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Is there a generational shift in preferences for forest carbon sequestration vs. preservation of agricultural landscapes?

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Abstract
Afforestation and reforestation are considered important measures for climate change mitigation. Because the land area available for tree planting may serve multiple purposes, striking the right balance between climate goals and other objectives is crucial. We conducted a survey of the Norwegian population to investigate potential land-use conflicts that may arise from executing a large-scale afforestation programme. Respondents were presented with three land-use alternatives to replace formerly grazed agricultural land. We used manipulated landscape photos to elicit their underlying value orientations. We combined multiple correspondence analysis with latent class regression models to reveal preference heterogeneity. Our models grouped respondents into three latent classes, with 24%, 24% and 52%, respectively, expressing a preference for forest carbon sequestration, recreation or agriculture as the most crucial land-use function to be retained. Birth year emerged as a strong predictor of class membership. Specifically, generations born before 1970 were more inclined to support the continuation of agricultural landscapes, while those born in 1980 and later showed a stronger inclination towards natural forest succession for carbon sequestration or recreational purposes. Quantitatively, every 10-year reduction in age increased the odds of a respondent belonging to the forestation or recreation class (relative to the agricultural class) by a factor of 2. Interestingly, even among respondents who were classified as most climate concerned, natural forests were 50% more likely to be preferred over monoculture spruce plantation as a policy option. This suggests that there may be public resistance to spruce planting for climate mitigation purposes in Norway.

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1 Introduction

Planting trees is one of the most cost-effective ways to remove CO_2 from the atmosphere (Domke et al. 2020; Bastin et al. 2019), in particular tree planting on abandoned agricultural lands (Chapman et al. 2020). IPCC (2019) has adopted afforestation and reforestation as land-based solutions for adaptation to and mitigation of climate change. The strategy has since been endorsed in a few countries (Durán and Barbosa 2019; Iversen et al. 2019).

However, tree planting is not a simple solution for mitigating climate change (Holl and Brancalion 2020). Land used for planting trees can serve multiple purposes other than as a carbon sink. These include being the basis for the development of value-creation sectors (e.g. food cultivation and commercial forestry), recreational and cultural values, as well as provision of life-support systems for humans and ecosystems (Chazdon and Brancalion 2019). When one sole ecosystem function or service is promoted, others may be undermined. For example, in boreal regions, maximising carbon sequestration would favour monoculture spruce plantations (Buongiorno et al. 2012), which may be aesthetically unappealing and give ecosystems of low biological quality. The grain-for-green planting programme in China, for example, has boosted carbon storage and sequestration by forests (Wang et al. 2018), but reduced farmland area by a quarter and caused rural household income to stagnate (Liang 2012). Striking the right balance between climate, environmental and socioeconomic objectives is vital for the success of afforestation programmes designed to mitigate climate change.

Compared to a biophysical assessment of feasible areas for forest plantations (and other land-based climate solutions), an assessment of their socioeconomic feasibility is much more fluid and dynamic. Several factors are at play. Heterogeneous and sometimes polarised preferences lead to resource use conflicts. The impact of a climate solution is constantly evolving or with a lag. A tree plantation affects multiple generations: the decision is made today by the current generations, while future generations and rural populations may feel the impacts more strongly. In the literature on attitudes to climate change and mitigation policies, studies have more typically focused on other socio-economic factors than age, political or value orientations or cross-country/geographical differences (Poortinga et al. 2012, 2019; McCright et al. 2016; Marquart-Pyatt et al. 2019; Weckroth and Ala-Mantila 2022). However, the evolving nature of public preferences, e.g. due to generational turnover or age differences, has not received much attention in the literature on forest carbon sequestration or climate mitigation policies more generally. In the related literature on acceptance and valuation of renewable energy deployment, there are, to our knowledge, no clear patterns regarding the effects of age or generational differences. For example, a critical review of 32 wind power preference studies using non-market valuation methods found no age effect (Mattmann et al. 2016). In the large, emerging literature on the acceptance of specific climate policies (typically instruments such as carbon taxes rather than land-based mitigation), age effects have not been thoroughly investigated (see for example reviews by Maestre-Andrés et al. 2019, Drews and Van den Bergh 2016).

Generational differences in general environmental concerns, rather than climate change attitudes or policy preferences per se, have more commonly been discussed in both theoretical and empirical studies. Inglehart's post-materialism postulated that public opinion in most advanced economies gradually shifts towards a greater emphasis on protecting the environment due to the improvement of societal prosperity (Inglehart 1981). This is similar to the Kuznets curve hypothesis in economics (Grossman and Krueger 1995). The concept of shifting baseline syndrome (Pauly 1995) in ecology supported the notion that an increasing emphasis on environmental values may be attributed to changes in underlying environmental conditions. The development can also go in the opposite direction. Studies show that individuals sharing similar socioeconomic characteristics and environmental conditions tend to have similar preferences, which were shaped earlier in their lives (Jensen and Olsen 2019) and remain relatively stable over time (Moors 2007). Skourtos et al. (2010) show that citizens' economic valuation of ecosystem services is stable in the short and medium term (less than 5 years) but not in the longer term (20 years). This could be called a cohort effect. There may also be a life-cycle effect. Individuals may adjust their emphasis on protecting the environment depending on their stage of life. Discounting theory suggests, for example, that individuals discount long-term benefits more if their residual lifespan is shorter (Read and Read 2004). Geys et al. (2021) found an inverted U-shaped life-cycle effect in a longitudinal survey of Norwegian citizens: the middle-aged respondents discounted the future environmental benefits less than both the younger and the older respondents (Sozou and Seymour 2003).

The purpose of this paper is two-fold: (i) to investigate the extent to which citizens in a high-income country are willing to accept large-scale landscape changes for climate change mitigation and (ii) to determine what manifest (including age and other observed variables) and latent factors drive their preferences. We conducted a national survey in Norway and asked respondents which of three landscape images (representing three land-use policies) they would choose and what motivated them to make that choice (see details in Table 2). Norway is an ideal country for conducting this research because an ambitious forest carbon sequestration programme on recently abandoned pastures has been piloted from 2015 in three counties (Iversen et al. 2019) and a more extensive roll-out is being considered. The pilot programme provided subsidy payments to private landowners to plant trees. However, the programme is controversial, emotions run deep, and views are divided (Grimsrud et al. 2020), so this study is a timely contribution.

