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Methodological and Ideological Options

GEM: A short “Growth-vs-Environment” Module for survey research

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ABSTRACT

Segmentation of survey respondents is a common tool in environmental communication as it helps to understand opinions of people and to deliver targeted messages. Prior research has segmented people based on their opinions about the relationship between economic growth and environmental sustainability. This involved an evaluation of 16 statements, which means considerable survey time and cost, particularly if administered by a third party, as well as cognitive burden on respondents, increasing the chance of incomplete responses. In this study, we apply a machine learning algorithm to results from past surveys among citizens and scientists to identify a robust, minimal set of questions that accurately segments respondents regarding their opinion on growth versus the environment. In particular, we distinguish three groups, called Green growth, Agrowth and Degrowth. To this end, we identify five perceptions, namely regarding ‘environmental protection’, ‘public services’, ‘life satisfaction’, ‘stability’ and ‘development space’. Prediction accuracy ranges between 81% and 89% across surveys and opinion segments. We apply the proposed set of questions on growth-vs-environment to a new survey from 2020 to illustrate its use as an efficient instrument in future surveys.

1. Introduction

Segmentation of survey respondents, also known as ‘audience segmentation’, is a common tool in environmental communication (Metag and Schäfer, 2018). Various segmentation models have been developed for different environmental issues, notably climate change (Hine et al., 2014). A somewhat neglected topic relevant to audience segmentation is the relationship between the environment and the economy.

In the context of the long-standing debate on economic growth versus environmental sustainability (Meadows et al., 1972; Turner, 2008; Jackson, 2009; Victor, 2012; van den Bergh and Kallis, 2012), some research has begun to understand segments of public opinion representing distinct attitudes and beliefs. The simplest, dichotomous classification used in many large-scale surveys (e.g. World Values Survey) is to group those who (do not) prefer environmental protection over economic growth, or who (do not) believe that economic growth is compatible with environmental protection (Drews et al., 2018). These classifications draw on single survey questions, which may fail to capture important dimensions of public opinion related to the growth debate. Moreover, measurement of constructs works usually better with multiple survey questions (Churchill, 1979). In response, recent research uses a wider set of survey questions, arguably arriving at more robust and nuanced results (e.g., Tomaselli et al., 2019).

We ourselves have contributed to this line of research in the form of surveys among citizens and scientists (Drews et al., 2019). These surveys built on prior theoretical analysis of the growth-environment debate, suggesting the existence of three main perspectives, sometimes labeled as ‘Green growth’, ‘Agrowth’ and ‘Degrowth’ (van den Bergh and Kallis, 2012; see also Jakob et al., 2020). One can generally say that supporters of Green growth argue that growth is needed to improve life satisfaction and can be harmonized with protecting the environment, proponents of Degrowth reject both propositions and therefore resist further growth or even strive for economic contraction, and advocates of Agrowth are indifferent about growth and hence refrain from any (de)growth aims. Using 16 survey questions, we identified three similar segments in samples of the general public and scientists (Drews et al., 2019), which are fairly consistent with the theoretical perspectives in the debate mentioned before. It may be noted that distinct labels have been used for the same or approximately the same positions, such as sustainable instead of green growth, or anti-growth, post-growth and zero-growth for degrowth. The appropriate label for degrowth has also been debated (Drews and Antal, 2016; Drews and Reese, 2018; Raworth,

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2015).

Construction of shorter survey instruments has been identified as a research need in the field of environmental segmentation studies (Metag and Schäfer, 2018). The quality of clustering public opinion depends on concise measures that reliably capture differences in people's attitudes or beliefs. A parsimonious way to elicit opinions avoids cognitive overload and fatigue of respondents to a survey. Moreover, researchers may hesitate to use relatively long sets of survey questions such as the 16-item instrument we developed, as they take up considerable survey time and increase survey costs. Here we use a machine learning algorithm to identify a concise and reliable instrument that will serve as a shortcut to the lengthy 16-item questionnaire being prohibitive for many research studies. In doing this, we follow the method in Chryst et al. (2018), who proposed a four-question shortcut for segmenting climate change views, which was originally comprised of 15 survey items.

Our principal aim is to identify a subset of questions capable of identifying the three segments of growth-vs-environment debate with sufficient accuracy, namely at the minimum 80% accurately categorized respondents in each of the three segments on out-of-sample validation data (Fawcett, 2006; Kleinbaum and Klein, 2010). As a result, we identify here a five-question instrument that satisfies this requirement. This can serve as a useful module to be part of a wide range of future surveys and experiments, not only those focused on environmental issues, but also broader public opinion surveys in which environmental awareness and concern are just one among other non-environmental elements.

2. Data and methods

2.1. Data

We base our analysis here on two related online surveys on opinions regarding growth-versus-environment, with overlapping questions (Drews and van den Bergh, 2016; and Drews and van den Bergh, 2017). The first was conducted in 2014 and covered 1008 respondents using quota sampling. It is representative of the general population of Spain in terms of age, gender, income, education and geographical regions (see Table A1 in the Appendix for descriptive statistics). The second survey was executed in 2015 and involved 814 researchers from many countries and a wide range of self-identified academic backgrounds, including general economics, environmental economics, economic growth studies, ecological economics, environmental social sciences, and environmental (natural and engineering) sciences (see Table A2 in the Appendix for descriptive statistics).

Both surveys included the same set of 16 statements to elicit views on the debate on economic growth versus environmental sustainability. Table 1 lists these along with summarizing labels as used in the previous

Table 1
Main statements of both surveys serving as input to the segmentation analysis.

Statement label	Statement wording
Life satisfaction	Continued economic growth is essential for improving people's life satisfaction.
Public services	Economic growth is necessary to finance public health and pension systems.
Stability	Without economic growth the economy will become less stable.
Environmental protection	Economic growth is necessary to finance environmental protection.
Full employment	Full employment can be achieved without economic growth.
Good life	A 'good life' without economic growth is possible.
Energy rebound	Energy savings due to technological advances are partly undone by further economic growth.
Environmental damage	Economic growth always harms the environment.
Development space	In view of limited natural resources, rich countries may have to give up their economic growth to assure that all poor people in the world can reach a fair standard of living.
Techno-fix	Technology can solve all environmental problems associated with economic growth.
Recovery	Future economic growth will recover and again be as high as in the past.
Post-materialism	Economic growth raises incomes which in turn make people care more about the environment.
Excessive political attention	Politicians are too concerned about economic growth.
Income inequality	Making the income distribution more equal should get a higher priority than economic growth.
Flawed welfare measure	The GDP is a flawed measure of social welfare.
Governmental control	Economic growth can be controlled by the government.

Note: The five statements providing an instrument to elicit opinions on the debate are marked with shading.

studies. For all the statements, respondents could provide answers on a 7-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree).

