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Nick Allum, Patrick Sturgis, Dimitra Tabourazi and Ian Brunton-Smith

The correlation between knowledge and attitudes has been the source of controversy in research on the public understanding of science (PUS). Although many studies, both quantitative and qualitative, have examined this issue, the results are at best diverse and at worst contradictory. In this paper, we review the evidence on the relationship between public attitudes and public knowledge about science across 40 countries using a meta-analytic approach. We fit multilevel models to data from 193 nationally representative surveys on PUS carried out since 1989. We find a small positive correlation between general attitudes towards science and general knowledge of scientific facts, after controlling for a range of possible confounding variables. This general relationship varies little across cultures but more substantially between different domains of science and technology. Our results suggest that PUS research needs to focus on understanding the mechanisms that underlie the clear association that exists between knowledge and attitudes about science.

1. To know science is to love it?

There has been no fiercer debate in the public understanding of science (PUS) than the one that centers on the contested relationship between public opinion and public knowledge about science and technology. In fact, one might legitimately characterize this as the fundamental question upon which work in this area concerns itself, albeit with a variety of substantive foci and methodological approaches. The main driver behind this research program at the outset was the need—at least as it was perceived by scientists and governments—to understand why publics in North America and Europe were becoming more skeptical about science as a "force for good." With this heightened state of public suspicion and anxiety about science and scientists rose the specter of major cuts in the funding of scientific programs of various kinds (Miller, 2004).

One of the key insights from the programs of research that were set in train in the 1980s is that both European and American publics possess low levels of basic "textbook" knowledge about science. For some, findings of this nature are taken as strong empirical confirmations of the existence of a "scientifically illiterate" public and provide the first pillar in the construction of the pervasive "deficit model" of public understanding of science (Irwin and Wynne, 1996; Sturgis and Allum, 2001). The deficit model sees public resistance to science and technology

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as underpinned by ignorance, superstition and fear. Public skepticism about technological innovations such as nuclear energy, microwave cooking and genetic science would be markedly reduced if citizens were better able to grasp the science upon which they are based. That is, a judgment when informed by scientific fact would tend to be more favorable and consistent with expert opinion than one expressed without recourse to such "objective" knowledge. Since the late 1980s, much academic debate has focused on examining and understanding the link between knowledge and attitudes about science. More recently, though, other factors have been proposed as providing the basis for understanding public attitudes to science and technology. Foremost amongst these is social and political trust—in scientists, regulatory authorities and industry (Grove-White et al., 2000; Priest, 2001; Wynne, 2001).

Yet, despite this concentration of effort on exploring the knowledge–attitude nexus, there remain more puzzles than certainties; more disagreement than consensus. Part of the reason for this present state of affairs is perhaps due to the way in which particular methodological approaches have become linked to, almost synonymous with, particular substantive positions (Einsiedel, 2000; Sturgis and Allum, 2004). Hence the quantitative survey method becomes synonymous with the "deficit model" and ethnographic studies inevitably emphasize the importance of "lay local" knowledge (Irwin and Michael, 2003). But even if one were to abandon the goal of distilling results from across the methodological divide into some kind of coherence, there is still confusion within these rather separate traditions as to how one should characterize what we know so far.

In this paper, we present an empirically based summary of what is known from the quantitative data thus far gathered. We review the evidence on the relationship between public attitudes and public knowledge about science and technology from the multitude of national surveys that have been carried out across the world during the past fifteen years in Europe, North America and beyond. We go beyond a simple summary to present a model that helps systematize the apparent diversity of findings in the existing PUS literature. More specifically, we firstly evaluate the associations between particular forms of scientific knowledge and particular attitude domains; secondly, we control for a range of possible confounding variables across all our analysis; thirdly, we estimate disparities between countries in the knowledge–attitude relationship and employ macro-level predictors that might explain these disparities.

The relationship between knowledge and attitudes to science

The correlation between knowledge and attitudes is the key parameter in PUS research. Of the many studies in this canon, most (e.g. Bauer et al., 1994; Grimston, 1994; McBeth and Oakes, 1996; Miller et al., 1997; Sturgis and Allum, 2000, 2001) consider what one might call "generalized" attitudes towards science. The empirical evidence from most of these studies points to a weak correlation between knowledge about scientific facts and processes and positive attitudes towards science. However, there is evidence that this link is weaker, and may sometimes be negative, for attitudes to specific technologies. Evans and Durant (1995) find, in the UK, that whilst "textbook" knowledge of general science is positively correlated with favorable attitudes to science in general, for specific technologies or scientific fields, a variety of correlations are found, including a negative one for morally contentious science such as human embryo research. Another example of what Durant and colleagues term the "chaotic" relationship between knowledge and attitudes is in relation to biotechnology. Perceptions of the "riskiness for society" of medical applications of biotechnology are greater amongst those who are less interested and knowledgeable about genetics. By contrast, in the case of agricultural biotechnology and genetically modified food, no such differences are found (Gaskell et al., 2001). In the US, Priest shows that knowledge of genetics is positively related to encouragement for biotechnology, even controlling for a range of other social psychological variables, notably institutional trust (Priest, 2001). Martin and Tait (1992) find that high levels of knowledge are related to both highly positive and highly negative attitudes towards agricultural biotechnology, suggesting that knowledge may sometimes be a predictor of the strength of attitudes rather than their valence (Pardo and Calvo, 2002). This is also the conclusion of Evans and Durant, who factor analyze a set of attitude items, stratifying by levels of scientific knowledge. The greater the level of knowledge, the more variance is explained by the common factors, indicating greater attitudinal consistency amongst the better informed (Evans and Durant, 1995). Hayes and Tariq find that scientific knowledge is a predictor of positive attitudes to science, despite controlling for a range of other variables, in particular gender (Hayes and Tariq, 2000, 2001; also see Sturgis and Allum, 2001). Overall these results tend to show that people who are more scientifically literate have more positive attitudes to science in general, but are not necessarily more positive about specific technological applications or specialized areas of scientific research.

Culture, knowledge and attitudes to science

Eurobarometer and other surveys conducted over the past fifteen years have afforded the opportunity for cross-cultural comparisons of attitudes and knowledge about science (European Commission, 2001; INRA, 1993). Empirical results from these surveys suggest that there is a good deal of diversity across Europe, North America and other parts of the world in public attitudes towards science and perhaps even greater variation in levels of science literacy. However, this fact alone does not necessarily imply that there is heterogeneity in the strength of association between these two constructs across cultures. On the one hand, one might posit invariant social psychological mechanisms that account for the correlation between informedness and attitudes. On the other, social, political and cultural disparities between nation states might plausibly affect the relationship in fundamental ways.

Bauer and colleagues have developed cross-cultural models based on this notion. Their research suggests, firstly, that there is indeed variation in the strength of this correlation across European countries and, secondly, that this variation can be explained by differences in national or regional socioeconomic conditions (Allum et al., 2002; Bauer et al., 1994; Durant et al., 2000). In this view, the shift from industrial to post-industrial society (Inglehart, 1990) is accompanied by changes in the relation between science, society and the public. At the industrial stage of development, science is idealized as the preferred route to economic expansion and social emancipation and the more citizens know about science, the more their attitudes conform to this stereotype. In post-industrial societies, science is taken for granted, knowledge becomes more specialized and a more skeptical and questioning public views science with greater suspicion, while expecting it to continue to deliver prosperity. In this situation, more knowledge can equally lead to greater skepticism as to optimism, due to the lack of a positive cultural stereotype for science. Operationalizing these concepts, Bauer et al. find a curvilinear relationship between the strength of the knowledge–attitude correlation at the country level, with a measure of gross domestic product (GDP). The correlation is lowest in countries that are most economically advanced and also in those countries that are least developed. High correlations are found for an intermediate group of European countries. While suggestive, these models suffer from the small number of data points on which they are based (only eleven countries in the original 1994 paper) and the aggregate nature of the analysis.