Citizens' land-use preferences have previously been investigated in the Nordic countries and internationally, such as preferences for forest structure/landscapes or peri-urban agricultural landscapes (Gundersen and Frivold 2008; Ives and Kendal 2013). These studies were completed before the climate aspect became critical. Consequently, the carbon sink function of land was not emphasised with few recent exceptions (e.g. Iversen et al. 2019). Similarly, as noted above, land-use perspectives have rarely been considered in studies of citizens' preferences for climate policies (e.g. Braun et al. 2018, Maestre-Andrés et al. 2019). We contribute to the literature by evaluating climate perceptions in the context of land-use alternatives. One important finding from our study is that strong climate concerns do not necessarily translate into consensus on prioritising land use for climate change mitigation.

This study also makes a methodological contribution by combining multiple correspondence analysis (MCA) with a latent class regression (LCR) model. LCR refers to a latent class model with covariates (Goodman 1974). In LCR studies, choices of covariates often involve some degree of subjectivity. Here, we use MCA, an exploratory and descriptive statistical method, to identify key covariates. MCA does not assume any data relationship a priori; instead, it lets the data speak for themselves (Fithian and Josse 2017). MCA can deal with a larger set of categorical variables (Greenacre and Blasius 2006). Previously, these two methods have been used separately in analysing survey data, e.g. MCA in health (e.g.

Thiessen and Blasius 1998) and latent class models in the social and behavioural sciences (e.g. Moors 2007). Studies rarely combine the two methods. This mixed approach can handle large dimensionality challenge of survey data (this study has 30 categorical variables) and allows us to detect heterogeneous age effects in the preferences for the preservation of agricultural landscapes.

2 Theory and survey design

Our survey experiment proceeds in four steps: (a) field trips and photo manipulation, (b) development of a survey questionnaire, (c) focus group interview and (d) web-based data collection.

Photos to elicit latent preferences

Photo elicitation (PE) is known for being an effective and powerful tool to communicate with participants (Domke et al. 2020). This study uses PE also to infer respondents' latent value orientation, i.e. their attitudes towards different land-use functions and services. Literature has explored the potential of PE in tapping "tacit" knowledge. A careful use of photos can uncover and convey deep aspects of habitus, i.e. the shaping of people by their upbringing (Vassenden and Jonvik 2022). Harper (2002) argued that while respondents may be separated by their socio-economic characteristics, photographs can bridge different social worlds. Empirical studies have found that photos can elicit classed points of view from the interviewees (Pape et al. 2013; Koppman 2015). This neat categorisation would not have been possible without using predefined photos, in which respondents are exposed to the same standardised sets of images.

Visual stimuli can, however, sometimes introduce bias and provoke ethical concerns. We follow the code of ethics for visualisation (Sheppard 2001). Specifically, for the survey, a professional photographer took photos in Vestland county, Norway, in summer 2019. The selected photos showed intact coastal heathland suitable for grazing—a typical setting for abandoned pastures in coastal Norway. These photos were used as a canvas for further manipulation to show the landscape changes with natural reforestation (mixed forest) or with planted Norwegian spruce forest.

Indicators of value orientation

The theory of environmental concern postulates that citizen's value orientation affects their beliefs, altitudes and ultimately their behavioural intentions (Stern et al. 1995). In this study, respondents' value orientation was captured through their choice of preferred landscape photos and answers to questions regarding the land-use functions that concerned them the most. This gives a total of eight item response indicators (see Table 2). Land-use functions and services were listed in a drop-down menu. These included functions related to agricultural, cultural, biodiversity and aesthetic values as well as values of accessibility, fire risk, forestry and carbon sequestration. The choice of these indicators was guided by the literature on value orientation Schwartz (2012) and was further tested in a pilot survey conducted in 2018 (Liu et al. 2021).

The environmental psychology literature commonly groups environmental value orientation into biospheric, altruistic and egoistic (De Groot and Steg 2008); that is, each assesses the cost and benefits to the individual, others or the ecosystem as a whole. This distinction of value orientation is theoretically clear but lacks empirical support. For example, altruistic orientation is often correlated with egoistic value orientation. We take a different approach by treating value orientation as latent (not directly observable), and its classification (or grouping) is obtained via latent class regression (LCR, see Sect. 3), where the eight selected indicators are treated as item response indicators (Drasgow and Hulin 1990). The derived groups representing different value orientation are independent of each other.

Focus group interview

The pilot design of our survey questionnaire was tested on two focus groups with a total of 11 university students. The focus groups were held in August 2019 in Bergen—the largest city on the Norwegian west coast and in a region considered for climate forest planting.

The focus groups confirmed the mixed opinions regarding the use of formerly grazed land. Few participants were aware of the role of vegetation in climate mitigation. Participants who preferred pasture landscapes mentioned growing up near such landscapes, while such memories where not brought up by participants who preferred forests. Improved accessibility for recreation in pastureland was highlighted by several participants. Spruce forests were typically not considered a positive landscape feature, but could be considered to increase carbon sequestration. The negative impacts on biodiversity from spruce forests were mentioned by several participants. Sitka spruce, an invasive species introduced to Norway in the 1950 s (Øyen and Nygaard 2020), was mentioned by a few as very negative.

Some modifications were made to the survey questionnaire based on the feedback from the focus groups, before it was twice evaluated by an expert group from the survey panel administrators to improve clarity.

Survey questionnaire and data collection

The questionnaire (in Table 2) started by providing respondents with a management scenario where the government[1] faces three land-use policy choices (represented by three landscape photos) for managing abandoned pasture: (a) continue with traditional grazing; (b) plant Norwegian spruce; (c) do nothing and these areas will be reforested naturally. To achieve land-use options requiring management, government would have to provide subsidy payments to private landowners. Each policy alternative was represented by a manipulated photo (adding different landscapes on the same canvas) to indicate what the landscape would typically look like under different land-use scenario. Reference was made to the significant portion of Norwegian pastureland that is no longer in use, and respondents were asked to choose one preferred policy and the three most important factors affecting their choices from a drop-down list. Moreover, we collected a rich set of background variables describing respondent's socioeconomic characteristics (30 variables with a total of 90 categories; see a summary in Table 1).

The primary data for the study were collected using the Norwegian Citizen Panel,[2] an online, probability-sample infrastructure for studying public opinion in Norway. The names

[1] The high degree of trust in government in Norway (OECD 2022) and the relatively small differences between conservatives (government at the time of the survey) and social democrats (current government) in terms of climate and land-use policies make reference to government in the survey unlikely to influence results or be problematic in other ways.

