PROJECT REPORT:

EXPLORING CITIZENS' RESPONSES TO SCIENCE IN PUBLIC POLICY THROUGH NATURAL LANGUAGE PROCESSING AND CONJOINT EXPERIMENTS

Under what conditions is science viewed as authoritative and trustworthy in policymaking? Our evidence suggests public willingness to engage with scientific content. On a nationally representative scale, polarisation around science appears to be driven less by anti-science sentiment and more by the perception that other forms of knowledge should also matter. Public participation in the production of science and clearer local relevance of research may mitigate 'epistemic inequalities' between experts and citizens.

This research was funded by the British Academy Science, Trust and Policy programme, with support from the UK Government (CST\220016).

Laszlo Horvath
Deborah Mabbett

5 March 2024

BIRKBECK CENTRE FOR BRITISH POLITICAL LIFE

Birkbeck UNIVERSITY OF LONDON
FACULTY OF HUMANITIES AND SOCIAL SCIENCES

Contents

Overview

Key findings

Under what conditions is science viewed as authoritative and trustworthy in policymaking? Key findings from this research indicate that:

- **The nature of disagreement matters:**
    - We distinguish between three kinds of disagreement that can arise over the use of science in policy. 'Orthogonal' disagreements arise where parties disagree on who has useful knowledge about the policy and what kind of knowledge that might be: science for some but other kinds of knowledge for others. By contrast, when 'epistemic peers' disagree, they acknowledge the relevance of science in general and respect scientific method, but disagree on the interpretation of results or have a different disciplinary focus (e.g. environmentalists vs plant scientists). Finally, in disagreements involving 'anti-science', opponents are deeply mistrustful of science.
    - We found no evidence of widespread anti-science views being in public responses to science. However, science does not always aid consensus-building on policies and can lead to polarised attitudes. Where there are orthogonal disagreements, non-science arguments (such as experiential evidence about the economic and social costs of policy) are relied on by opponents of the scientifically supported policy. Though opponents do not necessarily challenge relevant scientific findings, they reject the authority of science to settle the argument. We observed this with the Clean Air Zone case study.
    - By contrast, when 'epistemic peers' disagree, supporters and opponents may both draw on some form of scientific evidence, as seen with the GM crops case study. Here, we found evidence that (more, better) science can foster consensus about policy.

- **Democratic cues matter:**
    - Citizens view authorities using science generally as competent, fair, transparent, and trustworthy. However, 'democratic cues', such as public consultation and perceived public opinion towards policy, are sometimes more influential than science cues, especially when assessing authorities' transparency and fairness. Only in the assessment of perceived competency does science trump democracy.
        - Among the attitudes we studied, perceptions of fairness and transparency were most predictive of trust, competence less so. Trust, in turn, is our strongest predictor of intention to comply with a policy.
    - Public engagement in the production of science mitigates 'epistemic inequalities' between experts and citizens. Incorporating some form of citizen science increased citizens' perceptions that scientific research is competent, informative, benefits locals, and is trustworthy—even among opponents of Clean Air Zones.
    - People are not necessarily influenced most by the same scientific values that influence scientists. Overseas science bodies with international prestige elicited less support than local scientific work, including local research universities or members of the public involved in monitoring air pollution.

- **No crisis but room for clarity:**
    - Our evidence suggests a public willingness to engage with scientific content. In the survey experiment, respondents valued expert input, with their baseline attitudes already leaning towards support for the science-based policies they were presented with. In national and local media, we found frequent use of science facts and measurements.
    - Yet we know from the survey work that different characteristics of research lead to different responses. Citizens reading media reports may not be able to assess these characteristics: in particular, references to specific studies or science organisations were infrequent in the corpus (body of text) of news reports that we analysed (see interim report). Clearer communication between news media and promoters of science-based policies would be necessary to produce more transparent and informative reports.

Overview of methods

This research project collected two types of data:

- a textual corpus comprising news stories from UK print media as well as transcripts of Parliamentary debate, and

- a survey experiment embedded in a nationally representative poll.

Both data sources relate to each of our three science-based policy cases: Clean Air Zones, GM crops, and Mpox case investigation.

In the following sections, we briefly discuss the case selection strategy as well as both text and survey methods.

We then discuss exploratory insights, and the two major themes of this report: 'polarisation and the nature of disagreement' and 'democracy and democratic cues', drawing on both data sources.

Case selection

Our case studies represent three science-based policies within a fixed national political context (UK, but a mixture of local and national-level implementing authorities). They are:

- Clean Air Zones or (Ultra) Low Emission Zones, implemented by local governments to improve air quality. In Clean Air Zones, vehicles exceeding current emission standards have to pay a charge when driving through.

- Surveillance and case investigation by local and national health authorities following a suspected case of Mpox (Monkeypox) infection. This includes identifying contacts who were in proximity to the infected individual in order to isolate, test, or treat them.

- Approval of novel Genetically Modified (GM) crops by the UK Government's Department for Environment, Food & Rural Affairs (Defra) for experimental use, with controls to ensure safety for human or animal health and the environment.

We selected these cases because they display different degrees of political contestation, as well as divergence in the type of science being invoked in political debate, and in the ways it was invoked.

The regulation of GM crops (in most cases, authorisation for experimental use) has historically tended to be a case of widespread contestation by citizens who are concerned about food safety and environmental risks, and tend to mistrust science particularly when sponsored by the GM industry. In the UK, scepticism is still relatively widespread with nearly half of UK adults preferring food not to contain GM ingredients, according to a recent poll (but a quarter not minding either way, according to a YouGov/Beyond GM poll[1]). We see this case as one where scientific evidence is deemed relevant to guiding decisions, but where there is also significant divergence of values or interests.

There is also intense contestation over Clean Air Zones, but science plays a different role. While scientific evidence is recognised as relevant to the policy, it has to compete with other framings of the policy issues to do with cost and (in)convenience. Mpox public health interventions raise the potential for contestation of a different kind. At the time of the outbreak, infections in the UK were kept relatively low, and policies

[1] https://docs.cdn.yougov.com/2wqpwz0eid/BeyondGM_Results_221112_W.pdf

(contact tracing, vaccines) have been perceived to target particular groups, namely gay men and members of the wider LGBTQ+ communities. The scientific evidence is that other groups can also be at risk, raising the possibility that the public health response is seen as unfairly discriminatory. Those who oppose Mpox case investigation and surveillance will likely do so based on deeply held values around fairness or privacy protection.

Text study methods

All three policy cases are widely discussed in different UK-based forums, including traditional and social media. We captured text to explore this discussion in two key forums:

- the print media (national and local), from which we obtained news content querying the LexisNexis archive for policy-related keywords:
    - 'clean air zone' or 'low emission zone' or 'LEZ' or 'ULEZ'; in addition to a list of UK cities and towns with an existing or planned zone[2]
    - 'gm crop' or 'genetically modified crop' or 'gm food' or 'genetically modified food'
    - 'monkeypox' or 'Mpox'

- text segments from all parliament debate transcripts (both Houses and committees) that contained the same keywords as above, using the Hansard database.

From Lexis news we obtained 6,847 Clean Air Zone news stories, 2,176 Mpox stories, and 6,887 GM stories. From Hansard, we obtained 1,138 Clean Air, 2,124 GM, and 146 Mpox debate segments. See also the Appendix for more descriptive information about the corpus.

In this report, the analysis of the textual corpuses relies on the following key methods:

1. **Topic modelling:** Topic models summarise content in large text corpuses using a computational method. We use them in this exploratory way: the resulting 'topics' may represent key themes, events, key locations, etc. and they have been used in previous work to infer policy frames or narratives. The resulting topics are described by top keywords and a corresponding probability distribution which we report. Documents featuring the top keywords of topic T will be assigned some (high) probability of featuring topic T.

2. **Machine learning (ML) classification:** This builds on first manual classification of a sample of news stories and story segments into 'opposition' and 'support' texts, then processing using an ML algorithm to learn about which words and combinations of words are associated with support and which with opposition. This way, we not only learn about the vocabulary associated with different (media-) attitudes to our policies, but we are also able to assess the relative importance of 'science' vocabulary across these positions.

Additionally, we explored all named research and other organisations using Named Entity Recognition, and their role in the policy process, and drew a network representing their centrality in the policy discourse. We also explored the key scientific terms and different ways of identifying science content in text. Both of these are reported separately in our Interim Report to the British Academy.

[2] We introduced this strategy (explicit reference to cities and towns) since our interim report to obtain a better-defined corpus that has a more comparable size to the other two case studies.

Survey study methods

We completed the survey work in two phases: a pilot round which we discussed in the Interim Report to the British Academy, and the final survey work with Deltapoll comprising N = 1,596 respondents, with surveys completed 9–15 June 2023.

Respondent demographics mirror the UK national distribution on key demographics, such as age 18+, gender, and education, as well as 2019 General Election vote recall. In addition, we commissioned a sample that has an equal distribution of respondents across the UK's twelve statistical regions including Wales, Scotland, and Northern Ireland. This tackles the usual London bias in online surveys and ensures we have a good number of respondents from other locations where Clean Air Zones are implemented.

Embedded in the same Deltapoll survey, we designed three experiments, described below. The analytical strategy was pre-registered with AsPredicted (main effects plus subgroup analyses).

In this report, we analyse these data in two ways:

1. In the discussion below of descriptive findings, under the heading 'Baseline attitudes to science-based policies' we discuss public opinion about Clean Air Zones, GM, and Mpox interventions prior to any experimental manipulation. We also use regression modelling to explore the impact of respondent characteristics, such as demographics, on policy support.

2. In the discussions of 'Polarisation' and 'Democracy', we use survey experiments in which we present respondents with a series of policy cases and research programmes with varying descriptions of science.

'Conjoint' experiments allow manipulation of several such descriptors simultaneously and independently, resulting in a very large number of randomly generated cases.

We embedded a sequence of survey experiments falling into two categories:

- **Experiment 1 'Science vs Politics'** exploring the causal impact of an explicit science-frame (science justification) on perceptions of the implementing authority (local or national government), across the three case studies;

- **Experiment 2 'Science vs Science'** exploring the causal impact of different characteristics of research programmes on perceptions of scientific research itself, within two case studies:
    - Experiment 2A exploring perceptions of Clean Air Zone research
    - Experiment 2B exploring perceptions of GM research.

Experiment 1 'Science vs Politics' enabled us to explore whether science had a positive or a polarising effect on public attitudes to the policy—in particular, whether scientific support led respondents to evaluate the competence of the government more positively, and whether that evaluation varied according to the respondent's prior attitude to the policy. We assessed the impact of scientific expertise relative to other features of the policy process, such as whether a public consultation had been undertaken and whether opinion polls indicated public support for the policy.

Experiment 2 'Science vs Science' tested how people responded to different kinds of scientific input. These included the distinction made in the text analysis between 'technical' statements, such as pollution facts, and 'causal' statements, such as claims about the link between pollution and adverse health outcomes. We also examined whether the funding of scientific research, the location of the researchers (local, UK, or overseas), and the engagement of 'citizen scientists' made a difference.

Descriptive findings

This section outlines descriptive insights from our data, relating to both media discourse and public attitudes to the use of science in policymaking. We used these to develop and test hypotheses in subsequent sections.

Exploring topics

Topic models summarise content efficiently in large text corpuses, assuming little to no prior domain knowledge. The resulting 'topics' may represent nothing at all—we will call these 'junk topics'—but more often they reflect key themes, events, or even public policy frames converging on a distinct definition of the policy problem and an associated vocabulary. Topic modelling, including analysis of topics partitioned according to whether text segments supported or opposed the policy, enabled us to identify the following features of public discussion of science-based policy; these features then informed the structure of the survey experiment.

Science is used in several distinct ways in public debate, producing up to three 'science' topics in the topic analysis. Usually, one topic provides measurements and facts (the level of air pollution, success of GM trials in terms of yield, and the symptoms of Mpox). We refer to this as a 'technical' use of science. Other topics link technical scientific findings causally with health impacts (clean air and GM), climate change (clean air and GM) or health advice (Mpox). We used this distinction between technical and causal statements in designing the survey experiment on public responses to different kinds of scientific information.

Supporters and opponents of policies use science differently, but these differences varied across our case studies. In the discussion below of polarisation around science, we explain how we developed a classifier to identify statements as supporting or opposing a policy, We used the classifier to identify which keywords (words or combinations of words) were most predictive of support or opposition in the cases of GM crops and Clean Air Zones (there were not enough opposition texts to do this for Mpox). We found some evidence of orthogonal disagreements about Clean Air Zones, in the sense that the weight of science keywords in opposition texts is less than half of that in supporting texts.[3] By contrast, on GM crops we found a substantial weight given to science in any policy position in this corpus, suggesting that it is difficult to discuss the policy without engaging with the science content.

This difference between GM crops and Clean Air Zones in the *nature of the disagreement* informs our analysis of polarisation. Specifically we hypothesised that polarised responses to (additional) scientific input into policymaking are more likely in the Clean Air Zone study than in the GM crops study. We present our findings related to this hypothesis in the section on 'Polarisation' below.

The text analysis gave us information on relevant organisations that were engaged in the policy process and mentioned in the media and in Parliament. We had expected to use named entities in the survey experiment, as has been done in other work in this area (see, e.g., Heinzel & Liese 2021). However, we found that science statements are often made in the print media without reference to the organisations involved in producing them. This led us to use generic descriptions ('local university', etc.) in the survey experiment rather than referring to named entities.

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[3] Note that orthogonal claims can be supportive of the policy. For example, supporters of a Clean Air Zone may argue that it will improve economic activity by enhancing pedestrian access. This would generate non-science keywords in supporting texts, and would indicate that orthogonal knowledge is not structuring disagreement about the policy.

Tables 1–3 give examples of our topic model results for each policy, using the print corpus. For the remaining Hansard topics, two sets of inter-topic correlation heatmaps for both corpuses, and clarification of further methods (e.g. CorEX models), see the Appendix.

Table 1: Anchored CorEx (see the Appendix) Clean Air Zone topics in the print corpus.

	Topic category	Topic	Top keywords (anchor words **bold**)
1	Science	Facts & measures*	**nitrogen**, **dioxide**, **nitrogen_dioxide**, **air_quality**, **air_pollution**, level, limit, oxide, level_nitrogen, nitrogen_oxide
2	Science	Health impacts*	**health, death, lung**, asthma, toxic, disease, public_health, premature, child, quality
3	Science	Climate*	**climate**, **climate_change**, climate_emergency, tackle_climate, emergency, change, **action**, carbon, planet, net
4	Publics	Local interests*	**business**, small_business, small, **work**, business_case, financial, **community**, trader, firm, individual
5	Zones & Publics	Manchester protest	taxi, private, greater_manchester, hire, manchester, burnham, private_hire, andy, taxi_private, taxi_driver
6	Other	Transport alternatives	cycling, public_transport, walk, public, cycle, traffic, space, travel, street, route
7	Other	Transport other	van, daily, driver, compliant, pay, standard, emission_standard, non_compliant, non, coach
8	Other	Old and new energy	uk, energy, world, country, electric, future, fuel, increase, green, power
9		Junk topic	thing, time, leave, know, lot, family, news, money, speak, come
10	Politics	Local government	cabinet, councillor, cabinet_member, cllr, member, leader, proposal, council_leader, consultation, meeting
11	Politics	Other	lib, dem, lib_dem, liberal, home, liberal_democrats, democrats, happen, want, close
12	Zones	Scotland	scotland, scottish, glasgow, edinburgh, scottish_government, aberdeen, dundee, snp, earth, msp
13	Zones	London	khan, sadiq, mayor, london, sadiq_khan, londoners, expand, expansion, mayor_sadiq, tfl
14	Politics	Election campaign	labour, election, party, tory, candidate, vote, johnson, conservative, conservatives, boris
15	Politics	Policy definition	government, local, authority, local_authority, improve, include, measure, area, set, legal

*anchored topics—different science topics resulted across different iterations up to k = 15, see the Appendix. Anchored to ensure we keep these topics separate.

Table 2: CorEX GM topics in the print corpus.

	Topic category	Topic	Top keywords
1	Science	GM experiments	plant, gene, resistant, genetic, technology, scientist, grow, yield, research, develop
2	Politics	Nat'l politics	minister, policy, prime_minister, party, prime, state, political, labour, vote, secretary
3	Other	Prince Charles	prince, charles, man, old, family, mother, son, queen, love, prince_charles
4	Science	Health impacts	university, human, science, risk, health, base, lead, study, scientific, effect
5		Junk topic	thing, live, turn, look, book, bad, word, fact, story, leave
6		Junk topic	life, time, people, good, way, work, come, start, great, make
7	Politics	Brexit & trade	trade_deal, trade, brexit, deal, agreement, negotiation, standard, chicken, free_trade, chlorine
8		Junk topic	know, think, day, feel, school, try, like, social, ask, course
9	Publics	Citizens and businesses	price, pay, big, market, high, cost, business, company, low, large
10	Science	Climate	climate, climate_change, global, population, change, need, increase, energy, land, emission
11	Politics	EU regulation	eu, european, union, european_union, scotland, european_commission, ban, scottish, europe, uk
12	Publics	Farmers	farmer, farming, farm, feed, production, produce, animal, environment, consumer, soil

Table 3: CorEx Mpox topics in the print corpus.

	Topic	Top keywords
1	Science: symptoms 1	blemish_evolve, affliction, lesion_crust, blemish, week_heal, virus_difficult, superficial, blood_bodily, face_follow, measle_scabie
2	Junk topic	year, story, life, leave, police, old, claim, family, pay, lose
3	Science: symptoms 2	ache, headache, muscle, swollen, exhaustion, backache, rash, chill, fever, node
4	Publics: LGBTQ+ community	bisexual, sexual, gay, sexual_health, gay_bisexual, health_security, ukhsa, security, agency, sex
5	Junk topic	time, help, want, need, able, try, hope, woman, use, feel
6	Junk topic	newsletter, sign_daily, miss, news_scotland, miss_late, daily, sign, today, news, widget
7	Other: global outbreak	outbreak, global, spain, country, africa, world, centers, centers_disease, control_prevention, europe
8	Science science advice	dr, offer, dr_nick, phin, close_contact, smallpox, vaccination, nick, nhs, vaccine

Baseline attitudes to science-based policies

This section explores the survey data, specifically attitudes prior to experimental manipulation. We asked about baseline policy support for all three cases, where survey respondents received the same description of policy as we provided above in the section 'Case selection'. In addition, a battery of questions explored demographics, party ID ('In case of a general election, which of the parties would you vote for?') and trust in government as well as scientists.

Are citizens divided when it comes to the three policy case studies? All three distributions are skewed towards support for science-based policies, but Clean Air Zones have a somewhat larger opposition base. This is shown in Figure 1.

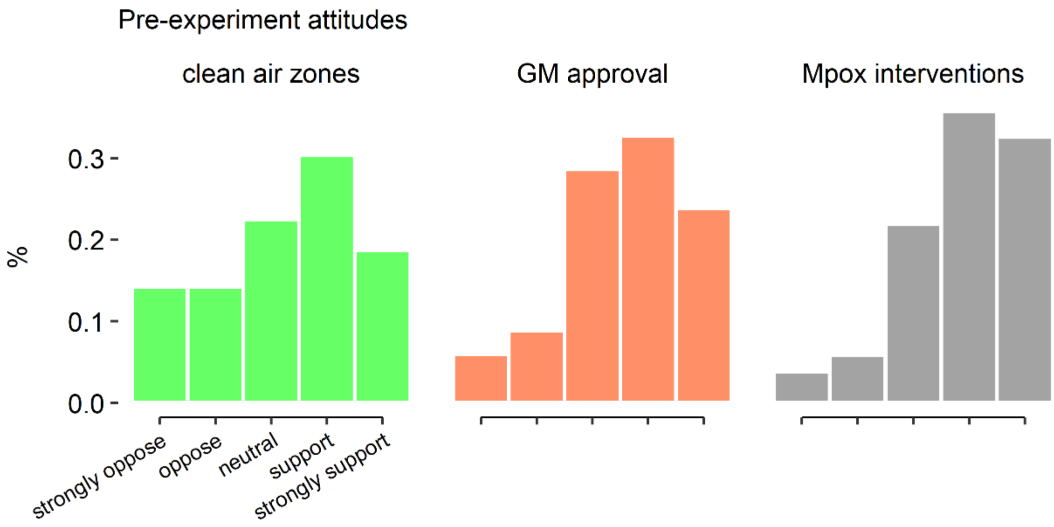


Fig. 1: Opposition to and support for science-based policies.

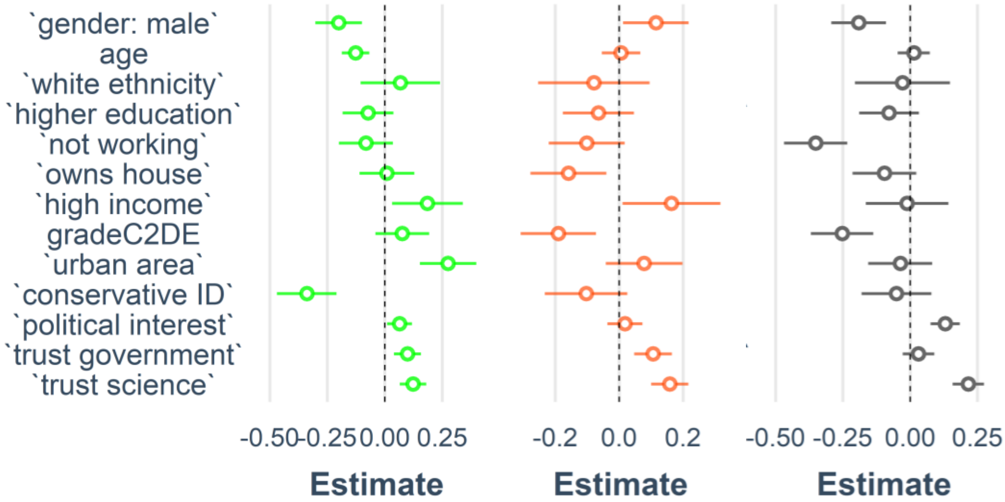
How can we explain this variation?

- *Caution 1*: this study is primarily set up to test experimentally the impact of science justification on policy support, rather than exploring the impact of different kinds of attitudes and demographics. But the experiments are embedded in a nationally representative survey (see Caution 3) and we hold some information about our respondents, which we briefly explore here.

- *Caution 2*: we also do not know (and did not have the scope to explore) how stable these preferences are—for example, some may have heard about these policies from our descriptions for the first time and may change their opinion during the experiment (but we explore how respondents who selected 'don't know' in this question later performed during the experiment).

- *Caution 3*: to achieve good representation across the UK and counter the usual metropolitan (London) bias, we asked Deltapoll to seek an equal number of respondents from each UK region. We have also calculated post-stratification weights to rebalance on geography. Inclusion/exclusion of these weights changes our results about the extent of geographical variation.

Figure 2 is a summary of three sets of regression models predicting policy support using basic individual-level predictors:



Note: dependent variables: support for **fee charging clean air zone (green)**, introduced by local government; support for **gm crops** for experimental use **(red)**, authorised by Defra; support **Mpox** surveillance and case investigation **(grey)**, by local and national health authorities. All effect sizes are expressed in standard deviation units. Age, political interest, trust in government, and trust in science are scaled and mean-centred continuous variables; all others are binary variables.

Fig. 2: Individual-level predictors of pre-experiment policy support.