In contrast to this picture of heterogeneity, Miller et al. (1997) compare attitudes and knowledge about science and technology in Europe, the US and Japan. In this work, Europe is treated as a single entity, which is, perhaps, a less than realistic assumption. However, notwithstanding this, Miller et al. fit a series of structural equation models of the determinants of attitudes and show little difference across these three cultures in the contribution of knowledge to the formation of public opinion. That the approaches of Bauer et al. and Miller et al. lead to divergent conclusions about cross-cultural differences in the knowledge–attitude correlation underlines the need for a more integrated and inclusive approach to the problem.

2. Measuring knowledge and attitudes

Measurement of these constructs in surveys has a long history and one that is not without its share of contentiousness. Since the seminal study of Davis (1958), the idea that it is possible to assess the distribution of general scientific knowledge in mass publics has gained currency. Following on from this early study, the National Science Foundation (NSF) began, in the US during the late 1970s, a series of surveys of public attitudes and knowledge about science and technology as part of its "Science Indicators" program. A variety of techniques for measuring knowledge about science were implemented in the early surveys, based mainly on self-reports, but in 1988, following collaboration between Jon Miller in the US and John Durant and colleagues in Britain, a series of factual quiz type questions that tapped "textbook" knowledge of science were developed (Durant et al., 1989; Miller, 1998). Known as the "Oxford Scale," these items, or various subsets, have been employed in a large number of public opinion surveys about science and technology ever since. The items are intended to capture one or more dimensions of what Miller refers to as "civic scientific literacy" (Miller, 1983, 1998). These dimensions are indicative of an understanding of the content of science (scientific facts), the processes of science (scientific method) and—although this dimension has rarely been measured—an understanding of the impacts of science and technology on society. Batteries of these items are usually administered by asking respondents to say whether they think a statement is "true," "false" or that they "don't know" the correct answer. Most of the true/false items tap what might be termed "textbook" type knowledge across a range of scientific domains, for example "antibiotics kill viruses as well as bacteria," "the center of the earth is very hot" and "all radioactivity is man-made."

Detailed examinations of these items, their measurement properties and conceptual adequacy, have been published by Miller (1998) and in a recent article by Pardo and Calvo (2004). According to the latter, the Oxford items have some methodological problems: low scale reliability (as measured by Cronbach's Alpha); some deficiency in cross-cultural equivalence (Peters, 2000); attenuated ability to discriminate between respondents owing to a preponderance of rather "easy to answer" items. In our view, these criticisms certainly carry some force. On the other hand, as Pardo and Calvo themselves admit, the Oxford items remain useful as approximate measures that capture variation in the distribution of scientific literacy across individuals, social groups and cultures. This conclusion is borne out by past studies that have utilized the Oxford items or scales derived from similar types of scientific knowledge quiz questions (Durant et al., 1989; Evans and Durant, 1995; Gaskell et al., 1999, 2001; Sturgis and Allum, 2001, 2004). In this paper, we only consider factual knowledge items and not those that relate to scientific method as these are not present in all the surveys we analyze here. Although this may limit the generality of the results to some extent, we are reassured by the moderate to high correlations between these dimensions that have been reported in previous work (e.g. Evans and Durant, 1995) and we have no reason to expect fundamental differences in patterns of association for factual and method scales.

Many surveys that assess citizens' scientific knowledge also carry batteries of items tapping their attitudes to science and technology. There is a good deal more heterogeneity in the range of attitudinal items that have been employed because of the varying substantive foci of particular surveys. Broadly, we distinguish between two types of question. The first kind encompasses those that elicit general orientations or dispositions towards science and technology and its social impacts. For example, respondents are asked how much they agree or disagree that “science and technology are making our lives easier and more comfortable” and that “science makes our way of life change too fast.” Both of these items, along with several others tapping the same type of generalized attitudes and beliefs, first appeared in the National Science Foundation’s Science and Engineering Indicators Survey series during the early 1980s (Miller, 2004) and have been used in many surveys since then, both in the US and elsewhere. The second variety of attitudinal question asks people’s views about particular scientific issues or specific technological applications. Whilst there are a large number of different domains of science and technology on which public opinion has been gathered, the most commonly (and comparably) asked questions for present purposes concern agricultural biotechnology, the environment, nuclear energy and genetic medicine.

As with the knowledge questions described earlier, attitude items such as these are not without their problems. Most of the criticism that has been made in this area concerns the general attitude questions. Although designed to elicit overall orientations towards organized science, they may suffer from being too general. This is in the sense that people will answer in idiosyncratic ways because there is no unequivocal focus in the wording of an individual question. Thus, some people may respond to a question that asks about the contribution of science and technology to modern life thinking about nuclear power, while others respond on the basis of their views about mobile phones. Of course, this lack of “invariance of meaning” is not a difficulty that is unique to PUS surveys. It is certainly well-known in political science (Bishop, 2005). However, the problem of individual items being interpreted in a variety of different ways is mitigated to some degree by aggregating responses from conceptually related items into a metric scale. In so doing, idiosyncratic, random variations in interpretation are “smoothed out” and a common core of meaning brought to the fore. Whilst this may seem obvious to those familiar with social psychological measurement, it has sometimes been lost on skeptics of survey methods in PUS whose critical focus tends to be directed towards the meaning of individual questions in isolation, rather than on the construct validity of aggregated scales (e.g. Irwin and Michael, 2003). Having said that, the attitude scales that have been used in the NSF and Eurobarometer surveys are based on a somewhat ad hoc mixture of items, some of which go back to the original 1959 study (Withey, 1959). In an article in this journal, Pardo and Calvo (2002) present a reanalysis of the 1992 Eurobarometer survey on PUS that suggests that there is, without doubt, a good deal of “fuzziness” in the various attitude scales that have been put to use by researchers over the years. They suggest more methodologically stringent and theoretically informed design for future attitudinal studies, whilst acknowledging that, as in the case of the knowledge scales, the existing measures are useful, if somewhat blunt, tools.

So, whilst we accept that the measures of knowledge and attitudes that we employ in this study are not without their flaws, the evidence suggests that they are fit for purpose. At all events, we would argue that our strategy in this paper, of pooling information from as many diverse measures as possible, is the most effective way to mitigate measurement error problems that might arise.

3. Towards an improved empirical foundation

So far, this brief review of the empirical research concerning the so-called “deficit model” of PUS has shown that a simple, positive, linear relationship between attitudes and knowledge about science under all circumstances is an over-simplification. Yet there is also plenty of evidence that knowledge, information and awareness can and do affect the way citizens relate to science and technology in differing contexts. That it is important to understand the contexts in which knowledges of various kinds are brought to bear on judgments about science and technology is a case that has been forcefully made by critics of early survey work on PUS (e.g. Irwin and Michael, 2003; Michael, 1996, 2002; Wynne, 1996). It is perhaps therefore surprising that there has been relatively little in the way of constructive engagement with this notion using the wealth of available survey data that has accrued up until now. Instead, there appears to have developed a bifurcation in theoretical and empirical research along largely methodological lines, with little cross-fertilization of ideas (see Sturgis and Allum, 2004 for a more focused discussion on this point).