[2] Norwegian Citizen Panel, https://www.uib.no/en/citizen

Table 1 Summary statistics of the survey data

Var	Name	Category	Freq	Share
1. Policy choices	Canvas.a	Pasture	819	82.2%
		Reforest	124	12.4%
		Spruce	53	5.3%
	Canvas.b	Pasture	771	77.4%
		Reforest	153	15.4%
		Spruce	72	7.2%
	Canvas.c	Pasture	694	69.7%
		Reforest	239	24%
		Spruce	63	6.3%
2. Motivations	Aesthetic	False	516	51.8%
		True	480	48.2%
	Accessibility	False	564	56.6%
		True	432	43.4%
	Forestry	Fals e	937	94.1%
		True	59	5.9%
	Grazing	False	417	41.9%
		True	579	58.1%
	Biodiversity	False	671	67.4%
		True	325	32.6%
	Culture	False	505	50.7%
		True	491	49.3%
	Carbon	False	889	89.3%
		True	107	10.7%
	Fire risk	False	980	98.4%
		True	16	1.6%
	Others	False	959	96.3%
		True	37	3.7%
3. Socio-demographic	Gender	Female	484	48.6%
		Male	512	51.4%
	Region	Nord-Norge	78	7.8%
		Oslo/Akershus	281	28.2%
		Sørlandet	39	3.9%
		Trøndelag	78	7.8%
		Vestlandet	293	29.4%
		Østlandet	227	22.8%
	Birth	<=1949	207	20.8%
		1950–1959	281	28.2%
		1960–1969	227	22.8%
		1970–1979	129	13%
		1980–1989	96	9.6%
		1990+	56	5.6%

Table 1 continued

Var	Name	Category	Freq	Share
	Education	< Elementary	64	6.4%
		Upper-secondary	281	28.2%
		University	625	62.8%
		Not answered	26	2.6%
3. Socio-demographic (con't)	Income	<150K	49	4.9%
		150–300K	128	12.9%
		300–400K	164	16.5%
		400–500K	190	19.1%
		500–600K	164	16.5%
		600–700K	118	11.8%
		700–1 M	122	12.2%
		>1 M	61	6.1%
	Party	Centre (SP)	176	17.7%
		Christian People's (KRF)	36	3.6%
		Conservative (H)	202	20.3%
		Green (MDG)	68	6.8%
		Labour (AP)	184	18.5%
		Liberal (V)	22	2.2%
		Progress (FRP)	61	6.1%
		Red (R)	56	5.6%
		Socialist Left (SV)	111	11.1%
		Other	80	8%
4. Upbringing	Reforested	False	737	74%
		True	259	26%
	Agriculture	False	500	50.2%
		True	496	49.8%
	Deciduous	False	652	65.5%
		True	344	34.5%
	None of these	False	782	78.5%
		True	214	21.5%
5. Profession	Grazing	False	893	89.7%
		True	103	10.3%
	Other agri	False	943	94.7%
		True	53	5.3%
	Tourism	False	962	96.6%
		True	34	3.4%
	Forestry	False	933	93.7%
		True	63	6.3%
	Research	False	972	97.6%
		True	24	2.4%
	Other	False	201	20.2%
		True	795	79.8%

Table 1 continued

Var	Name	Category	Freq	Share
6. Environ. concern	Climate	Not at all	22	2.2%
		Not very	129	13%
		Slightly	311	31.2%
		Very	335	33.6%
		Extremely	199	20%
	Env. member	False	762	76.5%
		True	234	23.5%

of potential participants were drawn at random from the Norwegian population registry, and they received a log-in code to the internet survey by post. Survey responses were collected on each respondent's computer, tablet or mobile phone. The data for the current study were taken from Wave 16 of the panel, which was collected in October–November 2019 (Ivarsflaten et al. 2019). The panel response rate was 73.2%. Nearly 1000 panel members were randomly selected for our landscape survey, and the item-nonresponse rate is less than 1% (Skjervheim et al. 2019). The descriptive statistics of the main variables are provided in Table 1. We compare the differences in the distribution of age and education between the samples and with population means and find that respondents over 60 years of age with higher education are over-represented in our sample (see page 15 in Ivarsflaten et al. 2019). We conducted a sensitivity test on the results to compare the impact of weighting the sample versus using the unweighted sample. The distribution of population for the variables used in weighting was obtained from the Norwegian National Registry.

3 Statistical methods

We assemble several quantitative models for the data analysis. A schematic diagram of our methodological approach is shown in Fig. 1.

Proportional odds model

Ordinal logistic regression (i.e. a proportional odds model) is used to study the relationship between citizens' concern about climate change and their birth cohort. The response has five ordered categories, ranging from "not at all concerned" to "extremely concerned" (Table 1). The lowest category ("not at all concerned") has only a 2.2% response rate, so we combined the two levels with lowest concern. The model is assumed to satisfy proportional odds. Following (Venables and Ripley 2022), a weighted ordinal logistic regression for a response Y with $k = 4$ levels has the following expression:

$$logit[P(Y \leq k)] = \alpha_k - \beta x, k = 1, ..., 4, \tag{1}$$

where P denotes the odds of the probability being rated equal to or lower than k. In our model, Y is concern about climate change and x is the birth cohort. α_k refers to the intercept corresponding to a rating level k.

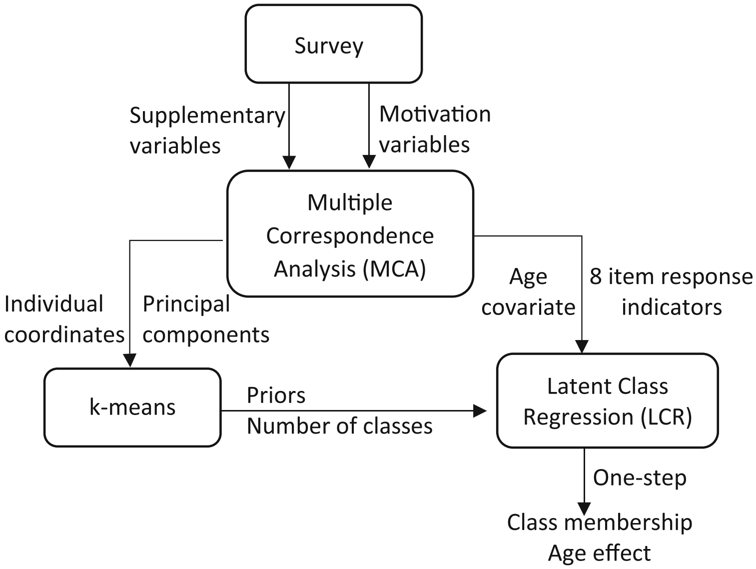


Fig. 1 A schematic diagram of the methodological approaches

The analysis was performed using the R package *MASS* (Venables and Ripley 2022). We include weights in the analysis to address sampling bias and adjust for the varying impact of each observation in the regression model. Four socio-demographic variables such as age, gender, geography and education are used to calculate the weights (available in Table 11 in Ivarsflaten et al. 2019).