One minor difference between the designs of the two surveys might be noted. Whereas in the scientific opinion survey respondents could select “no opinion” for each of the 16 statements, in the public opinion survey there was no such option. This difference explains why there are 143 missing observations in the scientists’ survey. In Drews et al. (2019) we tested if dropping these observations biases the sample by means of Kolmogorov-Smirnov test and a Wilcox rank sum test and both tests indicated there was no statistically significant bias.

Subsequently, Drews et al. (2019) used a Latent Class Analysis algorithm to segment the responses into distinct clusters of opinions. This established that in the scientists’ survey 31%, 44% and 25% of respondents belonged to the Green growth, Agrowth and Degrowth clusters, while in the public survey these shares were 29%, 43% and 18%, respectively. In the public survey, Drews et al. (2019) also identified a fourth cluster of “indifferent” respondents (10% of the sample or 97 respondents) who exhibited little variation in their responses to the 16 statements. In particular, over 99% of their responses were “4” on the Likert scale (i.e. neither disagree nor agree) for 14 out of 16 questions.[1] This result was interpreted as those people being indifferent, undecided, neutral or lacking awareness about the issue. It is possible that these people would have preferred to not respond since the public survey did not include a non-response option, as discussed above. For this reason, in the following we will use 671 complete responses of the scientists’ and 907 responses of the public survey. To test if omitting the indifferent cluster biases our results, we conducted a robustness test by applying the method to all 1008 respondents of the public survey and found that our results are robust (see Fig. A1 in the Appendix).

Comparing the three clusters produced based on the responses from the general public and scientists’ community, Drews et al. (2019) found stronger polarization between clusters of opinions among scientists than among the general public on statement like environmental protection, development space and life satisfaction. We will further address this in Section 3.

In addition, we use a third survey conducted between June–July 2020 in Spain to demonstrate that using our survey module allows obtaining the same three clusters as derived from the original study. Sampling was again done by using quotas on age, gender and geographical distribution, making the survey sample representative of the general population on these characteristics. The sample included 2200 respondents who took on average 19 min to finish. The response rate was 68%. More details on the survey can be found in Savin et al. (2020a, 2020b). See Table A3 in the Appendix for descriptive statistics of the sample.

2.2. Method

The literature offers different approaches to develop short instruments (Siblini et al., 2019). One example is linear discriminant analysis (Welling, 2005). It was used, e.g., in a study by Maibach et al. (2011) on climate change. The authors found that using a limited set of questions one can separate distinct opinion segments on climate change. The resulting combination replaced 36 items by only 15, thus considerably reducing the length of the questionnaire. Another popular technique is Principal Component Analysis (Jolliffe and Cadima, 2016), which was used by Vogel et al. (2020) to reduce a 21-item questionnaire on public leadership to just 11 items. More recently, Chryst et al. (2018) applied the Gradient Boosting Machines (GBM) algorithm (Natekin and Knoll, 2013) to further shorten the list of questions by Maibach et al. (2011) to identify opinion segments on climate change. GBM is a machine learning algorithm based on the principle of classification and regression trees (Breiman et al., 1984; Strobl et al., 2009). While basic regression trees are fast and intuitive in exploring complex datasets, they typically suffer from low robustness. With the evolution of computer power and machine learning algorithms, new methods based on regression trees such as ‘random forests’ and GBM have been proposed. Whereas random forests build an ensemble of independent trees, GBM builds an ensemble of simple successive trees with each tree learning and improving on the previous and ensuring robustness of results. We decided to use GBM because it has proven its high performance in general (Brownlee, 2019; Friedman, 2001) and particularly in developing short instruments replacing a 15-item instrument to just four items (more than 70% reduction).

In line with Chryst et al. (2018), we implement a three-step approach. First, we randomly withdraw from our data 10% of observations (held-out sample) to test the predictive power of our model in a third stage. Second, the remaining 90% of observations are analysed with the GBM algorithm. To this end, we use the associated package in R (Greenwell et al., 2019). Specifically, we use 1000 trees[2] and multinomial data distribution to build a prediction model. To validate the model, we use a 10-fold cross-validation. This means that GBM splits the 90% sample again into training and testing sets ten times randomly, trains the model on the first set and then evaluates its performance on the testing set, reporting average results. As an outcome, GBM ranks the 16 statements in their predictive power, which we later use for defining a sufficient set of statements with required prediction accuracy.

In the third step, we select the top ranked statements and evaluate their prediction quality on the 10% held-out sample by means of a multinomial logistic regression. In particular, using the three segments of opinions as the dependent variable, we successively fit to the 90% data sample a model consisting of the single best predicting variable ranked by GBM, and subsequently add further ones. Based on the regression results, we construct predictions of being classified to one of the three opinion segments and compare the predictions with the true values (the classes assigned earlier on the full set of 16 statements). This is done until a satisfactory accuracy of 80% was achieved. The reason to select the 80% accuracy threshold is that one typically has to strike a balance between the accuracy and the length of the survey module: the shorter it is, the lower is its accuracy. For example, Maibach et al. (2011) reduced 36 items to 15 (i.e. a 60% reduction) reaching 80% overall accuracy threshold (though the accuracy of distinct opinion clusters was lower). Chryst et al. (2018) reduced 15 items to just 4 (73% reduction), and in doing this employed a 70% accuracy threshold. We aim to reduce 16 items to 3–5 items (70–80% reduction) and adopt the 80% accuracy threshold both for aggregate accuracy as well as for accuracy for each opinion cluster.

Furthermore, recognizing the limited amount of data we have for training and validating our results, we repeat steps 1 and 3 described above for 100 different random seeds in separating the held-out sample, and measure prediction accuracy of the preselected subset of statements by fitting them via multinomial logistic regression and comparing associated predictions with the results. This way, given our relatively small dataset, one keeps the training data sample larger (90% vs 80% in Chryst et al. (2018)), while estimating the prediction accuracy not on a single held-out sample but on 100 random ones, i.e. varying the allocation of observations between the in- and out-of-samples each time. This approach is called cross-validation and is common in machine learning (Arlot and Celisse, 2010). Results reported in Section 3 pertain to averages and standard errors over the 100 restarts. This approach contributes to robustness of the findings.

[1] The two exceptions are life satisfaction and income inequality.

[2] Typically, GBM converges much faster, with 50–250 trees, but we keep the number larger as it involves relatively little computational time (GBM convergence took only a few minutes).