We consider that there are several aspects of this debate that could be clarified by enlisting all the available survey evidence to elaborate on a simplistic linear deficit model. Firstly, although there are many studies that show positive correlations between general attitudes and knowledge, little systematic evidence exists about the association between different subsets of scientific knowledge (e.g. genetic, environmental) and specific technologies (e.g. biotechnology, nuclear power). Secondly, not all published studies report correlations net of possible confounding variables like education and gender, without which any causal explanations must be viewed with particular suspicion. Thirdly, little is known about cross-cultural variation in the strength of correlations outside of Europe and the US and what might account for such variation if it is present. All three of these issues are addressed in the present study by adopting a meta-analytic approach. This allows us to combine the results from the large number of nationally representative survey datasets that have been compiled over the past fifteen years or so. In doing this, we not only arrive at a single composite estimate of the knowledge–attitude correlation in which we are most interested but we can also go some way to identifying the correlates of heterogeneity in this estimate across time and culture.

4. Data and methods

Meta-analysis

Meta-analytic techniques see effect sizes estimated from single studies as units drawn from a hypothetical population of possible studies. As such, relying on single studies for effect size estimates relies on the unlikely event that the single study is representative of all possible studies that could have been sampled from this population (Rosenthal, 1991). Thus the basic objective of meta-analysis is to provide pooled estimates of effect sizes through a weighted average of the effect sizes of the individual studies, with sampling variances calculated as a function of the sample size of each individual study.

A key aspect of any meta-analysis, therefore, is to conduct a thorough search of all published studies which should then be included in the pooled estimate (Wolf, 1986). We take a slightly different approach here. Rather than use results from published studies, we directly analyze the substantial number of public domain datasets on which most of the published studies have been based. This approach, we believe, brings with it two considerable advantages. First, not all published studies include the same, or even comparable, control variables in their analyses. Taking the raw data allows us to use the same control variables for each dataset and to choose ourselves the most comparable items to use in the knowledge and attitude scales. Second, there are many more datasets than there are published studies. We therefore achieve a much greater coverage of the population of effect sizes and mitigate the "publication bias" that increases the probability of Type I errors (Sterling et al., 1995). This is a problem that can make meta-analyses prone to overestimating effect sizes where the data are collected solely from published work (Thornton and Lee, 2000).

Typically, each separate study in a meta-analysis has particular idiosyncrasies that complicate the interpretation of the final pooled effect size. It is highly likely that there are, in most instances, systematic causes of between-study heterogeneity as well as variation due to sampling error alone. Indeed, we know this to be the case here: different datasets make use of different measures of knowledge and attitudes, different data collection modes and fieldwork agencies, to name just a few reasons to expect systematic differences between them. Some of these—like "house interviewer" effects for example—we simply treat as nuisance factors to be partialed out of our analysis. Others, though, such as the type of attitude and knowledge measures that appear in different surveys, constitute more interesting sources of heterogeneity, estimates of which speak directly to our substantive concerns.

Extending the meta-analytic framework using multilevel models

Multilevel analysis is common in educational research, where the natural structure of the data is typically hierarchical. In order to model the effect of say, parental social class on educational achievement in a sample of 16 year olds from a sample of classes within a sample of schools from a sample of areas across the country, it is unrealistic to treat each pupil as an independent analytic unit. Rather, pupils who share the same class, school or area will likely be more similar to each other than pupils drawn randomly from the population as a whole. Multilevel modeling (sometimes called hierarchical modeling) is a regression-based technique that takes account of these "nested" structures and provides efficient estimates of model parameters. It also permits the decomposition of variance across nested levels so that one can evaluate the relative importance of, say, class, school and area in accounting for variation in individual level outcomes. Finally, covariates can be introduced at each level to explain variance in individual outcomes owing to effects operating at these higher levels (Bryk and Raudenbusch, 1992). The structure of our meta-analytic dataset, represented in Figure 1, follows this hierarchical configuration.

We estimate one or more effects within each survey, depending on how many types of knowledge and attitude measures are included in each survey. These are at our lowest hierarchical level (shown in Figure 1 as Eff1, Eff2 at Level 1). Thus "survey" constitutes the second hierarchical level in our data (for example, "Eurobarometer" and "British Social Attitudes" at Level 2). Finally, each survey is fielded in a particular country (for example Britain and United States at Level 3). Hence we have a nested structure of the following order: effects within surveys within countries.

Research design

Our data collection and analytic methods took the following form. First, we made a comprehensive search for data sources and assembled a large number of raw survey datasets. Second, we derived a number of comparable knowledge and attitude scales in each survey (hereafter we refer to each national survey as a "sample"). Third, we ran ordinary least square (OLS) regressions of knowledge on attitudes, with additional control variables, for each sample. This yielded effect size estimates in the form of standardized partial regression coefficients of knowledge on attitude. Fourth, we compiled a new dataset that included these effect sizes, their standard errors and a range of other higher level variables relating to the year of the study, country, length of attitude scale and some aggregate country level variables such as GDP per capita and proportion of 18–24 year olds in tertiary education. Finally, this composite dataset was analyzed using MLwiN 2.0 (Rasbash et al., 2004).

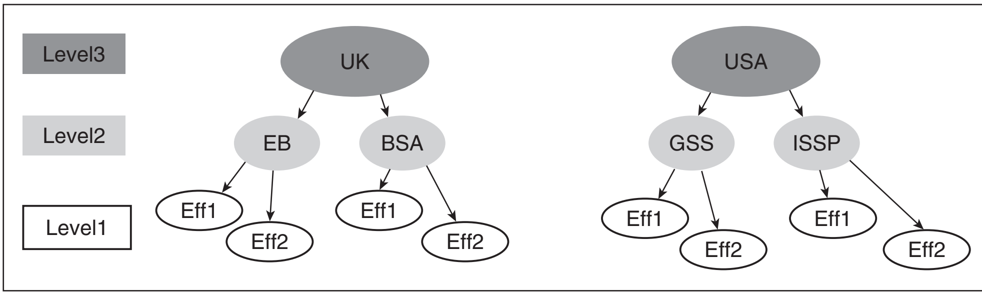

Figure 1. Multilevel structure of meta-analytic data.

Search strategy

In the first stage of the research, we conducted a systematic search of the literature via electronic sources. These included ISI Web of Knowledge, BIDS, Ingenta, MEDLINE, Psi-Com and the search engine Google. In order to identify relevant raw data, a range of other databases and websites around the world were used. These included ICPSR (Inter-University Consortium for Political and Social Research) and UKDA (UK Data Archive), NSF (National Science Foundation), Eurobarometer, Council of European Social Sciences Data Archives, CEORG (Central European Opinion Research Group) and NESSTAR (Networked Social Science Tools and Resources). Because results of searching these electronic databases are sensitive to the way queries are formed, we used a large number of keywords to ensure wide coverage. Eighteen were used: "public," "science," "knowledge," "citizens," "understanding," "technology," "survey," "biotechnology," "awareness," "environment," "risk," "perception," "measurement," "genetic," "literacy," "opinion," "engineering" and "attitudes." Keywords were separated by the words OR or AND. In addition, different forms of the same word were used. Usually this required the typing of a symbol such as an asterisk at the end of the stem of the word. This allowed all forms of the word to be included in the search results. The completion of this stage of the selection procedure resulted in approximately 300 articles, reports and datasets that appeared to have prima facie relevance to the concerns of our study.