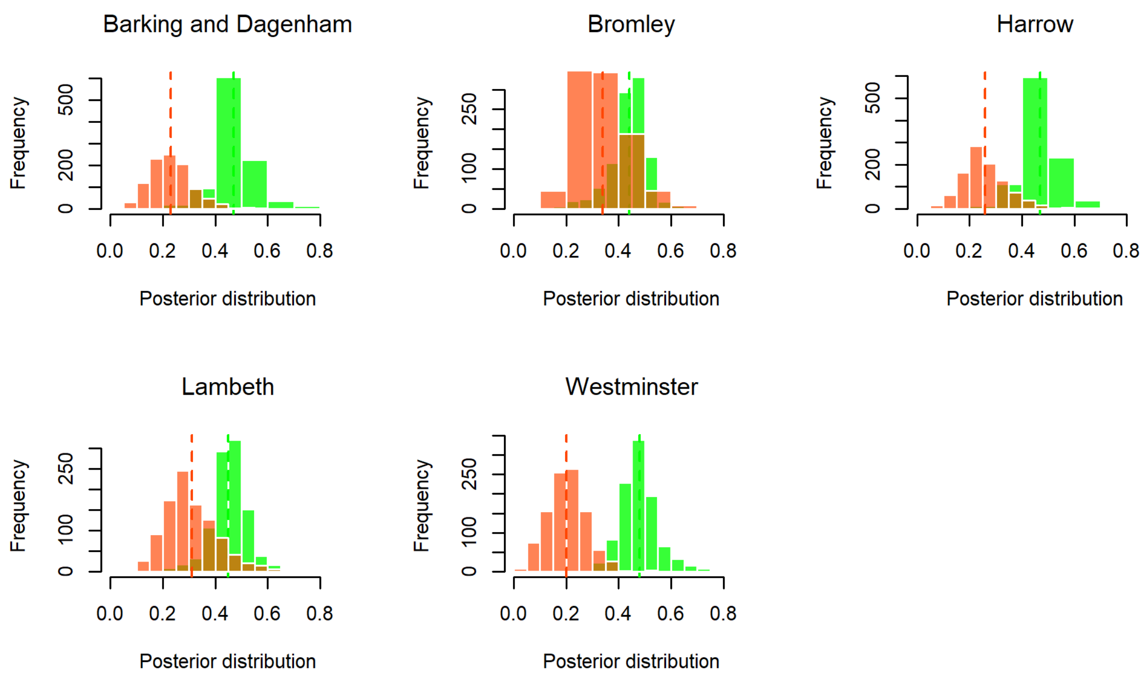
These individual-level variables have limited explanatory power (jointly about 7–8% of the variation in Clean Air Zone and GM attitudes, and 13% of Mpox attitudes). We note trust in government and trust in science predict support in all cases. In addition, Conservative Party ID predicts lack of support for Clean Air Zones.

We captured responses from 331 local authorities (LAs) which is slightly over 80% of all LAs in the UK. Some have very few respondents. We can formulate predictions about attitudes in these LAs using a method called multilevel regression poststratification (MRP), which is an efficient method that can 'borrow' information from distributions in other LAs.

Variation across LAs accounts for 32% of Clean Air Zone attitudes when applying poststratification weights. The same numbers for GM and Mpox are 22% and 17%—suggesting there is some geography to these too. We think some of this may be an artefact of the weighting procedure, but it seems that variation across groups (LAs) is significant either way.

A few examples in Figures 3–4 show Clean Air Zones in different LAs. We note that the percentage of opposition to Clean Air Zones varies, but does not seem to outweigh support in any of the cases.

We found two LA-level variables with comparable marginal impacts on support for Clean Air Zones: urban area, and existing Clean Air Zones. We did not find an effect associated with car ownership in the LA (aggregate figures, merged from 2021 Census).



The **red** distribution peaks at the **estimated % of opposition** to Clean Air Zones in the LA. The **green** distribution peaks at the **estimated % of support**. In Bromley, contestation is relatively close between opponents and supporters.

Fig. 3: Support and opposition to Clean Air Zones across selected London LAs.

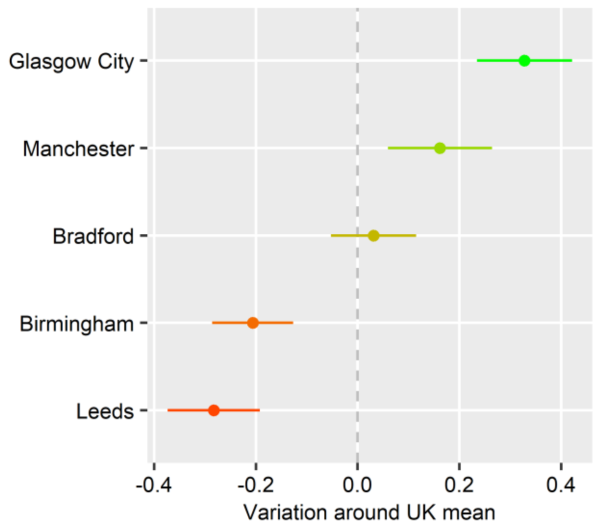


Fig. 4: Random effects plot showing variation of Clean Air Zone support in selected UK LAs.

Polarisation

Does science polarise? In this section, we summarise the findings from our working paper 'Polarisation, Consensus, and Citizens' Responses to Science-based Policies' which we have attached to this report. Here we only briefly sketch the theoretical argument but present the original findings in full. For a thorough discussion of previous literature and our theoretical framework, please refer to the attachment.

Political polarisation, broadly defined as the division of citizens into antagonistic political camps (Roberts 2022), is potentially damaging to democracy. Literature in social epistemology has introduced the concept of 'cognitive' polarisation, which occurs when disputants not only disagree but also discredit each other's evidence and knowledge (de Ridder 2021). In the realm of populist politics, such cognitive polarisation can manifest as explicitly anti-science sentiment, including sometimes a wholesale rejection of expertise and intellectualism (Morelock & Narita 2022).

To understand the role that science may play in the polarisation of attitudes towards a policy, we have to put it in context. In public policymaking (as opposed to, say, election campaigns), outcomes are co-produced by science and politics (Jasanoff 2004). The public receive both political and expert information about the merits of a policy. If adding (more) scientific knowledge to information available to the public widens the gap between opponents and supporters of the policy, we interpret this as evidence that science can have a polarising effect.

Opposition to a scientifically inspired policy does not necessarily tell us that opponents are 'anti-science'. They may instead reject the way that science has shaped the policy agenda to the exclusion of the issues they are concerned about ('orthogonal' disagreements), or indeed they may reflect disagreements where both parties think science is on their side (disagreements among 'epistemic peers'). According to de Ridder (2021), both anti-science attitudes and orthogonal disagreements can produce cognitive polarisation, while our category of disagreements among peers should not be polarising.

Figure 5 shows these three setups.

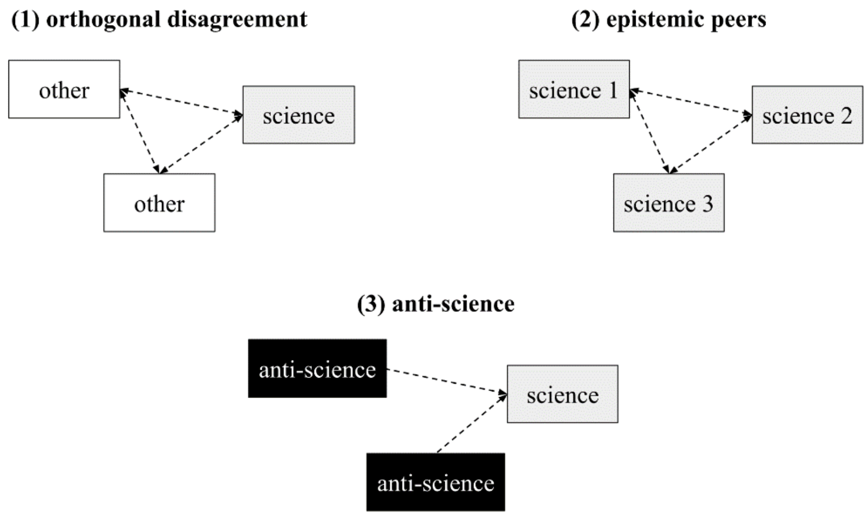


Fig. 5: Three scenarios of science-based disagreement.

We outline below how we established from the text analysis that there were different kinds of disagreement in the cases of Clean Air Zones and Genetically Modified (GM) crops. In the debate on Clean Air Zones, we found that the parties disagree on who has useful knowledge about the policy and what kind of knowledge that might be. Thus 'orthogonal' disagreements were characteristic of this case. By contrast, in the GM case we found that both sides of the debate used scientific evidence and arguments. Thus disagreement among epistemic peers was characteristic of this case.

We hypothesise that polarised responses to adding (more) scientific knowledge to information available to the public are more likely to arise in the Clean Air Zone case than in the GM case. We report the results of testing this hypothesis in the section on 'Survey evidence' below.

Text evidence

We followed standard computational procedures for large-scale text processing using the software library spaCy in Python, such as standardising similar words, removing uninformative words such as articles and numbers, and constructing a numerical representation of the corpus vocabulary. Then, our aims with the text were two-fold:

1. classifying opposition and support for policy (plus additional categories, see later)
2. identifying science content in these segments.

Classification often follows these steps: (a) a sample of the text data is hand-classified, (b) which is then processed with a classification algorithm to learn about which words and combinations of words are associated with which target category, (c) which classifier is then used to predict the rest of the sample. For this project, it is steps (a) to (b) that are most useful in order to examine the 'internal' learned features of the machine classifier in (b), to understand whether the words and combinations of words that distinguish between opposition and support contain science-related keywords. The out-of-sample predictions in (c) are now irrelevant; the final step of prediction is based solely on the learned features in (b).

For hand-coding, we first assigned a random sample of 300 complete news stories to three research assistants who were employed on our project. They were tasked with classifying the entire news story into one of the following categories:

- supportive of policy
- critical of policy
- neutral about policy
- policy does not go 'far enough'—a position we identified in an iterative process with the researchers who found these texts 'critical' of policy but supported its aims and justifications.

Then, the researchers went back to the news texts and identified particular segments within them (full sentences) that contained most information about different positions. This way we were able to learn about support and opposition within ambiguous (uncoded) or overall 'neutral' journalistic texts, extracting smaller, more informative, units. This way we obtained 271 additional segments for analysis.

To analyse this hand-coded sample, various algorithms are available to find the most predictive words and combinations of words for each policy position. We looked at all traditional algorithms available via the scikit-learn library in Python, compared them using Confusion Matrices, and found that a Logistic Regression classifier performed best. We note that at best we achieved only moderate accuracy given an imbalance of policy positions. This is informative for substantive reasons: our classifier found it difficult to decide whether to assign 'supportive' and 'not far enough' labels, but had more precision distinguishing 'supportive' and 'critical' texts.

Next, we turned to identifying science content. We approached this by constructing a small dictionary of terms which we compared with the classifier's vocabulary. The dictionary comprises:

- explicit attributions to science: science, study, research, expert
- 'technical' keywords used in scientific publications on these policies.

To identify a list of technical keywords, we queried the Web of Science database for the top published research articles covering our cases and retrieved the author-defined keywords; see a detailed discussion of this in the Interim Report.

Results

Table 4 shows the distribution of texts and segments per policy position. We found 178 texts with a clearly identifiable policy position, and the rest were searched again for classifiable smaller segments. The vast majority of our corpus expresses a positive attitude to the science-based policies, and this tendency is found across all three cases.

We did not find segments that opposed Mpox interventions, and only two articles and one segment that we classified as 'neutral'. This means we do not have evidence of disagreement about surveillance and case investigation of Mpox in our sample, and as such, will exclude it from further text analysis (but keep it in the survey study later). We also have a lack of 'not far enough' texts for GM crops (only two texts), so this category had to be excluded from the GM classifier as it contains too little information.

Table 4: Frequency of texts per policy position.

	News stories	Segments
Supportive	90	161
Opposing	23	73
Neutral	49	23
'Not far enough'	16	14

Next, we fit the logistic regression classifier described above, and examine it closely to understand which keywords (words or combinations of words) are most predictive of the four policy positions. We do this for Clean Air Zones and GM separately. Tables 5A–B show a preview of thirty most decisive keywords for each policy. Table 6 sums up weights by science-related keywords alone.

Table 5A: Most decisive keywords and weight in classifier: Clean Air Zones.

y = critical		y = neutral		y = supportive		y = not far enough	
weight	feature	weight	feature	weight	feature	weight	feature
+0.739	business	+0.505	say	+1.416	<BIAS>	+0.624	paris
+0.682	<BIAS>	+0.487	big	+0.395	government	+0.568	propose
+0.651	tax	+0.397	cut	+0.380	call	+0.414	require
+0.466	traffic	+0.380	councillor	+0.375	hail	+0.390	campaigner
+0.386	appear	+0.371	standard	+0.366	zones	+0.374	promise
+0.377	punish	+0.359	health	+0.348	welcome	+0.325	mr
+0.361	feel	+0.336	tricky	+0.332	want	+0.313	edinburgh
+0.350	backlash	+0.331	enlarged	+0.313	live	+0.308	package
+0.345	evidence	+0.313	scale	+0.304	exciting	+0.294	plan
+0.345	bath	+0.309	charge	+0.296	air	+0.289	environmental
+0.322	cost	+0.306	establish	+0.296	public health	+0.287	concern
+0.295	year	+0.305	ask	+0.285	step	+0.275	earth
+0.295	taxi	+0.303	question	+0.283	crisis	+0.273	seek
+0.277	good	+0.294	region	+0.283	legal	+0.263	city council
+0.266	scheme	+0.290	agree	+0.269	caz	+0.262	greater
+0.262	public	+0.289	size	*…1570 more positive…*		+0.258	funding
+0.262	test	+0.272	charge driver	*…2555 more negative…*		+0.253	envi camp*
+0.256	closure	+0.267	benefit	−0.275	leed	+0.251	clean
+0.254	choice	+0.260	small	−0.277	council	+0.250	consultation
…1929 more positive…		+0.252	age	−0.281	promise	+0.249	gr manch
…2196 more negative…		+0.242	ulez	−0.282	big	+0.245	area
−0.244	benefit	+0.234	achieve	−0.288	punish	+0.244	leader
−0.245	drive	+0.233	think	−0.289	area	+0.244	council
−0.245	scotland	+0.232	right	−0.293	scheme	+0.242	friend earth
−0.248	air	+0.223	burnham	−0.296	plan	+0.240	manchester
−0.260	level	+0.211	poise	−0.319	appear	+0.239	friend
−0.292	action	+0.211	jeopardise	−0.341	standard	*…2035 more positive…*	
−0.301	introduce	*…1187 more positive…*		−0.352	traffic	*…2090 more negative…*	
−0.307	city	*…2938 more negative…*		−0.361	good	−0.232	zones
−0.309	paris	−0.237	year	−0.382	tax	−0.271	road
−0.363	government	−0.321	car	−0.460	propose	−0.376	zone
−0.654	say	−1.470	<BIAS>	−0.540	business	−0.628	<BIAS>

* 'environmental campaign'

Table 5B: Most decisive keywords and weight in classifier: GM crops.

y = critical		y = neutral		y = supportive	
weight	feature	weight	feature	weight	feature
0.500	real	0.530	scientist	1.358	<BIAS>
0.453	<BIAS>	0.495	support	0.475	country
0.419	gm	0.453	guarantee	0.385	attitude
0.402	seed	0.452	uncertainty	0.371	benefit
0.344	cultivate	0.432	prediction	0.326	environmental
0.312	public	0.418	describe	0.322	grow
0.307	engineer	0.396	say	0.321	gm food
0.301	body	0.361	unite	0.318	base
0.297	human	0.347	note	0.306	modify
0.296	fail	0.336	commentator	0.302	result
0.256	vandal	0.335	community	0.287	bad
0.249	disaster	0.329	government	0.275	ban
0.248	herbicide	0.315	biotech	*… 2704 more positive …*	
0.247	multinat**	0.308	crop	*… 2369 more negative …*	
… 1565 more positive …		0.301	local	−0.282	support
… 3508 more negative …		0.300	stance	−0.286	sci comm*
−0.257	local	0.294	sci comm*	−0.287	engineer
−0.270	scientific	0.283	new	−0.293	damage
−0.272	test	0.249	comment	−0.295	guarantee
−0.285	gm food	0.235	trial	−0.299	gm
−0.292	find	0.233	fact	−0.309	industry
−0.294	reduce	0.231	approval	−0.310	community
−0.300	europe	0.228	change	−0.311	government
−0.301	feed	0.222	producer	−0.324	safety
−0.305	country	0.218	friends earth	−0.325	change
−0.315	attitude	0.218	friends	−0.333	animal
−0.341	science	0.218	scientific	−0.337	promise
−0.343	scientist	0.216	uk	−0.353	seed
−0.370	result	*… 1991 more positive …*		−0.399	herbicide
−0.377	crop	*… 3082 more negative …*		−0.413	scotland
−0.412	debate	−0.288	farmer	−0.447	real
−0.461	benefit	−1.811	<BIAS>	−0.626	describe

* 'scientific community'
** 'multinational'

The classifier matched each keyword with a weight. We use positive weights as measures of their marginal contribution to the classifier's decision whether to assign a particular label. Besides the top keywords shown above, there are a total of 31,929 keywords with some weight attached to them, of which 13,122 have positive weights. Of these, we identified 170 as science-related keywords with the dictionary method mentioned above. The sum of positive weights (or the total marginal contribution to classifier) across all science-related keywords is shown in Table 6.

Table 6: Sum of weights: science-related keywords.

Policy position	Clean Air Zones	GM crops
Critical	0.67	1.80
Neutral	0.79	2.50
Supportive	1.47	2.63
Not far enough	1.45	-

These results indicate some differences across the policy cases. We find some evidence of orthogonal disagreements about Clean Air Zones, in the sense that the weight of science keywords in opposition texts is less than half of that in supporting texts. Looking at the top keywords in Table 5A, this is confirmed: the most decisive keywords are ‘tax’, ‘traffic’, and ‘business’, which we take to imply concern about the redistributive effects of the policy and perceived harms to local businesses rather than emissions and the effects of air pollution. But we obtain a similar sum of weights in supporting and ‘not far enough texts’, which implies that these groups are epistemic peers. The latter group’s top keywords are ‘paris’ (the Paris Agreement on Climate Change), ‘environment’, and the ‘campaign’ groups (including Friends of the Earth, a top keyword), which suggest that this is about rejecting the proposed policy as insufficient in addressing climate change.

When it comes to GM crops, it is clearer that support and opposition are epistemic peers. There is a substantial amount of weight given to science in any policy position in this corpus, suggesting that it is difficult to discuss the policy without engaging with the science content. Interestingly, as shown in Table 5B, some of the most decisive science keywords are assigned to the neutral texts. We take this to suggest that science has a role in consensus building, rather than polarising the public discourse, but will return to this issue in the survey study.

Finally, we manually examined the subset of texts classified as opposition, specifically focusing on the segments where science and related keywords are mentioned, looking for evidence of anti-science. There are 104 such segments. We find scepticism towards evidence, for example on GM safety, or the lack of ‘good data that [Clean Air Zones] will improve health’, and even explicit mention of ‘anti-science’ in both corpuses. However, perhaps due to the nature of journalistic texts, the tone does not qualify as ‘epistemic disdain’, which would characterise anti-science. What we find qualifies more as ‘mitigated scepticism’—in other words, a questioning attitude and reluctance to take scientific findings on trust. In the GM debate, scientists supporting GM sometimes claim that their opponents are anti-science, but in our corpus those opponents present themselves as epistemic peers and put forward scientific evidence for their views. In short, we find no good evidence of disagreement of the anti-science type in our samples.

Survey evidence

To explore polarisation, we use a subset of results from Experiment 1, where respondents were asked to rate the authority implementing the particular science-based policy they read about. In this section, we focus on two dependent variables, both rated on five-point Likert scales: perceived competence, asked as 'If you had to say, how competent do you think the relevant authority has or has not been?' and intention to comply, asked as 'How likely is it that you would or would not comply with this policy, if asked by the authority?' We list these variables and discuss them more systematically in the section 'Democracy/Survey results'.

In this experiment, we generated series of four, randomly generated single profiles for each respondent to review, each describing one particular public policy and the circumstances of its adoption. The variables we varied were: expertise, which we explain below, as well as policy adopted (our three case studies), political consensus (agreement among MPs/local councillors), public opinion about the issue, and whether public consultation took place. In this section, we concentrate on the 'expertise' attribute, which displayed one of the following options in each trial:

- 'Expert advice not available'
- 'Expert supports proposal'
- 'Scientific research by UK university supports the proposal'
- 'The government's scientific advisor supports the proposal'.

Presence vs lack of any expertise at the time of adoption is crucial for us to assess its marginal contribution, while the vague 'expert', and the more specific 'scientific research' and in-house 'scientific advisor' attribute levels tap variation across how expertise is often used and communicated. These descriptions also needed to be high-level enough to be applicable across the three policy cases, and we needed to ensure that they do not imply interest group politics, such as NGO (non-governmental organisation) or industry support.

Our key statistic is the marginal mean support, which is the average rating respondents gave to the profiles whenever a particular attribute level was presented to them. In our case, it is interpretable as the average rating on the five-point scales measuring perceived competence of authority, or intention to comply with policy. We follow Leeper *et al.* (2020) and use these to analyse subgroup preferences, by prior policy support (see below).

Our key moderator is prior policy support, tapping pre-stimulus attitudes to Clean Air Zones, GM, and Mpox, all measured on five-point scales ranging from 'strongly favour' to 'strongly oppose', and had in addition a 'don't know' option. The distribution of 'don't know' responses is: 1.8% (Clean Air Zones), 3.2% (Mpox), 4.4% (GM).

Responses to the conjoint experiment are analysed by prior policy support.

Results

In Figure 1 previously we showed the distribution of prior attitudes to the policies, with flatter distributions implying more polarised prior attitudes. We noted they are all at least slightly skewed towards policy support, but Clean Air Zones have a bigger opposition base. Excluding moderates, the weighted percentages of support (including strongly support) vs opposition (including strongly oppose), and 95% CIs (confidence intervals) are:

- Clean Air Zones: 0.44 [0.40,0.48] vs 0.30 [0.26,0.34]
- Mpox case investigation: 0.62 [0.58,0.67] vs 0.09 [0.06,0.12]
- GM approval: 0.51 [0.47,0.56] vs 0.14 [0.11,0.17]

These results suggest that, although none of these policies faces extreme levels of polarisation, Clean Air Zones are closest to representing a polarised case. What does this mean for the associations between science and respondents' attitudes?

Analysing the conjoint results, our primary interest is in the effect of science by prior support and by policy area. Before we come to that, here we briefly note that overall, without accounting for subgroups, expertise is valued by our respondents. Compared to the baseline of 'no expert advice available', ratings of perceived competence are expected to increase (average marginal component effects) by 0.24 (*SE* (standard error) = 0.04, for expert support), 0.28 (*SE* = 0.04, government scientific advisor), and 0.30 (*SE* = 0.04, university research), $p < 0.01$ in each case. These are the largest effects compared with the impact of other attributes. At the same time, compliance intentions are expected to increase a little less as a result of expertise, by 0.20 (*SE* = 0.04, experts), 0.14 (*SE* = 0.04, government science advisor), and 0.15 (*SE* = 0.04, university research), $p < 0.01$ in each case.

