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BEATLES
BEHAVIOURAL CHANGE TOWARDS
Climate-Smart Agriculture

CO-CREATING BEHAVIOURAL CHANGE TOWARDS CLIMATE-SMART FOOD SYSTEMS

D4.1 Portfolio of fair value propositions v1

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Executive Summary

Climate-smart agriculture is a key focus of European policies to address sustainability and global warming challenges facing agriculture. However, these policies have struggled to effectively promote sustainable behaviours due to a lack of consideration for individual differences among farmers and consumers. This deliverable provides a segmentation analysis of European farmers and consumers aiming to profile farmers and consumers based on their unique characteristics and needs and help tailor policies and interventions. Market segmentation analysis identifies homogenous segments with similar characteristics that enable targeted policymaking. The study highlights common and specific lock-in factors among farmers and consumers, emphasizing the importance of collective action, fair distribution of value across the value chain and trust between agri-food value chain actors. By understanding and addressing these factors, policymakers can foster transformative change towards sustainability. The findings from the segmentation studies provide insights and will be further used, at later stages of the BEATLES project, for developing tailored fair value propositions and promoting sustainable behaviours in agriculture and food consumption.

This deliverable is conducted by independent researchers engaged in Task 4.1 within Work Package 4 and contributes to THE BEATLES project outcomes.

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List of Terms and Definitions

Abbreviation	Definition
CSA	Climate smart agriculture
CSA-CB	CSA cautious expectation farmers
CSA-NU	CSA non-users
CSA-SB	CSA high expectation farmers
CSA-U	CSA users
NSB	Non - sustainable buyers
PSB	Price - sensitive buyers
SB	Sustainable buyers
s.e.	Standard error

Table 1: Terms and Definitions

1. Why farmer and consumer market segmentation: conceptual argumentation

1.1 Segmentation analysis

In the 2nd half of the 20th century agriculture heavily based on business models in which food prices were expected to be kept low due to high production efficiency of intensive food production. Nowadays, the agriculture is in an urgent need to transfer from such production efficiency to climate smart systems, where not only the food security is at stake, but also the nature and guarantee for sustainable future.

Climate- smart agriculture, therefore, has become a major topic for European policies. The effectiveness of the policies to foster sustainable behaviour and to solve global warming issues has been challenging so far. Sustainable farming behaviour in terms of innovating in nature-inclusive, circular, and climate-smart practices and technologies, as well as sustainable consumption choices by consumers need to change drastically to meet climate goals. One of the arguments why policies have limited impact on behavioural change is that the European policies refer to large groups of populations neglecting differences in small groups of farmers and consumers (Poortinga and Darnton 2016).

However, every farm has its unique geo location, demographical characteristics, farm production systems, as well as psychological, behavioural, and business motives, in which education, household conditions, personal values vary. Similar counts for consumers. Every consumer as an individual with its own motives and behavioural triggers for certain choices. To target individual challenges is a mission impossible for the policies. Therefore, a segmentation of farmers and consumers with similar needs and characteristics can help adjust policies to target individual groups effectively. Segmentation analysis, in general, is to identify market segments with homogenous characteristics and needs, based on demographic, behavioural and psychographic factors (Wedel and Kamakura 2000).

Understanding market segments of farmers is important for targeted policy making, such as for providing tools and mechanisms for the transition to CSA that resonates with norms, values, perceptions, and motivations. Consumer segmentation seeks to understand the extent to which the climate concerns are considered when making food choices. Consumer segments can be used to target the policies and communications to similar consumer groups, and to motivate them make more sustainable choices in food consumption. Individual actors are more likely to be responsive to innovations if these are relevant to their potentially differing requirements. However, if the number of actors increases, which is always the case if consumers and farmers are involved, targeting everyone with a tailor-made policy campaign is far too costly. In such a case, a segmentation of these actors based upon their individual scores may benefit policy design and implementation. A segmentation helps to understand homogenous target groups better, but also enables policy makers to shift away from a one-size fits-all policy approach.

Moreover, farmer and consumer segments clarify the end user markets for sustainable products that can be used to design tailored fair value propositions per segment. Whenever value propositions are perceived fair within the segments, the resistance to change can be reduced and commitment to change towards climate-smart food systems can be fostered. Market segmentation for sustainable, climate-smart products and fair value propositions per segment are part of the business model innovation process. Once market segments for sustainable products

are identified, business modelling and fair value creation will provide roadmaps to transformative change towards sustainable, climate-smart food systems.

Within segments, the high and low extremes regarding the scores on, for example, perceived costs, benefits, and social norms may not only suggest the potential bottlenecks and opportunities of the transition campaign, but also the dos and don'ts of targeting strategies (Kornelis et al. 2010). Between segments, the group differences and similarities are also highly informative. The differences benefit differentiation strategies, whereas the similarities provide guidelines for assembly decisions. A well-known strategy, incorporating assembly and differentiation decisions, is to develop the same innovation strategy for multiple segments, and to position it differently in each of these segments. For an illustrative application, see Kornelis et al. (2010).

Additional relevant research questions, in the context of segmentation are: Are there segments of consumers and segments of farmers that match with each other in terms of goals and motives? Does information about the specific needs and motives of consumer segments stimulate segments of farmers to change their farm policies? Does information about the needs and motives of farmer and consumer segments benefit the actionability of the other actors in the food chain to adopt innovations of sustainability?

