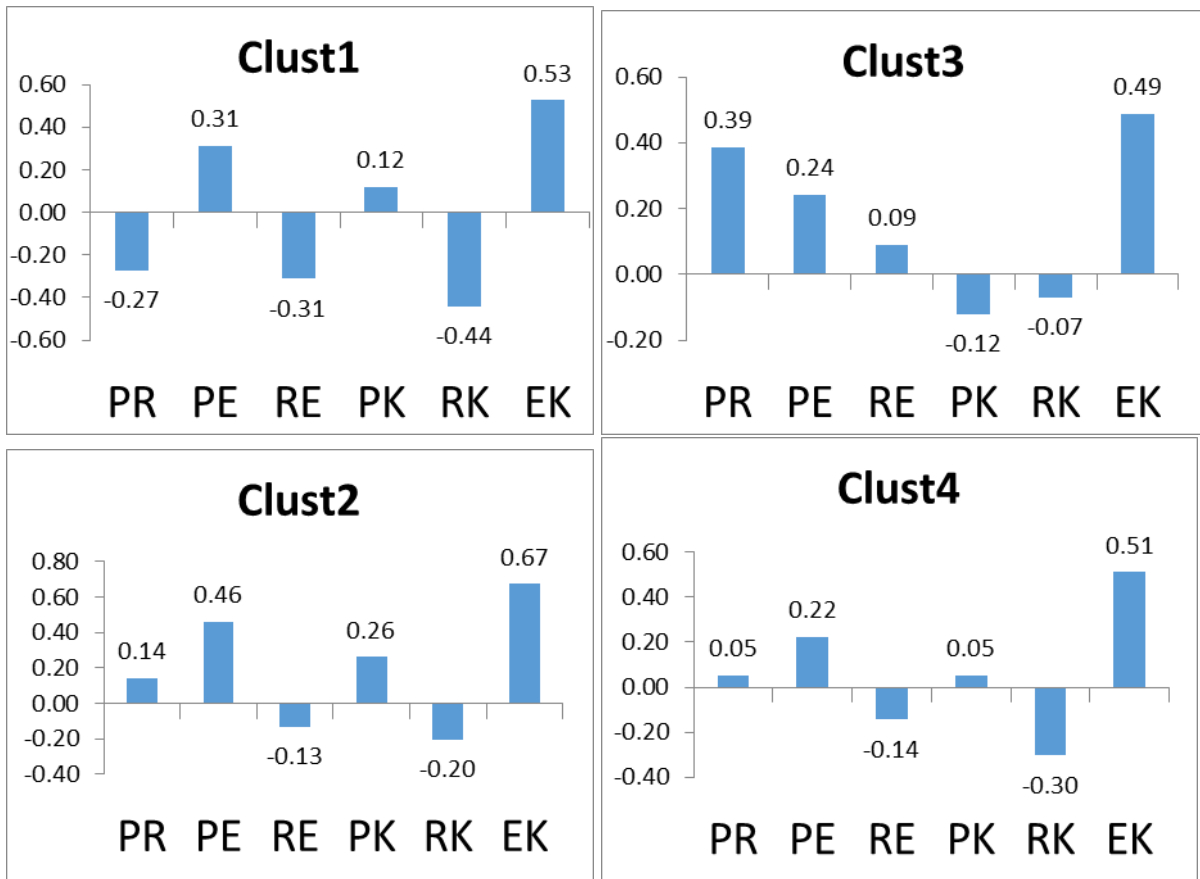


Figure A6: Correlation profiles between the four dimensions on each cluster which underlie the z-value profiles reported in Figure 2 in the text.

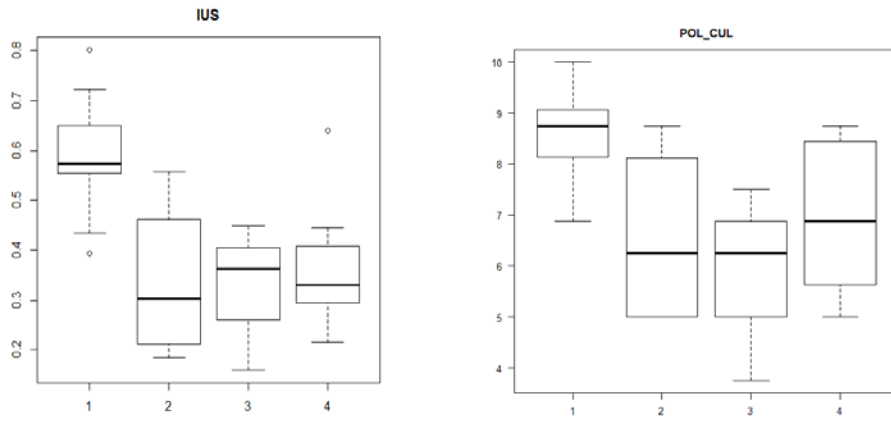


Figure A7: Box plots for European Union Innovation Scoreboard (IUS) and Freedom House-Economist Political Culture index (Pol_Cul) for the four culture of science. The pattern is the same as with HDI. HDI, IUS and Pol_Cul are highly correlated.