Split by prior support, we notice significant variation in responses to the science prompt, $F(8,6368) = 12.67$, $p < 0.01$. Figure 6 shows that science advice increases the perceived competence of authorities, mostly for those who supported the policy. Opponents agree that authorities' perceived competence is boosted with science advice, but much less so. We expect that some of this is due to policy-specific variation, which we will return to below.

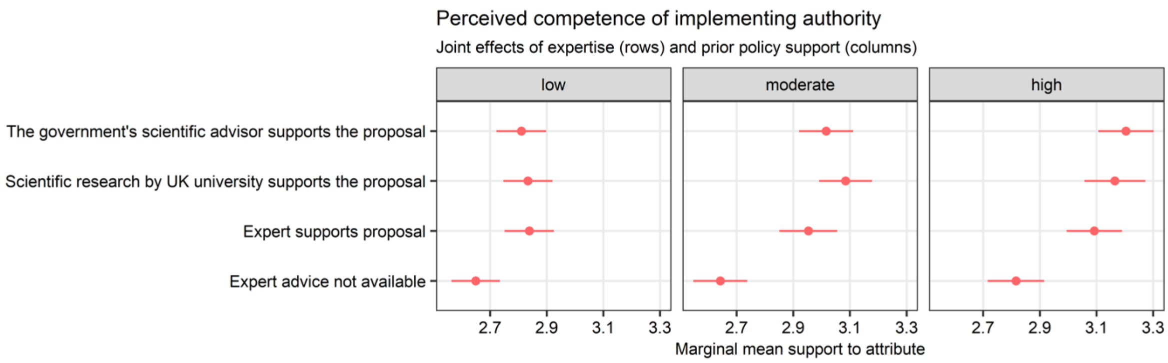


Fig. 6: Perceived competence of authority, by prior attitudes.

Figure 7 shows the same subgroup variation, but the dependent variable is intention to comply with policies. This variation is also statistically significant, $F(8,6368) = 64.25$, $p < 0.01$, but some of the patterns have changed. For opponents, science still has a small but significant contribution. For moderates and especially for supporters of the policy, this is no longer the case, with 95% CIs overlapping between 'no expert advice' and forms of science advice. We interpret this to mean that supporters' decision to comply is not sensitive to science advice, but other factors matter, such as high trust and perceptions of legitimacy (we return to this in the section 'Democracy/Survey evidence'.

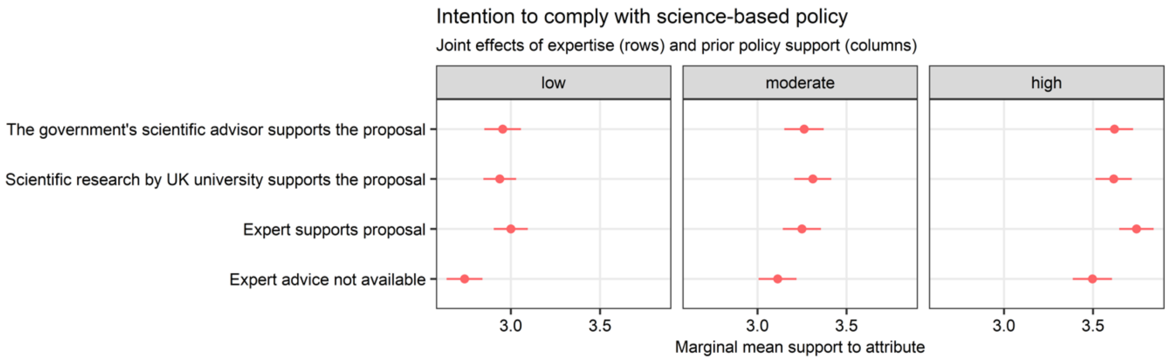


Fig. 7 Intention to comply, by prior attitudes.

We now turn to further interacting these effects with policy area. Adding policy case adds further significant variation to the previous perceived competence model, $F(16,6360) = 9.50$, $p < 0.01$. Figure 8 shows the marginal means for each group. It clarifies that opponents thought authorities implementing a Clean Air Zone were no more competent if they followed science advice, while the increase is still significant for supporters. For Clean Air Zones, it seems that differences in perceived competence between opponents and supporters persist, or in fact increase, when science justifications are provided. We take this as evidence of polarisation. We find no such dynamic for the other two case studies.

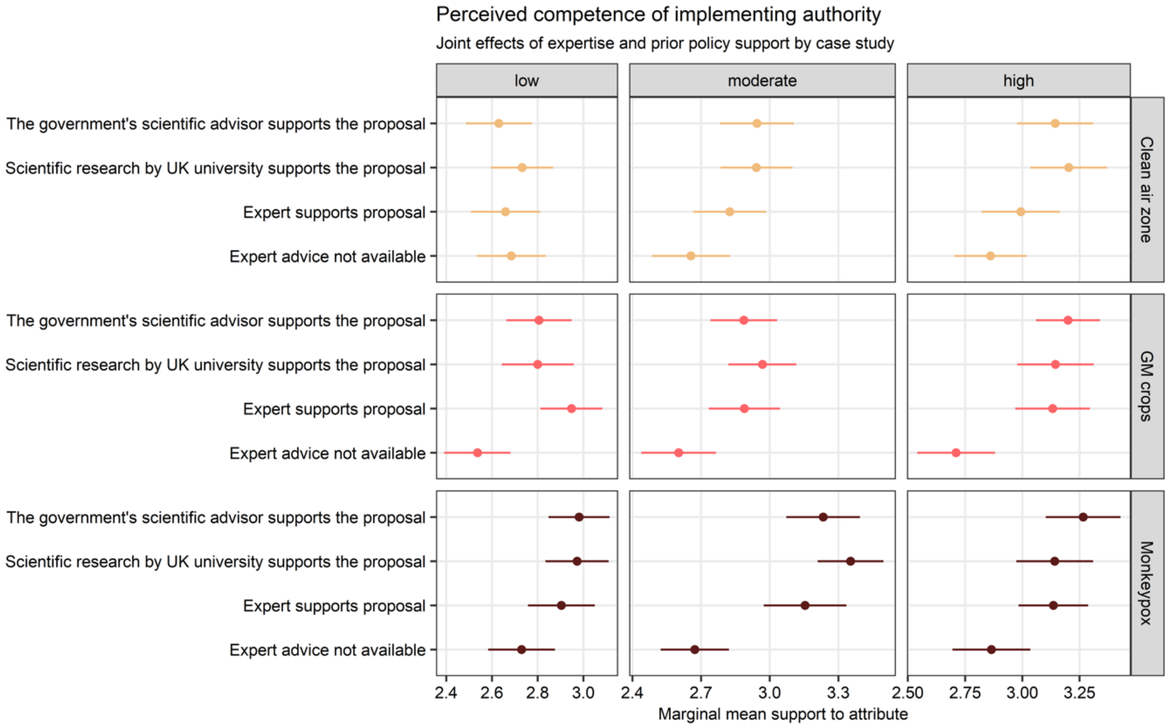


Fig. 8: Perceived competence, by policy area.

Turning to intention to comply, we get a similar picture. Figure 9 shows subgroup variation, which is still significant, $F(16,6360) = 37.59$, $p < 0.01$. Looking at opponents of Clean Air Zones, there is a small marginal increase in intention to comply when scientific support is available, but the 95% CIs overlap and we cannot rule out null effects. Science has virtually no effect on intention to comply with Clean Air Zones for moderates and supporters. Looking at the other policies, science has a more noticeable but still marginal impact on compliance, and we cannot rule out null effects.

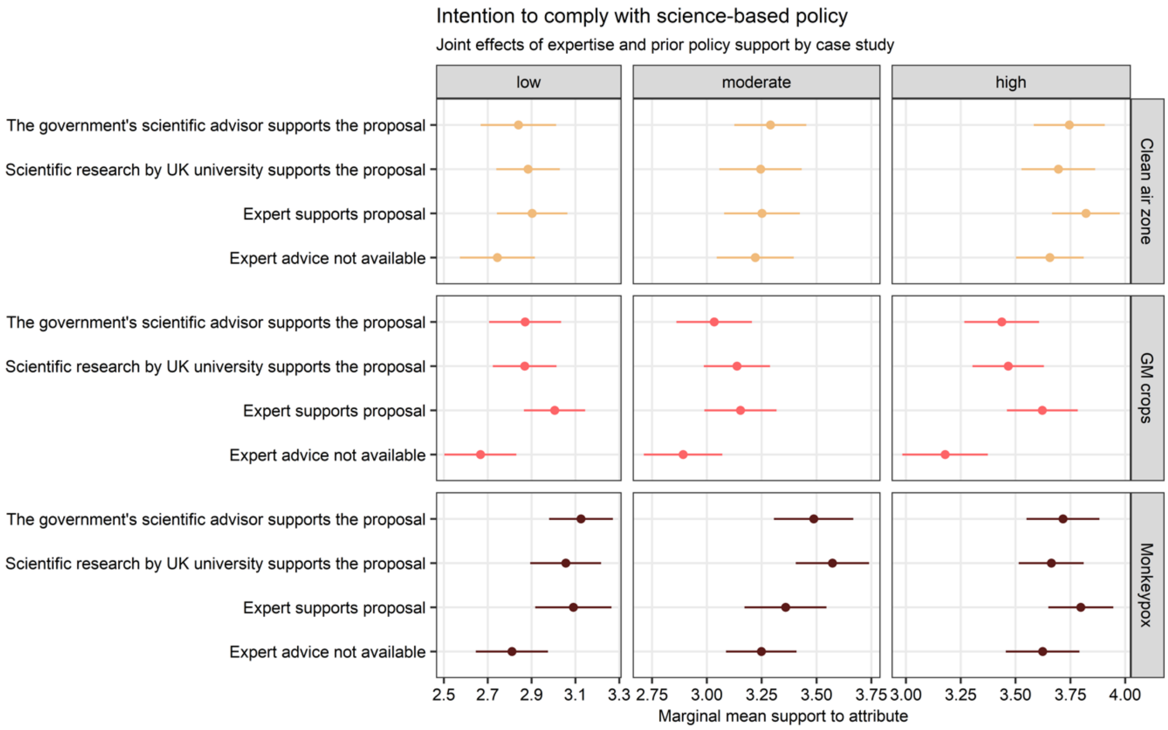


Fig. 9: Intention to comply, by policy area.

Discussion

Drawing on the text analysis of our three case studies, we identified three different types of disagreement that may have implications for polarisation: 'orthogonal disagreements' where scientific justification is met with other forms of knowledge, such as experiential knowledge; disagreements among 'epistemic peers' where science is met with competing scientific claims; and disagreements where science is met with anti-scientific views. The latter were referenced in the news media with very low frequency and anti-science was not further explored. However, it is worth noting that, by definition, it represents the most extreme case of polarisation around science.

As for the other two types of disagreement, we found the following in our survey experiment. Opponents of Clean Air Zone policies perceived authorities who followed science advice to be no more competent than those who did not follow any expert advice. Regarding compliance, we hypothesised less polarisation, assuming opponents would still likely comply with trusted, legitimate (state) action. Overall, across the different policy cases, we found some evidence pointing in this direction. However, when it comes to Clean Air Zones specifically, science only very marginally increased intention to comply.

Regarding 'epistemic peers' debating the potential and pitfalls of GM technology, science seems to be contributing more towards consensus than polarisation in the survey experiment. We found that both perceived competence and intention to comply among opponents increased with science justification.

We acknowledge some limitations. Our text study explored the public discourse in the news media, which is most useful for specific policies (e.g. local news for Clean Air Zones), but it limited our discovery of anti-science. Exploring the social media discourse continues to be a way to understand more niche anti-science views, although it comes with the caveat that social media likely overrepresents polarising views. We also note that the conjoint experiment explored how prior attitudes condition/mitigate the impact of science on policy ratings, rather than exploring the reverse relationship to establish a causal claim. Understanding polarisation around science-based policies would benefit from more long-term observational survey work over time.

Democracy

Much public policy is made beyond the public gaze. It is subject to 'output-oriented legitimation', meaning that, if it works, it will be accepted by citizens. In these policy areas, the principal challenges for science-based policymaking are to maximise the instrumental effectiveness of science advice (for example, by sponsoring appropriate research projects), and to 'insert' science into the policy process in ways which facilitate agreement around the scientifically preferred policy. If the contending factions in the policy community accept that their disagreement is resolvable through research, we are in the world of 'technocratic modes of settlement' (Radaelli 1999).

There are some circumstances where it matters that the public find technocratic modes of settlement appropriate and legitimate. Public cooperation may be needed for policy effectiveness, meaning that the policy has to be presented and explained. Even if the public is willing to accept a technocratic solution in principle, increased public scrutiny may find that the issue at hand is not yet 'settled' given scientific uncertainty. Uncertainty is often assumed to undermine scientific authority, although recent evidence suggests that exposure to scientific uncertainty (probabilistic statements) does not lead to scepticism (Gustafson & Rice 2020). Output legitimation may fail, triggering a search for accountability. It becomes relevant to know whether and when the public will think it appropriate for policy decisions to be led by the science.

Furthermore, many science-based or science-informed policies are hybrids of knowledge-based and value-based judgments and decisions (Soneryd & Sundqvist, 2023). Public policy issues are not like scientific research questions. They are not chosen or designed to be susceptible to answers generated by scientific methods. They are likely to engage a range of disciplinary competences and pose questions which require balancing different moral and ethical imperatives (Jasanoff 2004). Thus scientists who take on the role of experts in a public policy debate almost inevitably take positions which transgress the boundaries of their expertise (Pellizzoni 2011).

One possible response to this transgression is that the public do not accept the legitimacy of technocratic modes of settlement at all; instead, they might take the view that all kinds of decisions should be made through democratic modes of settlement. However, this does not have to entail the rejection of a substantial role for science in public policy. On the contrary, democratic decision-making will be facilitated by ensuring the creation of shared knowledge. But this would imply that the public will be more accepting of science that stays within its boundaries by contributing factual knowledge, while science may be seen as over-reaching when factual knowledge and causal claims are entangled with policy recommendations.

Survey results

We distilled these issues into two main sets of questions in our experimental survey design. First, we examined how scientific input was evaluated relative to other 'democratic' inputs, such as public consultations. We wanted to see whether this evaluation varied across the three cases (Clean Air Zones, GM crops, and Mpox) given the different 'values' issues that each presents. We also wanted to see if there was 'rivalry' in respondents' evaluations of scientific and democratic inputs. Were responses positive for one and negative for the other, in different contexts? (The short answer is no.)

Second, we examined how the public view the quality of scientific inputs with different attributes. Were assessments adversely affected by uncertainty in the science? Were they more positive when the scientific contribution stuck to factual information (technical statements, as identified in the text analysis) or did the public also accept causal claims? Did the status of the researchers matter to the public as it might matter to scientists? We were particularly interested in reactions to 'citizen science'. Advocates of citizen science propose practices where the public, outside of institutionalised science, contribute not just to policymaking via public consultation but more directly to the production of scientific knowledge itself. For example, participatory 'citizen sensing' communities are local citizen scientists who collect and publish air quality data—a practice publicised recently in the UK to aid research on Clean Air Zones (Mahajan *et al.* 2022).

In the survey experiments discussed below, we explored public attitudes by presenting respondents with a randomly varying list of characteristics of the policy process and examining how these affected (a) their evaluations of the implementing authority (central or local government) and (b) their evaluations of different scientific research programmes.

From the perspective of survey respondents, the procedure is as follows. In Experiment 1, each trial consists of a summary table in which we specified what politicians, the public, and the experts thought about the particular policy that was adopted. In each trial, we named the policy (one of the three case studies) that was implemented including the implementing authority. We also indicated expert involvement, including whether scientific research or the government's science advisor supported the proposal. Other features were also varied simultaneously: extent of political consensus, whether there was public consultation, and what public opinion is about the policy. There are therefore 144 potential adoption scenarios, and each respondent viewed a series of four scenarios, resulting in ~6,000 evaluations across the sample. After each summary table, respondents were asked to indicate their perceptions of authorities ('dependent variables'), namely:

- trust in authority delivering the policy
- their perceived competence in policymaking
- fairness of the adoption process
- transparency of the adoption process
- respondent's intention to comply with policy.
  We did not specify what 'compliance' would look like in practice—a limitation we acknowledge. Perhaps clearest is compliance with Clean Air Zones: paying a fine or upgrading a car if a vehicle is polluting. For the Mpox case investigation it is sharing contact tracing information with public health authorities, whereas for GM crops it implies accepting if a product is approved and sold on the market, eventually.

In Experiments 2A and 2B, we presented specific scientific claims to go beyond the high-level expertise prompt of Experiment 1. We conducted two separate studies of Clean Air Zones and GM foods, with four trials each. We did not design a follow-up study on Mpox.

Rather than rating an authority on competence, fairness, etc., the task in these 'science vs science' experiments is to compare two alternative scientific research programmes in terms of:

- Which one is better set up to benefit local residents more?
- Which one is better set up to inform the future course of policy more?
- Which group of researchers is more competent?
- Which group respondents trust more to find out information about the subject matter?

The characteristics we varied were:

- Claim framing: is the evidence submitted about pollution facts, or causal statements linking pollution to health outcomes?
- Separate or entangled evidence: does the evidence link explicitly to the proposed policy (Clean Air Zones) or not?
- Certainty: whether experts need to continue working to understand the problem in the local area or whether there is consensus
- Funder: whether the UK government (public) or the car industry funded the research
- Research organisation (RO) type: local, UK, or overseas research university
- Community involvement in research: whether data was not collected locally, or it was collected locally by researchers, or whether local citizens contributed data ('sensing groups'), or whether they were involved in research design (citizen science).

We present the results systematically, considering the impact of each attribute on each dependent variable ('main effects'). We then examine the relationship between the different kinds of dependent variables in Experiment 1 and ask which perceptions are most predictive of trust, and intention to comply, as the two key concepts outlined in our research proposal. Finally, we present the impact of key attributes by respondent characteristics ('subgroup effects'), namely low vs high trust in science (measured originally on a trust Likert scale), low vs high self-assessed knowledge about science (a four-point scale), and partisanship measured by a standard vote intention question.

Main effects: Science vs Politics

Panels A–E in Figure 10 show the results for each dependent variable. We make the following observations:

- 'Perceived competence of authorities' is the most sensitive to presence/absence of science support. The results below show respondents thought the authority to be most competent if the policy process included 'scientific research by UK university', although this is comparable to other forms of expertise, including the in-house government scientific advisor's.

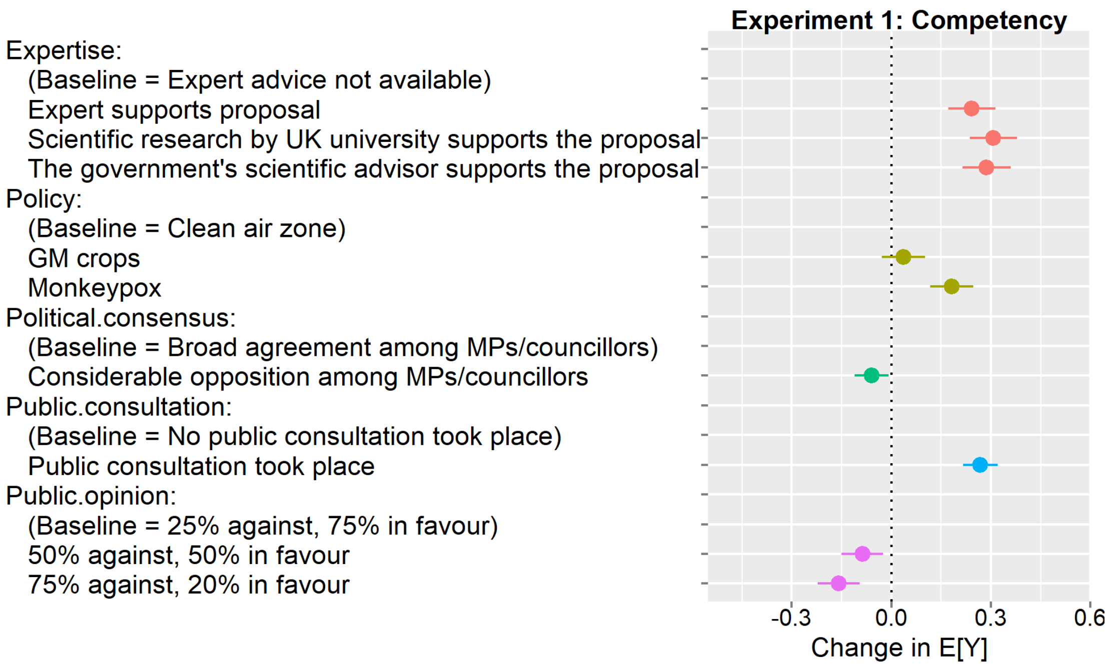
- However, the information governments source via public consultation is also recognised as a relevant form of knowledge, comparable to the information provided by experts.

- When it comes to the other dependent variables, expertise effects can lag behind public consultation and/or public opinion effects. This is especially the case for fairness and transparency. It seems that in these cases citizens' democratic considerations outweigh the need for expertise. But this is not to say that expertise does not matter: across the board, expertise remains a key heuristic.

- We note that the effect associated with most expertise types tends to outweigh that of a split public opinion poll (50–50).

- There are somewhat nuanced policy-specific patterns, which emerge when analysing the experiment results by subgroups—see the final subsection below.