In this study, market segmentation identifies market segments with homogenous characteristics about behaviour towards climate-smart practices and products to enable the design of effective business models and policies that match the target groups' needs, rather than a one-size fits all approach. This study has two goal of segmentation analysis:

1. farmers' segments for policy design and implementation
2. consumer segments for sustainable, climate-smart products.

The market segments will be used to develop fair value propositions and fair business models.

2. Farmer Segmentation Analysis

2.1 Methodology

2.1.1 Data collection

This section is based on farmer survey administered in six European countries: Denmark, Germany, The Netherlands, Lithuania, Spain, Slovenia. The survey was designed online using Qualtrics software tools. The survey collected responses between 1 January and 30 March 2023. The survey was translated into six local languages and presented respondents in a way that they could choose the preferred language for response. The translation was crucial to ensure a higher number of responses, as we wanted to include opinion of people that are not fluent in English.

Survey questions have been constructed based on the preliminary literature review focusing on individual, systemic, policy related decision-making factors. The survey contained 96 multiple-choice questions of seven-point Likert scale, and two open questions (Annex A). The questions in the survey were compulsory. However, if a respondent decided to discontinue filling out the survey before completing it, the remaining questions would be left unanswered. The use case leaders have received the weblink to the online survey. Survey has been distributed by the BEATLES use case partners throughout their own network and connections in the country. Additionally, use case leaders have promoted the survey during the various events where farmers have been present. In total, the data collection took place between 20 December 2022 and 14 March 2023.

2.1.2 Respondents

A total of 630 European farmers was considered in the segmentation study. To ensure that potential heterogeneity among farmers from different European countries was captured by the segmentation model, data were collected in various European countries with a focus on Denmark (107 farmers), Germany (20), Lithuania (262), The Netherlands (75), Slovenia (59), and Spain (101). Besides these countries, responses from farmers from Belgium, Greece, and Italy were also obtained (5). In one case, the farmer's residence was unknown. Although the dataset contains observations from distinct EU regions, the country profile is uneven, with more than one-third of the farmers living in Lithuania. We account for this facet in the empirical analysis (Section 2.2).

2.1.3 Measures

In our empirical analysis we distinguish between core variables, and two types of background variables: (1) covariates and (2) further-profiling variables.

Core variables are used to discriminate groups of respondents, who differ in lock-ins and leverages regarding the intentional use of CSA practices and technologies. We considered 24 core variables in Farmers' survey (Table 2). All variables, factors and measures as constructs used in this study are presented in Annex A. The core variable segmentation base includes one factor that indicates the farmers' intention to use CSA, and five different types of incentive factors that explain the differences in intentions and preferences across the segments. Doing so, we distinguish personal, product-related, economic factors, social factors, and systemic factors. All these factors are measured as constructs (see also Annex A).

Covariates are background variables that are actively used to identify the number of segments. An illustrative example of a potentially valuable covariate is the country of residence. For example, if it is the case that respondents in a specific country have more knowledge about climate-smart initiatives than respondents in another country, then the variable country of residence may help to discriminate between segments that differ in level of knowledge. In this example, the level of knowledge is the core variable as this variable helps to identify segments of interest, and the country of residence is a covariate, because it may help to better discriminate among the segments of interest.

In addition, further-profiling variables refer to descriptive characteristics that do not enhance the model's performance beyond the inclusion of classifying covariates. So, their inclusion in the model has no influence on the model parameter estimates that discriminate among the segments. However, after the segments have been identified (based upon the core variables and the influence of the covariates), the further-profiling variables are useful to obtain a more insightful picture of the distinct segments. The set of background variables consists of general observable variables, such as income or farm size (Table 2).

Core variables		Background variables	
Core variable	**Measure**	**Covariates**	**Profiling variables**
Intention	Stated intention	Residence Economic motives Non- economic motives Income Age	Participation in cooperative Production type Ownership status Education Gender Household size Farming size Farming experience Information source usage • *Social media* • *Family friends* • *Mass media* • *Other farmers* • *Farmer associations* • *Training courses* • *Events* • *Advisors* Extension and advisory services usage • *Farmer training* • *Farm visits* • *Field demos* • *Farmer days* • *Workshops* • *Advisory services*
Incentives	Personal • *CSA knowledge* • *Certainty preference* • *Investment risk avoidance* • *Financial risk avoidance* • *Behavioural control* • *Self-responsibility* Production related factors • *Perceived usefulness* • *Ease of use* • *Compatibility* • *CSA experience* Social • *Market willingness* • *Descriptive norm* • *Injunctive norm* • *Contribution condition* • *Perceived contribution others* • *Perceived honesty* Institutional • *Policies, regulations* • *Certification* • *Access to credit* Economic • *Financial situation* • *Economic situation* • *Access to market*		

Table 2: Variables in the farmer segmentation model

2.1.4 Methodological framework

The methodological framework consisted of two main steps:

(i) reliability analyses and
(ii) mixture model analysis.

First, we performed reliability analyses to assess the adequacy of the measurement of the constructs under consideration. Most of the considered constructs were built based upon existing literature and measured by three or more items. For these items we used Cronbach-α values to establish their reliability. In several cases, the constructs were measured-by two items (e.g., descriptive norms and injunctive norms). In addition to Cronbach α, we also calculated, the correlation coefficient to inspect their reliability. In instances involving business-practice motives, such as economic and non-economic motives, where a definitive rationale for the number of underlying constructs was not available a priori, we conducted a principal components analysis to investigate the inherent structure.