Multiple correspondence analysis (MCA) and *k*-means clustering (KM)

We use MCA to explore complex data relationships and summarise them into a smaller set of latent variables or principal components (PC). Key variable relationships are uncovered by projecting variable coordinates in a PC-map. The responses in our survey (Table 1) are high-dimensional (30 variables and 90 attributes), categorical (including binary and Likert-scale ordinal variables) and have multiple potentially correlated variables. MCA is a dimension reduction technique like principal component analysis but designed for categorical data (Greenacre and Blasius 2006).

Specifically, we treat the land-use functions perceived as most important by each respondent (termed "motivation variables" in Table 1) as the active variables to form principal dimensions. We exclude two of the motivation variables that concerned fire risk and other land-use functions not listed due to their low frequency (2% and 4% of all choices, respectively). All socio-demographic variables and background information (a full list is given in Table 1) were treated as "supplementary variables," which do not contribute to the principal dimensions but aid the interpretations. Associations between variables are measured as the chi-squared distance, which informs dissimilarity between individuals (row) or between different categories of the variables (column) (Di Franco 2016); for instance, two respondents (i and j) who gave the same answers to all questions will be overlapped in an MCA graphical "map"; similarly, two column points close to each other means these points have similar effects.

The input to the *k*-means cluster (KM) analysis is based on the MCA (see Fig. 1), which assigns each respondent a coordinate for each principal dimension. KM utilises the information on the first two principal dimensions for initial classification, accomplished via the R package *cluster* (Maechler et al. 2021). The cluster analysis divides the respondents into three clusters using the Hartigan-Wong (1979) method. These results are then used to set the initial values (prior probabilities) for the classification performed by the latent class regression model.

Latent class regression model (LCR)

LCR refines class membership allocation and quantifies the age co-variate effect. An LCR is a probability-based finite mixture model (Goodman 1974). It outperforms *k*-means (KM) clustering by being more flexible (allowing cluster-specific error variances as compared to assuming equal variances) and yielding soft (probability) instead of hard (belonging to a class or not) class membership (Vermunt 2011). We introduce the KM clustering here to aid LCR analysis. The most common algorithm used to find maximum likelihood in an LCR is the expectation maximisation (EM), which is sensitive to initial conditions (Jain et al. 1999). The pre-classification results from the KM clustering set appropriate initial values (priors) for the LCR so that local optima can be avoided. This function is not part of *poLCA* (v 1.4) (Linzer and Lewis 2011), the R package that we used to perform the analysis.

We run LCR models with seven "motivation variables" and choices of preferred landscape photos as the dependent variables or item response indicators and birth cohort as the covariate. This model specification is built on the MCA analysis, which has indicated that photo choices and birth cohort are the two most important supplementary variables associated with the first two principal dimensions (see Table 3). The photo choices are endogenous; we hence treat the choices as an item response indicator; the birth cohort is used as an exogenous covariate of the LCR. Respondents' photo choices of the three canvases are highly correlated (see Fig. 3), and the final LCR model selects the responses to the last (third) canvas due to relatively higher variance in responses. In *poLCA*, the coefficients of the covariate are estimated simultaneously (one-step approach) as part of the latent class model to assign class membership (Linzer and Lewis 2011).

4 Results

Climate concerned citizens

More than 50% of the survey respondents indicated that they were very or extremely concerned about climate change, with a median respondent being "very concerned" (Fig. 2). The ordinal logit regression results show that the cohorts born before 1980 are statistically similar to each other (overlapping confidence internals in the figure), but have a significantly lower climate concern than the cohorts born in the 1980 s and 1990 s (hereafter 1980+). The odds of the 1980+ cohort being one level more climate concerned are higher than the reference group (born before 1960) by a factor of 1.8. In terms of predicted mean probability, the 1980+ cohort is 10% more likely than the reference group to be in the extremely concerned

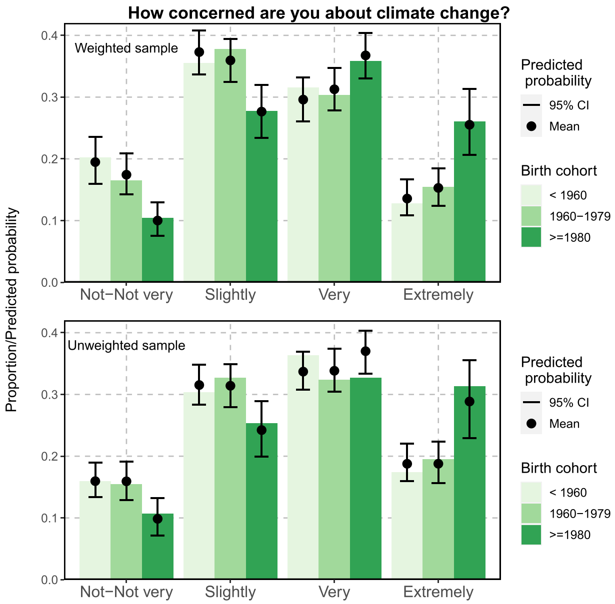


Fig. 2 Degree of climate concerns differentiated by birth cohorts. The color gradient displays the weighted proportion of respondents (upper panel) and the unweighted proportion (lower panel) based on the raw data. Mean probabilities and their 95% confidence intervals are predicted by the proportional odds model in Eq. 1

group, but 6% less likely to state that they are not at all or not very concerned about climate change (mean probabilities in the lower panel of Fig. 2). These findings are derived from the unweighted model, which aligns closely with the results obtained from the weighted model (depicted in the upper panel of Fig. 2).