A



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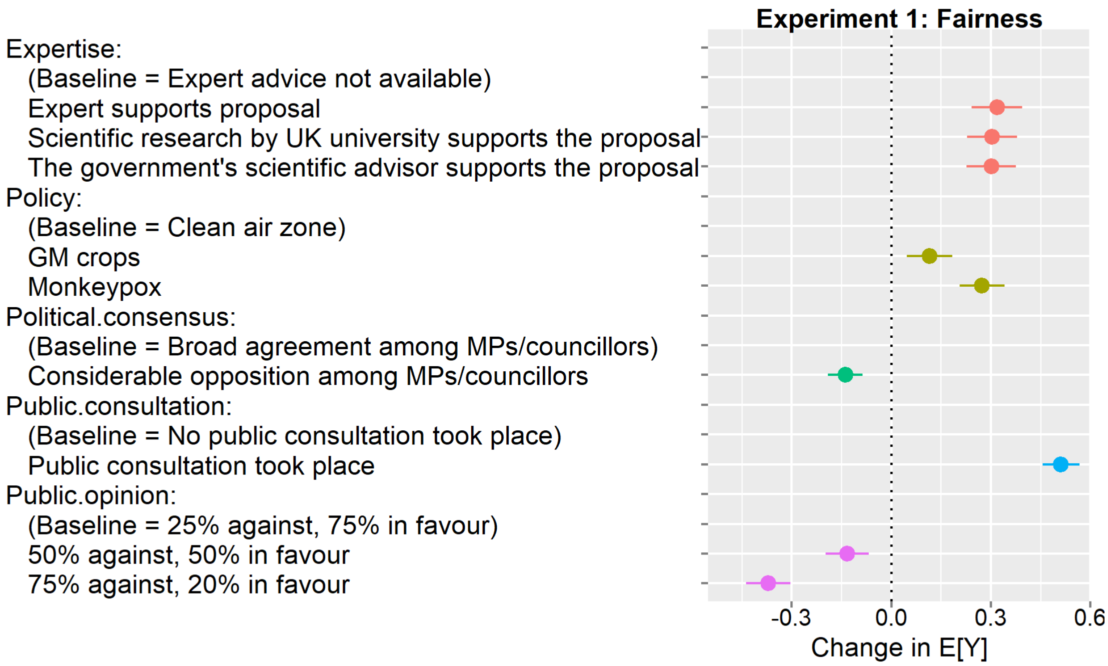

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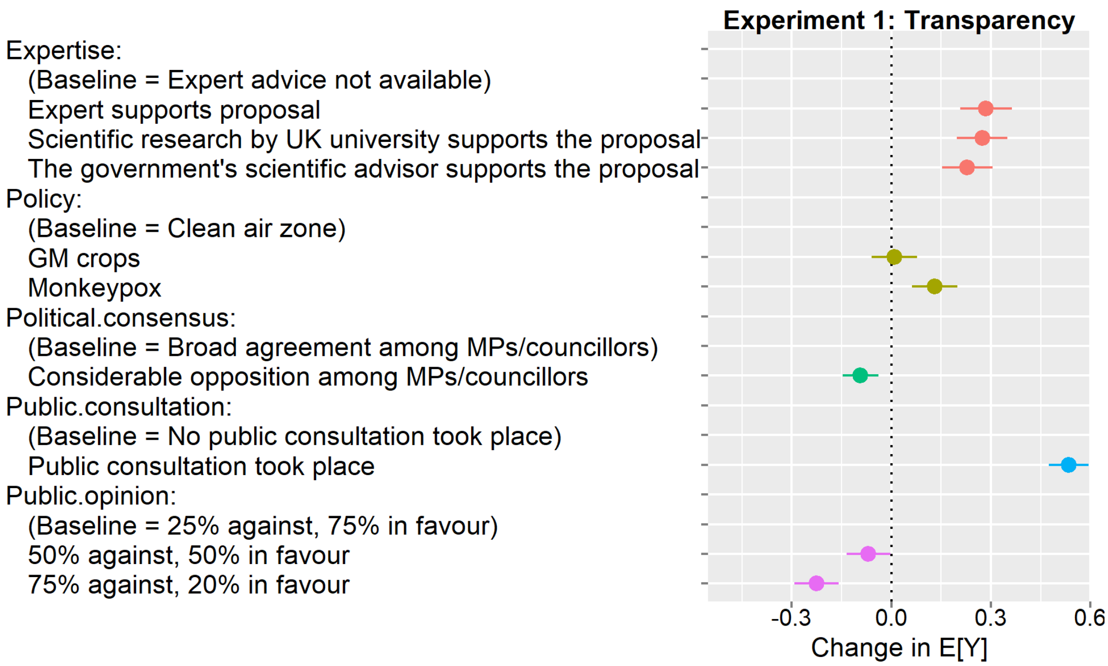

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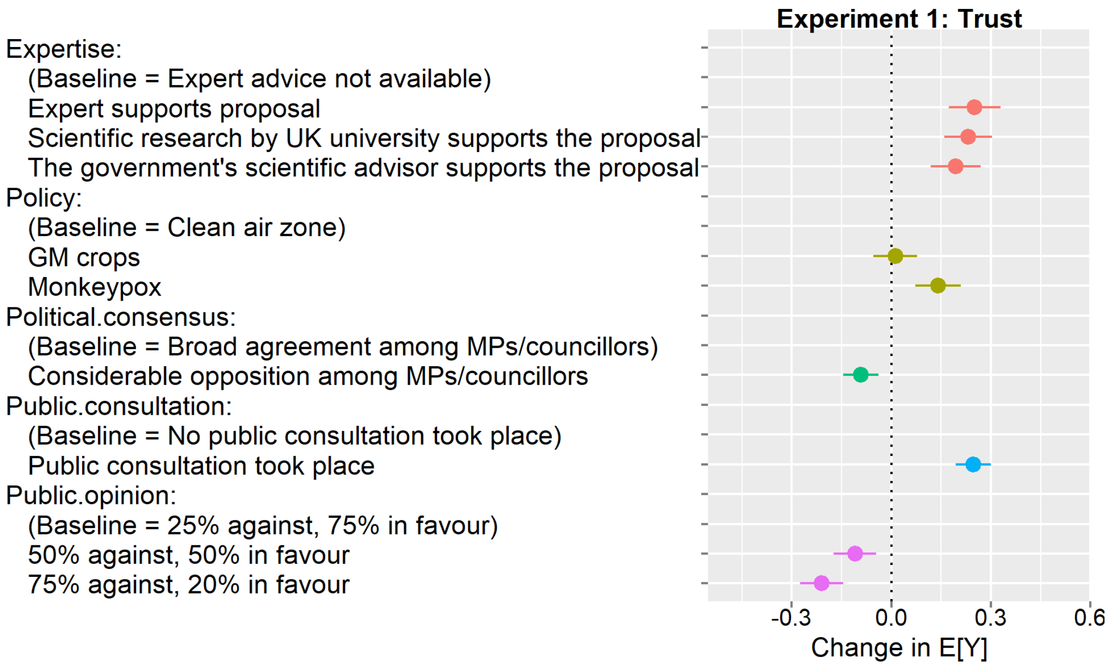

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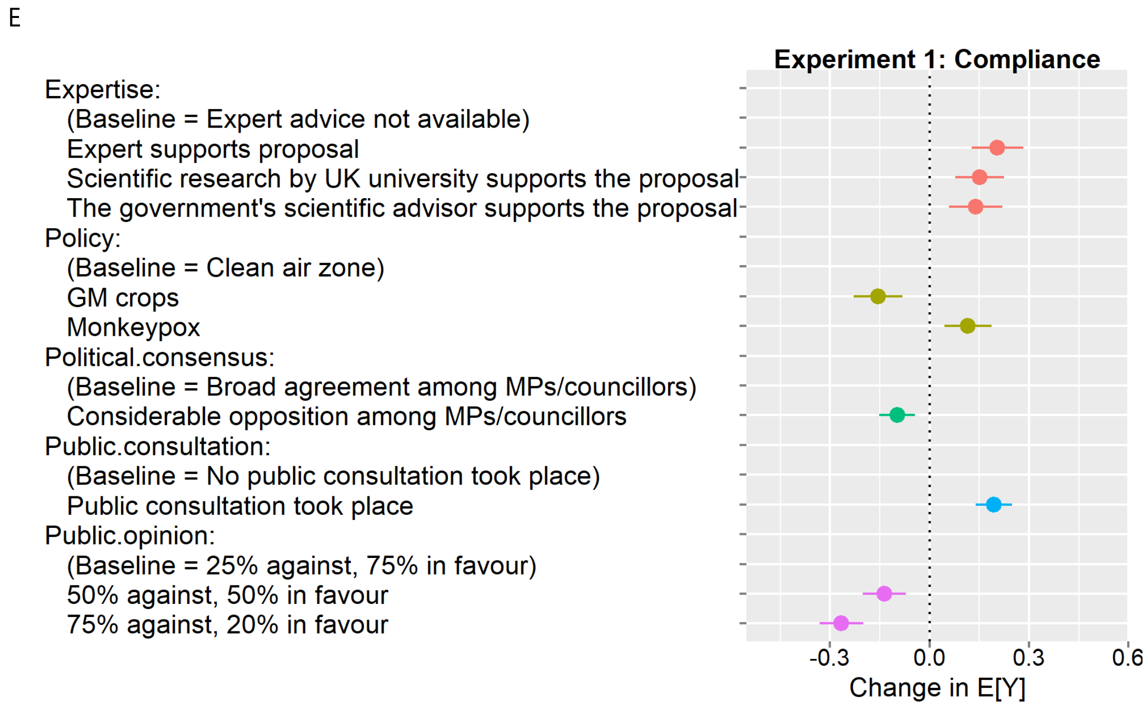


Fig. 10: Experiment 1 results: Main effects for each dependent variable (Average Marginal Component Effects).

Main effects: Science vs science

Panels A–H of Figure 11 show the main effects of Experiments 2A and 2B. We make the following observations:

- Across GM and Clean Air Zones, as well as all of the four dependent variables tapping perceptions of research, the impact of more traditional science communication variables (framing, entanglement, certainty) is very small in comparison with democratic considerations. The most 'competent', 'informative', 'locally beneficial', and 'trusted' research groups were those that were equipped with some form of local input or engaged citizen science. There is also a preference for public funding rather than private funding. UK and local research universities were also preferable to research by overseas universities.

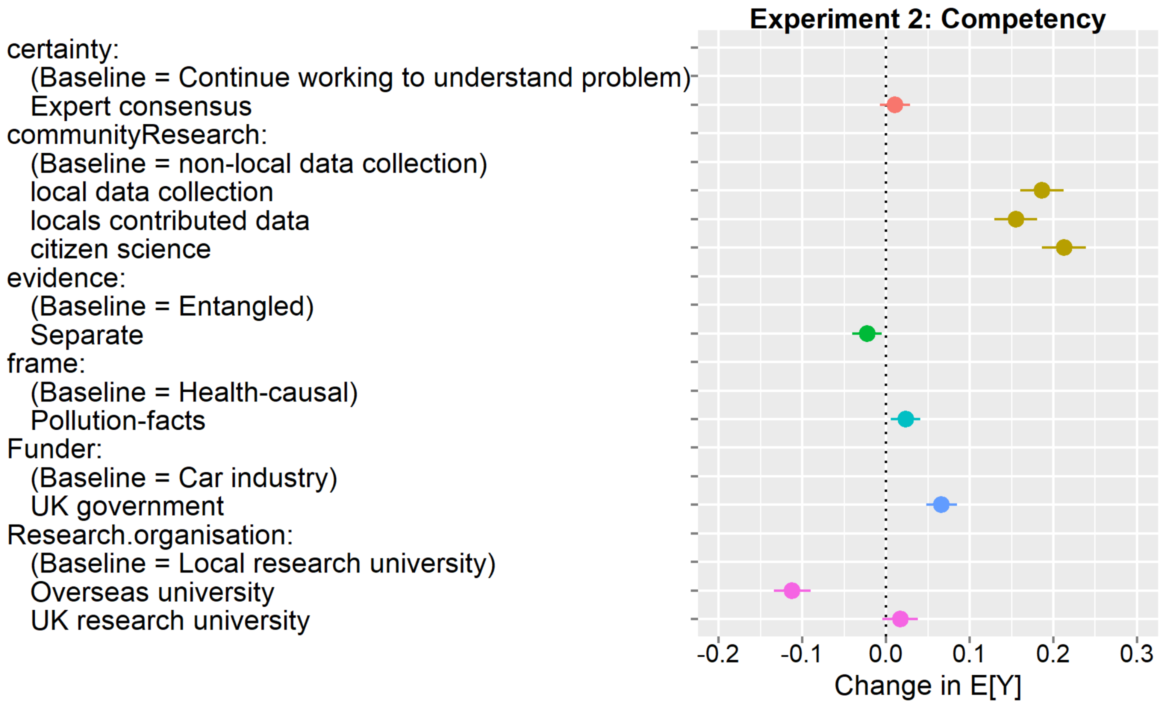
- The degree of certainty in scientific findings did not make a difference when it came to competency evaluations.

- We found small effects associated with framing with Clean Air Zones—although we expected a health frame to increase perceptions that research is useful (competent, trusted, etc.), we found that citizens gave more positive assessments when scientists provided measurements and facts about the subject matter. At the same time, they valued explicit links between the science and the policy proposal—'entangled evidence'. Nevertheless, these are small effects.

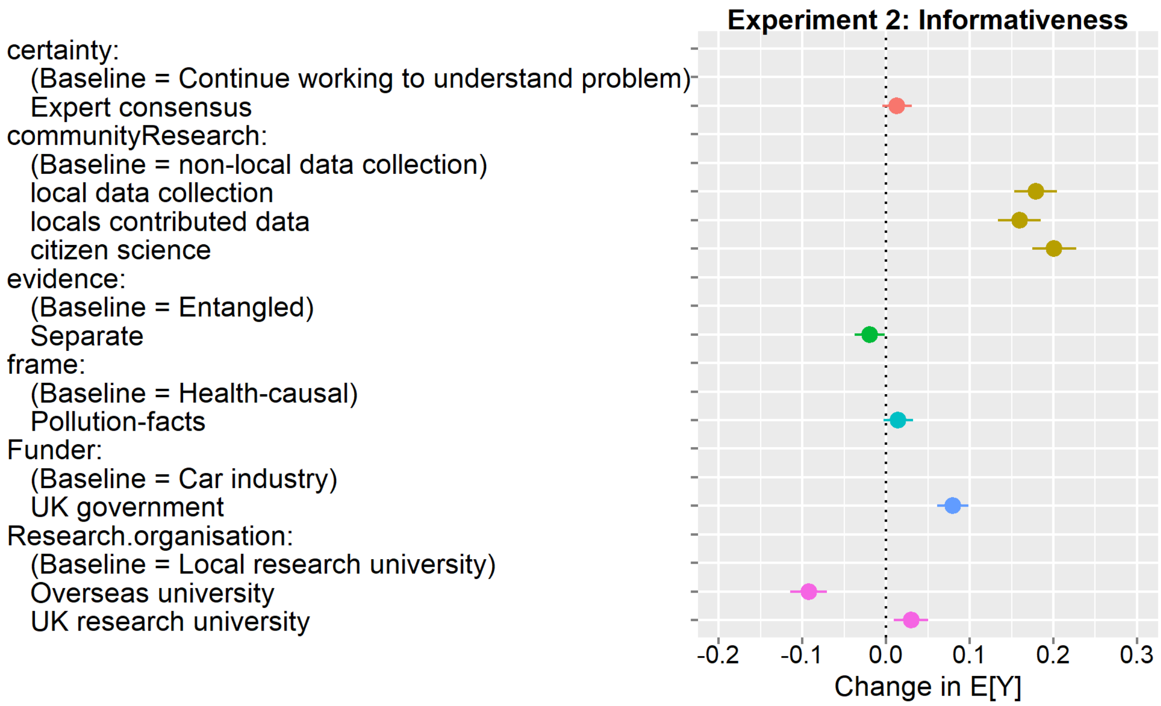
- Citizen science has highest support for 'local benefit' and we also note 'UK research university' has the edge over 'local research university' when it comes to 'informativeness', but not when it comes to local benefits.

- With Clean Air Zones, we presented pollution facts separately from causal claims about health. Most GM research is inherently experimental—and therefore causal—and it would not make much sense to present facts about, for example, low yield. We have, therefore, one fewer characteristic here—factual claims about increased yield were presented either separately or entangled with the policy recommendation. In addition, we adjusted industry funding to come from the food industry rather than the car industry, and citizen science was not about local citizens' involvement in research but about rural communities.

A - Clean air zones, perceived competence



B – Clean air zones, perceived informativeness



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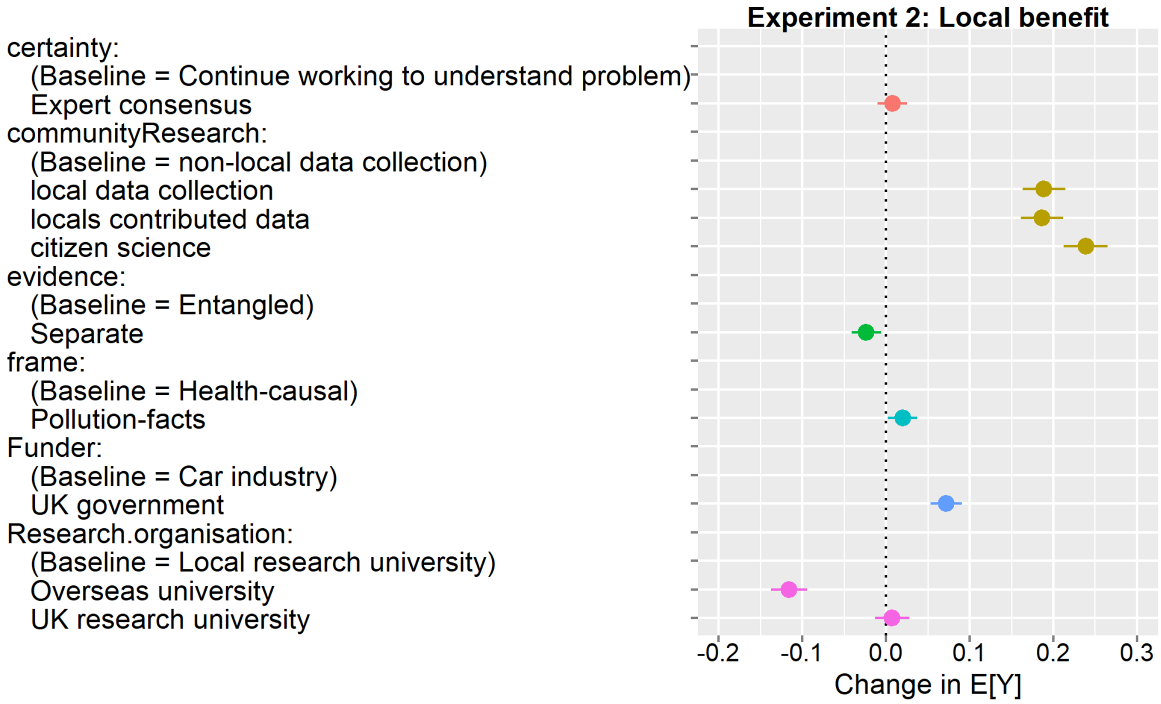
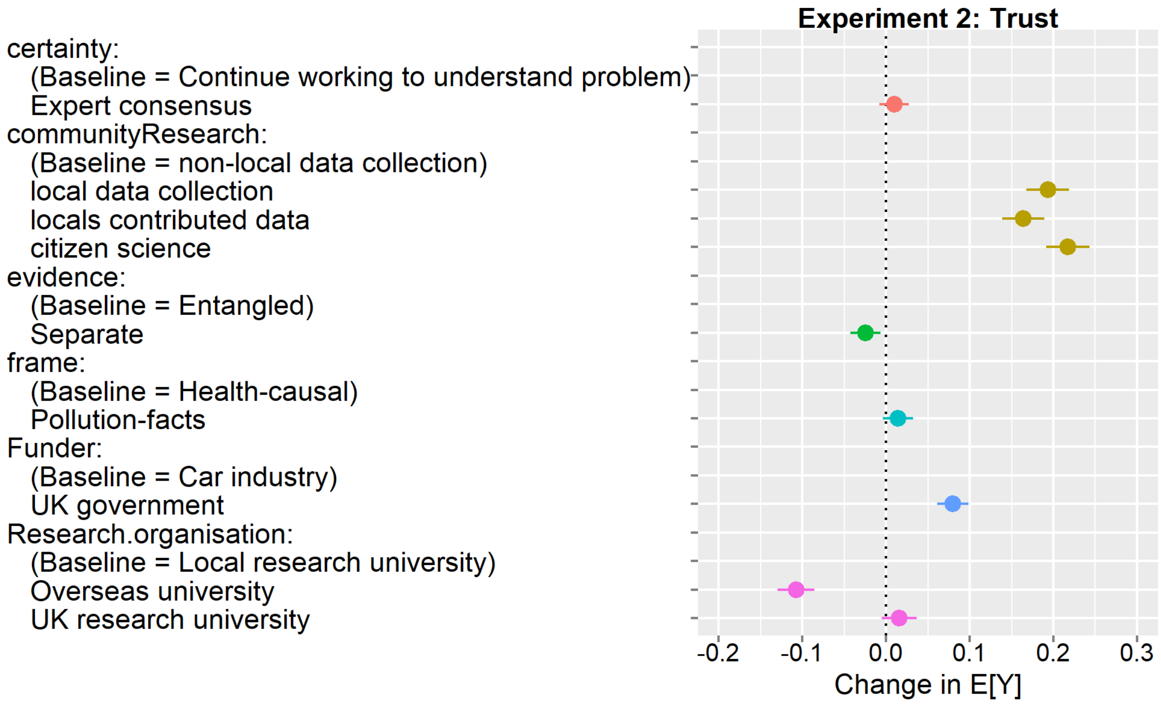
C – Clean air zones, perceived local benefits of research



D – Clean air zones, perceived trustworthiness



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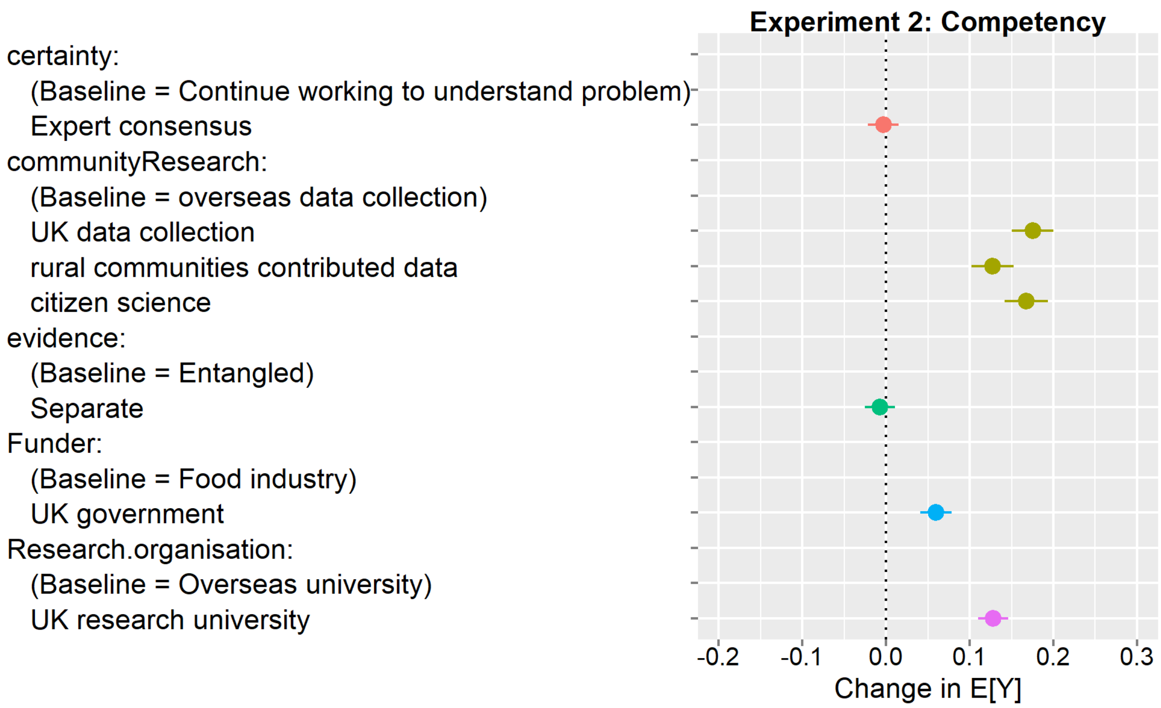
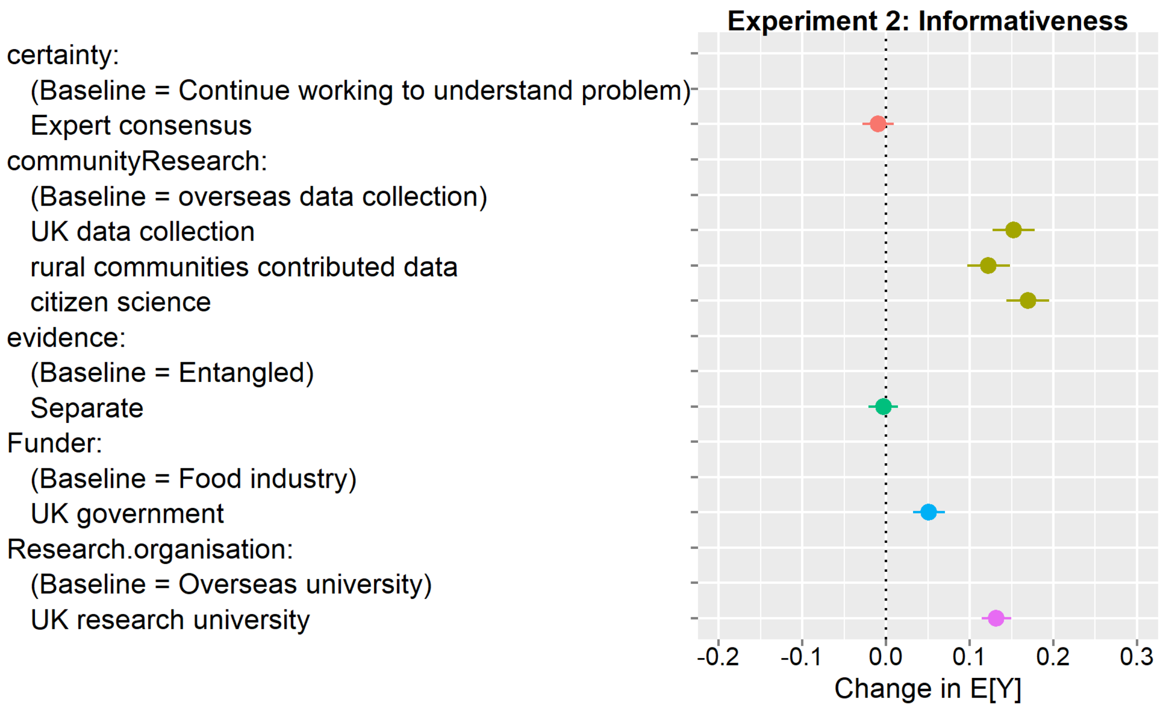
E – GM crops, perceived competence