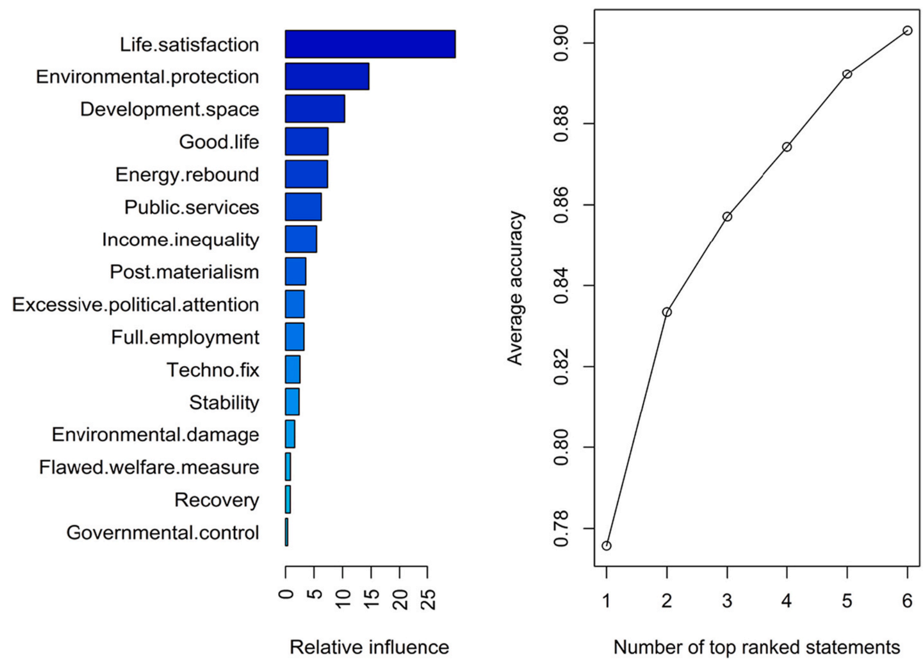

Fig. 1. Results from applying GBM on scientists' survey. The left panel shows the rank of 16 statements, while the right panel provides the average accuracy in predicting the true segmentation.
Note: Results for accuracy are averaged over 100 restarts with different starting seed.

3. Results

Given the differences in the audiences of our two surveys addressed in Section 2.1, in the following section we will apply the procedure described in Section 2.2 first on each of the two primary surveys separately, and then pool the two data samples together to find a parsimonious instrument that can correctly classify the survey respondents for different audiences. To illustrate how the survey module works, we subsequently apply it to a recent survey conducted in Spain in 2020. Accordingly, this section consists of four subsections for each of the exercises, with the third providing the overall five-statement instrument and the fourth validating the instrument on a recent dataset.

3.1. Scientists' survey

Results for the survey of scientists are presented in Fig. 1. The left panel shows the most influential variables in explaining the clustering membership on the y-axis, while the x-axis captures their relative influence, i.e. the improvement that variables produce in the regression trees (equivalent for mean squared error for a standard regression) averaged over all the regression trees used. The relative influence is normalized to sum up to 1, i.e. expressed in %. The variables producing the largest improvement may be considered as the most important ones. We can see that the 'life satisfaction' statement leads with a big margin followed by 'environmental protection' and 'development space'. Together these three variables produce an accuracy[3] of 85.7% on average over 100 restarts, which satisfies our requirement on prediction accuracy stated earlier. The standard error in prediction accuracy over 100 restarts was 0.46%, which implies that the confidence band of mean ± two standard errors also lies well above the 80% requirement. Furthermore, to make sure that prediction accuracy is high across all the three opinion segments, in Table 2 below we report means and standard errors of accuracy for Green growth, Agrowth and Degrowth separately. As one can see, our model has a slightly better accuracy for Degrowth and Green growth. Table 3 reports estimates of the resulting multinomial regression model. Interpretation of the coefficients is as follows. If a respondent chose the answer "strongly agree" instead of "strongly disagree" for the statement on life satisfaction ("Continued economic growth is essential for improving people's life satisfaction."), then the odds of being classified in the Green growth (vs Degrowth) cluster increase by factor 3.4 to 1.

Table 2
Accuracy, precision and recall of predictions (in %) based on survey among scientists using the top three statements for each of the three opinion segments.

	Green growth	Agrowth	Degrowth
Accuracy	88.9 (0.7)	82.1 (0.6)	88.1 (0.6)
Precision	81.7 (1.1)	80.6 (0.9)	83.7 (1.1)
Recall	84.2 (1.2)	79.5 (0.9)	83.4 (1.1)

Note: Means with standard errors in parentheses.

3.2. Public survey

When we repeat the procedure on the public survey, we find that the rank of most predictive statements, shown in Fig. 2, is different from what we find for scientists. While the 'environmental protection' statement is still among the top three, the other two most predictive items with a considerable margin are 'public services' and 'stability'. These three indicators together achieve an average accuracy of 83.0% (with a standard error of 0.3%) satisfying our requirement on prediction quality. The fact that statements like 'development space' score lower here may be that among the general public economic growth is primarily associated with low unemployment and a good standard of living. On the other hand, scientists name among their first associations with

[3] Accuracy measures the fraction of instances correctly predicted. The maximum value it can take is 100%, meaning that observations with predicted class A should actually be assigned to that class, while no observation of class A is assigned to a different class. Average accuracy is then obtained as an average per class accuracy of the survey instrument. Precision measures the effectiveness of the classifier to avoid false positives (i.e. classify observations from other classes to the focal class) while recall measures the effectiveness in limiting false negatives (i.e. classify observations from the focal class to other classes). See Sokolova and Lapalme (2009) for more details.

Table 3
Results of the multinomial logistic model based on the survey among scientists.

		Agrowth	Green growth
Life satisfaction	Disagree	1.589*** (0.547)	−1.357 (1.380)
	Somewhat disagree	3.342*** (0.645)	1.673 (1.137)
	Neutral	3.940*** (0.941)	3.488*** (1.263)
	Somewhat agree	3.512*** (0.892)	4.577*** (1.163)
	Agree	23.553*** (0.441)	25.513*** (0.441)
	Strongly agree	−0.128 (1.794)	3.421** (1.731)
Environmental protection	Disagree	0.611 (0.510)	−0.529 (0.988)
	Somewhat disagree	1.879*** (0.607)	0.387 (1.023)
	Neutral	2.449*** (0.909)	−0.280 (1.296)
	Somewhat agree	4.179*** (0.895)	3.717*** (1.135)
	Agree	26.136*** (0.418)	27.328*** (0.418)
	Strongly agree	17.272*** (0.469)	19.114*** (0.469)
Development space	Disagree	2.947* (1.515)	1.585 (1.535)
	Somewhat disagree	3.131** (1.484)	0.487 (1.523)
	Neutral	2.298 (1.429)	−1.943 (1.516)
	Somewhat agree	1.383 (1.381)	−2.562* (1.436)
	Agree	1.319 (1.370)	−2.306 (1.441)
	Strongly agree	−2.178 (1.434)	−4.474*** (1.527)
Constant		−3.985*** (1.440)	−2.129 (1.515)
Akaike Inf. Crit.		570.662	570.662

Note: Results are reported as odds-ratios. Degrowth is a reference group. Reference response is 1 (“strongly disagree”). Asterisks ***, **, and * denote 1%, 5%, and 10% significance, respectively.

economic growth also the side effect of increasing pollution and environmental degradation, pointing out that this growth is unsustainable (Savin et al., 2020a; Savin et al., 2020b). Examining prediction accuracy for each of the three opinion segments (Table 4), we find slightly better results for the Degrowth cluster and worse for the Green growth cluster. The resulting multinomial model is reported in Table 5.