Climate and biodiversity concerns form the first principal component

MCA identified the four most important principal components associated with the land-use function choices and landscape photo choices. Jointly, these four components account for 60% of the total variance, and the first two explain about 26% and 19%, respectively, of the variance (Fig. 3A). Based on the variable contributions (indicated by label sizes in Fig. 3A and R^2 values in Table 3), the first dimension primarily concerns carbon sequestration potential ($R^2 = 0.6$) and biodiversity ($R^2 = 0.4$), and the second-dimension links positively with landscape aesthetics ($R^2 = 0.6$) but negatively with cultural values ($R^2 = 0.3$). These results suggest that dimension 1 (labelled "low environmental concern $\longleftrightarrow$ high environmental concern" in Fig. 3) captures the degree of climate and biodiversity concerns of the respondents, and that dimension 2 (labelled "more aesthetics $\longleftrightarrow$ more grazing") reflects the trade-off between recreational values (i.e. landscape aesthetics and accessibility) and cultural values of an agricultural landscape.

Figure 3B sheds further light on the characteristics of respondents pertaining to the first two dimensions. The closer two variables are located on the factorial map, the more strongly they are correlated (Di Franco 2016). Two separate groups have emerged in the graphical representation of the data relationships in MCA: (a) individuals who are positively correlated with the climate dimension (dimension 1): born in year 1980 and after, with a relatively

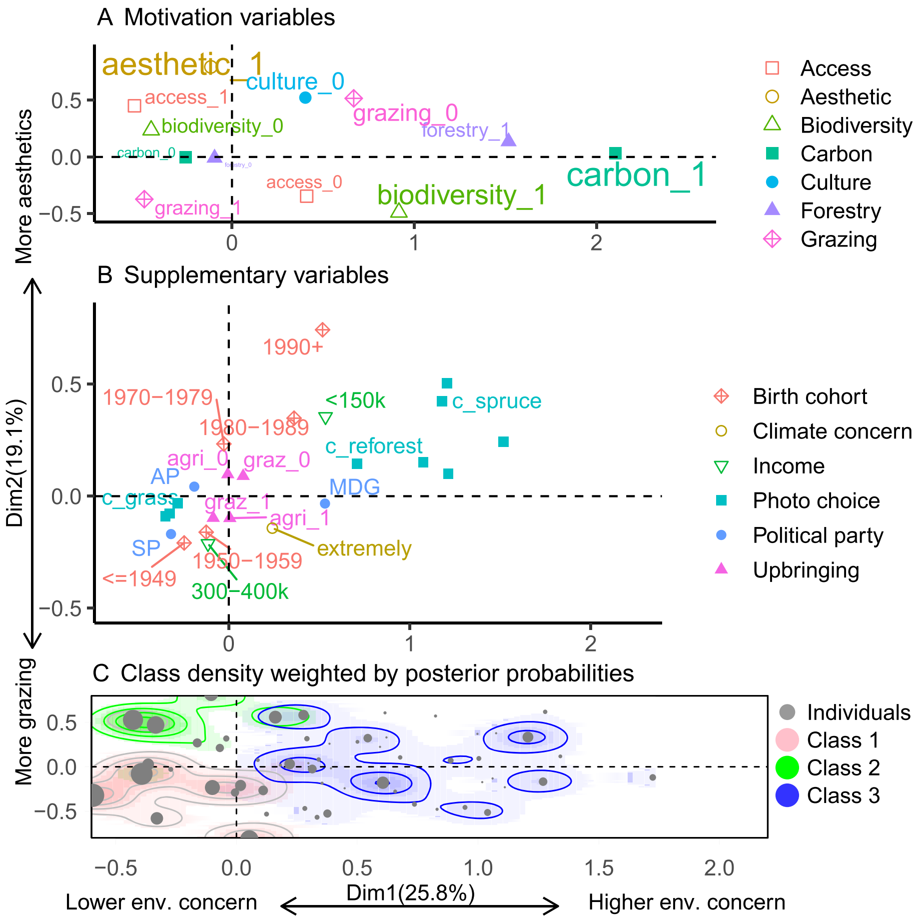


Fig. 3 MCA representations and class membership distribution in the factorial map formed by the first two principal components (Dim1 & 2) that jointly explain 45% variance of the data. **A** Variable contributions to the dimensions. The label size is proportional to the variable contribution, e.g. climate and biodiversity contribute the most to Dim1 and aesthetic to Dim2. **B** Association between supplementary variables (99% CI) and dimensions. The further the distance between two categories, the more dissimilar they are, e.g. a clear separation between age groups suggests a strong age effect. **C** Posterior probabilities weighted kernel density shows the distribution of respondents in the same factorial map. Overlapping individuals give similar responses, and overlapping contour lines indicate uncertainty in class assignment

low income, and a lack of agricultural experiences or experiences with grazing animals in their childhood, who intend to vote for the Green party (MDG) in the next election, and who supports either spruce plantation or natural succession as a policy alternative; (b) individuals who are less concerned about climate change but who attach great importance to cultural values of farmland (quadrant IV), who were born before 1960, are supporters of the Centre Party (SP), have experienced grazing animals in their upbringing, and want traditional grazing to continue. Figure 3B indicates that birth cohort and choice of landscape photos are two important variables for classifying respondents. This can be further confirmed from the correlation matrix in Table 3 in the Appendix.

Latent class membership and the age effect

LCR separated the respondents into three latent classes (Fig. 3C) according to their value orientation, measured by the eight selected item response indicators. Classes 1 to 3 account for 52%, 24% and 24%, respectively, of the respondents. The allocation is a refinement of the initial k-means (KM) clustering results. Figure 3C shows the probability density for each class in the factorial map. The density is weighted by posterior probabilities from the LCR.

Each of the identified classes has its own profile. Class 1 is characterised by a high probability of prioritising animal grazing and the cultural value of the land, class 2 prioritises landscape aesthetics and accessibility, and class 3 favours biodiversity and carbon sequestration potential. In terms of preferred landscape photos, Fig. 4A shows that both class 1 and 2 choose grassland predominantly with item response probabilities of 0.93 and 0.76, respectively. By contrast, natural succession of forest is the most likely option for class 3 (probability of 0.67). Based on their item response prevalence, we label these classes agriculture (class 1), recreation (class 2) and forestation (class 3).