F – GM crops, perceived informativeness of research



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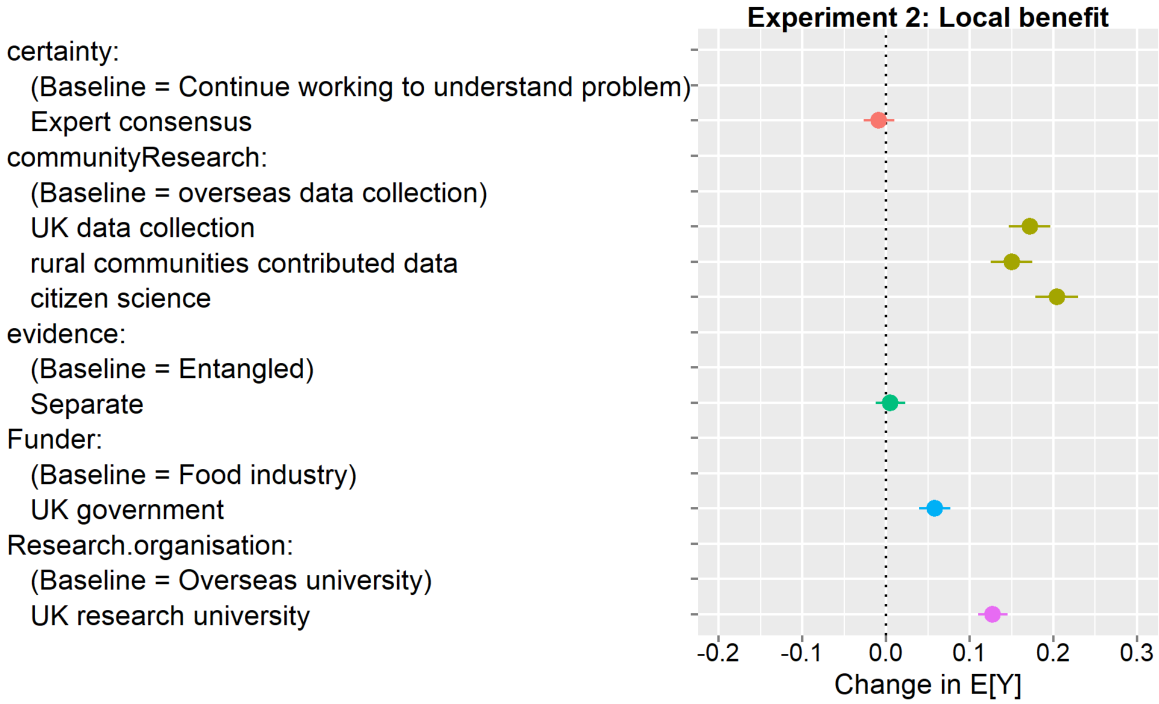
G – GM, perceived local benefits of research



H – GM, perceived trustworthiness

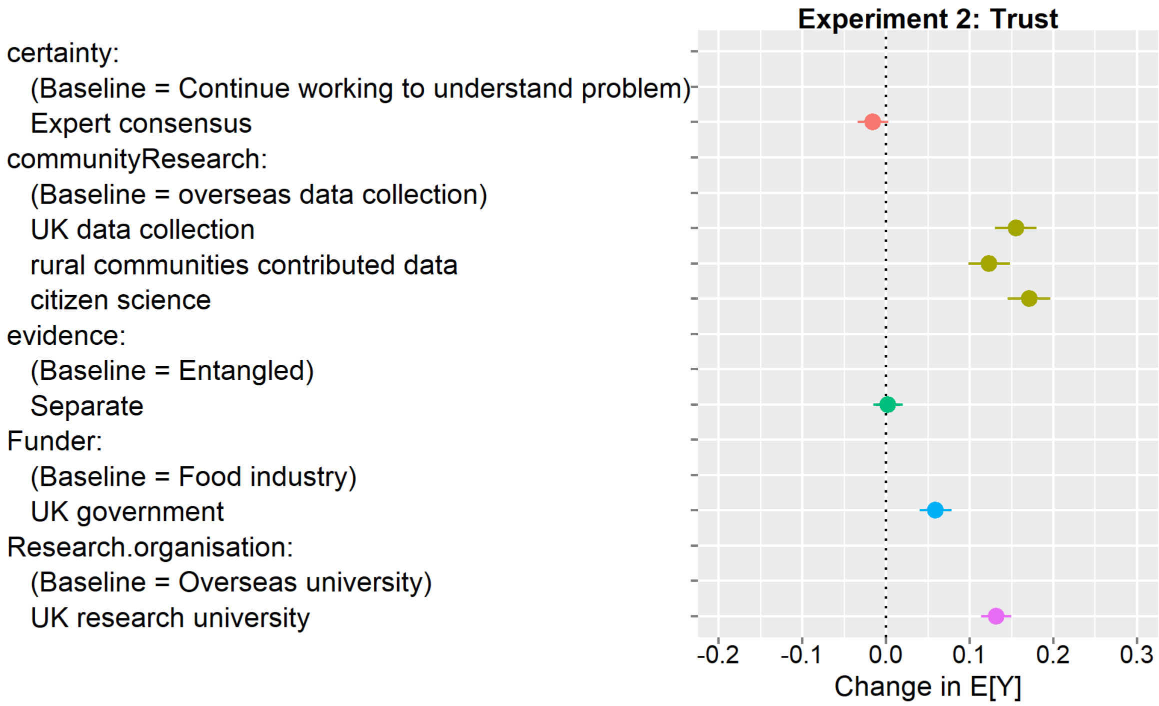


Fig. 11: Experiment 2A (Clear Air Zones) and 2B (GM) results: Main effects for each dependent variable (Average Marginal Component Effects).

Relationship among dependent variables

So far, we have used Experiment 1 to understand the extent to which expertise, among other variables, influences a range of attitudes to policy. In this section, we pool all of these attitudes together and explore their relationship.

Specifically, in one multilevel regression model, we predicted 'trust' using the ratings on 'fairness', 'transparency', and 'competency' (policy/trial-level variables) as well as respondents' overall trust in government and science (individual-level variables).

We found that, while all of these are related to trust, perceived competence, which is most sensitive to science justification, is the least influential in predicting trust ratings. By contrast, overall trust in government and perceived fairness of policy are most influential.

In the second multilevel regression, we predicted intentions to comply using the rest of the ratings, including trust, as well as trust in government and trust in science. Perceived competence continues to have minimal impact while trust is most predictive of compliance. In contrast to the first regression, trust in science emerges as an additional strong predictor.

Fig. 12 Relationship among dependent variables: predicting trust and intended compliance.

Subgroup effects

Do subgroups of respondents respond to our experimental stimuli differently? We find subgroup variation, especially when further broken down by specific policy. We explored the impact of prior attitudes in the section ‘Polarisation’ above.

Additional figures in the Appendix show subgroup analysis by trust in science, self-assessed knowledge about science, and by partisanship. Our results are:

- Low trust in science should be correlated with zero or negative effects of expert input on policy support. We find some evidence for this, but only very clearly in the case of Clean Air Zones. In the GM and Mpox cases, lack of trust is nonetheless accompanied by marginal increases in policy support when experts are involved, although these effects are often not significant.
- However, low trust also means higher assessments of GM and clean air research groups that have a form of citizen science input.
- Whether respondents know ‘little’ or ‘a lot’ about science makes no difference to how they respond to our experiments. Response patterns are also similar across partisan subgroups.

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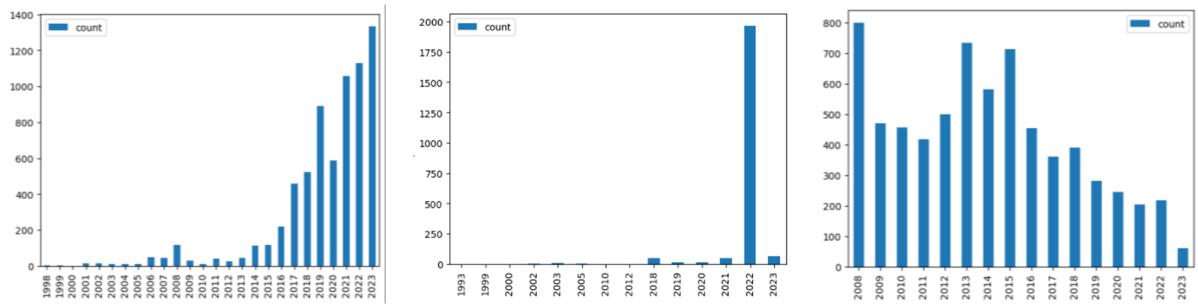
Appendix

News corpus: further details



Clean Air Zone news stories
N = 6,847

Mpox news stories
N = 2,176

GM news stories*
N = 6,887

* timeline cut at 2008 to obtain a similar corpus size to Clean Air Zones.
We extracted all clean air and Mpox articles that matched our keyword search criteria.

Fig. A1: Distribution of documents over time in news corpus.

Table A1: Overview of sources (print titles) in news corpus.

Clean Air Zones 278 sources		**Mpox** 145 sources		**GM** 304 sources	
	N		N		N
The Evening Standard	788	The Independent	555	The Guardian	662
The Independent	452	Daily Record	344	The Times	592
Birmingham Evening Mail	416	The Herald	76	The Independent	504
Bath Chronicle	312	The Western Mail	52	The Daily Telegraph	360
The Herald	308	Daily Star	45	Financial Times	349
Birmingham Post	288	Scottish Daily Mail	40	Daily Mail	232
Bradford Telegraph	223	The National	32	The Sunday Times	195
South Wales Guardian	1	Barry and District News	1	Daily Echo	1
Romsey Advertiser	1	Western Morning News	1	Scarborough Evening News	1
Falmouth Packet	1	Central Fife Times	1	Keighley News	1
Clacton and Frinton Gazette	1	Brentwood Gazette	1	The Gazette	1
The Scottish Farmer	1	Braintree and Witham Times	1	Lynn News Friday	1

Topic models

CorEx models and anchoring

In topic models, the optimal number of topics can be determined computationally or by assessing the results qualitatively as we change the number of topics. We used a combination of these approaches; see the line diagrams and figure notes in Figures A7 and A8.

We use correlation explanation (CorEx) topic models for their flexibility to accommodate ‘anchor’ words. Anchoring (or ‘seeding’) incorporates some domain knowledge in the otherwise exploratory process of topic modelling. We use anchoring in a technical way:

- We anchored a topic with keywords ‘science’ and ‘research’ in the (few) cases when it did not emerge organically.

- We also anchored if subsequent iterations of topic modelling (for example, changing the number of topics) meant the disappearance of an otherwise substantively interesting topic. We found this was the case with clean air topics where a sometimes standalone ‘climate & environment’ topic kept collapsing into others (e.g. ‘health’). We wanted to keep this climate topic to compare with GM’s ‘climate’ topic (which we did not need to anchor).

We obtained many interpretable topics, although more so in the news corpus than in the parliament (Hansard) corpus. One set of topics broadly relates to science and science justification, and another set clearly relates to the public response. The latter includes MPs voicing constituency views in the Hansard corpus, and vox-pops reporting on local discontent in the news corpus.

We show these topics systematically for each policy and each corpus type (news, Hansard) in Tables A2–A6. In addition, we check correlation between topics across the documents, primarily to explore how science content overlaps with other content, see corresponding Figures A2–A6.

- The correlation (overlap of topics within documents) between ‘science’ and ‘public response’ depends on policy. There is little to no correlation between science and responses in Clean Air Zone texts, suggesting stories and debate segments drawing on the former will not at the same time be drawing on the latter. When it comes to GM and Mpox, there is lots of overlap between science topics and public response topics (farmers in the GM case, LGBTQ communities in Mpox) in the news corpus, but fewer in Hansard segments.

Entire Hansard transcripts, rather than segments, contain lots of different topics and each will likely draw on expertise. However, there are only very few transcripts, insufficient for topic analysis (in fact, there may not be variation in use of expertise at all). To process these texts with topic models, we use text segments. However, this means that Hansard transcripts have low baseline probability of being about multiple topics due to the small size of segments.

Additional topic model results

Table A2: CorEx Clean Air Zone topics in Hansard segments.

	Topic category	Topic	Top keywords
1		Junk (event)	ask_secretary, state, secretary, ask, food, food_rural, state_environment, affairs, rural, environment
2	Politics	Policy definition	quality, improve, improve_quality, limit, measure, publish, include, set, december, approach
3	Science	Facts & measures	nitrogen_dioxide, dioxide, nitrogen, roadside, extend
4		Junk (parliamentary vocabulary)	hon, hon_friend, friend, right, member, agree, mayor, people, debate, bring
5	Publics	Scrappage scheme	scrappage, scrappage_scheme, scheme, help, fund, car, funding, vehicle, issue
6	Zones	Scotland	scotland, glasgow, cunningham, roseanna_cunningham, roseanna, active_travel, scottish, active, city, cabinet
7	Science	Climate	pollution, tackle, action, climate, reduce, bus, introduce, climate_change, active, fleet
8	Politics	Local government	government, city, tfl, authority, expansion, expand, national, october, lord, central
9	Other	Transport alternatives	use, encourage, fuel, mr, electric, travel, public, increase, act, compliance
10	Other	Other	assessment, impact, effect, potential, need, propose, proposal, create, large
11	Other	Other	new, key, uk, decision, non, level, technology, commitment, develop, priority
12	Publics	Local interests	business, road, small, world, strategy, cost, network, lead, change, clear
13	Other	Other	department, financial, implementation, area, provide, consider, drive, expect, launch, pollute
14	Publics?	Local interests?	step, number, discussion, traffic, result, pay, old, benefit, review, service

Table A3: Anchored CorEx GM topics in Hansard segments.

	Topic category	Topic	Top keywords (anchor words **bold**)
1	Science	Science misc.*	**research, science**, evidence, fund, conduct, base, review, impact, wales, current
2	Publics	Farmers	farm_scale, scale, farm, evaluation, result, publish
3	Politics	EU regulation	european, ec, council, regulation, commission, proposal, labelling, biotechnology, process, product
4		Junk (event)	affairs, rural, environment, environment_rural, department, trade, consultation
5		Junk (event)	ask_secretary, secretary, state, ask, baroness, scottish, plan, time, recent, executive
6		Junk (parliamentary vocabulary)	hon, member, debate, know, want, agree, say, matter, noble, think
7	Science	GM experiments	trial, field, list, seed, herbicide, eu, national, import, policy, consent
8		Junk (event)	majesty, ask_majesty, countess, countess_mar, mar, government, uk, new, study
9		Junk (event)	rural_affairs, state_environment, consider, secretary_state, contain, contamination
10	Science	Health impacts	health, state_health, standards, standards_agency, agency, human, safety, animal, effect, feed
11	Publics	Constituency concern	issue, minister, concern, public, example, answer, official, question, maize, people
12		Junk (event)	statement, include, produce, environmental, deal, work, pesticide, market, legislation, level
13	Politics	International relations	country, develop, friend, international, development, right, benefit, farming, world, organic
14	Politics	EU regulation	deliberate, deliberate_release, kingdom, united_kingdom, union, european_union, united, release, regulations, england

*anchored topic—otherwise no science cluster. With this one anchored, we obtain three.

Inter-topic correlations

These correlation heatmaps show the relationship between topics—refer to Tables 1–3 and Tables A2–A3 to identify topics by their ID number.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1															
2	0.51														
3	0.09	0.17													
4	-0.02	0.04	0.07												
5	0.11	0.04	0.03	0.27											
6	0.18	0.29	0.25	0.15	0.15										
7	0.18	0.12	0.01	0.19	0.31	0.03									
8	0.21	0.37	0.29	0.17	0.14	0.52	0.07								
9	-0.07	0.11	0.12	0.20	0.16	0.26	0.19	0.39							
10	0.08	0.16	0.16	0.26	0.31	0.33	0.15	0.21	0.31						
11	-0.11	0.10	0.18	0.18	0.15	0.42	-0.02	0.42	0.59	0.32					
12	0.07	0.16	0.16	0.01	-0.03	0.21	0.04	0.27	0.11	-0.01	0.13				
13	0.05	0.14	0.04	-0.08	-0.20	-0.06	0.05	0.09	0.08	-0.11	0.04	-0.25			
14	-0.02	0.16	0.16	0.08	0.06	0.09	-0.01	0.28	0.37	0.31	0.41	0.07	0.27		
15	0.35	0.40	0.24	0.21	0.31	0.50	0.29	0.55	0.35	0.48	0.30	0.26	-0.06	0.23	

Fig. A2: Relationship among Clean Air Zone topics in print corpus (correlation heatmap).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1														
2	-0.08													
3	-0.06	0.18												
4	-0.08	-0.17	-0.09											
5	0.01	-0.05	-0.04	-0.06										
6	-0.02	0.09	-0.04	-0.04	-0.05									
7	-0.22	0.22	0.15	-0.16	-0.02	0.12								
8	0.06	0.04	0.04	0.08	-0.15	0.08	0.01							
9	-0.12	-0.09	-0.07	0.07	-0.00	0.05	0.07	0.01						
10	0.14	-0.03	0.02	-0.02	0.05	-0.04	-0.14	0.03	-0.05					
11	-0.12	0.06	0.09	0.03	-0.00	0.05	0.10	0.04	0.02	-0.01				
12	0.14	-0.13	-0.05	0.11	0.09	-0.03	-0.21	0.06	0.02	0.11	-0.01			
13	0.13	-0.01	-0.07	0.04	-0.06	0.03	-0.07	0.15	0.06	0.05	-0.04	0.05		
14	0.09	0.08	-0.05	0.02	-0.04	-0.05	-0.07	0.07	-0.03	-0.04	-0.02	-0.02	0.10	

Fig. A3: Relationship among Clean Air Zone topics in Hansard corpus (correlation heatmap).

Fig. A4: Relationship among GM topics in print corpus (correlations heatmap).

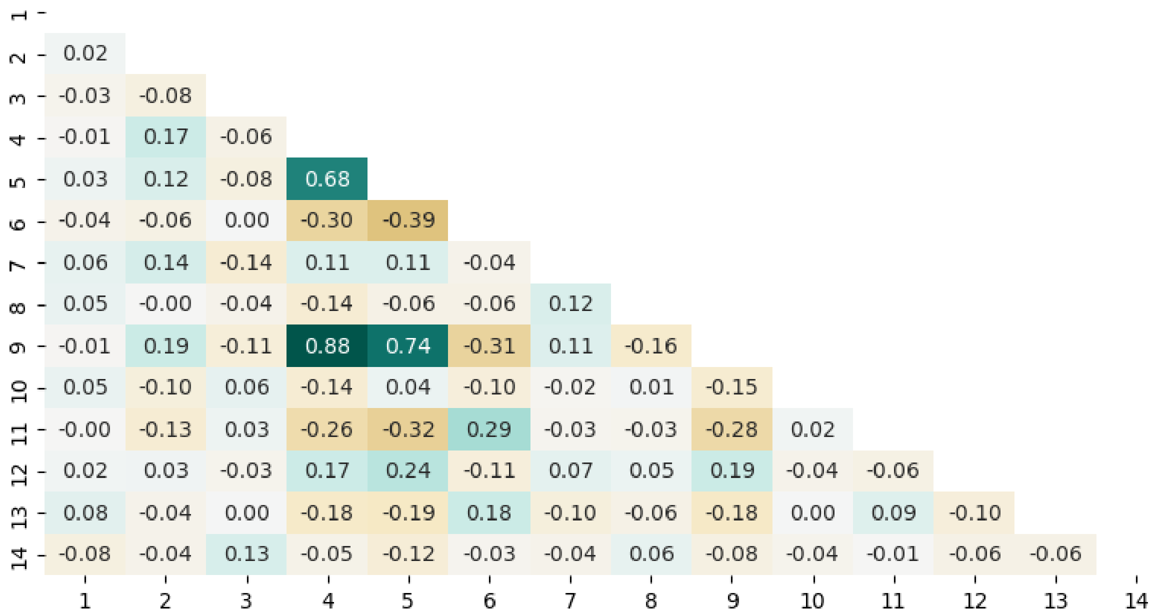


Fig. A5: Relationship among GM topics in Hansard corpus (correlation heatmap).

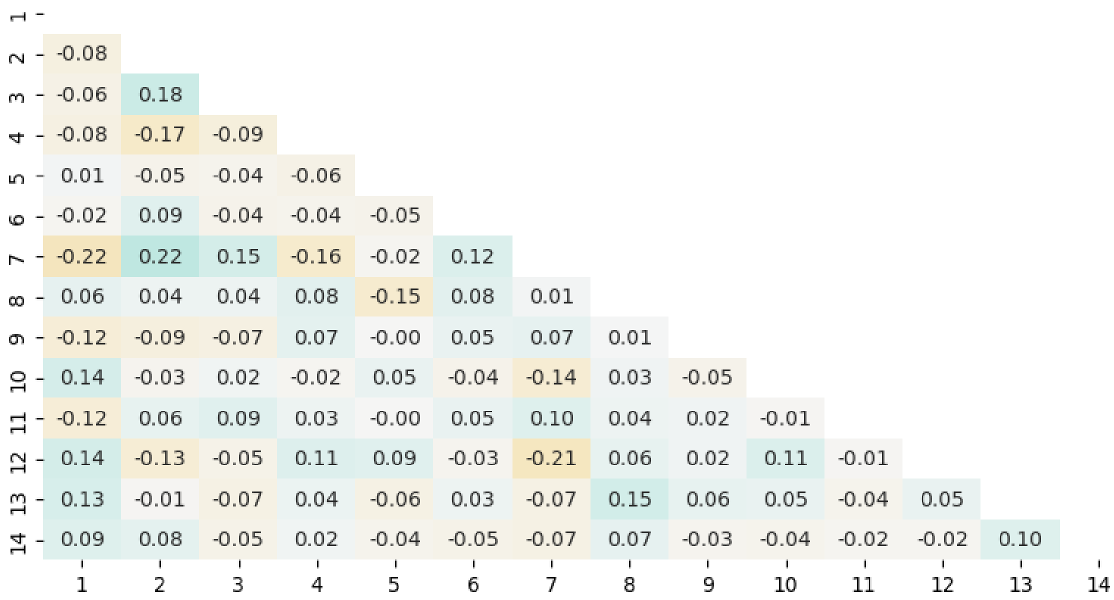
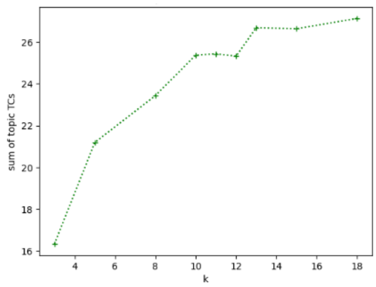


Fig. A6: Relationship among Mpox topics in print corpus, (correlations heatmap).