In the second stage, the criteria for inclusion in or exclusion from the meta-analysis sample were specified. Each article or report obtained in stage one was manually searched and evaluated according to more specific criteria. Only articles relating to national surveys with random sample designs were retained. Within these, only surveys that included measures of knowledge and attitudes were eligible for inclusion. From this pool of articles and other documents we were able to identify the final list of datasets to be used in the analysis. Despite taking a systematic and comprehensive approach, it is possible, of course, that we have missed some eligible datasets. However, owing to the procedures employed, and our own knowledge of the field, we are satisfied that we have included in our analysis the vast majority of relevant and available data at the time of writing.

Datasets and measures

We obtained 193 samples of data from our search procedures that contain the required measures for the meta-analysis. This number treats each country's sample within an international dataset, such as Eurobarometer or ISSP, as a separate entity. These samples are spread across 40 separate countries and span 15 years of data collection from 1989 to 2004. All selected samples are based on random designs and aim to represent the general national population in each country, although there is uncertainty over response rates and sampling procedures in each country, owing to a lack of complete documentation. For example, in the case of the Eurobarometer surveys, a face-to-face multistage clustered design is employed while random digit dial telephone samples are used in most of the US studies.

We found that the knowledge items included across the 193 samples could be categorized as falling into two distinct types of scale: general textbook scientific knowledge (variants of the Oxford scale) and scales tapping knowledge of biology and genetics (including items such as "ordinary tomatoes do not contain genes, while genetically modified tomatoes do"). This reflects the fact that there are a relatively large number of public attitude surveys on biotechnology. It was also, in some cases, possible to create scales that tapped knowledge about environmental science, but these were too few in number for inclusion as predictors in separate effect size estimates in the meta-analysis. The two types of knowledge scale are made up of between four and ten items, with each sample yielding either a biotechnology or a general knowledge scale, but not both.

The attitude items included in the 193 samples could be grouped into five substantive areas. The scales we derive measure views about 1) science in general, 2) nuclear power, 3) genetic medicine, 4) genetically modified food, and 5) environmental science. Where possible, multiple indicators have been used to reduce the potential error associated with single item measures. However, to maximize the potential number of effect sizes available for analysis, these measures were not exclusively derived using multiple indicators.

The scales were derived as mean scores across items, with scale length ranging from one to twelve items. A summary of these scales, along with some indicative examples of the items used to generate them, is presented in Table 1. Having created these scales for each sample, we were then able to estimate effect sizes for each sample. For some samples, for which more than one attitude scale was available, multiple effect sizes could be estimated. The distribution of samples and effect sizes by country is shown in Table 2.

Generation of effect size estimates

One of the aims of this research, as mentioned earlier, is to obtain estimates of the correlation between knowledge and attitudes net of confounding factors. We took advantage of some standard sociodemographic measures, present in all of the surveys, to use as control variables in our analysis. Gender, education and age were controlled in each of the OLS regressions that were carried out across all of the datasets. The basic OLS regression model took the form:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + e$$

where Y = attitude to science, X_1 = scientific knowledge, X_2 = gender, X_3 = age in years, and X_4 = educational level. We estimated this model for each combination of knowledge and attitude variables in each survey. We then took the standardized effect size for b_1, our measure of the relationship between attitude and knowledge, and entered this into our composite dataset, along with the sample size (used to generate the standard errors of the effect sizes). The final composite dataset used to carry out the multilevel meta-analysis contained 499 effect sizes.

The meta-analysis

The meta-analysis that we present here can be viewed as a special case of a multilevel model, as we have a hierarchical dataset with effect sizes nested within samples, nested within countries. By using a multilevel model, one can incorporate multiple effect sizes from the same

Table 1. Knowledge and attitude scales with example items

Scale	Range	Example items
Knowledge		
General knowledge	6 to 10	The oxygen we breathe comes from plants? (*true or false*) Lasers work by focusing sound waves? (*true or false*)
Biotechnology knowledge	4 to 10	Ordinary tomatoes do not contain genes, while genetically modified tomatoes do? (*true or false*) It is not possible to transfer animal genes into plants? (*true or false*)
Attitude		
General	2 to 8	We believe too often in science, not enough in feelings and faith? (*strongly agree, agree, neither, disagree, strongly disagree*) Overall, modern science does more harm than good? (strongly agree, agree, neither, disagree, strongly disagree)
Health	2 to 12	To what extent do you agree or disagree that introducing human genes into bacteria to produce medicines or vaccines … Is useful to society?…Is morally acceptable? … should be encouraged? (*strongly agree, agree, neither, disagree, strongly disagree*) To what extent do you agree or disagree that cloning cells or tissues to replace a patient's diseased cells that are not functioning properly … Is useful to society? … Is morally acceptable? … should be encouraged? (*strongly agree, agree, neither, disagree, strongly disagree*)
GM food	1 to 12	Genetically modified food threatens the natural order of things? (*tend to agree, tend to disagree*) To what extent do you agree or disagree that there is no particular danger from genetically modified food? (*tend to agree, tend to disagree*)
Nuclear	1 to 12	In general do you think that nuclear power stations are … Extremely dangerous? … very dangerous?...somewhat dangerous? … Not very dangerous? … Or not at all dangerous?
Environment	1 to 12	Modern science will solve our environmental problems with little change to our way of life? (*strongly agree, agree, neither, disagree, strongly disagree*) Scientific and technological research play an important role in protecting the environment and repairing it? (*strongly agree, agree, neither, disagree, strongly disagree*)

sample into the same analysis (Hox, 2002). The multilevel model is also a more flexible meta-analytic model, allowing characteristics at each level to be included in the model to explain heterogeneity in effect sizes across and within samples. In the standard approach, effect sizes from each study are assumed to be fixed effects—estimates of an overall unknown population effect. However, when there is substantial heterogeneity between these estimates, a random effects model may be more appropriate. This model assumes that all studies estimate their own unique, unknown "study effects" which are themselves distributed around an unknown population effect (Lambert and Abrams, 1995). In the present investigation, by using a multilevel model, we estimate parameters for a random effects model but with the addition of fixed effects to explain between-sample and between-country heterogeneity.

Variables in the model

Table 3 shows the variables that we employ in our analysis, grouped by hierarchical level. The multilevel model we estimate has three substantive levels—effect size, sample and country. However, the effect sizes that we have are themselves estimates with sampling variances and

Table 2. Distribution of samples and effect sizes by country

Country	Abbreviation	Effect sizes	Samples	Period
Britain	GBR	32	13	1989–2003
Northern Ireland	NIR	27	11	1989–2002
Germany	DEU	26	11	1989–2005
Ireland	IRL	26	10	1989–2003
Netherlands	NLD	26	10	1989–2004
Spain	ESP	26	10	1989–2002
Denmark	DNK	23	9	1989–2004
Italy	ITA	23	9	1989–2002
Portugal	PRT	23	9	1989–2002
Belgium	BEL	20	8	1989–2002
France	FRA	20	8	1989–2003
Greece	GRC	20	8	1989–2004
Luxembourg	LUX	20	8	1989–2003
America	USA	16	10	1988–2001
Austria	AUT	16	6	1996–2002
Finland	FIN	16	6	1996–2002
Sweden	SWE	16	6	1996–2002
Norway	NOR	13	5	1993–2002
Bulgaria	BGR	9	3	1993–2003
Czech Republic	CZE	9	3	1993–2003
Slovenia	SVN	9	3	1993–2004
Canada	CAN	6	2	1993–2001
Hungary	HUN	6	2	1993–2002
Israel	ISR	6	2	1993–2003
Japan	JPN	6	2	1993–2004
New Zealand	NZL	6	2	1993–2000
Philippines	PHL	6	2	1993–2002
Poland	POL	6	2	1993–2005
Russia	RUS	6	2	1993–2002
Latvia	LVA	5	2	2000–2002
Australia	AUS	3	1	1993
Cyprus	CYP	3	1	2002
Estonia	EST	3	1	2002
Lithuania	LTU	3	1	2002
Malta	MLT	3	1	2002
Mexico	MEX	3	1	2000
Romania	ROM	3	1	2002
Slovakia	SVK	3	1	2002
Switzerland	CHE	3	1	2000
Turkey	TUR	3	1	2002