The logistic regression model of the LCR (summarised in Table 4) shows that the probability of belonging to the agricultural class (class 1) is lower for the younger cohorts than for the older ones. In quantitative terms, every unit increase in cohort level (i.e. subtracting 10 years from age) will increase the odds of a respondent moving from cluster agriculture to cluster recreation by a factor of 2 (i.e. $e^{0.67}$) and from cluster agriculture to cluster forestation by a factor of 1.9 (i.e. $e^{0.65}$). This effect is illustrated visually in Fig. 4B. Notably, the cohort born in the 1970s appears to be a transitional cohort (Fig. 4B): those born before 1970 are more likely to be in class 1 and those born after 1979 class 2 or 3.

5 Discussion

Converting abandoned farmland into planted forest has been adopted as an important climate initiative by national governments. Land areas that are bio-physically feasible for plantation may not be perceived as suitable from a socio-economic perspective. This national survey from Norway shows that the revealed preferences for planting trees to reduce climate impact vs the preservation of agricultural landscapes change by age group. On average, Norwegian citizens are quite concerned about climate change, regardless of their age. However, they are divided with respect to the use of abandoned farmland for climate mitigation. Those born before 1970 tend to dislike the proposed forest carbon sequestration programme (i.e. spruce plantations), whereas younger people (born in the 1980 s or 1990 s) are more supportive. Interestingly, the respondents who were classified as most climate concerned prefer naturally reforested mixed forest to planting spruce as a land-use alternative to manage abandoned farmland.

Based on feedback from focus group interviews and findings from literature, we may consider several possible explanations for why respondents in different age groups favoured one ecosystem function over the other. Starting with the result that those who are younger favour land management for climate objectives more than those who are older do, several students in the focus group indicated their willingness to plant more spruce to increase carbon sequestration by accepting more negative impacts on the landscape. The environmental psychology literature asserts that individuals begin to shape their pro-environmental attitudes and behaviours in childhood and that these stabilise in adulthood (Kaiser et al. 2014). This implies that a generation, a group of individuals born in the same period with shared events

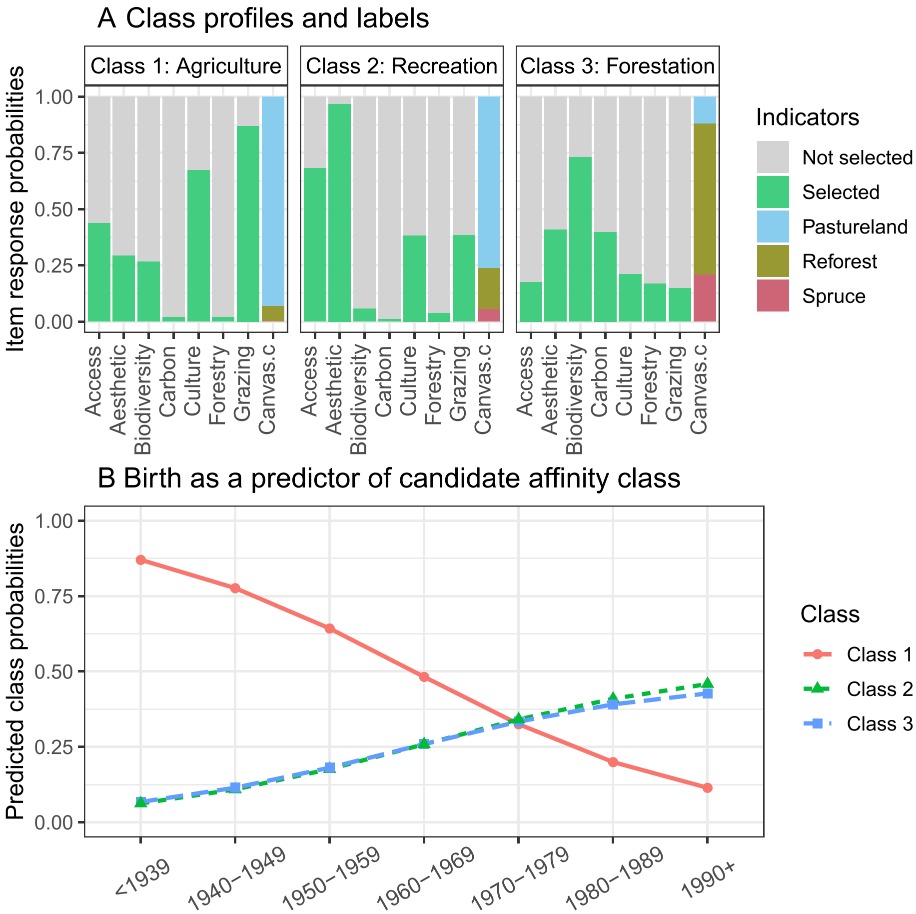


Fig. 4 **A** shows class profiles and labels (added by researchers). **B** shows the probability distribution of class membership by birth cohorts. The results are based on the model treating motivation and photo choice (i.e. the third canvas or canvas.c) variables as item response indicators and ordered birth cohort as a covariate (see Table 4)

and experiences (Mannheim 1970), tends to form a similar environmental valuation system (Parry and Urwin 2011). Anecdotal evidence[3] suggests that the generations born before 1960 in Norway have experienced many world events and threats (cold war, nuclear threats) during their growing up and life so far, and therefore, the climate crisis may be perceived as another of these threats and not as the only threat to mankind. By contrast, generations born after 1980 have probably learned more about the climate crisis at both global and national level while growing up, when they are most susceptible to influence. Another explanation from economics, as predicted by the theory of discounting (Read and Read 2004), may be that those who are older think that the detrimental effects of the climate crisis will not occur in their own lifetime. Long-term benefits are discounted more when one's remaining lifespan is shorter (Hersch and Viscusi 2006).

[3] Giertsen F (2022), "Tidsånden som formet generasjonene" (The zeitgeist that shaped the generations) (in Norwegian). Aftenposten Innsikt.

Why is the younger population less willing to preserve agricultural landscapes? The shifting baseline syndrome theory (Pauly 1995), proposed by ecologists, may offer some insight. The discrepancy lies in the shifting true environmental baseline experienced by different generations. For the pre-1960 generation from the Norwegian coastal regions, the "true" baseline means grassland maintained by traditional animal grazing (Liu et al. 2021). For generations born after 1980 s, who were often raised in the city and to a larger extent have lost touch with how agriculture is practised, the baseline may be different and more heterogeneous (Swanwick 2009). This phenomenon may be attributed to a lack of inter-generational communication and transfer of traditions, diminishing of experience (e.g. rural experience) and amnesia (Papworth et al. 2009).