3.3. Pooled dataset

Next, we pool the two datasets together to see what would be the rank of statements and their accuracy on the whole set of observations we have. Fig. 3 demonstrates the results. The top five statements reach

Table 4
Accuracy, precision and recall of predictions (in %) based on a survey among the general public, using the top three statements for each of the three opinion segments.

	Green growth	Agrowth	Degrowth
Accuracy	82.6 (0.5)	82.1 (0.4)	84.6 (0.4)
Precision	79.6 (1.1)	79.5 (0.6)	79.1 (0.7)
Recall	72.1 (1.0)	83.8 (0.6)	78.9 (0.7)

Note: Means with standard errors in parentheses.

Table 5
Results of the multinomial logistic model based on the survey among general public.

		Agrowth	Green growth
Public services	Disagree	10.321*** (0.925)	−0.612 (1.283)
	Somewhat disagree	14.930*** (0.385)	−16.416*** (0.000)
	Neutral	14.666*** (0.373)	0.728*** (1.194)
	Somewhat agree	15.550*** (0.368)	1.526 (1.119)
	Agree	15.558*** (0.368)	3.250*** (1.122)
	Strongly agree	17.065*** (0.870)	5.839** (1.432)
Stability	Disagree	15.438*** (0.562)	2.009* (1.211)
	Somewhat disagree	18.166*** (0.380)	2.049 (1.275)
	Neutral	18.362*** (0.325)	0.643 (1.230)
	Somewhat agree	19.434*** (0.337)	2.794** (1.164)
	Agree	19.910*** (0.459)	5.141*** (1.202)
	Strongly agree	16.145*** (1.063)	6.167*** (1.454)
Environmental protection	Disagree	1.665* (0.851)	0.659 (0.789)
	Somewhat disagree	3.346** (0.848)	0.710 (0.814)
	Neutral	4.575*** (0.860)	2.284*** (0.798)
	Somewhat agree	5.255*** (0.878)	2.159*** (0.810)
	Agree	4.936*** (0.952)	3.285*** (0.861)
	Strongly agree	2.856*** (1.085)	2.758*** (0.982)
Constant		−36.300*** (0.638)	−6.573*** (1.613)
Akaike Inf. Crit.		911.286	911.286

Note: Results are reported as odds-ratios. Degrowth is a reference group. Reference response is 1 (“strongly disagree”). Asterisks ***, **, and * denote 1%, 5%, and 10% significance, respectively.

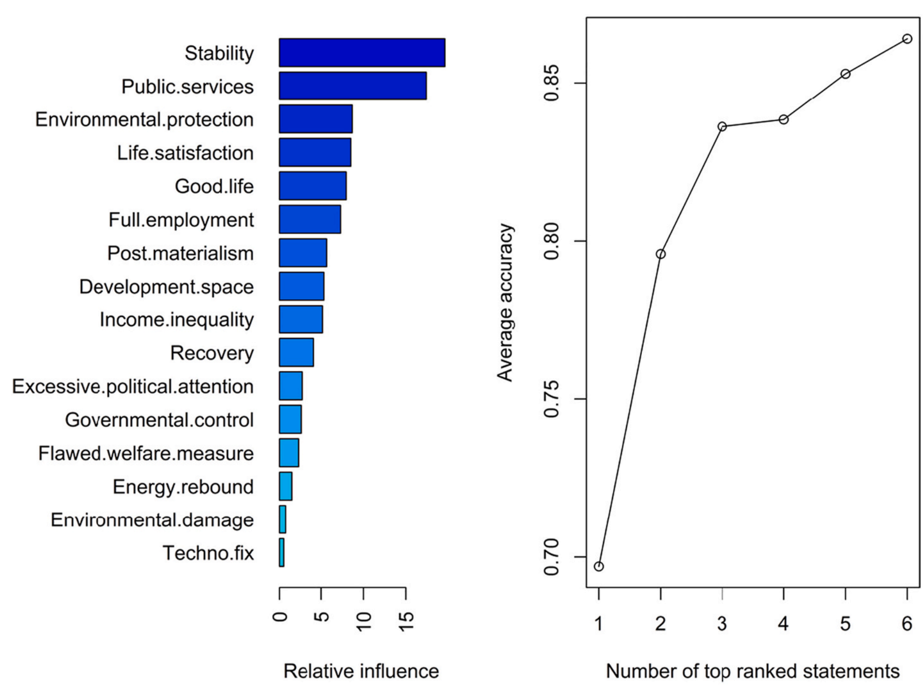

Fig. 2. Results from applying GBM on public survey. The left panel shows the rank of 16 statements, while the right panel provides the average accuracy in predicting the true segmentation.
Note: Results for accuracy are averaged over 100 restarts with different starting seed.

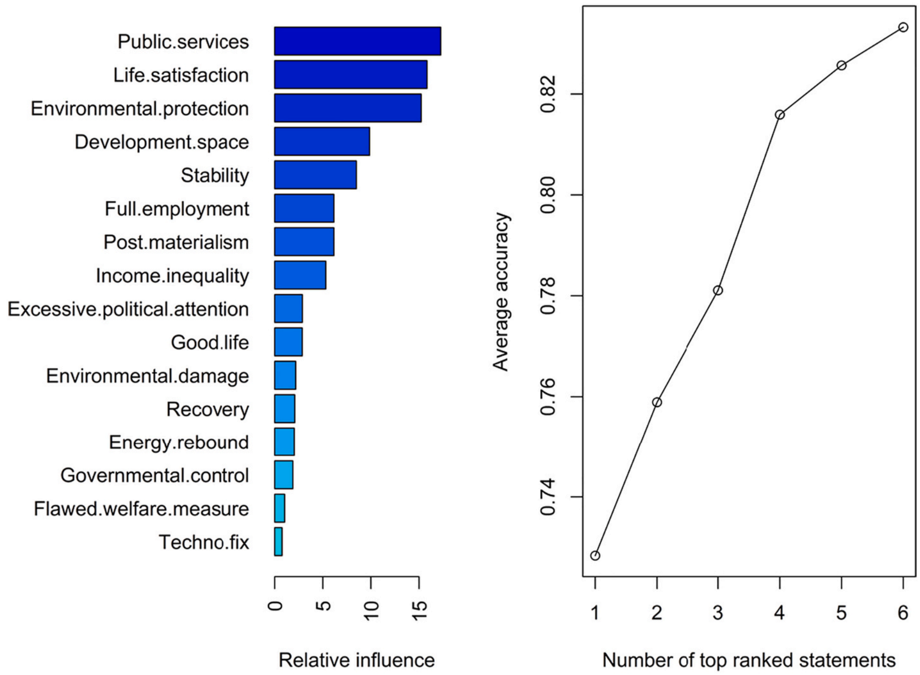

Fig. 3. Results from applying GBM pooled dataset. The left panel shows the rank of 16 statements, while the right panel provides the average accuracy in predicting the true segmentation.
Note: Results for accuracy are averaged over 100 restarts with different starting seed.