Table 3. Description of variables by hierarchical level

Hierarchical level	Description of variable
1	Standard error of effect size
2	Effect size
	Type of attitude (general, GM food, nuclear, environmental, genetic medicine)
	Number of items in attitude scale
3	Domain of knowledge (biology, general)
	Sample year
4	Country
	GDP per capita
	Number of Internet connections per 1000 population
	Percentage of 18–24 year olds enrolled in tertiary education

we need to include this information in the model. This is achieved by calculating the standard error for each effect size and including this as a variable at the lowest hierarchical level.[1]

In fact, because the sample sizes for all the surveys tend to be large, the incorporation of the standard errors of the effect sizes turns out to have a minimal effect on the precision of our multilevel parameter estimates. To all substantive intents and purposes, then, this feature of the model can be ignored in the remainder of the paper.

At level 2, we introduce variables that indicate the type of science attitude on which each effect size is based and the number of items used in the construction of each attitude scale. At level 3, there is a dichotomous variable indicating whether the knowledge scale measures general or biology knowledge and a continuous variable denoting the year in which the survey was conducted. At level 4, the country level, a number of contextual variables have been derived from external data sources. The idea here is to see if country or "cultural" variation can be explained by macro-level characteristics of each of the 40 countries. The percentage of individuals enrolled in tertiary education was one contextual factor that was judged to offer insight into the unexplained country level variance. This is designed to act as a proxy for the extent to which countries have knowledge-based economies, an aspect of post-industrialism, and also perhaps the extent to which education is valued within the culture. GDP per capita was also included at this level, as a general indicator of economic advancement. Finally, the number of Internet connections per 1000 of the population has been included as a fixed effect at level 4. This serves as a measure of technological advancement. The Internet can be viewed as a tangible example of science and technology entering the home and becoming an everyday part of life, which in turn, acts as an indicator of the cultural climate for science and technology.

Despite all of these being objective socioeconomic indicators of some kind, we refer to them as "cultural" variables because we believe that they are diagnostic of different habits and orientations towards science and technology between countries (Allum et al., 2002). We prefer this approach over the use of more direct "cultural" or social psychological indicators such as aggregated beliefs about societal goals and values across countries because this might invite a tautology in our interpretation of any observed "effects" that might arise.

All of these variables were sourced from the World Employment Report (International Labour Organisation, 2001) and refer to 2001. Because our dataset spans 15 years or more these macro-variables for a single time period act as rough-and-ready indicators rather than precise measures. However, we believe that, as the rank ordering of the 40 nations on these variables has not altered greatly since 1988 (with the exception of Internet penetration), their static nature does not pose too serious a problem for the validity of our inferences.

The meta-analytic models were fit using the MLwiN 2.0 software package (Rasbash et al., 2004), using the restricted iterative general least squares (RIGLS) estimation method (Hox, 2002). The model fitting approach was as follows: first we fitted a simple variance components model (referred to here as the unconditional model), where only the intercept (the weighted mean pooled effect size) and its variance are estimated. As well as the pooled effect size estimate, the main interest here is to inspect how the total variance in this parameter is partitioned across the three substantive levels. This will indicate how much of the variation is between effects, between samples and between countries. The second model fitted introduces all of the fixed covariates described earlier. By adding these predictors, and their product–term interactions, we obtain estimates of the pooled effect sizes for different combinations of knowledge and attitude domains, as well as the country level macro-variable effects.

Equation (1) specifies the fixed part of the model. The subscripts refer to the level at which a variable is entered. So, for example the beta coefficient for *GMfood* refers to the *j*th effect size within the *k*th sample within the *l*th country. Interactions between knowledge and attitude domains are shown as, for example, *GMfood*bioknowledge*. Fitting this interaction will allow us to estimate the effect of knowledge on attitude for genetically modified (GM) food attitudes and biology knowledge. Finally the standard error of the original OLS estimates is shown as e_{1ijkl}.

$$\begin{aligned}\text{effect} = {} & \beta_{0jkl} + \beta_2\text{health}_{jkl} + \beta_3\text{GMfood}_{jkl} + \beta_4\text{nuclear}_{jkl} + \beta_5\text{environment}_{jkl} \\ & + \beta_6\text{bioknowledge}_{kl} + \beta_7\text{health*bioknowledge}_{jkl} \\ & + \beta_8\text{GMfood*bioknowledge}_{jkl} + \beta_9\text{environment*bioknowledge}_{jkl} \\ & + \beta_{10}\text{year}_{kl} + \beta_{11}\text{scalelength}_{jkl} + \beta_{12}\text{Internet}_i + \beta_{13}\text{education}_i + \beta_{14}\text{GDP}_i \\ & + e_{1ijkl}\text{st.error}_{jkl} \end{aligned} \tag{1}$$

$$\beta_{0jkl} = \beta_0 + f_{0l} + v_{0kl} + u_{0jkl} \tag{2}$$

As well as estimating the direction and magnitude of the fixed effects, we can also examine the extent to which these factors account for cross-cultural heterogeneity in the unconditional model. Evidence of this will arise if the relative proportions of variance that sample and country contribute to the random intercept change after controlling for the fixed effects. Equation (2) shows the decomposition of the variance of the intercept where f_{0l} denotes country, v_{0kl} denotes sample and u_{0jkl} is effect size. And finally, to reiterate, all of the individual effect sizes are conditional on age, education and gender, as these were included as covariates in the original OLS regressions used to generate the effect sizes.

5. Results

Overall effect size and partitioning of variance

Considering first the unconditional model, the overall relationship between knowledge of science and attitude to science is shown in Table 4 as the model 1 intercept, which is essentially a weighted mean of all the effect sizes. This initial model does not, of course, take into account the domain of knowledge or attitude. The weighted mean standardized regression coefficient for the effect of knowledge on attitude, controlling for age, education and gender is small,[2] at 0.08, but statistically significant at the conventional 5 percent level. When the breadth of this meta-analysis is considered, spanning 15 years, 40 countries and 193 studies, we consider this prima facie evidence for the existence of a stable positive relationship between science literacy and attitudes to science and technology.[3]

The unconditional model provides baseline information about the proportion of variance in effect size that is partitioned at each level of the analysis. Variance estimates from both unconditional and multivariate models are shown in the lower part of column 1 of Table 4. The estimates show that the large majority of total variation, around 88 percent, is between effect sizes themselves (level 2). This is not altogether surprising, as we know that there are a variety of domains of knowledge and attitude contained in the overall estimate. What does come as something of a surprise, even at this stage, is the rather modest contribution of cross-cultural variation (level 4), a mere 10 percent, to the overall picture. There is no statistically significant variance at level 3. This means that effect sizes do not appear to vary as a function of "house effects," interviewer style, survey mode or other sample-specific unobserved variables.