In this survey, we investigated public climate attitudes through the lens of land-use practices. Large national and international surveys of people's climate attitudes have rarely investigated age effects, and results are often mixed or inconsistent (Poortinga et al. 2019; Marquart-Pyatt et al. 2019). According to a recent study by Weckroth et al. (2022), most findings to date suggest that men, older people and less educated people are more sceptical and less concerned about climate change. However, other recent studies document opposite or mixed results regarding the effect of age (Ballew et al. 2020) and indicate that the effect may vary across countries. Tranter and Booth (2015), for example, find that age is an inconsistent predictor, with older citizens more environmentally concerned in Austria, Canada and Denmark, but younger people more concerned in France, Germany and Spain.

A lack of consistent evidence on age, age cohort or generational effects in climate surveys may in part be due to age being a "confounder" (i.e. a variable that influences both the dependent variable and independent variables). First, the age cohort effect we observed here is a combination of time or period effect and life-cycle effect (different life stage) (Geys et al. 2021). As noted, these two effects may offset each other. Furthermore, the resulting overall age effect might be country specific. A solution is to use panel data or longitudinal data (Geys et al. 2021). However, most of the surveys of climate and environmental preferences or attitudes to date have been cross-sectional. Second, age is often correlated with other socio-demographic variables, including income, political party preference and education. This was also the case in our data. The mixed method applied here allows us to circumvent the issue: MCA singles out birth cohort as the important supplementary variable, and KM and LCR stratify respondents into three classes, making age effects class specific and more profound. Moors (2007) made a similar remark on environmental concerns, that is, the cohort effect is more profound in the "authoritarian" latent class than the class labelled "economic materialist".

Our online survey was distributed to a large non-commercial population panel with a panel response rate of 73% (Ivarsflaten et al. 2019), but it still suffers from a sample representativeness problem (Schouten et al. 2009). Compared to the actual population, our sample underrepresents the subset of respondents born after 1990 by approximately 15% and overrepresents those born before 1960 by approximately 20% (see page 15 in Ivarsflaten et al. 2019). Since sample weighting by observable characteristics may introduce biases of its own (Dutz et al. 2021), we decided not to use this in our main analysis. Our MCA results suggest that education is not an important factor (Table 3). Unequal representation of age groups does not bias age-group specific estimates, but it affects the precision of these estimates. Minor differences in the results obtained from the weighted and unweighted models are evident in Fig. 2. Because the age signal is so clear in both MCA (see Fig. 3B) and LCR analysis, somewhat reduced precision in relatively less sampled age groups is not affecting our conclusions regarding the age effect. However, the distribution of class membership may change with sample, e.g. the proportion of citizens who would support the forest carbon sequestration programme in Norway may differ if we were to extrapolate the results to the entire population.

Other considerations to mention are the following: First, LCA assumes local independence, that is, manifest variables are independent of each other within latent classes. This assumption is often difficult to satisfy. One solution is to increase the number of classes Vermunt (2011), but this may lead to the problem of artificial classes (Vassenden and Jonvik 2022). Researchers thus need to strike a balance between the number of classes and interpretability of these classes. Secondly, the photos used for our survey were selected and manipulated by researchers. Sheppard (2001) warned of the structuring influence of manipulated photos. To avoid this, researchers must make sure that data generated using these images provide a truthful and ethical reflection of the research subject.

6 Concluding remarks

The generational differences in views on how abandoned farmland should be managed have broad policy implications. Age structure and composition may have a considerable impact on designing acceptable environmental and climate policies for the future (Geys et al. 2021). For example, some climate policies and measures considered today may affect geographical areas or socioeconomic groups where the generational shift may be an important source of conflict and resistance. It may be that, as the younger generation grows older gradually replacing the older generation of today, such conflicts may be reduced over time.

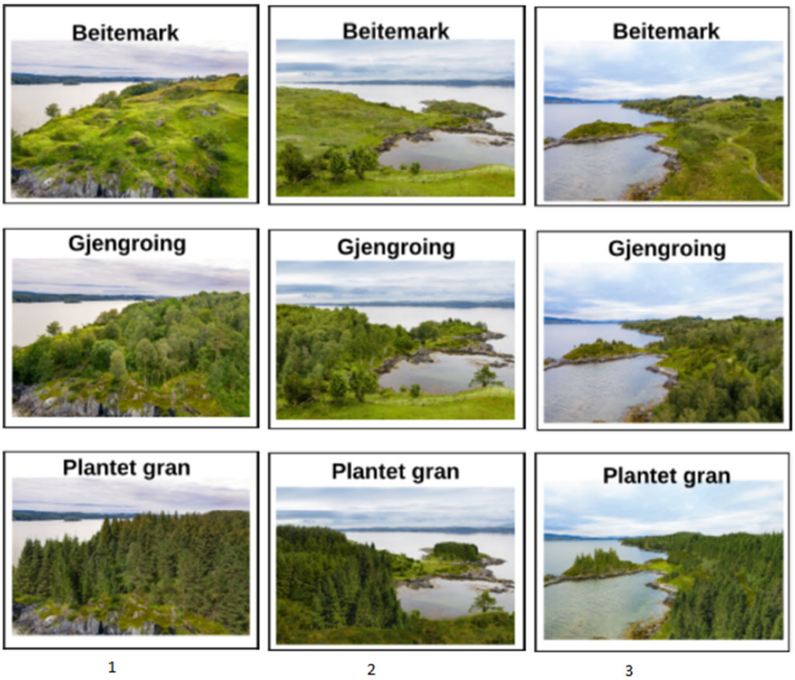
However, the finding that the “do nothing” policy—letting the abandoned farmland areas be reforested naturally (mixed forest) and no further intervention required—is more popular than planting spruce even for the group most concerned about climate change, is another source of conflict with afforestation as a climate measure. Several studies document the negative impacts of monocultural plantations on biodiversity (e.g. Felton et al. 2016). Moreover, planting spruce involves clearing of the existing vegetation cover and disturbing northern peatlands, which have sequestered a vast amount of carbon from the atmosphere (Maljanen et al. 2010). Some scientists thus cast doubt on the net carbon effect of monocultural plantations and instead advocate regeneration of natural forests to store carbon (Lewis et al. 2019). However, the “do nothing” option does not produce economic spillover effects and may hence not be politically appealing. Future work needs to focus on these specific conflicts and trade-offs between economic, biodiversity and climate goals.