82.8% accuracy (with standard error 0.2%) and comprise the same top statements discussed earlier. The three statements with the highest relative influence, above 10%, are 'environmental protection', 'public services' and 'life satisfaction'. The other two statements on 'stability' and 'development space' have a lower relative influence of around 8–10%.

Table 6 summarizes the prediction accuracy of this instrument both on the pooled dataset but also on the two surveys separately. It shows that the proposed five-item instrument scores well on all three datasets (individual surveys and the pooled sample), for each reaching 80% prediction accuracy or higher. This demonstrates that the 5-item instrument obtained for the pooled dataset also works well when applied to each of the survey samples separately. Note that by using a 5- rather than 3-item instrument (Section 3.1–3.2), we can reach an accuracy that is either the same (for the scientific survey) or higher (for the general public survey) on both surveys separately.

Table 6
Accuracy, precision and recall of predictions (in %) made with five-item instrument for each of the three opinion segments.

Prediction based on		Green growth	Agrowth	Degrowth
Pooled dataset	Average accuracy	82.8 (0.2)		
	Accuracy	82.1 (0.3)	81.0 (0.2)	86.1 (0.3)
	Precision	77.9 (0.5)	77.5 (0.4)	82.5 (0.5)
	Recall	71.8 (0.7)	82.9 (0.4)	80.0 (0.5)
Scientists' survey	Average accuracy	86.5 (0.4)		
	Accuracy	87.1 (0.6)	84.1 (0.5)	89.4 (0.5)
	Precision	83.9 (1.1)	81.1 (0.9)	85.7 (0.9)
	Recall	79.0 (1.2)	83.3 (0.8)	85.7 (1.1)
Public survey	Average accuracy	86.0 (0.3)		
	Accuracy	87.3 (0.5)	84.8 (0.4)	87.0 (0.4)
	Precision	83.3 (0.9)	82.9 (0.6)	84.1 (0.7)
	Recall	78.4 (1.0)	86.7 (0.5)	81.3 (0.8)

Note: Means with standard errors in parentheses.

t is worth noting that the results for the pooled dataset are slightly worse than on any of the two surveys taken separately, which is due to it being less homogeneous than each individual dataset. As we know from Section 3.1 and 3.2, same statements serve differently in their prediction accuracy in the two surveys. For example, the 'stability' statement distinguishes well respondents among the general public but functions less well for scientists. Logically, their estimates in the multinomial regression differ considerably. Hence, when fitting the multinomial regression model to both samples at the same time results in certain averaging of the estimates, which moderately reduces the quality of out-of-sample prediction (Table 7).

3.4. Applying the survey module on a recent survey from 2020

In the following section we present results of applying the identified survey module to recent survey data for Spain from 2020 which has not been used for constructing it. The data contains only the selected five statements, and in line with Drews et al. (2019) we use Latent Class Analysis to cluster the observations. The number of clusters is selected on the basis of three commonly used information criteria: the consistent Akaike criterion (cAIC), the Bayesion criterion (BIC) and the adjusted BIC (aBIC). All three criteria suggest three clusters (see Fig. A2 in the Appendix). The three derived clusters have the following proportions: Green growth (22.3%), Agrowth (50.2%) and Degrowth (27.6%). This demonstrates that since 2014 the share of people supporting Green growth has fallen, while the share of Agrowth has risen. As one can see from Fig. 4, the clusters are different across all five survey items except for 'development space'. The latter perhaps can be explained by two arguments. First, development space has been ranked high in our survey tool particularly on the sample of scientists and the pooled sample of survey respondents, while for the general public it was considered less important (see Fig. 2). Bearing this in mind we try to segment the general public with a three-item module below showing that it can reach almost the same result. Second, the timing of the questionnaire (COVID-19 in 2020) may have stimulated stronger solidarity between people so that they tend to respond consistently high on this dimension irrespective of the cluster membership. As the sole purpose here is to show

Table 7
Results of the multinomial logistic model with five-item instrument.