Taking account of different domains of knowledge and attitude

Adding fixed covariates to the unconditional model provides a more detailed picture of the relationship between knowledge and attitude towards science. Table 4 shows parameter estimates

Table 4. Multilevel model parameter estimates

		Model 1	Model 2
		Unconditional	With covariates
Unstandardized coefficients			
	Intercept	0.080(.006)*	0.136(0.011)*
Level 2	Attitude type		
	Genetic medicine		0.079(0.049)
	GM food		–0.105(0.013)*
	Nuclear		–0.021(0.012)
	Environment		–0.163(0.011)*
Level 3	Knowledge type		
	Biology/genetics		–0.051(0.015)*
	Attitude/knowledge interactions		
	Genetic med*biology		–0.045(0.052)
	GM food*biology		0.093(0.019)*
	Environment*biology		0.197(0.022)*
	Year		–.00038(0.001)
	Attitude scale length		–.00126(0.002)
Level 4	GDP per capita		–0.000001(.000001)
	Tertiary education		0.001(.0004)*
	Internet diffusion		.00013(.00006)
Variance components			
Level 2	σ^2_u	0.007(0.0006)*	0.003(0.0004)*
	% of total unexplained variance	88	79
Level 3	σ^2_v	0.0002(0.0004)	0.0006(0.0003)
	% of total unexplained variance	2	13
Level 4	σ^2_f	0.0008(0.0004)*	0.0003(0.0002)
	% of total unexplained variance	10	8

Notes: Standard errors in parentheses
$*p < .05$

for this model alongside those for the unconditional model. With the covariates representing domain of knowledge and attitude now in the model, the intercept should be interpreted as the pooled effect size for general scientific knowledge predicting general science attitudes. This coefficient, 0.14, is almost double the pooled estimate from the unconditional model. This indicates that the correlation between general knowledge and a range of specific applications of science is weaker than the correlation between general knowledge and general attitudes.

Looking at the parameters for each attitude domain, we see that there is no significant difference in the correlation between general attitudes and general knowledge compared to its correlation with attitudes to both nuclear power and genetic medicine. This is indicated by the non-significant parameter estimates for these two domains. However, GM food and environmental science have statistically significant effects of -0.10 and -0.16 respectively. The intercept (grand mean) is .14, so summing this with the coefficient for GM food yields the model-predicted effect size for general knowledge on GM food, which is approximately zero. Doing the same for environmental science yields a small negative predicted effect size. Our results therefore indicate that there is in actual fact no relationship between general knowledge and attitude to GM food and a small negative relationship between general knowledge and attitudes to environmental science.

The main effect of biotechnology knowledge is –0.05, which means that the relationship between biotechnology knowledge and general attitudes is weaker than when general knowledge is considered (predicted effect size is equal to the sum of the intercept and –0.06). Neither the year in which the survey was conducted nor the number of items in the attitude scales has any statistically significant influence on the effect sizes.

Interaction terms have been added to the model, which makes it possible to evaluate differences in effect sizes when particular combinations of knowledge and attitude domains are considered. The main finding here is that when biology knowledge is used to predict biotechnology attitudes, the strength of the relationship is "restored" to a similar level to that observed for the general knowledge and attitudes relationship. The estimate for this interaction is positive, at 0.09. The interpretation of the interaction coefficient here is that it is the difference between the expected effect size for general knowledge with biotechnology attitudes and biology knowledge with biotechnology attitudes.

Strangely, perhaps, an even bigger effect is seen when biology knowledge is paired with environmental science (0.20). This seems to run counter to our general finding that when knowledge and attitudes relate to the same substantive domain, the correlation between them is stronger. The interaction for genetic medicine attitudes and biology knowledge is not significant. The interaction between biology knowledge and nuclear power attitudes is omitted since no datasets were obtained that contained indicators of both.

In terms of variance components, the result of adding these explanatory variables to the model is to reduce the unexplained variance in the unconditional model by about 50 percent. This is shown in the comparison between variance estimates of 0.007 and 0.003 in models 1 and 2 respectively. This means that, as expected, a substantial proportion (about half) of the variation in effect sizes from our dataset results from the type of knowledge and attitude that is being examined.

However, it also indicates that there are other unobserved causes of heterogeneity in effect sizes not captured in the model, as the model 2 variance estimate is still statistically significant. This is likely due in part to the fact that different items are used to create the scales across surveys, even where we have classified them broadly as pertaining to "GM food attitude," "general attitude" and so on. By controlling for sample year and attitude scale length, we have ruled out at least these two possible causes of this heterogeneity. The fact that it appears to make no difference which year the survey is carried out suggests a stable, time-invariant mechanism linking knowledge and attitudes.

Examining cross-cultural variation

From the unconditional model it is clear that there is very little cross-national variation in the relationship between knowledge and attitudes, an interesting finding in itself when one considers the range of national cultures included in this analysis. However, given that cross-cultural factors nevertheless appear to account for about 10 percent of the unexplained variation in effect sizes, it is interesting to see whether we can understand this cross-cultural variation by including some selected country level variables as fixed effects at level 4. To this end we include in our model the percentage of the population (of eligible age) enrolled in tertiary education, GDP per capita, and the number of Internet connections per 1000 of the population. GDP is often identified as a useful indicator of development, and is one used by Bauer, Durant and Evans as evidence for their post-industrialism or "two cultures" thesis (Bauer et al., 1994; Durant et al., 2000). As can be seen in Table 4, when included along with our additional macro-level variables, GDP per capita has no significant impact on the relationship

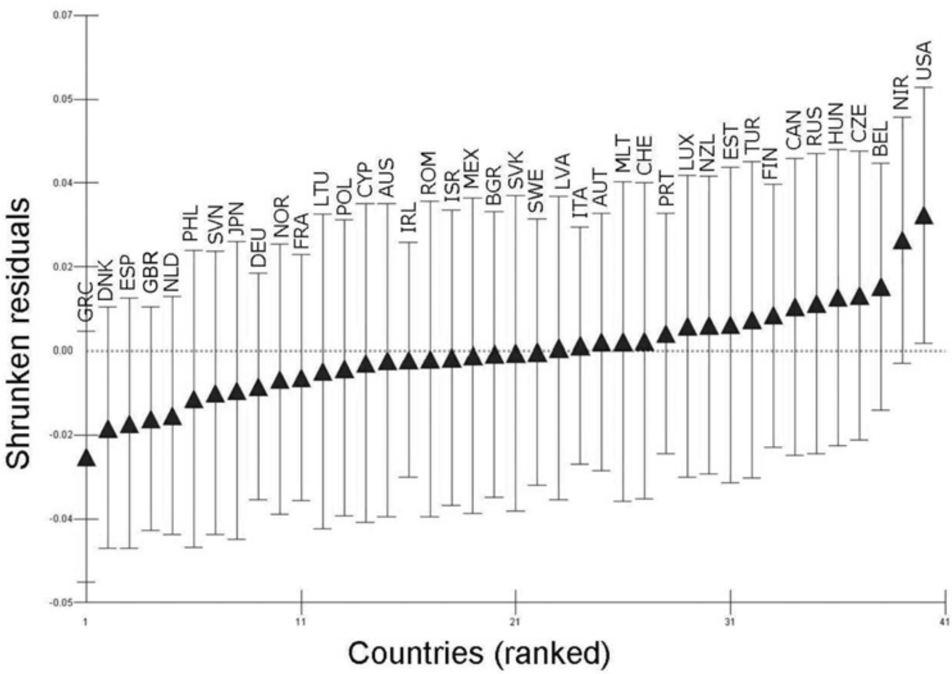

Figure 2. Country residuals with 95% confidence intervals.

between knowledge and attitudes. In fact, there is no effect even if one fits the model without the other macro-level variables. This runs counter to expectations derived from the "two cultures" thesis. One possible reason for this is that, unlike previous studies, our approach here is to ground the analysis at the individual level whilst simultaneously incorporating aggregate level effects. Previous studies that have only analyzed country level aggregate measures have possibly overestimated the effect of GDP and other macro-level variables owing to an ecological artefact.