Second, we applied a finite-mixture model approach to uncover farmer segments. Conceptually, we identified farmer segments based on the mentioned core variables, hereby accounting for the possibility that segment membership may depend on the set of covariates. In the farmer segmentation study, we established the optimal number of segments using a mixture model that initially included all core variables of Table 2, and country of residence as a covariate. To determine the optimal number of segments, we employed seven alternative models ranging from one to seven segments. Models exceeding seven segments were not considered, as the resulting number of parameters would yield an excessive ratio relative to the total number of observations.

Third, we compared the seven alternative models based on a number of criteria. First, the overall fit of the models was established by means of the Consistent Akaike Information Criterion (CAIC) and the entropy R^2 value (Cleaver and Wedel 2001; Kornelis et al. 2010). The CAIC serves the purpose of identifying the optimal balance between model fit and parsimony. This was particularly valuable given that the number of segments directly influences their respective sizes: as the number of segments increases (decreases), their sizes tend to decrease (increase). Additionally, the entropy R^2 value assesses the dispersion of assignment probabilities among individuals across the segments. This aspect was noteworthy as a higher likelihood of an individual belonging exclusively to a specific segment indicates greater distinctiveness among the identified segments.

Fourth, we thoroughly examined the segment profiles of each model, employing Wald tests to assess the discriminative capacity of the core variables and covariates across the seven models. In case where some variables did not demonstrate significant contribution, we excluded them as segment indicators and utilized them instead as background variables to enhance the characterization of the segments. In addition, we evaluated whether there was empirical justification to incorporate any of the background variables as supplementary core variables or covariates in the model selection procedure. Based on these findings, the models were re-estimated accordingly.

Subsequently, we employed expert opinion to assess the extent to which alternative models yielded divergent conclusions regarding the adoption of climate-smart initiatives among individual segments, which constitutes the focal point of this study. In cases where these empirical findings exhibited robustness across the alternative models, we prioritized the more parsimonious alternatives (i.e., number of parameters), considering the size of the dataset. Consequently, if the empirical findings did not differ substantially, we favoured a smaller number of larger groups over a larger number of smaller groups, aiming to maintain a balance between model complexity and interpretability.

Finally, we employed a triangulation approach by integrating statistical tests with expert opinion to determine the optimal model. This strategy was employed to strike a balance between the empirical analysis of real-life data and the practical relevance for managerial decision-making.

2.2 Empirical analysis

2.2.1 Reliability analysis

All constructs in the dataset were found to be reliable with all Cronbach α's >0.7, except for risk tolerance. The item-scores related to risk tolerance, therefore, entered the models as single-item variables. The two-item constructs were also found to be reliable with all correlation coefficients >0.6. In the case of business-practice motives, a principal components analysis was performed. We found two distinct constructs economic farming motives and non-economic farming motives.

Economic farming motives are measured by "It is important to me that running my farm business has low production costs, produces the highest quality products, has a low labour need, results in high yields, results in a high income, is good for the employment in my rural area". Non-economic variables are measured by "It is important to me that running my farm business produces in an environmentally friendly way, produces with care for animal welfare, produces fairly priced products, produces with care for public health, maintains the tradition of my family" (see Table 8). A complete list of the item questions, constructs, and reliability measures are given in Annex A.

2.2.2 Identifying the segments

Our finite-mixture model analysis commenced with a comprehensive model incorporating all variables from the segmentation base (Table 3), while also incorporating country of residence as a covariate to address its uneven distribution among farmers. We varied the number of segments from one to seven. Notably, all alternative models demonstrated excellent model fit as evidenced by the entropy R^2 values, all of which exceeded 0.86. Furthermore, the seven-segment model yielded the lowest CAIC value.

Afterward, we examined the segment profiles for each alternative model and utilized the empirical findings to identify potential covariates. Based on these results, we identified additional potential covariates, such as cooperative membership, income level, economic farming motive, non-economic farming motive, production type, gender, age, and residence. After re-running the seven models by using fifty starting values for each model estimation, the Wald tests indicated that residence, income, economic farming motive, and non-economic farming motive were significant covariates in all alternative models, age was a significant covariate in the models with three to seven segments, and production type and cooperative were significant covariates in the six and seven segment models. We found a minimum CAIC value for the four-segment model (45315) with an entropy R^2 of 0.91 as extremely high.

In the next step, we examined the three-, four-, and five-segment model by excluding non-significant covariates, aiming to explore if these three alternative models lead to distinct conclusions regarding the inclination of farmer segments towards the use of climate-smart initiatives. In the three-segment model, the Wald tests indicated that the core variable performance of others does not discriminate between the three segments. This outcome differed from the four-, and five-segment solutions, where all core variables were significantly able to distinguish between the segments. The entropy R^2 of these new alternative models with excluded covariates were 0.90, 0.90, and 0.91, respectively, and the CAIC-values were 45248, 45143, and 45156, respectively.

Based on these results, we selected the four-segment model as our empirical model of primary interest. This decision was motivated by several factors: the model exhibited the lowest CAIC value among the three-, four-, and five-segment alternatives, demonstrated an excellent entropy R^2, and represented the most parsimonious model where all core variables played a discriminating role in differentiating farmer segments.

In summary, our analysis revealed the presence of four distinct farmer segments characterized by varying scores for lock-ins related to the adoption of climate-smart practices and technologies. Furthermore, segment membership showed associations with country of residence, economic and non-economic farming motives, income, and age. The next sub-sections present the results of the segmentation analysis in details.