		Pooled dataset		Scientists' survey		Public survey	
		Agrowth	Green growth	Agrowth	Green growth	Agrowth	Green growth
Environmental protection	Disagree	0.885** (0.400)	0.712 (0.642)	0.668 (0.611)	−1.241 (1.526)	1.700* (0.973)	1.632 (1.072)
	Somewhat disagree	1.986*** (0.421)	1.138* (0.660)	2.024*** (0.714)	0.006 (1.515)	3.518*** (0.972)	1.761 (1.086)
	Neutral	2.533*** (0.448)	1.396** (0.649)	1.882* (0.974)	−1.783 (1.820)	5.118*** (1.007)	3.577*** (1.078)
	Somewhat agree	3.303*** (0.458)	2.328*** (0.631)	3.749*** (0.985)	2.259 (1.562)	6.351*** (1.068)	4.032*** (1.117)
	Agree	3.362*** (0.627)	3.802*** (0.748)	27.381*** (0.700)	27.648*** (0.700)	5.726*** (1.195)	4.837*** (1.204)
	Strongly agree	2.258*** (0.809)	3.771*** (0.883)	22.697*** (0.792)	24.176*** (0.792)	2.876** (1.388)	3.615*** (1.371)
Public services	Disagree	12.396*** (0.302)	−2.761** (1.114)	15.633*** (0.505)	−2.156 (2.216)	7.039*** (1.186)	−1.820 (2.885)
	Somewhat disagree	13.540*** (0.254)	−2.569** (1.042)	16.019*** (0.513)	−3.934* (2.069)	14.393*** (0.472)	−28.109*** (0.000)
	Neutral	13.791*** (0.260)	−1.020 (0.933)	16.498*** (0.495)	−2.450 (2.033)	14.166*** (0.451)	2.091 (2.777)
	Somewhat agree	13.988*** (0.254)	0.274 (0.868)	17.203*** (0.563)	0.832 (1.912)	14.685*** (0.391)	2.744 (2.747)
	Agree	13.891*** (0.299)	1.133 (0.872)	17.765*** (0.782)	2.479 (2.065)	14.496*** (0.436)	4.621* (2.750)
	Strongly agree	14.312*** (0.560)	2.474** (0.962)	16.512*** (1.230)	1.690 (2.271)	15.961*** (1.014)	7.116** (2.884)
Life Satisfaction	Disagree	1.491*** (0.516)	0.316 (0.993)	1.947*** (0.654)	−0.518 (1.568)	28.669*** (0.788)	15.971*** (1.107)
	Somewhat disagree	2.211*** (0.529)	0.041 (0.973)	3.739*** (0.764)	0.945 (1.386)	31.560*** (0.449)	15.764*** (1.360)
	Neutral	1.974*** (0.548)	1.852** (0.901)	3.910*** (0.992)	3.423** (1.504)	32.103*** (0.443)	17.968*** (0.885)
	Somewhat agree	1.610*** (0.524)	2.329*** (0.815)	3.841*** (1.078)	4.610*** (1.431)	31.608*** (0.355)	18.323*** (0.648)
	Agree	3.145*** (0.592)	4.288*** (0.848)	39.569*** (0.545)	41.154*** (0.545)	34.317*** (0.484)	21.696*** (0.709)
	Strongly agree	1.508** (0.666)	3.635*** (0.889)	−0.651 (2.471)	2.691 (2.176)	33.248*** (0.638)	21.944*** (0.778)
Development space	Disagree	3.302*** (0.927)	0.408 (0.697)	5.041*** (1.851)	2.512 (1.913)	16.510*** (0.596)	−0.322 (1.361)
	Somewhat disagree	3.456*** (0.903)	−1.132* (0.684)	4.256** (1.746)	0.345 (1.862)	16.836*** (0.430)	−3.013** (1.361)
	Neutral	3.880*** (0.900)	−2.102*** (0.686)	3.461** (1.697)	−2.537 (1.901)	17.567*** (0.413)	−2.020 (1.322)
	Somewhat agree	3.017*** (0.881)	−2.666*** (0.663)	2.519 (1.633)	−3.645** (1.808)	15.953*** (0.354)	−3.061** (1.285)
	Agree	2.636*** (0.884)	−2.647*** (0.667)	2.615 (1.624)	−2.709 (1.816)	15.072*** (0.419)	−3.754*** (1.334)
	Strongly agree	0.562 (0.906)	−3.247*** (0.686)	−1.276 (1.645)	−5.999*** (1.822)	13.171*** (0.559)	−3.486*** (1.328)
Stability	Disagree	16.916*** (0.281)	1.057 (0.949)	14.110*** (0.466)	−1.477 (2.440)	15.542*** (0.739)	0.832 (1.697)
	Somewhat disagree	17.310*** (0.275)	0.589 (0.960)	14.532*** (0.521)	0.417 (2.472)	19.277*** (0.485)	0.486 (1.730)
	Neutral	17.159*** (0.259)	−0.169 (0.920)	15.053*** (0.536)	0.236 (2.432)	18.717*** (0.395)	−1.510 (1.667)
	Somewhat agree	18.341*** (0.252)	1.669* (0.882)	15.641*** (0.471)	1.801 (2.340)	20.320*** (0.416)	1.911 (1.544)
	Agree	17.876*** (0.309)	2.621*** (0.887)	14.131*** (0.595)	1.391 (2.385)	20.457*** (0.549)	3.918** (1.573)
	Strongly agree	16.002*** (0.622)	3.509*** (1.046)	11.965*** (1.258)	2.008 (2.770)	17.364*** (1.211)	6.132*** (2.030)
Constant	−36.755*** (0.776)	−3.810*** (1.220)	−36.356*** (1.379)	−1.767 (2.431)	−84.624*** (0.597)	−25.012*** (2.622)	
Akaike Inf. Crit.	1464.604	1464.604	494.932	494.932	699.566	699.566	

Note: Results are reported as odds-ratios. Degrowth is a reference group. Reference response is 1 ("strongly disagree"). Asterisks ***, **, and * denote 1%, 5%, and 10% significance, respectively.

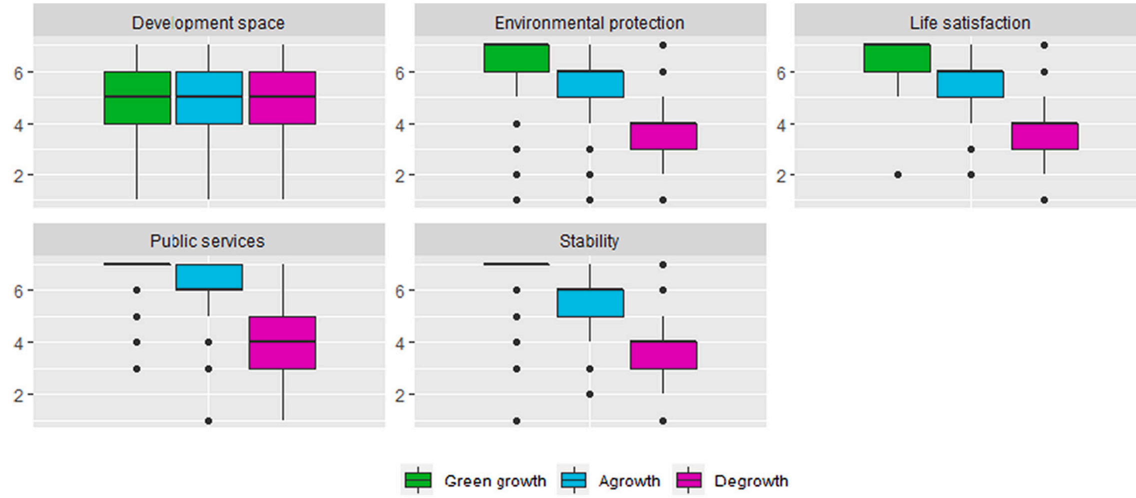

Fig. 4. Response distribution among the three clusters for the five items making up the survey module.

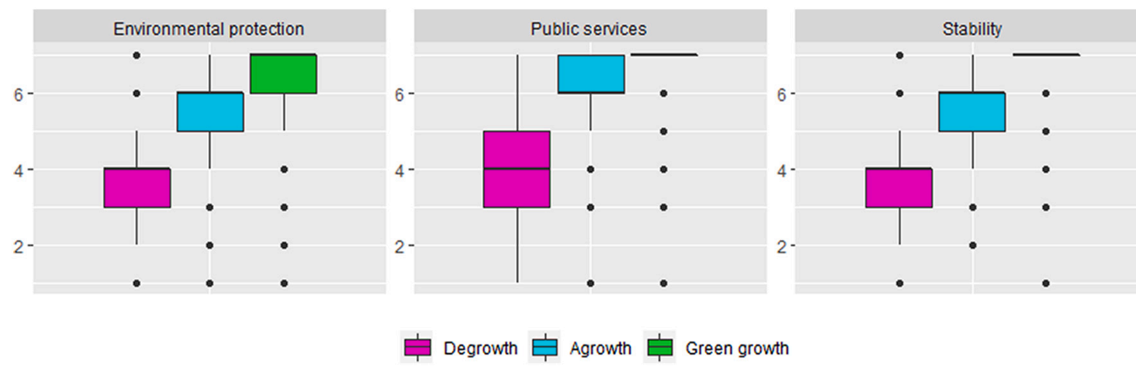

Fig. 5. Distribution of responses on the three items from our survey module in the public opinion survey.