The inclusion of tertiary education and the number of Internet connections eliminates all significant country level unexplained variance from the model, although the estimate for Internet connections is not statistically significant. Percentage in tertiary education has a small positive effect on the knowledge/attitude relationship (0.001), suggesting that in more educationally advanced cultures, the link between knowing about science and supporting science becomes stronger or more deeply embedded.

Another way to examine the extent of cultural variation is by examining the residuals plot in Figure 2. The plot shows the deviation from the mean pooled effect size, controlling for all of the covariates in the model. Confidence intervals of 95 percent surround the estimates, which are known as shrunken estimates or "posterior Bayes estimates" in the multilevel modeling framework.

They are not equivalent simply to standard OLS residuals because they are shrunken towards the overall mean as an increasing function of the standard errors of the country intercepts (Bryk and Raudenbusch, 1992). In simple terms, this means that in the case that only a few data points exist for a country, its residual will be "pulled" toward the grand mean more than that of a country that provides many data points. As would be expected, given that in the full model there is no significant cross-cultural heterogeneity (non-significant random effects at level 4), the observed mean effect sizes do not depart significantly from their expected values.

This is shown by the confidence intervals that overlap the mean and, in all but one case, the confidence intervals of all the other countries. The exception is the US, where the correlation between knowledge and attitudes is significantly higher than our model would predict.

In sum, then, there is very little cross-cultural variation in the correlation between knowledge and attitudes. What variation there is can be explained with a single country level indicator of the proportion of the population going on to higher education. However, we would caution against over-interpreting this parameter; we have a limited range of cultural variables available to us and while this result is suggestive, it may well be that the proportion of citizens in tertiary education stands as a proxy for other unmeasured causes.

6. Discussion

We began this paper by highlighting the centrality of debates about the knowledge–attitude nexus in PUS research. In the empirical study presented here, we have attempted to move some of these debates forward just a little. Our results provide, we believe, a firmer empirical foundation than has thus far been available on which to evaluate the claims and counter claims that characterize the lively and important debates about scientific literacy and mass opinion about science. By synthesizing results from public opinion surveys, carried out in many countries during the past fifteen years, we have tried to address some key questions about the relationship between knowledge and attitudes amongst mass publics and the role that national cultures play in moderating this relationship.

Our findings suggest that, if one examines all measured knowledge and attitude domains, there is a small but positive relationship. Perhaps we might characterize the importance of this as "shallow but broad." Those scholars who take the falsity of the "deficit model" as axiomatic will no doubt want to focus on the low magnitude of the overall effect. Those who believe that "knowledge matters" will likely emphasize the robustness of the relationship—over so many national contexts and over time.

Of equal, or perhaps greater, interest is the discovery of systematic differences in this relationship according to the degree of consonance between knowledge and attitude domains. The correlation between general "textbook" knowledge and attitudes towards science as a whole is almost twice as high as the overall estimate whereas, for example, the correlation between general knowledge and attitudes to GM food is practically zero. However, when knowledge relates to biology and genetics, it becomes a considerably stronger predictor of a person's attitudes towards GM food. This lends support to the idea that it is focused, one might even say "local," types of knowledge that are most important if we are to understand how opinions are generated amongst different publics with different interests and modes of interacting with science and technology in everyday life.

The other focus of this paper has been on cross-cultural aspects of the knowledge–attitude relationship. Previous work has suggested that there is a great deal of variation in the association between science literacy and attitudes to science between countries and that some of this variation is related to the degree of local economic development. Our results suggest that much of what has been interpreted as cultural variation can be accounted for mainly by variation in the relative proportion of individuals with particular attributes within countries rather than "culture" per se. Our analysis shows that only 10 percent of the variation in the knowledge–attitude correlation can be explained by country level processes or mechanisms—much less than would be indicated by considering aggregate measures, as has previously been the rule. What can explain this rather modest degree of cross-cultural disparity? In our model, we looked at three possible macro-level indicators for an explanation. Neither GDP per capita nor

Internet diffusion were significantly associated with cultural variation. However, the percentage of young people enrolled in tertiary education in a country is linked to stronger knowledge–attitude correlations and can account for all of the cross-country variation in our initial variance components analysis. We would not, however, want to over-interpret this finding, as we do not yet have a theoretical basis for building a model at this level, beyond the "two cultures" approach. This is, though, a promising avenue for future research. It would also be of great interest to extend this type of analysis to a wider range of countries, from Africa, Asia and the Middle East, to test the cultural invariance hypothesis more thoroughly.

Finally, it will not have escaped the reader's notice that in our presentation we have avoided straying into the realm of causal explanation regarding the association between knowledge and attitudes about science. However, we believe that by showing that there is a persistent link between knowledge and attitudes, we have at least established that there is an explanandum in need of an explanation. In emphasizing the inadequacy of scientific literacy as a comprehensive framework for understanding public responses to science and technology, we believe that scholars have overlooked the need to nevertheless provide a satisfactory account of how knowledge of science relates to preferences regarding its technological implementation in society. Understanding the social and psychological mechanisms that generate the associations we observe in this analysis must surely be an important future avenue of research in public understanding of science.

We began this paper with an aphorism: "to know science is to love it." How has this notion fared, in the light of our empirical analysis? The picture is clearly much more complex than this simple maxim would suggest. Nevertheless, as with the most enduring pieces of folklore, it appears to contain at least a grain of truth.

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Notes

1 Following Hox (2002), we calculate the standard error as $\sqrt{(1/n - 1)}$ and include this as the only variable at level 1. Level 1 variance is constrained to unity in the model to reflect that fact that it is already known (estimated in our original OLS regressions).
2 Using Cohen's (1992) typology of effect size magnitudes.
3 We tested the robustness of this result against any omissions we may inadvertently have made in the selection of existing datasets. We simulated 200 additional effect sizes of zero magnitude and ran the same analysis. When these zero effects were added, the overall weighted mean fell from .08 to .05, but remained significant. Hence we believe that our results are quite robust against possible bias from omitted data sources.

References

Allum, N.C., Boy, D. and Bauer, M.W. (2002) "European Regions and the Knowledge Deficit Model," in M. Bauer and G. Gaskell (eds) *Biotechnology: the Making of a Global Controversy*, pp. 224–43. Cambridge: Cambridge University Press.

Bauer, M.W., Durant, J. and Evans, G. (1994) "European Public Perceptions of Science," *International Journal of Public Opinion Research* 6(2): 163–86.

Bishop, G. (2005) *The Illusion of Public Opinion: Fact and Artifact in American Public Opinion Polls*. Oxford: Rowman and Littlefield.

Bryk, A. and Raudenbusch, S. (1992) *Hierarchical Linear Models: Applications and Data Analysis Methods*. London: SAGE.

Cohen, J. (1992) "A Power Primer," *Psychological Bulletin* 112: 155–9.

Davis, R.C. (1958) "The Public Impact of Science in the Mass Media. A Report on a Nation-wide Survey for the National Association of Science Writers." Ann Arbor, University of Michigan, Institute for Social Research, Survey Research Center.

Durant, J., Evans, G. and Thomas, P. (1989) "The Public Understanding of Science," *Nature* 340(6228): 11–14.