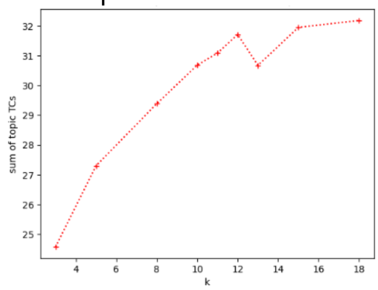
Optimal number of topics

The figures below show our calculations to determine the optimal number of topics. CorEX discovers latent factors (core topics) that explain the correlations in the data without assuming a specific generative model. CorEX's focus is on maximising information in the data ('total correlation') and finding informative latent factors. We selected number of topics based on how total correlation is maximised (at peaks of the line graphs below, or at points where the additional gain in total correlation is only incremental).

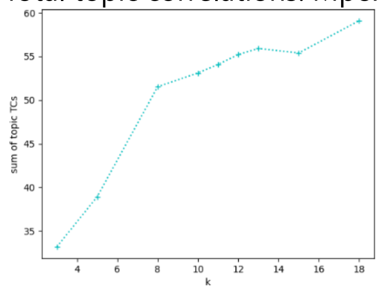
Total topic correlations: Clean air



Total topic correlations: GM



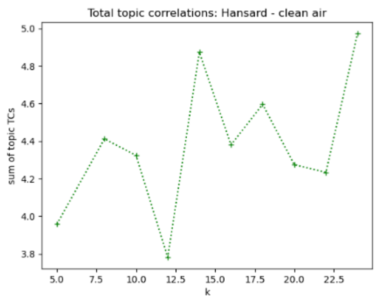
Total topic correlations: Mpox



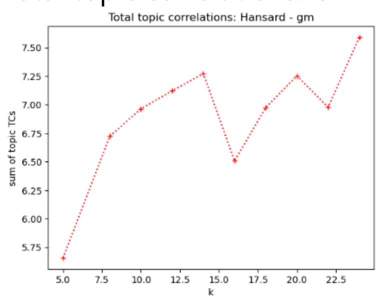
Small incremental change in total correlation implies additional topics no longer contribute to explaining corpus.

Fig. A7: Total correlation by number of topics—print.

Total topic correlations: Clean air



Total topic correlations: GM



Total topic correlations: Mpox

Too few segments

Small incremental change in total correlation implies additional topics no longer contribute to explaining corpus.

Fig. A8: Total correlation by number of topics—Hansard.

Experiment results by trust in science, knowledge of science, and partisanship

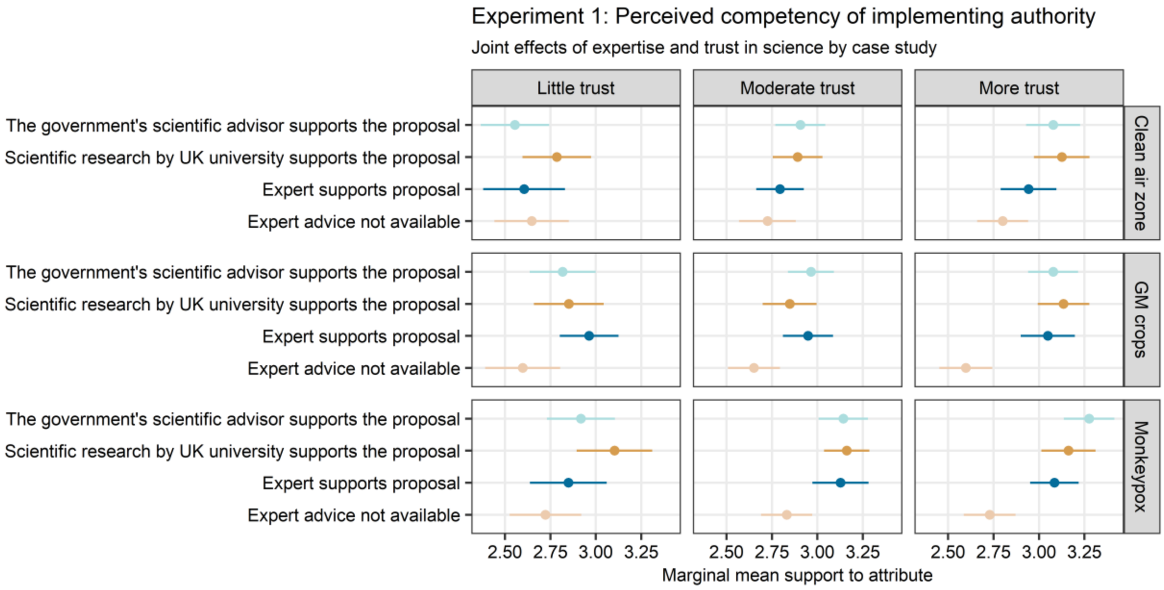
Yellow highlight shows which survey question we used for subsetting the survey results:

- Trust in science (little, moderate, more)
- Self-assessed knowledge of science (little, moderate, more)
- Partisanship (Conservative, Labour, Other, Would not vote/DK (Don't Know)

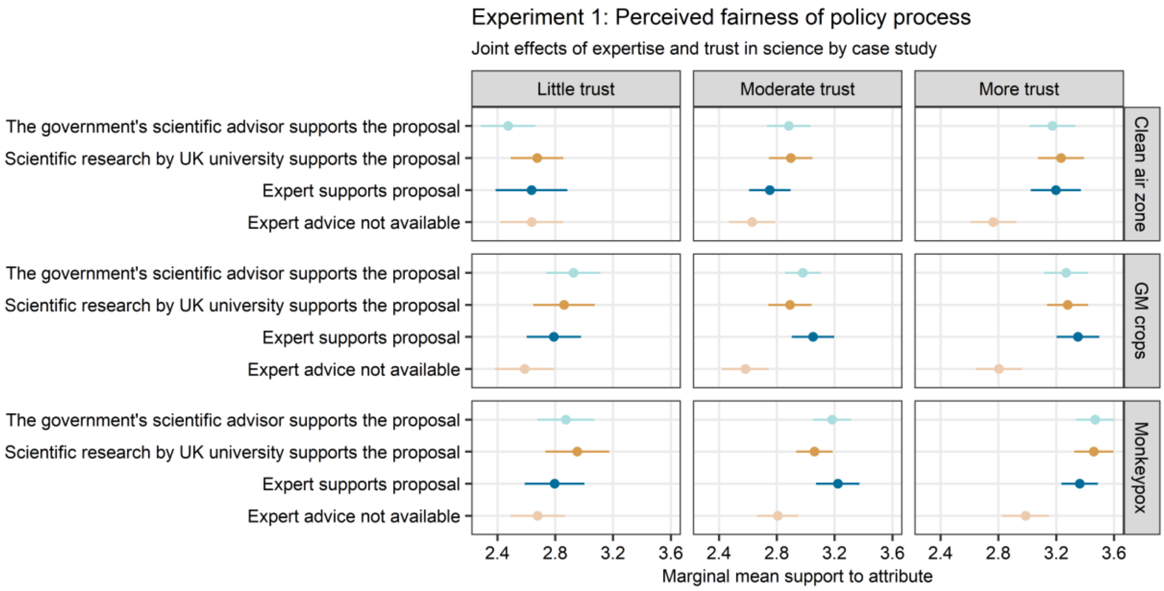
Please refer to the Democracy/Survey results section for differences between Experiments 1/2 and the dependent variables shown across the subpanels.

Group A: 'Science vs politics' experiments, responses to expertise stimuli by trust in science

A1



A2



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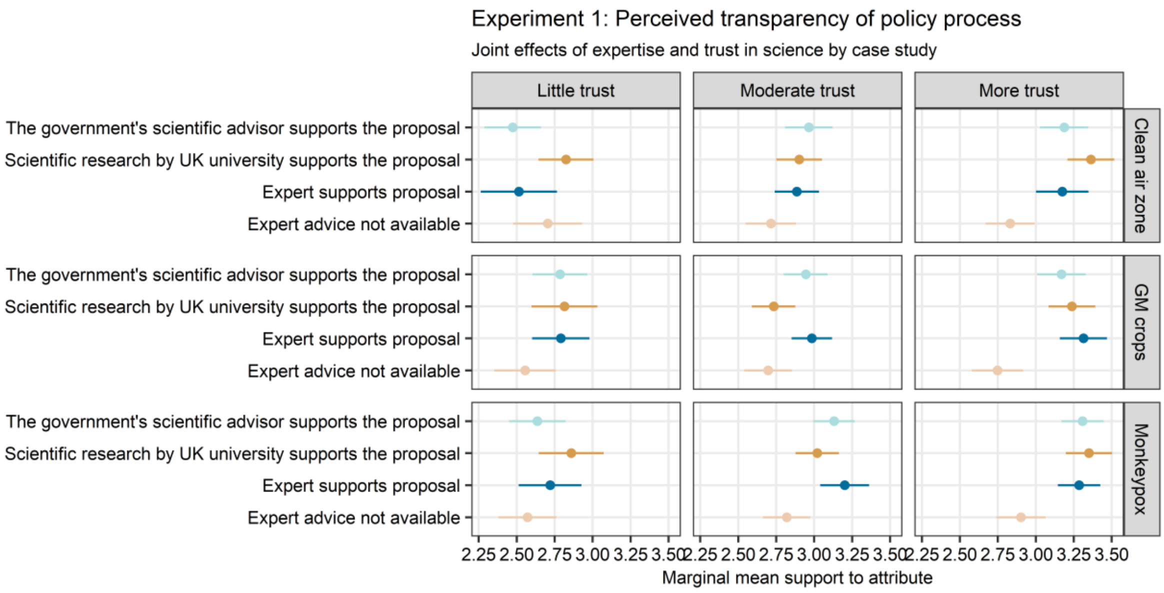
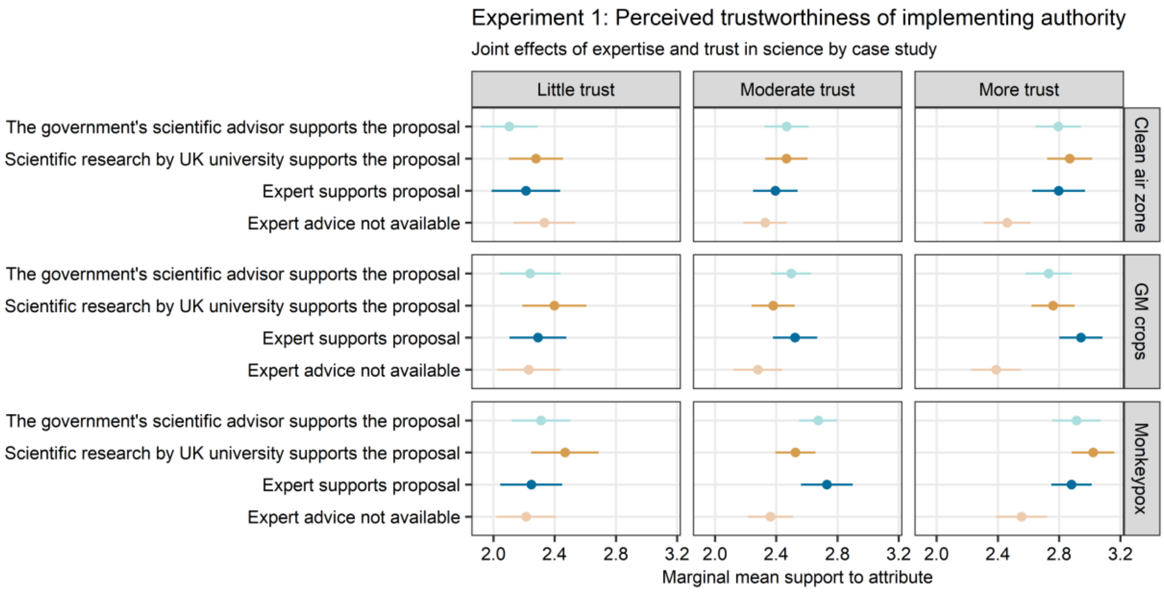
A3



A4



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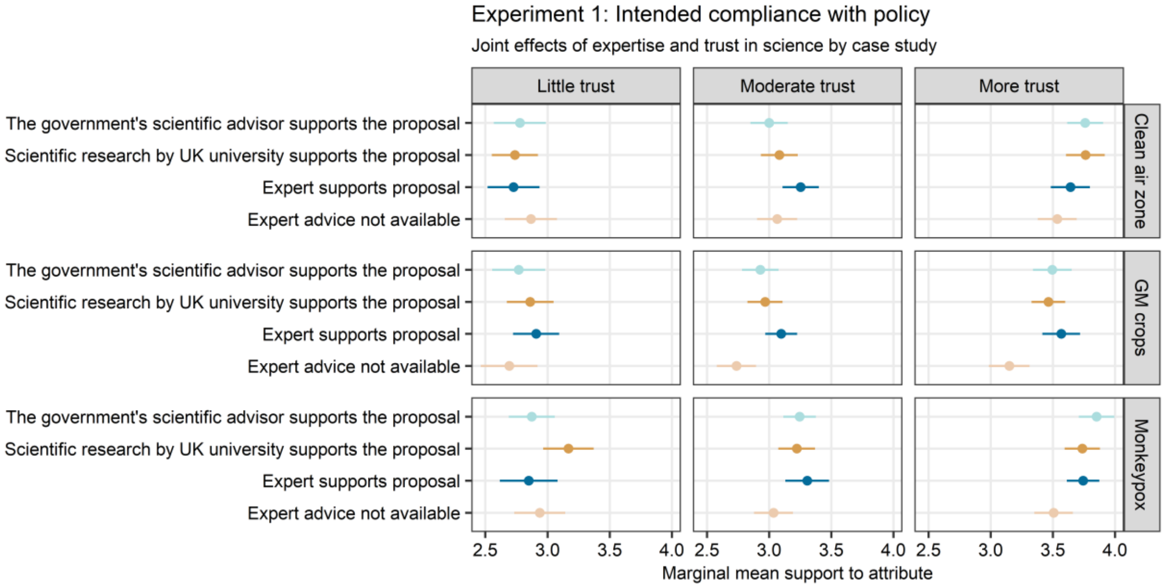
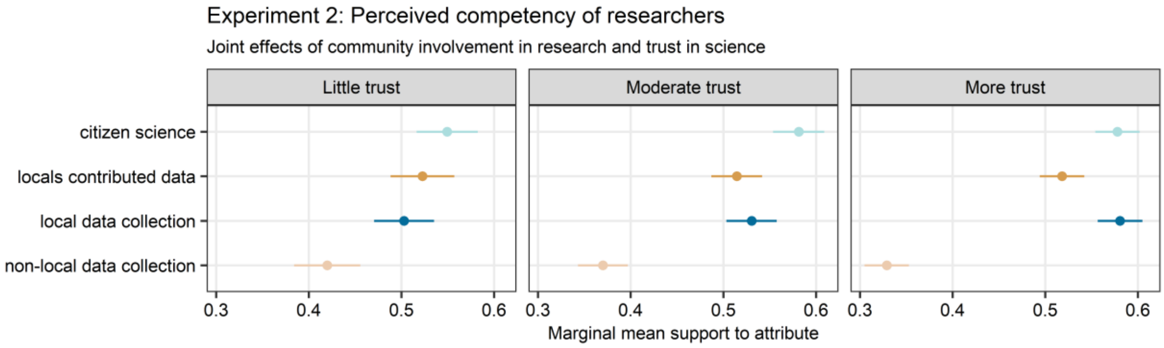
A5

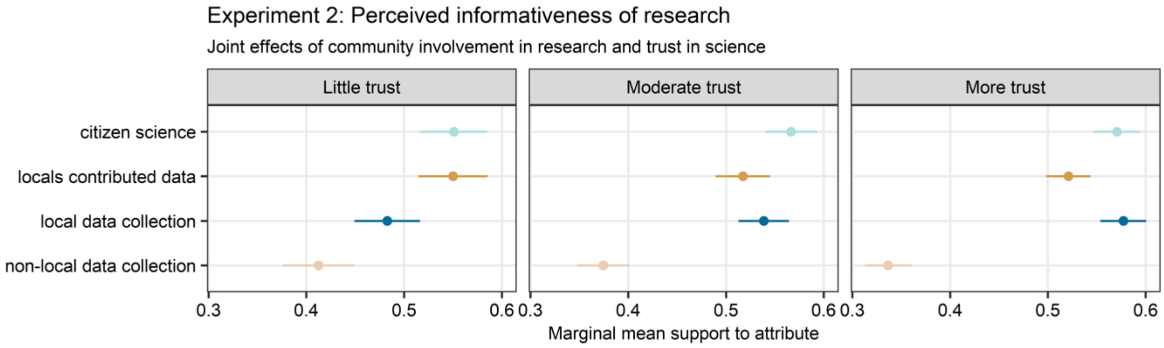


Group B: 'Science vs science' comparing Clean Air Zone research, community involvement by trust in science

B1



B2



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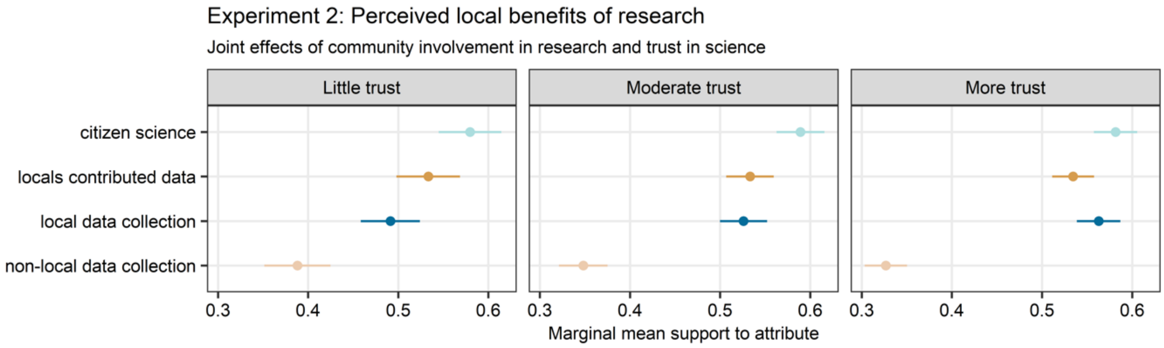
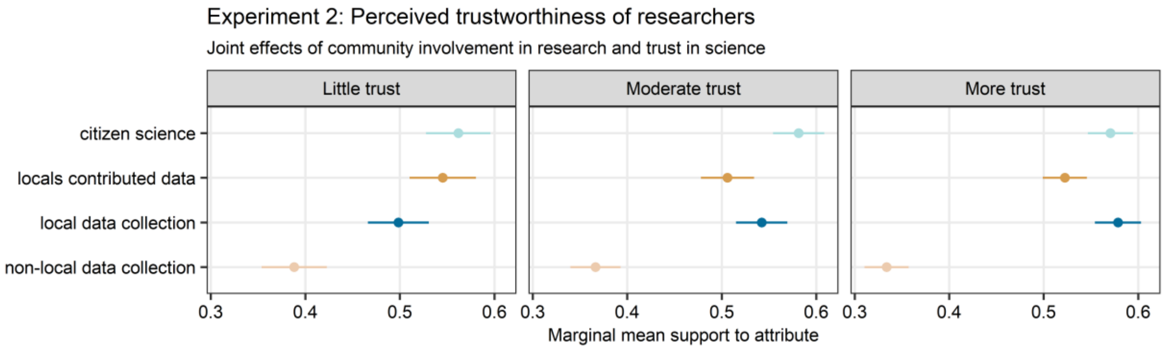
B3

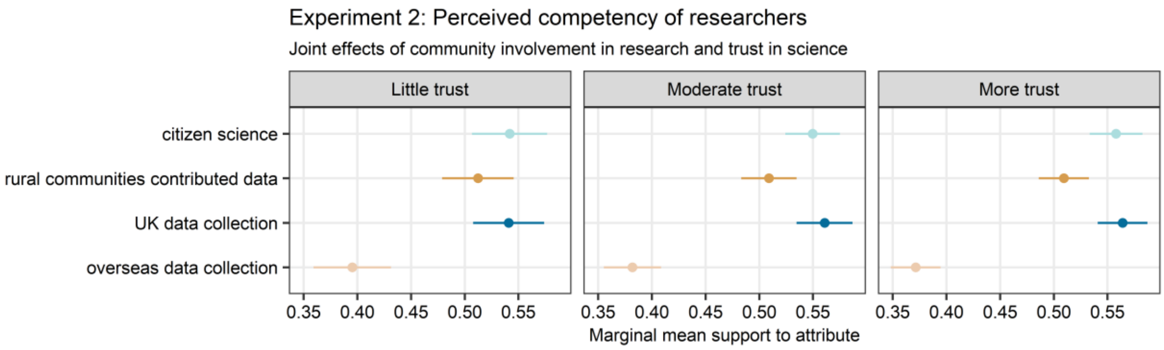


B4

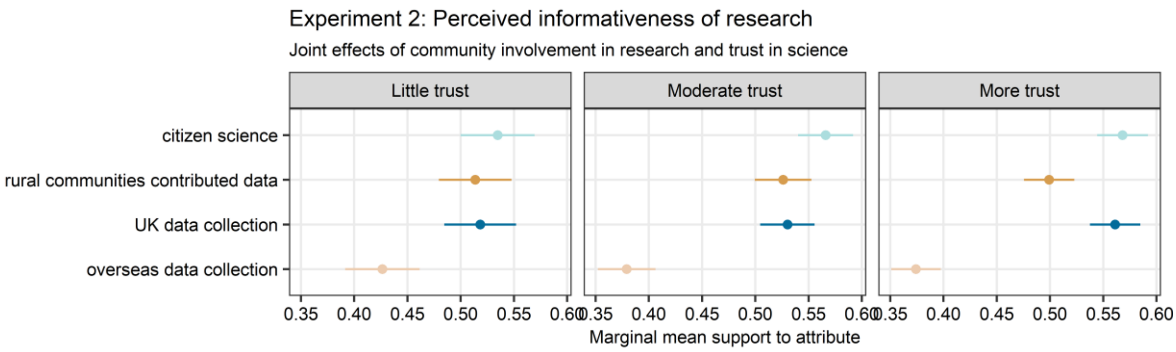


Group C: 'Science vs science'—comparing GM research, community involvement by trust in science