2.2.3 Segment size

The segments identified in our study are all substantial in size, with descending sizes as follows: 34%, 28%, 24%, and 13%. To explore the distinct profiles of these segments, we examine segments through potential lock-ins, specific to each segment. Initially, we explore potential variations among segments regarding farmer perceptions of production-related factors associated with CSA initiatives and their intentions to use them, employing these distinctions to assign appropriate segment labels. Subsequently, we investigate the (dis)similarities among the segments in relation to the remaining factors outlined in Table 2.

2.2.4 Profiling the four segments

We characterize every segment based on the score patterns for the core variables, and its background profile (Annex A). A graphical illustration of the mean scores of the core constructs are given in Figure 1. Although we have concluded that these characterizing variables do not improve model performance above and beyond the classifying covariates, they are still useful to obtain a more insightful picture of the distinct segments.

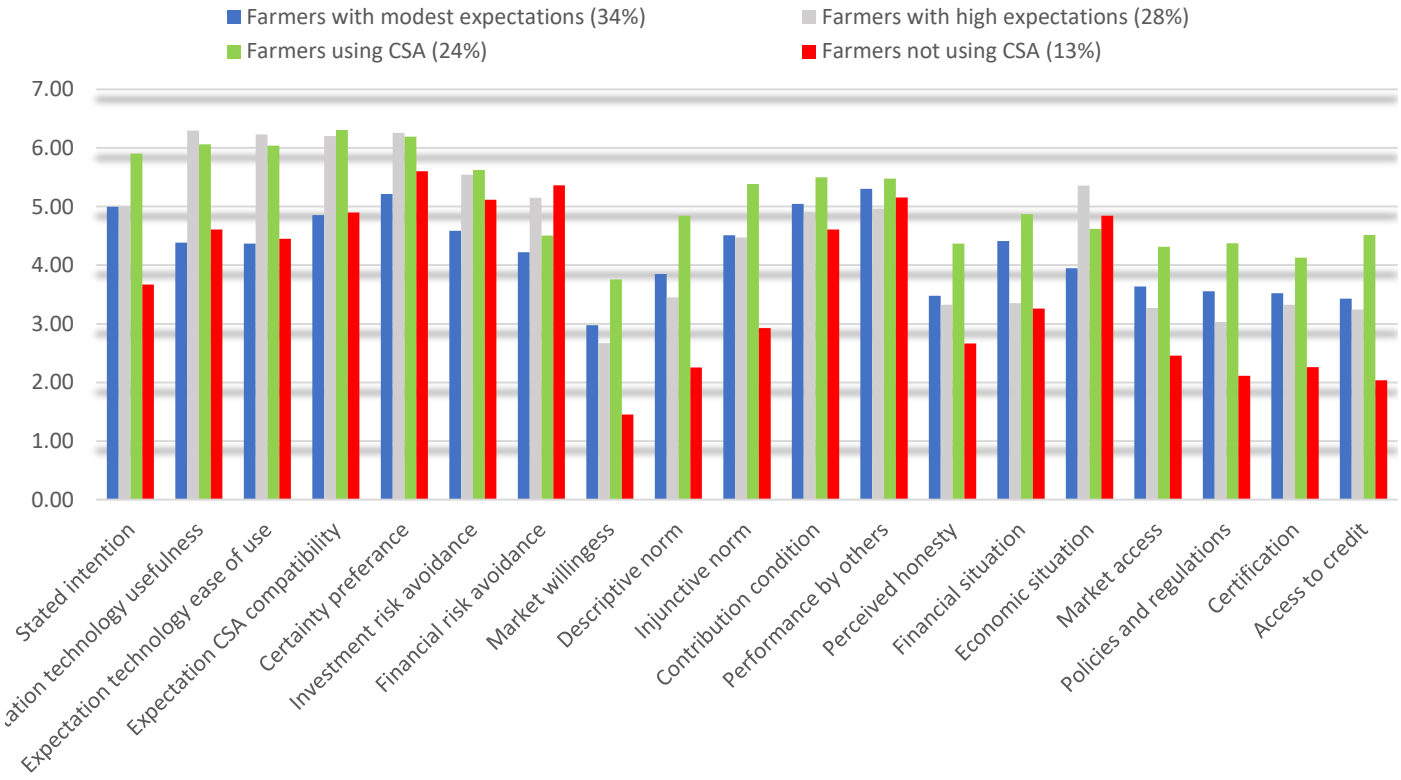

Figure 1: Core variable scores in the scale of [1:7] by segment

One of the four farmer segments shows a high intention to use climate-smart initiatives in the near future as compared to the other groups (segment size is 24%, and the mean score is 5.91 on a seven-point scale), and one group shows a low intention to use climate-smart initiatives in the near future (size is 13% and mean rating is 3.67). The other two groups give a medium score (5.00 for both segments) as compared to the other two segments (Table 2).

All groups expect that climate-smart initiatives will be useful for their farming business, will be easy to use, and that it fits in their regular job activities, as all these scores are above the midpoint of the scale (Table 3). However, two out of the four segments show high ratings on these factors (ranging from 6.04 to 6.31), whereas the other two segments give, as comparison to the other segments, medium ratings (ranging from 4.37 to 4.90).

Regarding CSA knowledge, over 50% of its members within every segment are familiar with the concept of climate-smart initiatives, ranging from 56% to 86%. Among these segments, one has a majority of members who have practical experience with climate-smart initiatives (68%), whereas the remaining three segments have only a minority with such experience, ranging from 29% to 46%.