Durant, J., Bauer, M.W., Gaskell, G., Midden, C., Liakopoulos, M. and Scholten, E. (2000) "Two Cultures of Public Understanding of Science and Technology in Europe," in M. Dierkes and C. von Grote (eds) *Between Understanding and Trust: The Public, Science and Technology*, pp. 131–56. Amsterdam: Harwood.

Einsiedel, E. (2000) "Understanding 'Publics' in the Public Understanding of Science," in M. Dierkes and C. von Grote (eds) *Between Understanding and Trust: The Public, Science and Technology*, pp. 205–16. Amsterdam: Harwood.

European Commission (2001) *Europeans, Science and Technology*. Brussels: European Commission.

Evans, G. and Durant, J. (1995) "The Relationship between Knowledge and Attitudes in the Public Understanding of Science in Britain," *Public Understanding of Science* 4(1): 57–74.

Gaskell, G., Allum, N.C., Bauer, M.W. and Durant, J. (1999) "Worlds Apart? The Reception of Genetically Modified Foods in Europe and the US," *Science* 16 July: 384–7.

Gaskell, G., Allum, N.C., Wagner, W., Hviid Nielsen, T., Jelsoe, E., Kohring, M. and Bauer, M.W. (2001) "In the Public Eye: Representations of Biotechnology in Europe," in G. Gaskell and M. Bauer (eds) *Biotechnology 1996–2000: the Years of Controversy*, pp. 53–79. London: Science Museum Publications.

Grimston, M.C. (1994) "Public Opinion Surveys in the UK," *Nuclear Europe Worldscan* 14(7–8): 98.

Grove-White, R., Macnaghten, P. and Wynne, B. (2000) "Wising Up: the Public and New Technologies," Lancaster, Lancaster University, Centre for the Study of Environmental Change (CSEC).

Hayes, B.C. and Tariq, V.N. (2000) "Gender Differences in Scientific Knowledge and Attitudes toward Science: a Comparative Study of Four Anglo-American Nations," *Public Understanding of Science* 9(4): 433–47.

Hayes, B.C. and Tariq, V.N. (2001) "Gender Differences in Scientific Knowledge and Attitudes toward Science: a Reply to a Reply," *Public Understanding of Science* 10(4): 431–3.

Hox, J.J. (2002) *Multilevel Analysis: Techniques and Applications*. Mahwah, NJ: Lawrence Erlbaum.

Inglehart, R. (1990) *Culture Shift in Advanced Societies*. Princeton: Princeton University Press.

International Labour Organisation (2001) *World Employment Report*. Geneva: ILO.

International Research Associates Europe (INRA) (1993) *Europeans, Science and Technology: Public Understanding and Attitudes*. Brussels.

Irwin, A. and Michael, M. (2003) *Science, Social Theory and Public Knowledge*. Maidenhead: Open University Press.

Irwin, A. and Wynne, B. (1996) *Misunderstanding Science? The Public Reconstruction of Science and Technology*. Cambridge: Cambridge University Press.

Lambert, P. and Abrams, K. (1995) "Meta-analysis Using Multilevel Models," *Multilevel Modelling Newsletter* 7(2): 16–18.

McBeth, M.K. and Oakes, A.S. (1996) "Citizens' Perceptions of Risks Associated with Moving Radiological Waste," *Risk Analysis* 16: 421–7.

Martin, S. and Tait, J. (1992) "Attitudes of Selected Public Groups in the U.K. to Biotechnology," in J. Durant (ed.) *Biotechnology in Public: a Review of Recent Research*, pp. 28–41. London: Science Museum Publications.

Michael, M. (1996) "Ignoring Science: Discourses of Ignorance in the Public Understanding of Science," in A. Irwin and B. Wynne (eds) *Misunderstanding Science? The Public Reconstruction of Science and Technology*, pp. 107–25. Cambridge: Cambridge University Press.

Michael, M. (2002) "Comprehension, Apprehension, Prehension: Heterogeneity and the Public Understanding of Science," *Science, Technology & Human Values* 27(3): 357–8.

Miller, J.D. (1983) "Scientific Literacy: a Conceptual and Empirical Review," *Daedalus* 11: 29–48.

Miller, J.D. (1998) "The Measurement of Scientific Literacy," *Public Understanding of Science* 7: 203–23.

Miller, J.D. (2004) "Public Understanding of, and Attitudes toward, Scientific Research: What We Know and What We Need to Know," *Public Understanding of Science* 13(3): 273–94.

Miller, J.D., Pardo, R. and Niwa, F. (1997) *Public Perceptions of Science and Technology: a Comparative Study of the European Union, the United States, Japan and Canada*. Bilbao: Fundacion BBV.

Pardo, R. and Calvo, F. (2002) "Attitudes toward Science among the European Public: a Methodological Analysis," *Public Understanding of Science* 11: 155–95.

Pardo, R. and Calvo, F. (2004) "The Cognitive Dimensions of Public Perceptions of Science: Methodological Issues," *Public Understanding of Science* 13: 203–27.

Peters, H.P. (2000) "From Information to Attitudes? Thoughts on the Relationship between Knowledge about Science and Technology and Attitudes toward Technology," in M. Dierkes and C. von Grote (eds) *Between Understanding and Trust: The Public, Science and Technology*, pp. 265–86. Amsterdam: Harwood.

Priest, S.H. (2001) "Misplaced Faith: Communication Variables as Predictors of Encouragement for Biotechnology Development," *Science Communication* 23(2): 97–110.

Rasbash, J., Steele, F., Browne, W. and Prosser, B. (2004) *A User's Guide to MLwiN Version 2.0*. London: Institute of Education.

Rosenthal, R. (1991) *Meta-analysis Procedures for Social Research*. Newbury Park, CA: SAGE.

Sterling, T.D., Rosenbaum, W.L. and Weinkam, J.J. (1995) "Publication Decisions Revisited: The Effect of the Outcome of Statistical Tests on the Decision to Publish and Vice Versa," *American Statistician* 49(1): 108–12.

Sturgis, P.J. and Allum, N.C. (2000) "The Impact of Knowledge on Attitudes toward Biotechnology: Using Regression Models to Simulate a Better-informed Public," Paper presented at the British Psychological Society (Social Psychology Section), Nottingham.

Sturgis, P.J. and Allum, N.C. (2001) "Gender Differences in Scientific Knowledge and Attitudes toward Science: Reply to Hayes and Tariq," *Public Understanding of Science* 10(4): 427–30.

Sturgis, P.J. and Allum, N.C. (2004) "Science in Society: Re-evaluating the Deficit Model of Public Attitudes," *Public Understanding of Science* 13(1): 55–74.

Thornton, A. and Lee, P. (2000) "Publication Bias in Meta-analysis: Its Causes and Consequences," *Journal of Clinical Epidemiology* 53(2): 207.

Withey, S.B. (1959) "Public Opinion about Science and Scientists," *Public Opinion Quarterly* 23: 382–8.

Wolf, F.M. (1986) *Meta-analysis: Quantitative Methods for Research Synthesis*. Thousand Oaks, CA: SAGE.

Wynne, B. (1996) "May the Sheep Safely Graze? A Reflexive View of the Expert-Lay Knowledge Divide," in S. Lash, B. Szerszynski and B. Wynne (eds) *Risk, Environment and Modernity: Towards a New Ecology*, pp. 44–83. London: SAGE.

Wynne, B. (2001) "Expert Discourses of Risk and Ethics on Genetically Manipulated Organisms: the Weaving of Public Alienation," *Politeia* 17(62): 51–76.

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