C1



C2



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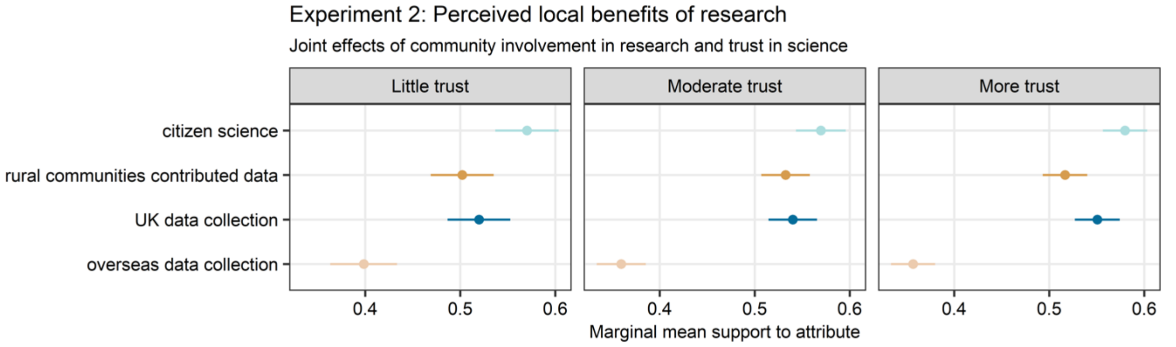
C3



C4

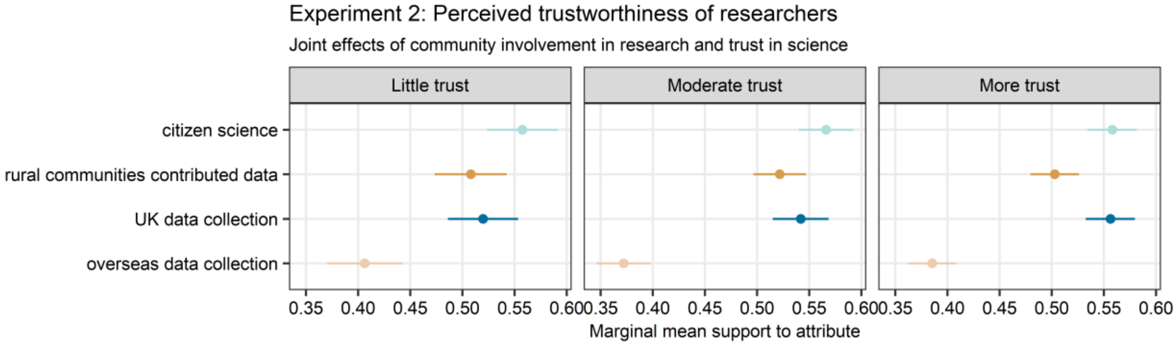
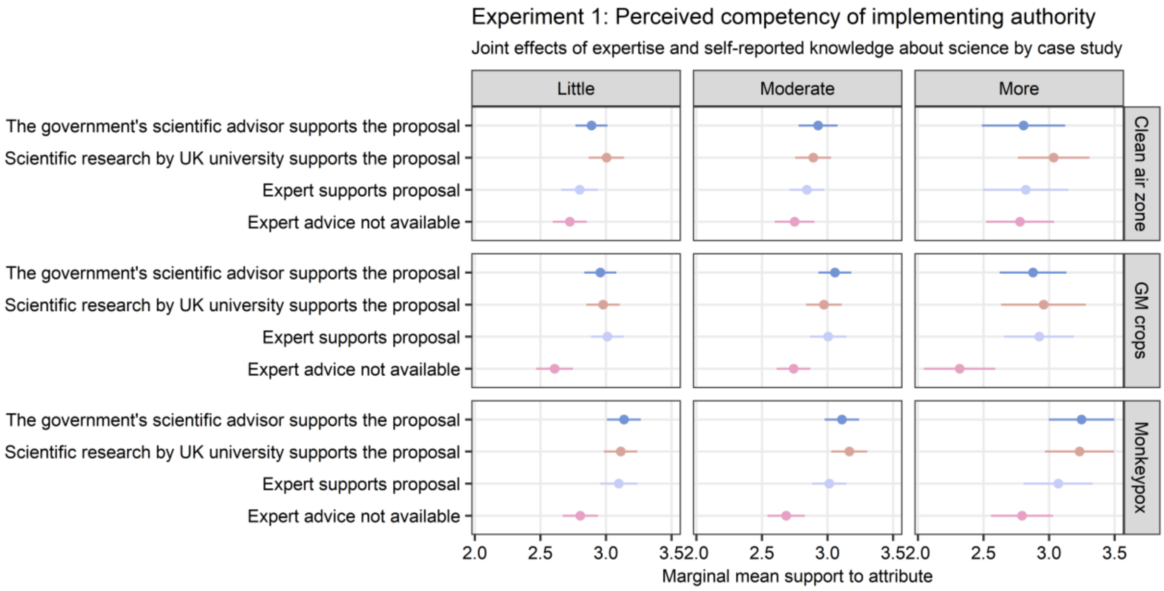


Fig. A9: Conjoint experiment results by trust in science—all dependent variables.

Group A: 'Science vs politics' experiments, responses to expertise stimuli by knowledge of science

A1



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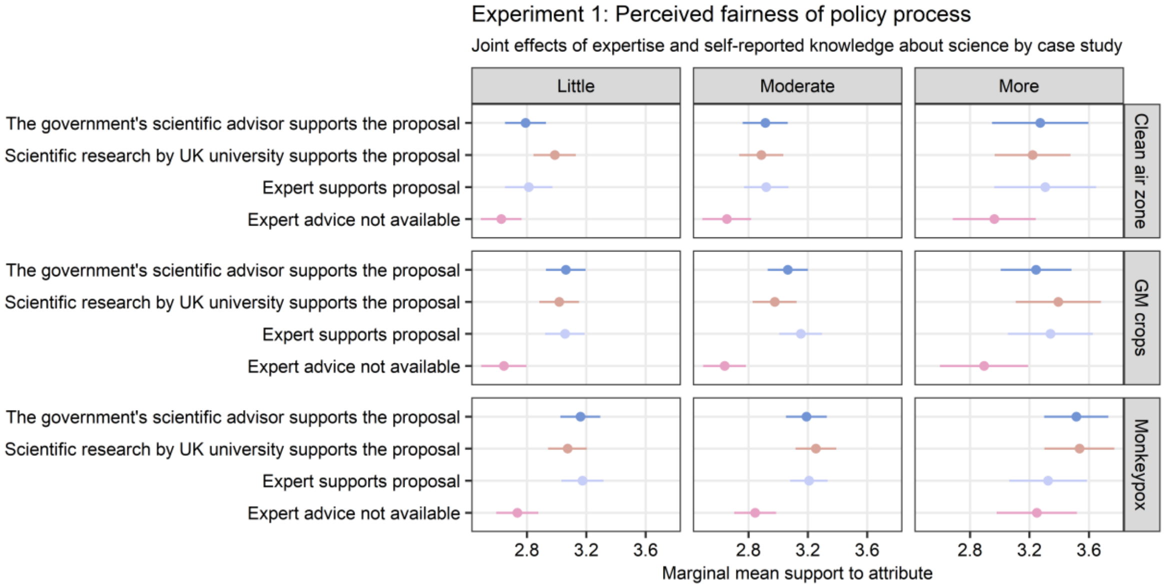
A2



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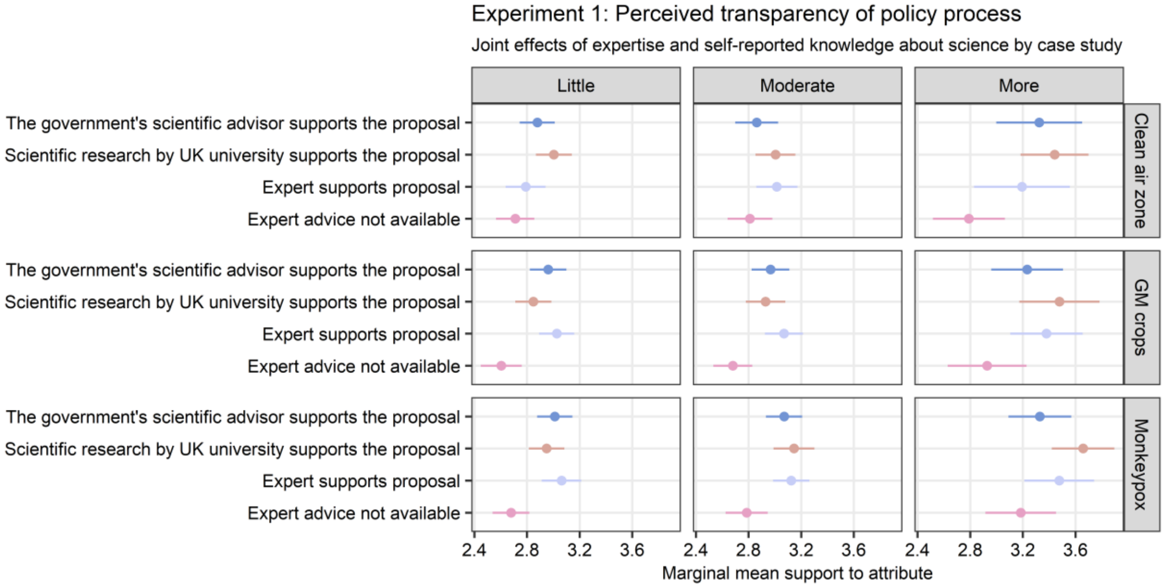

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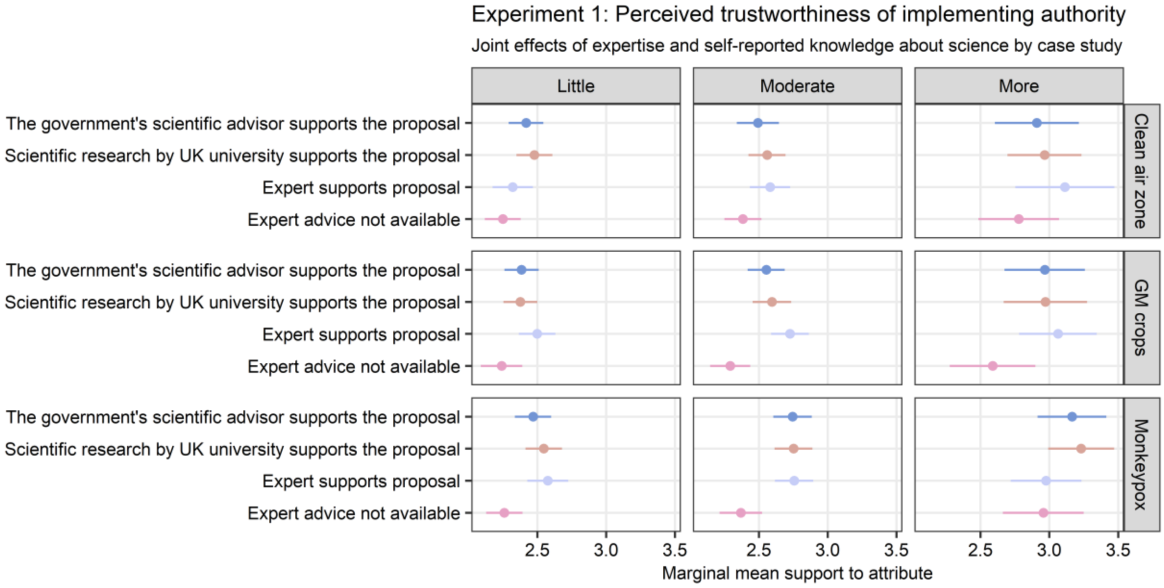
A4



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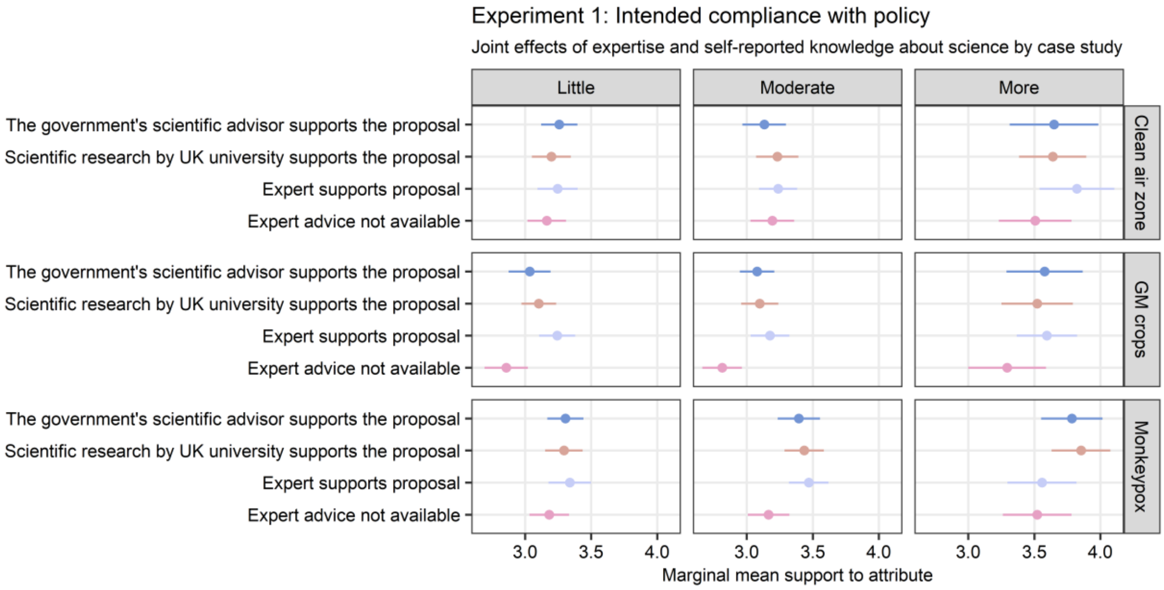
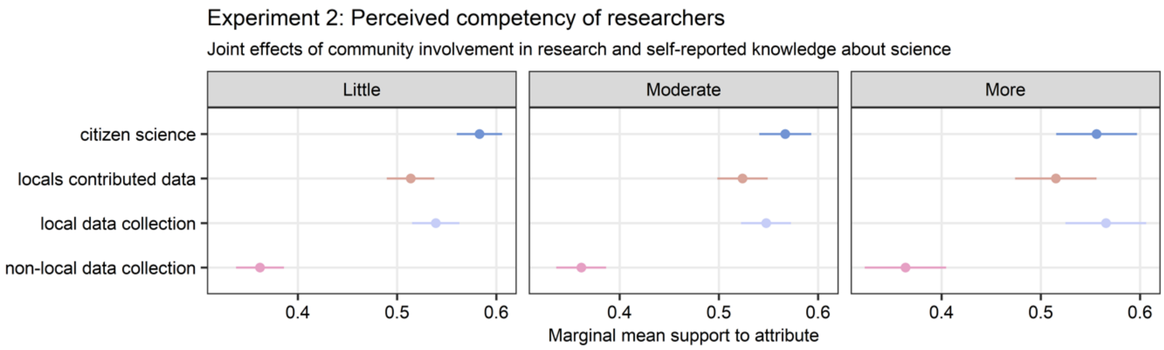


Group B: 'Science vs science' comparing clean air zone research, community involvement by knowledge of science

B1



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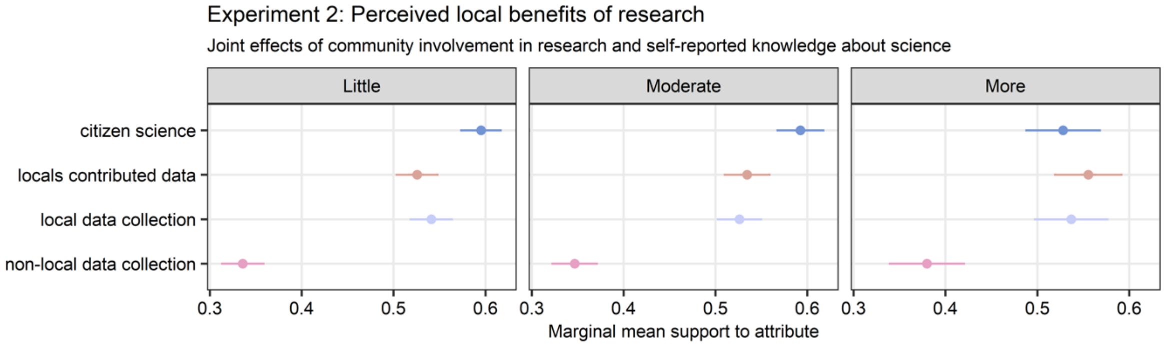
B2



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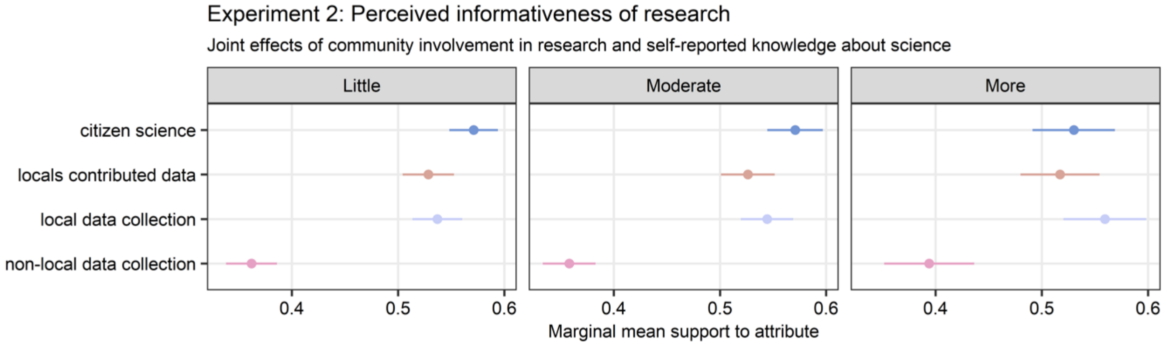

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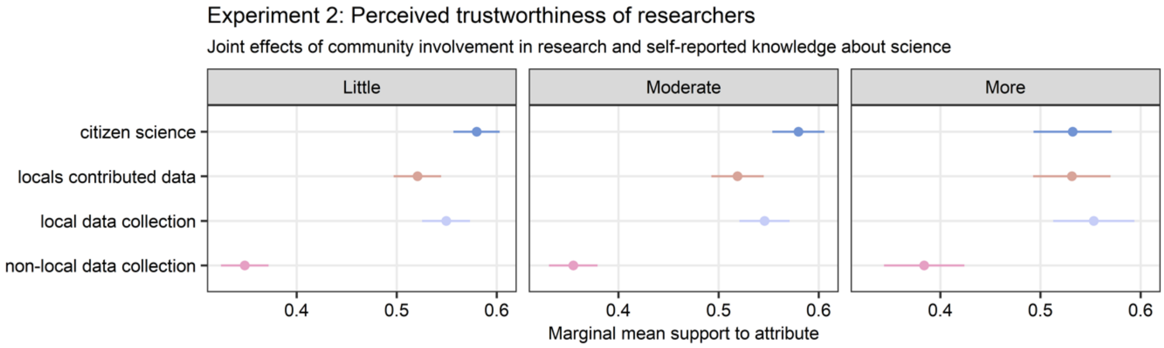
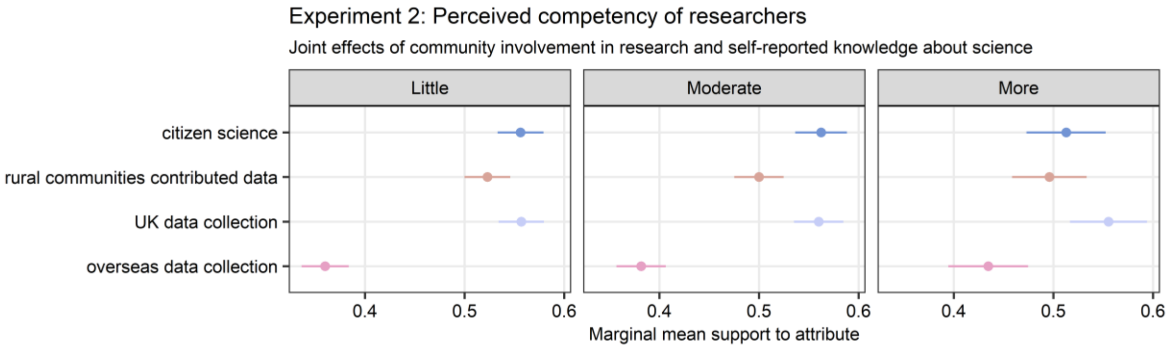


Group C: 'Science vs science'—comparing GM research, community involvement by knowledge of science

C1



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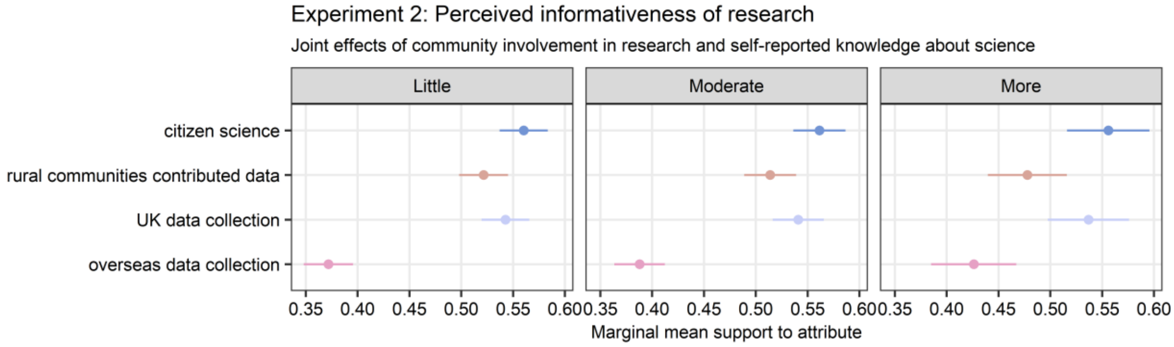
C2



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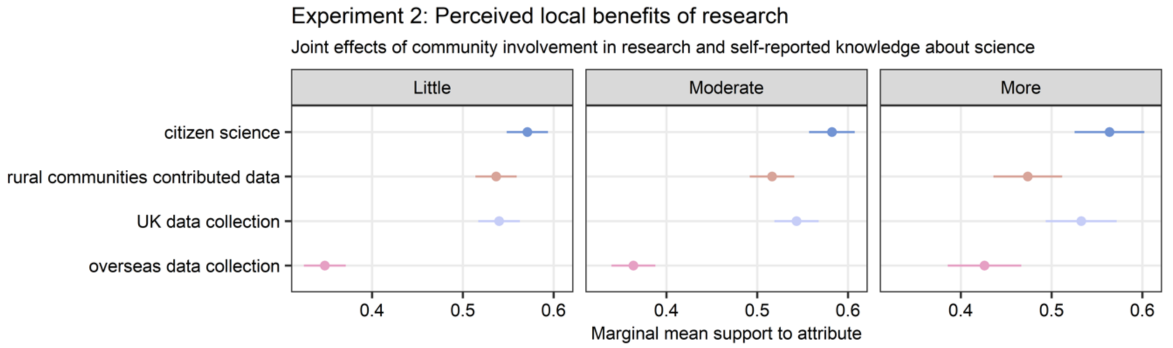