Based on the segment characteristics with respect to the expectations, belief, intention and use of climate-smart agricultural practices and technologies we refer to the four segments as described in Table 3:

- ➔ Segment 1: Farmers with modest expectations (34%). This segment has Low Experience, Medium Expectations, Medium Intention to use CSA.
- ➔ Segment 2: Farmers with high expectations (28%). This segment has Low Experience, High Expectations, Medium Intention,
- ➔ Segment 3: Farmers using CSA (24%). This segment has Medium Experience, High Expectations, High Intention,
- ➔ Segment 4: Farmers not using CSA (13%). This segment has Low Experience, Medium Expectations, Low Intention. Below, we further characterize the (dis)similarities among the segments by means of the other variables.

	Segment 1	*s.e.*	Segment 2	*s.e.*	Segment 3	*s.e.*	Segment 4	*s.e.*
	Farmers with modest expectations		Farmers with high expectations		Farmers using CSA		Farmers not using CSA	
Segment Size	34%	*.02*	28%	*.02*	24%	*.02*	13%	*.01*
Stated intention	5.00	*.08*	5.00	*.09*	5.91	*.09*	3.67	*.20*
Expectation technology usefulness	4.39	*.09*	6.30	*.06*	6.06	*.08*	4.61	*.24*
Expectation technology ease of use	4.37	*.08*	6.23	*.06*	6.04	*.07*	4.45	*.23*
Expectation CSA compatibility	4.85	*.09*	6.20	*.06*	6.31	*.06*	4.90	*.21*
CSA knowledge [a]	65 %	*.03*	86 %	*.03*	84%	*.03*	56%	*.06*
CSA experience [a]	46 %	*.04*	45%	*.04*	68%	*.04*	29%	*.05*

[a] The given figures are within segment **percentages**, because this is not a construct but a nominal variable.
s.e. – standard error
The constructs are measured with a seven-point scale with 'certainly disagree' and 'certainly agree' at the, respectively, left, and right extremes.

Table 3: Mean scores of CSA intention and expectation, and within segment percentages of CSA knowledge and experience

2.2.5 Personal factors

Table 4 gives the mean scores on statements related to personal factors. All segments think that they have a responsibility to contribute to a more sustainable food system, and they all prefer certainty over uncertainty, and try to avoid (financial) risks. Out of the four segments, only farmers with a low experience, medium expectation of and a low intention to use climate-smart initiatives (13%) indicate that they do not have the ability to use climate-smart initiatives (perceived behavioural control, mean score of 3.55 on a seven-point scale).

	Segment 1	s.e.	Segment 2	s.e.	Segment 3	s.e.	Segment 4	s.e.
	Farmers with modest expectations		Farmers with high expectations		Farmers using CSA		Farmers not using CSA	
Segment size	34%	*.02*	28%	*.02*	24%	*.02*	13%	*.01*
Certainty preference	5.22	*.09*	6.26	*.06*	6.19	*.07*	5.60	*.18*
Risk avoidance	4.59	*.10*	5.55	*.09*	5.62	*.09*	5.12	*.20*
Financial risk avoidance	4.22	*.11*	5.15	*.14*	4.51	*.16*	5.36	*.19*
Behavioural control	4.62	*.07*	4.64	*.09*	5.67	*.08*	3.55	*.17*
Self-responsibility	5.33	*.07*	6.04	*.05*	6.12	*.06*	5.21	*.15*

s.e. – standard error
The constructs are measured with a seven-point scale with 'certainly disagree' and 'certainly agree' at the, respectively, left, and right extremes.

Table 4: Mean scores on personal factors

2.2.6 Social factors

Table 5 presents the outcomes of the social-factors scores. All segments fear that consumers and business partners are unwilling to pay a fair price for foods that are produced with the help of climate-smart agricultural initiatives (market willingness) with mean scores ranging from 1.45 to 3.76. Out of the four segments, only farmers with medium experience, high expectation and high intention scores see other farmers using climate-smart initiatives (descriptive norm, 4.84), and believe that other actors in the food-supply chain are honest about their pro-sustainability contributions (perceived honesty, 4.37). Only farmers that belong to the Segment 4, non-CSA farmers, think that others would not approve the use of climate-smart initiatives in their farming business practice (injunctive norm, 2.93). In addition, all segments think that they do more for a sustainable environment than the other food-system actors, including consumers (performance by others), and state that they are only willing to contribute to a more sustainable environment if the other actors make a fair share (contribution condition).

	Segment 1	s.e.	Segment 2	s.e.	Segment 3	s.e.	Segment 4	s.e.
	Farmers with modest expectations		Farmers with high expectations		Farmers using CSA		Farmers not using CSA	
Segment size	34%	*.02*	28%	*.02*	24%	*.02*	13%	*.01*
Market willingness	2.98	*.09*	2.67	*.10*	3.76	*.13*	1.45	*.07*
Descriptive norm	3.85	*.08*	3.45	*.11*	4.84	*.10*	2.26	*.13*
Injunctive norm	4.51	*.07*	4.47	*.10*	5.38	*.08*	2.93	*.17*
Contribution condition	5.05	*.10*	4.90	*.12*	5.50	*.11*	4.61	*.22*
Performance by others	5.30	*.08*	4.96	*.11*	5.48	*.10*	5.16	*.21*
Perceived honesty	3.48	*.07*	3.33	*.07*	4.37	*.10*	2.66	*.13*

s.e. – standard error
The constructs are measured with a seven-point scale with 'certainly disagree' and 'certainly agree' at the, respectively, left, and right extremes.