In conclusion, planting trees as a climate change mitigating measure needs to balance multiple competing demands for land use. Our results inform the ongoing discussions on the forest carbon sequestration programme in Norway. Globally, the gap between high-level climate commitments and the implementation challenges on the ground remains large (Chazdon and Brancalion 2019). By providing a practical case study in Norway, we offer a useful taxonomy to identify potential land-use conflicts arising from enforcing land-based climate solutions.

Appendix

Table 2 Main survey questions (translated from Norwegian)

No.	Questions
A considerable part of Norwegian pasture is no longer in use. Imagine that the government can choose from three different options for these areas:	
1	Continue with traditional grazing, keeping the landscape open
2	Plant Norwegian spruce, which involves dense planting of spruce trees (about two trees per $10\,m^2$)
3	Do nothing, which means the areas will be reforested naturally
r16km-skog2: The image montages below show how the same landscape will typically look when it is grazed (beitemark), when it becomes reforested on its own accord (gjengroing) or when it is planted with spruce forests (plantet gran).	
We will now display three sets with three landscape images in each set.	
Which landscape image do you like best?	
(This is screen 1 of 3.) You will get the opportunity to write comments after set no. 3	



r16km-skog3: What was important for you when you chose the landscape you liked the most?

(Select up to 3 options)

Table 2 continued

No.	Questions
1	How nice the landscape looked
2	Accessibility in the landscape
3	That the landscape is used for forestry
4	That the landscape is used for grazing
5	Natural biodiversity
6	Culture landscape
7	Absorption of greenhouse gases in vegetation
8	Risk of forest fire
9	Other factors (please indicate)
10	Do not know

Table 3 Dimension description based on correlations between variables and principal dimensions

Dimension 1 Categories	Estimate	Variables	R^2	**Dimension 2** Categories	Estimate	Variables	R^2
	Motivation variables				*Motivation variables*		
carbon_1	0.598	Carbon	0.53	aesthetic_1	0.335	Aesthetic	0.59
carbon_0	−0.598	Carbon	0.53	aesthetic_0	−0.335	Aesthetic	0.59
biodiversity_1	0.345	Biodiversity	0.41	culture_1	−0.232	Culture	0.28
biodiversity_0	−0.345	Biodiversity	0.41	culture_0	0.232	Culture	0.28
grazing_0	0.292	Grazing	0.32	grazing_1	−0.194	Grazing	0.19
grazing_1	−0.292	Grazing	0.32	grazing_0	0.194	Grazing	0.19
access_1	−0.24	Access	0.22	access_1	0.174	Access	0.16
access_0	0.24	Access	0.22	access_0	−0.174	Access	0.16
culture_1	−0.207	Culture	0.17	biodiversity_0	0.158	Biodiversity	0.12
culture_0	0.207	Culture	0.17	biodiversity_1	−0.158	Biodiversity	0.12
forestry_1	0.409	Forestry	0.14		*Supplementary variables*		
forestry_0	−0.409	Forestry	0.14	1980–1989	0.088	Birth cohort	0.07
aesthetic_1	−0.057	Aesthetic	0.01	1990+	0.26	Birth cohort	0.07
aesthetic_0	0.057	Aesthetic	0.01	<=1949	−0.155	Birth cohort	0.07
	Supplementary variables			1970–1979	0.038	Birth cohort	0.07
a_spruce	0.356	Canvas.a	0.37	1950–1959	−0.134	Birth cohort	0.07
a_reforest	0.201	Canvas.a	0.37	b_reforest	−0.018	Canvas.b	0.03
a_pasture	−0.557	Canvas.a	0.37	b_pasture	−0.118	Canvas.b	0.03
b_reforest	0.215	Canvas.b	0.36	b_spruce	0.136	Canvas.b	0.03
b_pasture	−0.496	Canvas.b	0.36	300-400k	−0.116	Income	0.02
b_spruce	0.281	Canvas.b	0.36	<150k	0.132	Income	0.02

Table 3 continued

Dimension 1				Dimension 2			
Categories	Estimate	Variables	R^2	Categories	Estimate	Variables	R^2
c_reforest	0.1	Canvas.c	0.29	c_pasture	−0.108	Canvas.c	0.02
c_spruce	0.338	Canvas.c	0.29	c_spruce	0.115	Canvas.c	0.02
c_pasture	−0.438	Canvas.c	0.29	c_reforest	−0.006	Canvas.c	0.02
AP	−0.139	Party	0.05	grazi_0	0.041	Upbring grazing	0.01
SP	−0.204	Party	0.05	grazi_1	−0.041	Upbring grazing	0.01
MDG	0.227	Party	0.05	agric_1	−0.043	Upbring agriculture	0.01
<=1949	−0.175	Birth cohort	0.05	agric_0	0.043	Upbring agriculture	0.01
1990+	0.213	Birth cohort	0.05	extremely	−0.066	Climate concern	0.01
1980–1989	0.133	Birth cohort	0.05	no-not_very	0.073	Climate concern	0.01
1950–1959	−0.114	Birth cohort	0.05				
<150k	0.24	Income	0.03				
extremely	0.114	Climate concern	0.02				
slightly	−0.069	Climate concern	0.02				
rural	−0.054	Residence	0.01				
grazi_0	0.042	Upbring grazing	0.01				
grazi_1	−0.042	Upbring grazing	0.01				
decid_1	0.043	Upbring deciduous	0.01				
decid_0	−0.043	Upbring deciduous	0.01				

The results are based on ANOVA analysis of individual coordinates and a categorical variable with the contrast sum equal to 0. All variables listed in Table 1 were included in the analysis, only statistically significant (95%) categories are kept in the table

Table 4 Parameter estimates from latent class regression model

N=996	Class 2 (recreation)			Class 3 (forestation)		
Variables	Coeff	S.E	Pr(> $\|t\|$)	Coeff	S.E	Pr(> $\|t\|$)
(Intercept)[a]	−3.30***	0.41	0.00	−3.20***	0.31	0.00
Birth cohort[b]	0.67***	0.09	0.00	0.65***	0.08	0.00
Membership allocations:						
Class 1 (52%): Class 2 (24%): Class 3 (24%)						

Notes:
The results are interpreted relative to the "Class 1 (Agriculture)"
b: Ordered birth cohorts (old→young) are treated as a numeric variable
Significance codes: *** p<0.001, ** p<0.01, * p<0.05

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Declarations

Conflict of interest The authors declare no competing interests.

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