C4

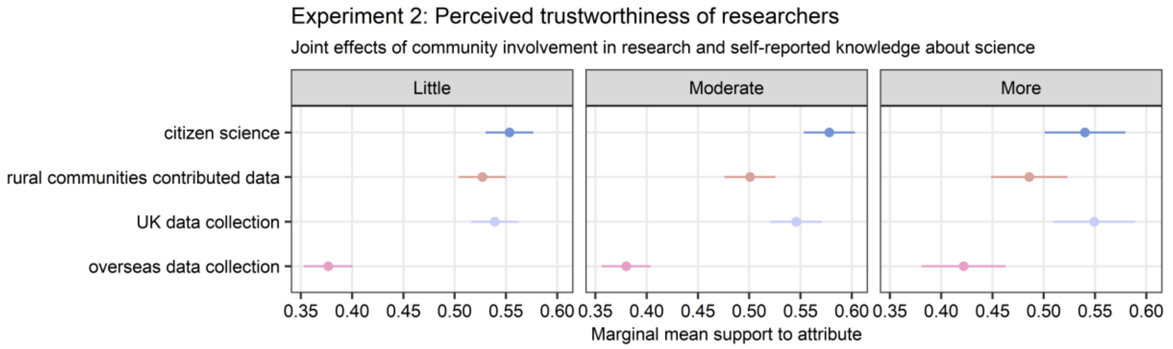

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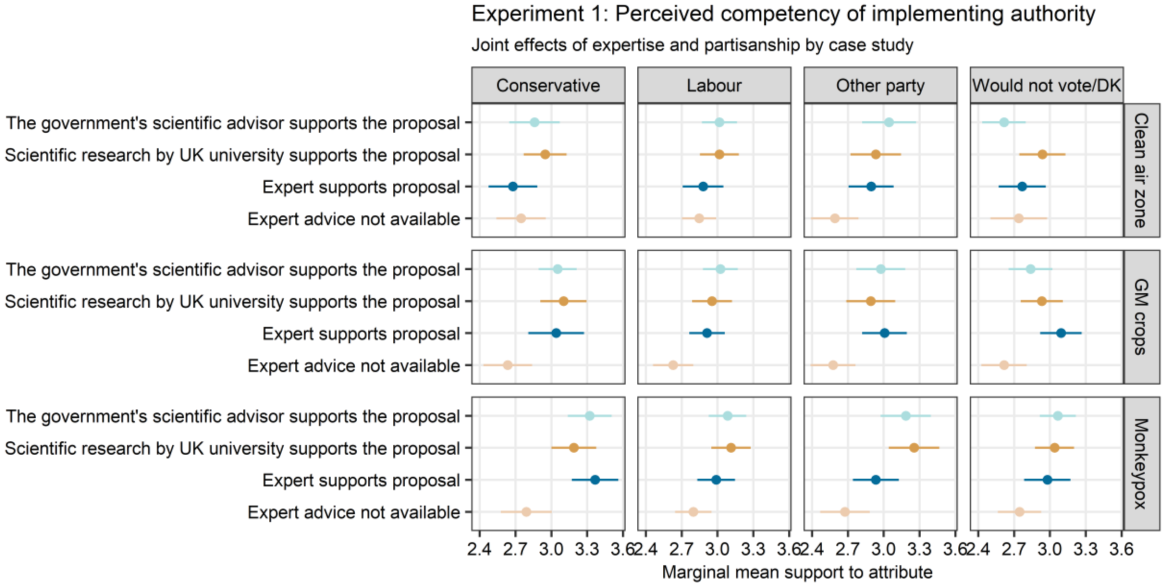
Fig. A10: Conjoint experiment results by self-assessed knowledge of science—all dependent variables

Group A: 'Science vs politics' experiments, responses to expertise stimuli by partisanship

A1



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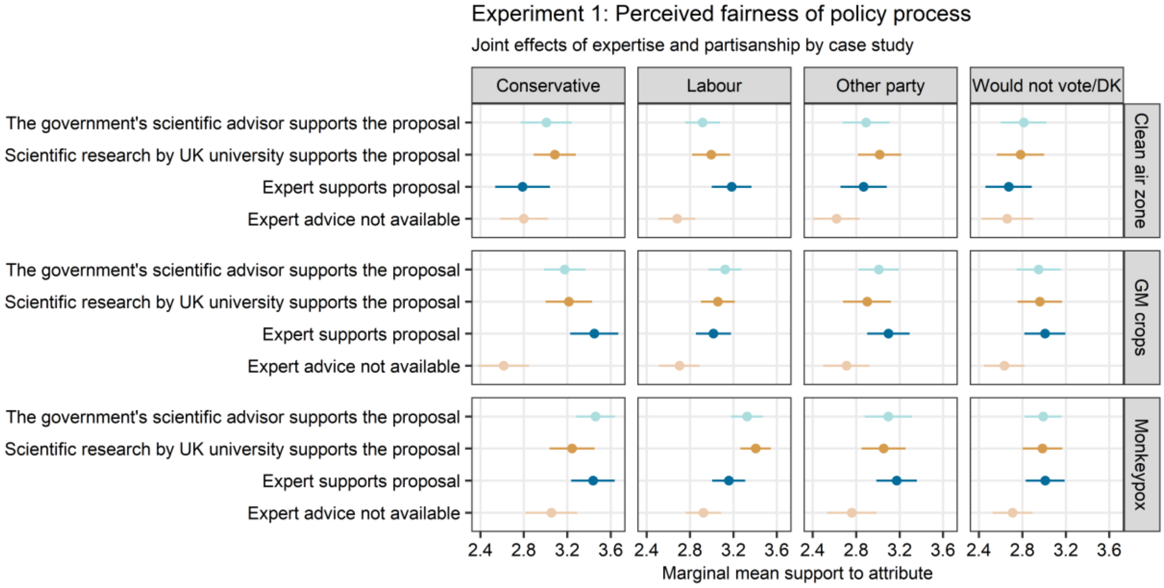

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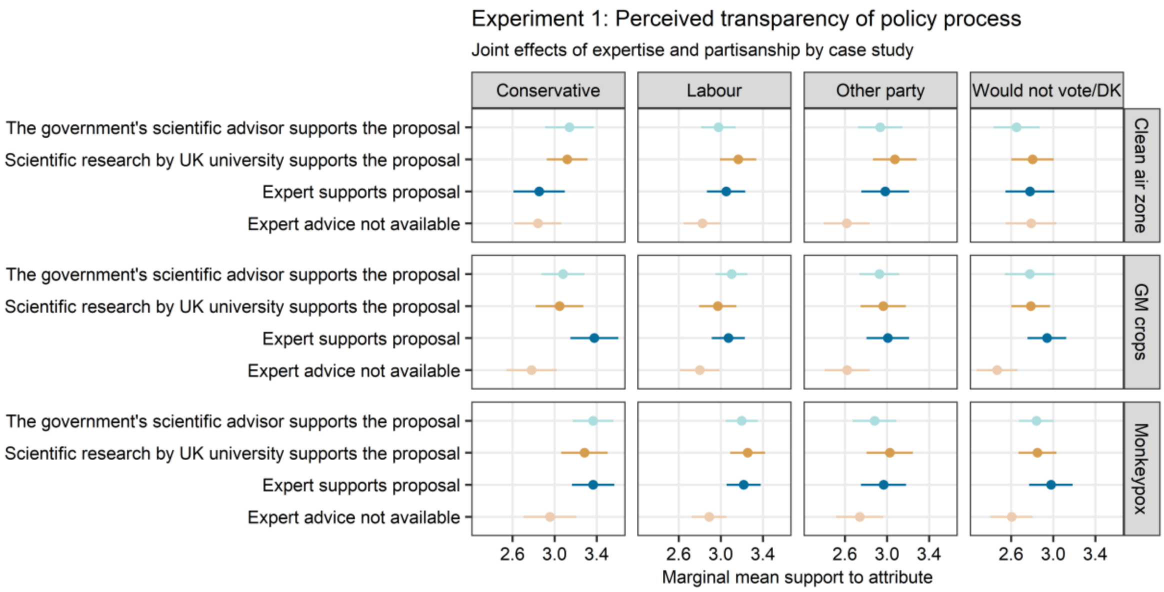

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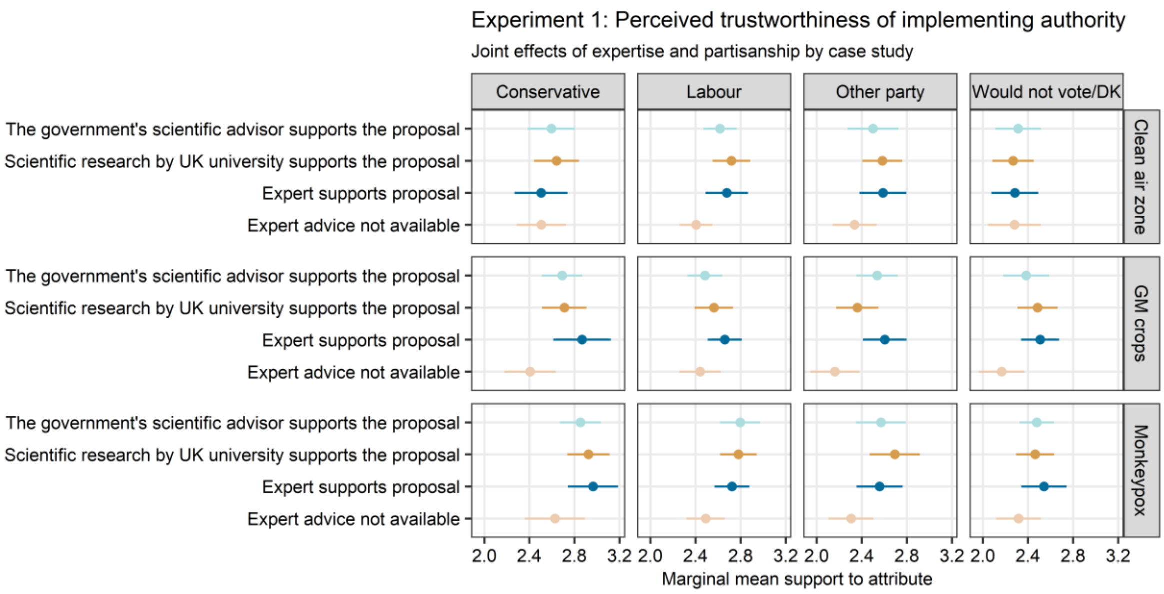

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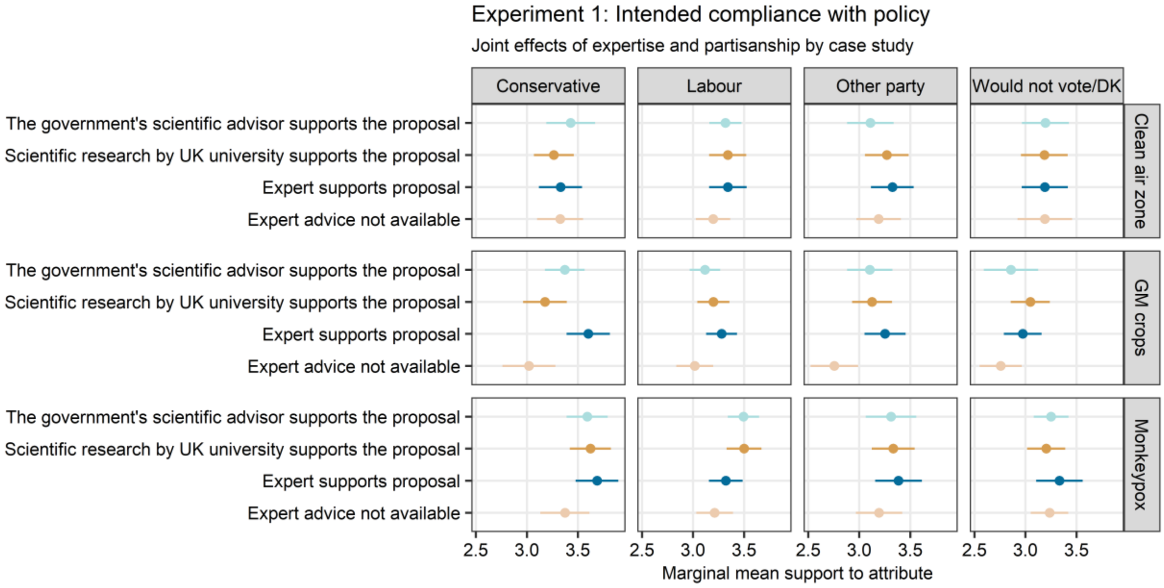
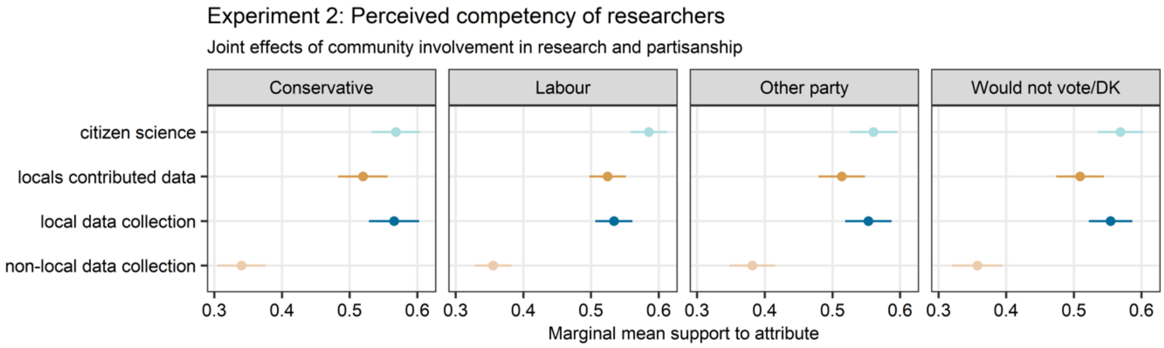
A5



Group B: 'Science vs science' comparing clean air zone research, community involvement by partisanship

B1



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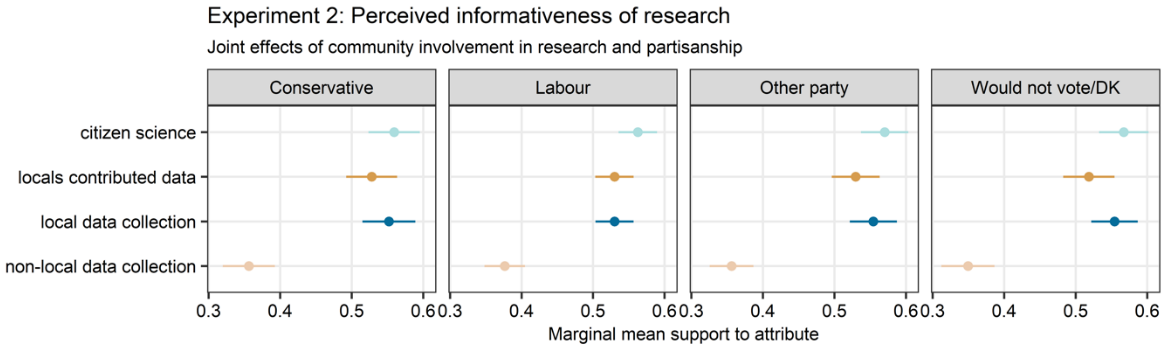

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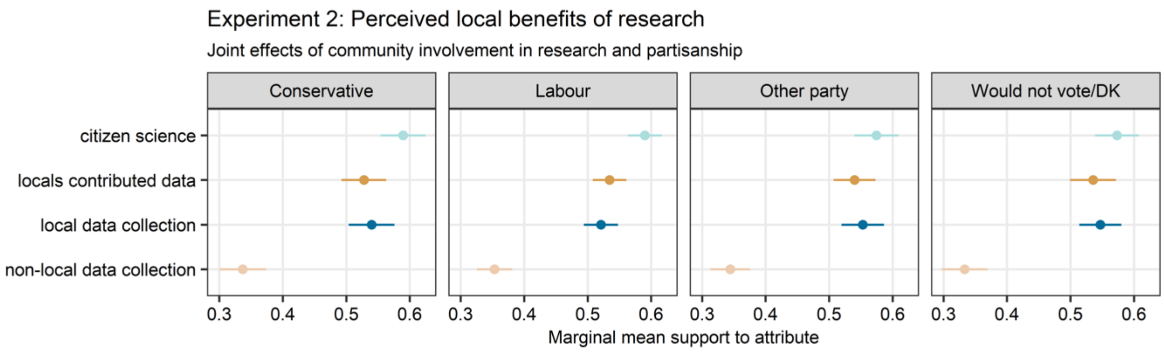

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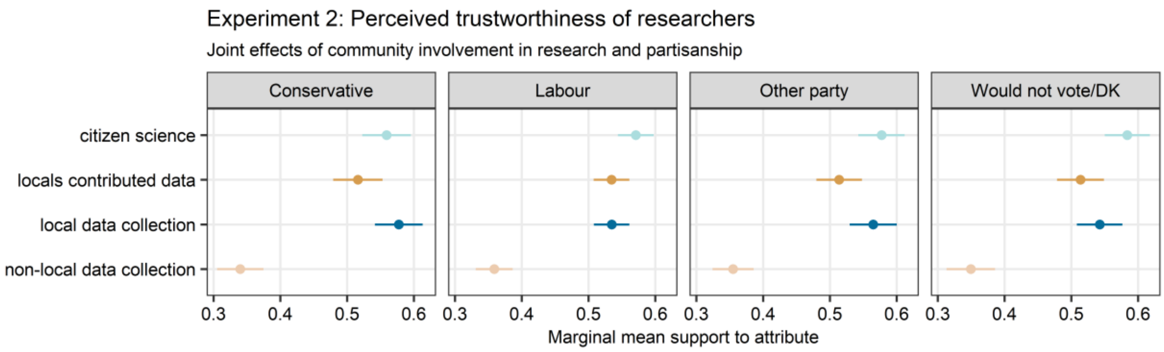
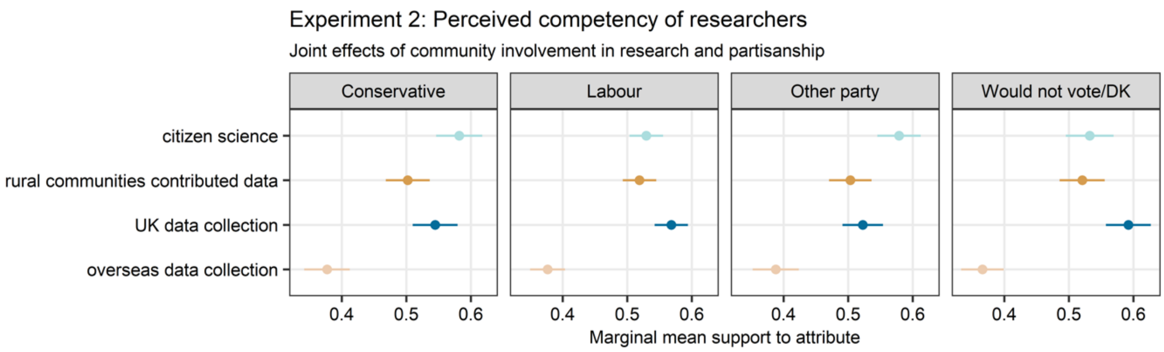


Group C: 'Science vs science' – comparing GM research, community involvement by partisanship

C1



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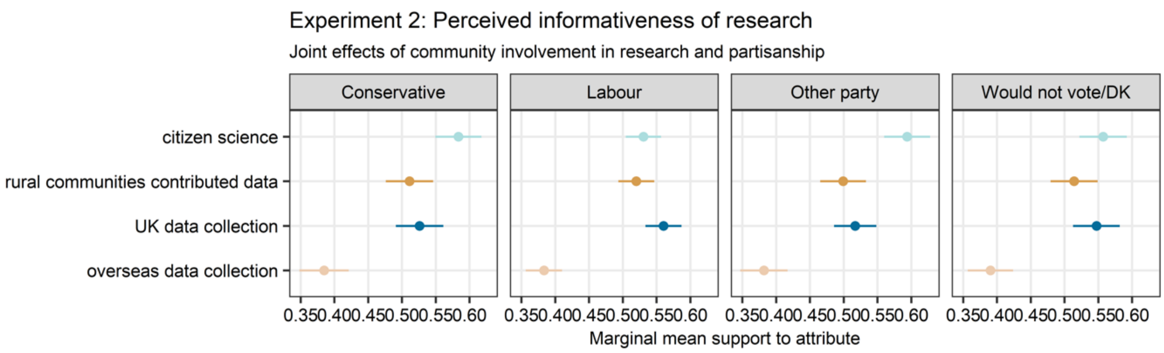

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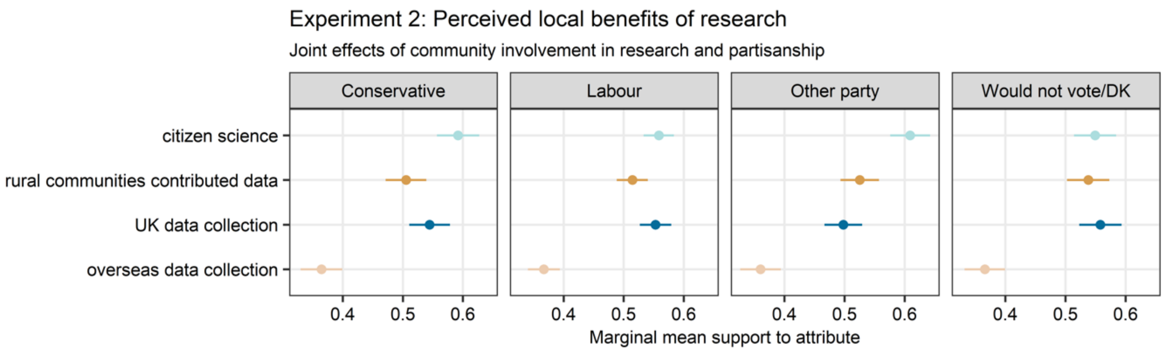
C3



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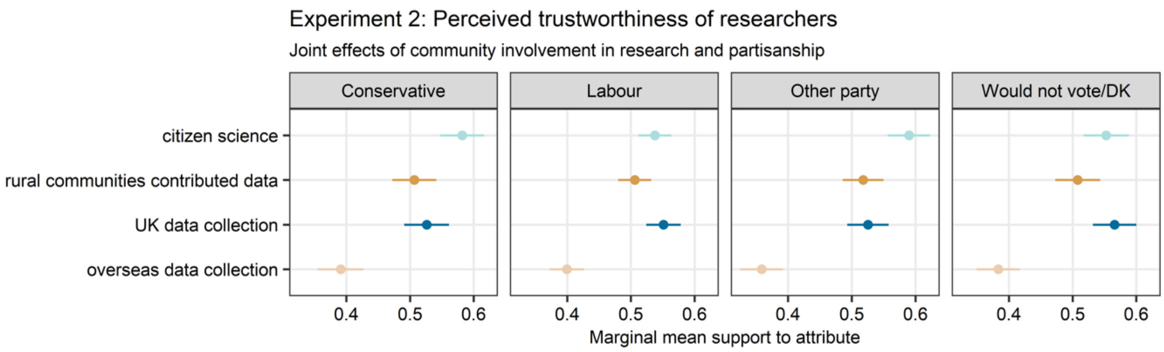

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Fig. A11: Conjoint experiment results by partisanship—all dependent variables.