Table 5: Mean scores on social factors

2.2.7 Economic factors

Mean scores on the economic factors are given in Table 6. Two segments, namely farmers with high expectations (Segment 2) and farmers not using CSA (Segment 4), highlight their challenging financial circumstances. Conversely, farmers belonging to the other two segments (Segment 1 and Segment 3) indicate that they are in a favourable financial position. All segments show neutral to positive perception of the current economic situation ranging from 3.95 to 5.36, which are not significantly different from the midpoint of the seven-point scale. Finally, among the identified segments, only Segment 3 consisting of farmers using CSA report experiencing ease in accessing the market for input purchasing and output sales. In contrast, the remaining three segments face challenges in this aspect.

	Segment 1	s.e.	Segment 2	s.e.	Segment 3	s.e.	Segment 4	s.e.
	Farmers with modest expectations		Farmers with high expectations		Farmers using CSA		Farmers not using CSA	
Segment Size	34%	*0.02*	28%	*0.02*	24%	*0.02*	13%	*0.01*
Financial situation	4.41	*0.09*	3.35	*0.12*	4.87	*0.12*	3.26	*0.18*
Economic situation	3.95	*0.10*	5.36	*0.12*	4.62	*0.14*	4.85	*0.24*
Market access	3.63	*0.07*	3.27	*0.10*	4.31	*0.11*	2.46	*0.13*

s.e. – standard error
The constructs are measured with a seven-point scale with 'certainly disagree' and 'certainly agree' at the, respectively, left, and right extremes.

Table 6: Mean scores on economic factors

2.2.8 Institutional factors

Table 7 provides the scores on institutional factors. The scores on these factors are univocal. As Table 7 shows, Segment 3 is the only segment that surpasses the midpoint of the seven-point scale, indicating their positive perception towards existing policies, regulations, and governmental support (policies regulations). They also find it easy to obtain certification for climate-smart agriculture initiatives (certification) and have no difficulties accessing credit (access to credit). This contrasts with the scores of the other three segments (Segment 1, 2, 4), where farmers show significantly lower scores compared to the other segments (ranging from 2.03 to 2.26).

	Segment 1	*s.e.*	Segment 2	*s.e.*	Segment 3	*s.e.*	Segment 4	*s.e.*
	Farmers with modest expectations		Farmers with high expectations		Farmers using CSA		Farmers not using CSA	
Segment Size	34%	*.02*	28%	*.02*	24%	*.02*	13%	*.01*
Policies regulations	3.55	*.09*	3.03	*.13*	4.37	*.14*	2.11	*.15*
Certification	3.52	*.07*	3.33	*.09*	4.13	*.11*	2.26	*.12*
Access to credit	3.43	*.09*	3.24	*.12*	4.52	*.12*	2.03	*.13*

s.e. – standard error
The constructs are measured with a seven-point scale with 'certainly disagree' and 'certainly agree' at the, respectively, left, and right extremes.

Table 7: Mean scores on institutional factors

2.2.9 Further profiling

We further characterize each of the segments by looking at the distribution of the farmers over the segments for the background variables in the study. Indeed, if the percentage of farmers that show particular scoring patterns are over- or underrepresented (with respect to segment size) in one of the segments, this may help to further profile the segments. Here, we discuss several key characteristics of the segments. A complete table of all background variables is given in Annex A.

In Table 8, we give the distribution of the total sample across segments. The Segment 1, farmers with modest expectations (34% of the sample) has an over-representation of Danish, German, and Dutch farmers. Remarkably, 54% of the Danish, 69% of the German, and 90% of the Dutch farmers in the sample belong to this segment. The Segment 2, farmers with high expectations, (28%) has an over-representation of Lithuanian farmers. About sixty percent (58%) of the Lithuanian farmers in the sample, belongs to Segment 2. In contrast, Segment 3, Farmers using CSA (24%) has an over-representation of Danish farmers, i.e., 44% of the Danish farmers in the sample belong to this segment. The Segment 4, farmers not using CSA (13% of the sample) shows an over-representation of Spanish (26%) and Slovenian farmers (30%).

Farmers who show the highest importance ratings on economic farming motives, which include low costs and high yields, are over-represented in the Segment 2, Segment 3, and Segment 4 (respectively, 38%, 34%, and 17%). Segment 2 and Segment 3 also show over-representation of farmers who have the highest importance ratings on non-economic farming motives, which includes contributions to a more sustainable food system (respectively, 36% and 38%).

Segment 1, farmers with modest expectations, shows an over-representation of farmers below 30 years of age (below 20 accounts for 29% and from 20 to 29 accounts for 56% of the sample

distribution), whereas the Segment 2 reveals an over-representation of farmers who are older than 60 years of age (47%).

Among the farmers in the sample earning less than 10,000 Euros annually, 60% are affiliated with Segment 2, classified as CSA high expectation farmers. Conversely, segment 3, consisting of CSA users, demonstrates an overrepresentation of higher income groups.

Segment 1, farmers with modest expectations, has an over-representation of farmers that work for a cooperative (48% of the sample), whereas Segment 2, farmers with high expectations, has an over-representation of farmers who do not work for a cooperative (36%). Additionally, Segment 1, farmers with modest expectations, exhibits an overrepresentation of arable crops and livestock farmers, constituting 41% and 38% respectively. Whereas, Segment 4, farmers not using CSA, is overrepresented by orchards (29%) and vineyards (46%).

Finally, all segments were found to be accessible through both traditional and modern media channels.