Table 8
Confusion matrix for clustered constructed with two versions of the survey module based on the survey from 2020.

		Clusters based on three-items instrument		
		Green growth	Agrowth	Degrowth
Clusters based on five-items instrument	Green growth	441	42	6
	Agrowth	24	1060	20
	Degrowth	1	38	568

that clusters can be developed reliably by using the five items, we refrain from any interpretation of differences in the sizes of the clusters compared to earlier results.

Since here we are working with survey data from the general public, one may then ask if using only three out of five items (public services, stability, environmental protection) would produce distinct results. To test this, we apply an instrument limited to these three items. The cluster proportions in this case look very similar: Green growth (23.4%), Agrowth (47.6%) and Degrowth (29%). In this case, clusters differ well on all three dimensions used for classifying the responses (Fig. 5).

To see how the three clusters using the 5- and 3-item instrument coincide, we build a confusion matrix (Table 8). As only 131 out of 2200 responses (i.e. 6%) are classified differently by the two versions of the instrument, we conclude that the results for the 5-item instrument are robust.

Table 9
Multinomial logit regression analysis of cluster membership and additional survey variables.

	Clusters based on five-items instrument		Clusters based on three-items instrument	
	Degrowth	Green growth	Degrowth	Green growth
Age	−0.024***	0.011***	−0.021***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Gender	−0.515***	−0.016	−0.514***	0.008
	(0.123)	(0.127)	(0.123)	(0.129)
Growth-vs-environment strategy	0.819***	−0.607***	0.811***	−0.605***
	(0.078)	(0.123)	(0.077)	(0.125)
Political orientation	−0.041	0.157***	−0.029	0.172***
	(0.027)	(0.025)	(0.026)	(0.025)
Constant	−0.682*	−0.749*	−0.873**	−1.080**
	(0.375)	(0.438)	(0.374)	(0.447)
Akaike Inf. Crit.	3622.98	3622.98	3574.37	3574.37

Note: Agrowth is the reference group. Standard deviations in parentheses. Asterisks ***, **, and * denote 1%, 5%, and 10% significance, respectively.

To demonstrate that the clusters identified using 5-item instrument have similar characteristics to clusters identified in Drews et al. (2019), we regress the cluster membership using multinomial logit model on age, gender, political orientation and preferred growth-vs-environment strategy (single-item question present in both surveys). The results are summarized in Table 9. In line with Drews et al. (2019), Table 3), we find that the Green growth cluster prefers a public policy that combines economic growth and environmental sustainability, assuming that both objectives are compatible (see the negative coefficient of the preferred "growth-vs-environment strategy"), while the Degrowth cluster prefers a public policy that has the goal of stopping economic growth (largest value of the associated variable). This result can be seen as a validation of the clustering made by means of our survey module, as these preferences reflect the main beliefs of each cluster. Also, similar to Drews et al. (2019), we find that members of the Green growth cluster are older and those of the Degrowth younger than members of the Agrowth cluster. Moreover, compared to Agrowth, supporters of Degrowth include more men and slightly more left-wing political views. Overall, these results can be viewed as further support for the validity of our instrument.

4. Conclusion

This study has identified a reduced set of survey questions to be used for segmenting an audience into three clusters of the growth-vs-environment debate, namely Green growth, Agrowth and Degrowth. To segment an audience consisting of the general public, a three-item solution is sufficient to achieve good accuracy. These three items address aspects of public services, economic stability and environmental protection. To segment an audience made up of scientists, or more generally people familiar with the debate, another three-item instrument seems appropriate. It covers environmental protection, but in contrast to the three-item instrument for the general public, addresses the link to people's life satisfaction and the question of development space for rich and poor countries. We also derived a five-item instrument based on pooling data on opinions by the general public and scientists. This instrument, which represents a combination of solutions for the separate samples, achieves sufficient prediction accuracy for the pooled dataset, and the same or a higher accuracy for the two samples. Indeed, it is especially useful when one is uncertain about the type of audience one has in mind for segmentation and communication. Moreover, while earlier studies tested their instrument only among the general public, our instrument passes a different, arguably harder, test for validity: namely, we show that this instrument can be used even for structurally different populations and still delivers a good performance.

A limitation of the present study is that we used only two surveys, one for Spanish citizens and one for scientists worldwide. Hence, it would be good to test the proposed instrument for public surveys in other countries. Another limitation is that most items in our survey module (in contrast to the full set of 16 items) involve 'positive' wording about growth. This might introduce so-called acquiescence bias of responses (Krosnick, 1999). Further research might test whether using alternative expressions of the same underlying ideas provide similar results.

Our survey module GEM can serve as a basis for a variety of future empirical studies that aim to address views on academic and societal debate surrounding growth and environment. In addition, it can become a part of larger questionnaires that have a broader aim, such as assessing environmental attitudes, support for climate policy, or opinions about the state of the economy. Despite the importance of the debate on growth versus the environment, empirical studies of public opinion on environmental issues often lack a thorough tool to identify opinions in it. A short survey module like GEM could easily be incorporated in a larger survey questionnaire. This would have several advantages; it would avoid ad hoc formulations that hamper comparability of findings between studies; and it would save other researchers time and efforts to examine the relevant literature in order to develop an own set of questions to elicit growth-versus-environment opinions. Such incorporation of standard instruments is already common in psychological research, and could benefit environmental studies.

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Declaration of Competing Interest

None.

Appendix A. Appendix

Table A1
Key socio-demographic characteristics of the public opinion survey in 2014 ($N = 907$).

Variables	Description	Mean (SD) or %
Gender	Female	48.1%
Age	18 to 64 years	40.82 (12.46)
Household income	1 (≤1000 €) to 5 (≥3000 €)	2.78 (1.25)
Educational attainment	1 (primary education) to 4 (postgraduate degree)	2.62 (0.76)
Political orientation	1 (left-wing) to 9 (right-wing)	3.95 (2.01)

Table A2
Key socio-demographic characteristics of the scientific opinion survey ($N = 671$).