	Segment 1	Segment 2	Segment 3	Segment 4	Total
	Farmers with modest expectations	Farmers with high expectations	Farmers using CSA	Farmers not using CSA	
Segment size	34%	28%	24%	13%	
Residence					
DK	54	1	44	1	100
DE	69	0	8	23	100
NL	90	0	4	6	100
LT	6	58	24	12	100
ES	33	16	25	26	100
SI	37	14	20	30	100
Residence Unknown	100	0	0	0	100
Other Residence	80	20	0	0	100
Economic farming motive					
low to moderate important (1 - 4.8)	67	06	08	19	100
moderate important (5 - 5.5)	40	23	23	13	100
important (5.67 - 5.83)	22	41	29	09	100
highly important (6 - 6.17)	28	37	26	09	100
very highly important (6.33 – 7)	11	38	34	17	100
Non-economic farming motive					
low to moderate important (1 - 5.2)	50	14	11	21	100
moderate important (5.4 - 5.6)	40	25	15	16	100
important (5.8 – 6)	31	39	23	08	100
highly important (6.2 - 6.4)	36	22	33	09	100
very highly important (6.6 – 7)	11	36	38	15	100
Age					
<20	49	0	44	7	100
20-29	56	10	27	8	100
30-39	33	28	21	18	100
40-49	34	31	23	12	100
50-59	33	27	23	17	100
>60	20	47	21	11	100
Income					
No income	24	36	13	27	100
EUR 10.000 or less	14	61	13	13	100
EUR 10.001 to EUR 25.000	20	41	20	20	100
EUR 25.001 to EUR 50.000	46	20	22	12	100
EUR 50.001 to EUR 75.000	48	15	27	11	100
EUR 75.001 to EUR 100.000	34	20	36	11	100
EUR 100.001 or more	22	32	32	13	100
I really don't know	60	8	19	13	100
I'd rather not say	38	24	26	12	100
Cooperative					
yes, I do	48	17	20	15	100
no, I don't	25	36	26	12	100
Production type					
Arable crops	41	23	24	13	100
Open field vegetables	30	30	23	17	100
Orchards	10	28	33	29	100
Vineyards	32	14	9	46	100
Livestock	39	25	26	10	100
Mixed farming	25	41	23	11	100

Table 8: Distribution (%) of the total sample across farmer segments

2.3 Discussion

Our study reveals a clear segmentation structure consisting of four segments of farmers with distinct profiles that combine expectations about the usefulness of climate-smart agricultural initiatives and the intention to use these initiatives in the near future. The finding that three out of four segments show a low experience with climate-smart agricultural initiatives and a low to medium intention to use them in the near future indicates a potential lock-in, because past and current experience is an important driver of future actions (Tey and Brindal 2012).

These three segments together (Segment 1: CSA cautious expectation farmers, Segment 2 CSA high expectation farmers and Segment 4 Non-CSA farmers) account for 76% of the sample population. The possible relevance of experience is also reflected in the finding that the only segment with a small majority of experienced farmers is also the segment with the highest scores (24%) in intention to use CSA practices and technologies in the future. Hence, our conclusion suggests that approximately three-quarters of the farmers in the sample face a potential lock-in due to a lack of experience. One possible strategy to address this barrier could be the implementation of low-cost try-out opportunities, enabling farmers to gain practical experiences.

Table 4 reveals that the absence of behavioural control, serving as a personal lock-in factor, is prominent among farmers who are not currently using CSA initiatives and have no intention to do so (Segment 4: farmers not using CSA, comprising 13% of the sample). In this context, it is crucial to ascertain the underlying factors contributing to farmers' inability due to constraints, such as time, resources, or due to the luck of willingness. Understanding these determinants is important for developing the most suitable strategy to overcome the barrier for this segment of farmers.

There are several potential lock-ins that can be found in the social environment of farmers. First, all segments believe that their business partners and consumers are not willing to pay a fair price for foods, which are produced with the help of climate-smart initiatives (100%). Second, all segments believe that they do more for a sustainable environment, than the other actors in the food chain, including consumers (100%). Third, all segments indicate that they are only willing to contribute to a higher sustainability standard if the other actor also make a fair share (100%). Fourth, three of the four farmer segments have a low level of trust in the honesty of the other actors in the food-supply chain regarding their pro-sustainable activities (76% of the sample). All these barriers are related to the challenge of collective action (White et al. 2019). More sustainable behaviours often require collective action, which implies that a large group of individuals must undertake pro-environmental behaviours for the benefits to be fully realized. If farmers are not aware of this interplay, or do not trust the commitment of other actors, it may hamper their willingness to deliver their share in the collective action. A possible lever may be to involve a trusted authority (i.e., an NGO or an EU public authority) in the collective action that monitors the behaviour changes of the food-chain actors. In addition, we found more lock-ins in the social environment of farmers. Three out of the four segments (76% of the population sample) indicate that they do not see other farmers, who are similar to them, using climate-smart initiatives. A remedy for this lock-in may be to inform these segments about the use and experience of other farmers regarding climate-smart initiatives. In one of the four segments (13% of the population), farmers state that people who are important to them, will not approve a shift towards the use of climate-smart initiatives. Such an injunctive norm can be powerful, and it is challenging to find interventions that can effectively change them.

Two economic lock-ins were identified in the empirical analysis. Two segments (41% of the sample) report to have challenges with their financial resources, and three segments (76% of the sample) state that they have difficulties to access the market in order to buy inputs and sell outputs. Trying to make market access more convenient for these groups of farmers may be a lever for this economic lock-in.