Variable	*n*	Variable	*n*	Variable	*n*
Age		**Research field**		**Political ideology**	
<30 years	19	GrowEc	34	Very left	46
30–39	218	GrowEnv	31	Left	206
40–49	200	OthEc	75	Slightly left	190
50–59	113	EnvEc	228	Center	108
≥60	87	EcoEc	131	Slightly right	50
Gender		EnvSoc	156	Right	28
Female	162	EnvSci	16	Very right	3
Male	498	**# publications grow/env**		Don't know	31

Table A2 (*continued*)

Variable	*n*	Variable	*n*	Variable	*n*
Education		0	213	**Citizenship**	
PhD	586	1–3	187	North America	160
Other	85	4–10	185	EU	337
Professional affiliation		11–29	54	Asia	65
Academia	553	≥30	32	Africa	16
Government	36	**# publications growth**		Australia and Oceania	27
Private	33	0	355	Central and Southern America	15
Other	47	1–3	77	Other	51
Income of country of origin[a]		4–9	40		
High	589	10–19	23		
Middle/low	82	≥20	19		

[a] We use the classification of The World Bank for high and middle/low income countries: http://data.worldbank.org/about/country-and-lending-groups. The research fields are described in Section 2 in Drews and van den Bergh (2017). Not all numbers add up to N = 671 due to missing data.

Table A3
Key socio-demographic characteristics of the public opinion survey in 2020 ($N = 2200$).

Variables	Description	Mean (SD) or %
Gender	Female	51%
Age	18 to 88 years	45.50 (15.09)
Household income	1 (No income) to 5 (≥4000€)	2.58 (1.14)
Educational attainment	1 (Less than 5 years of school) to 8 (University)	5.02 (1.32)
Political orientation	1 (left-wing) to 10 (right-wing)	4.44 (2.41)

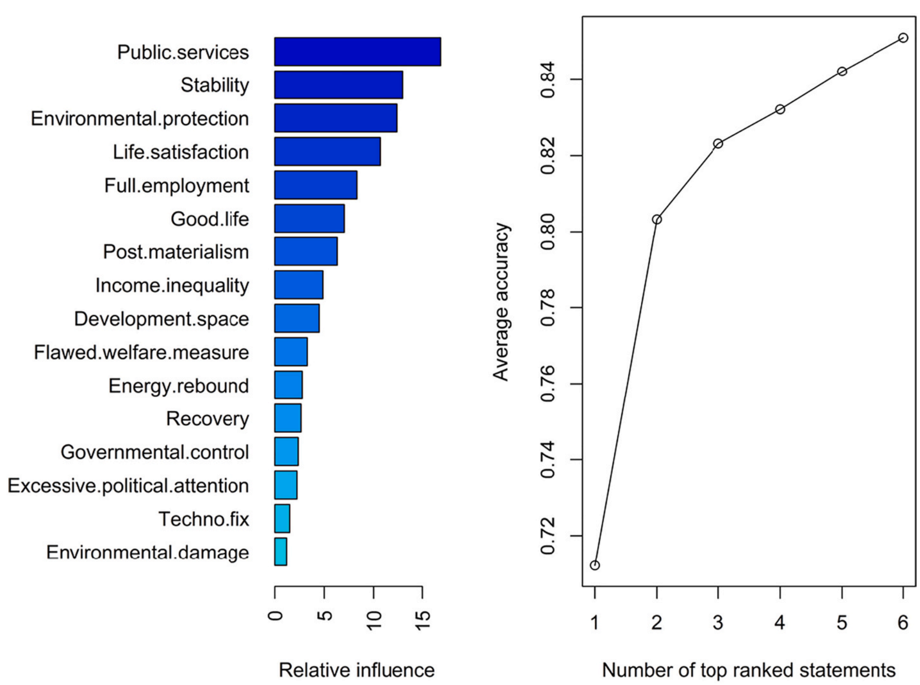

Fig. A1. Results from applying GBM on public survey keeping 101 respondents from the Indifferent cluster. The left panel shows the rank of 16 statements, while the right panel provides the average accuracy in predicting the true segmentation.
Note: Results for accuracy are averaged over 100 restarts with different starting seed.

As one can see from comparing Fig. A1 and Fig. 2, the top three statements with highest relative influence remain the same, while average accuracy of the survey module including those statements reaches 82.3%, which is above our threshold. Table A4 below further illustrates that accuracy of predicting each of the four clusters with the survey instrument remains high. This evidence supports the robustness of our results obtained earlier, namely that our proposed instrument has a good accuracy in classifying opinions on the growth-vs-environment debate.

Table A4
Accuracy, precision and recall of predictions (in %) based on survey among general pubic survey, keeping 101 respondents from the Indifferent cluster and using top three statements for each of the four opinion segments.

	Green growth	Agrowth	Degrowth	Indifferent
Accuracy	81.9 (0.6)	81.1 (0.3)	82.5 (0.4)	81.6 (0.7)
Precision	75.5 (1.2)	75.8 (0.6)	78.0 (0.6)	73.5 (1.5)
Recall	72.4 (1.1)	80.4 (0.6)	77.8 (0.8)	73.1 (1.5)

Note: Means with standard errors in parentheses.

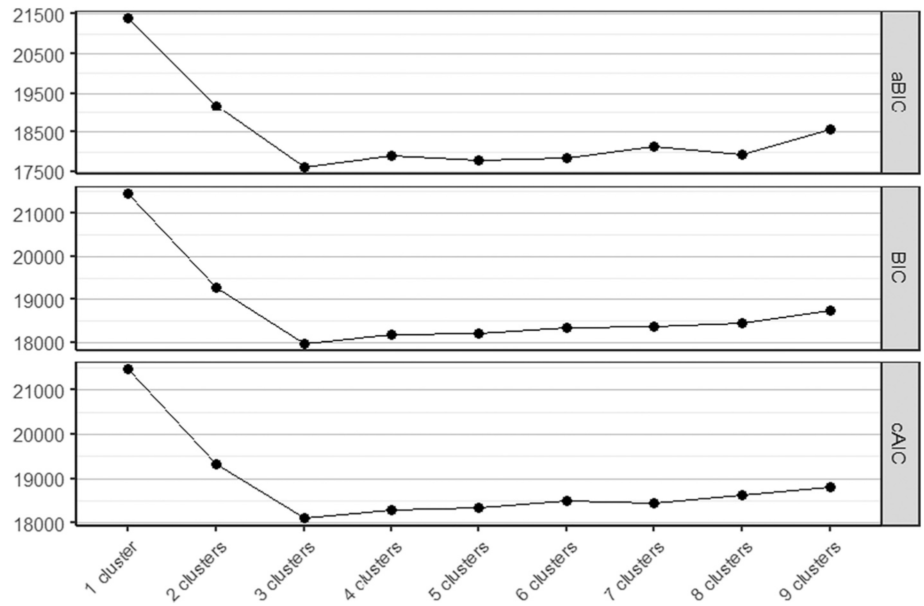

Fig. A2. Plot of information criteria for 1- to 9-cluster solutions for the public opinion survey in 2020.

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