Among the four segments, only one (comprising 24% of the sample) does not face institutional lock-ins. This segment are the CSA users or expressed intention to use CSA in a near future. In contrast, the remaining three segments, together representing 76% of the sample, express challenges in obtaining essential certifications, accessing credit facilities, and receiving adequate government support.

In the empirical analysis, we have successfully demonstrated that the identified segments possess key attributes of being identifiable, accessible, and significant in size. Additional factors contributing to the effectiveness of segmentation include stability, responsiveness, and actionability. The stability of the segments relies on the persistence of their defining characteristics, primarily represented by potential lock-ins hindering the adoption of climate-smart initiatives. As discussed above, these lock-ins are not easily overcome, indicating that the identified segments are likely stable enough to support the implementation and evaluation of intervention strategies aimed at addressing one or more lock-ins. Therefore, the found segments are probably stable enough for the implementation and evaluation of an intervention strategy that aims to tackle one or more lock-ins. The performance of the segmentation in terms of responsiveness and actionability will vary depending on the specific objectives of policymakers or other stakeholders. In summary, our findings highlight the presence of multiple lock-ins that may hinder farmers' adoption of climate-smart initiatives.

3. Consumer segmentation analysis

3.1 Data collection

This study is based on consumer survey in eight European countries: Denmark, Germany, The Netherlands, Lithuania, Spain, Slovenia, Greece, and Italy. The survey was designed online using Qualtrics software tools. The survey collected responses between 1 January and 30 March 2023. The survey was translated into six local languages and presented respondents in a way that they could choose the preferred language for response. The translation was crucial to ensure a higher number of responses, as we wanted to include opinion of people that are not fluent in English.

The survey questions were developed following a preliminary literature review that emphasized individual, systemic, and policy-related factors influencing decision-making. The consumer survey comprised 105 multiple-choice questions utilizing a 7-point Likert scale, along with 5 open-ended questions (Annex B). Respondents had the option to choose which questions to answer. Distribution of the survey was facilitated through the BEATLES use case partners, who shared the survey with their network and connections within the respective use case country. The survey was distributed through websites, social media posts, e-mails, mainly by Beatles use-case partners and project partners.

3.2 Respondents

A total of 1218 European consumers was considered in the segmentation study. Data was collected using an online questionnaire. To ensure that potential heterogeneity among consumers from different European countries was captured by the segmentation model, data were collected in various European countries with a focus on Denmark (109 consumers), Germany (107), Lithuania (157), The Netherlands (123), Slovenia (587), Spain (81), Greece (17), and Italy (15). Besides these countries, responses from consumers living in France, Portugal, Sweden, Belgium, Finland, Slovakia, Austria, Hungary, Switzerland, and Poland were also obtained (20). In two cases, the consumers' residence is unknown. Although the dataset contains observations from distinct EU

regions, the country profile is uneven, with 48% of the respondents living in Slovenia. We account for this facet in the empirical analysis.

3.3 Measures

In our empirical analysis we distinguish between core variables, and two types of background variables: covariates, and further-profiling variables.

Core variables were used to distinguish between groups of respondents exhibiting variations in lock-ins and levers regarding to the intentional purchase of CSA-produced foods. Annex B presents a comprehensive overview of all variables used in the consumer study. The selection of core variables was guided by the following rationale. We included *stated willingness to pay a premium* for CSA-produced food products and the *stated preference* for CSA-produced food as key components of the segmentation basis. These variables offer insights into potential barriers experienced by specific respondent groups, aligning with the central focus of our study. Willingness to pay a premium is operationalized as a construct, while stated preference for potatoes is measured using four single-item variables.

Respondents were presented with four choice scenarios involving CSA-produced and non-CSA-produced potatoes: (1) the CSA-produced potato had the same price as the alternative (i.e. the non-CSA-produced potato); (2) the CSA-produced potato had a higher price than the alternative; (3) the CSA-potato had the baseline price, but the alternative was on discount; (4) the CSA-potato had a lower price due to a subsidy.

These variables aim to capture empirical knowledge regarding the trade-off between a collective sustainability goal and personal costs. Potatoes were chosen as an empirical object due to their widespread consumption across EU countries. Additionally, we examined various types of incentive factors to explain the disparities in willingness and preferences across the segments. In doing so, we distinguish personal, product-related, economic system, social system, and institutional system factors. All these factors are measured as constructs (Annex B).

Covariates are background variables used in the identification of segment numbers. An illustrative example of a potentially valuable covariate is the country of residence. This consideration is due to fact that certain EU countries are over- or under-represented within the sample dataset.

Meanwhile, further-profiling variables refer to descriptive characteristics that do not enhance the model's performance beyond the inclusion of classifying covariates. However, they are useful to obtain a more insightful picture of the distinct segments. The set of background variables consists of general observable variables, such as income, and domain-specific latent variables, such as food-choice motives.

The complete set of variables that was used in the consumer segmentation study is summarized in Table 9.

Core variables	Measures	Covariates	Further profiling variables
Intention / preference	Willingness to pay premium Preference ➔ CSA higher price ➔ Regular discount ➔ Equal price ➔ CSA subsidy	Residence Motive cheap Habit formation	Information interest Gender Age Education Employment Nr. household persons Nr. Household children Agglomeration Income Motive sustainable Motive health Motive no additives Motive appearance Motive nutritious Source social media Source family/friends Source newspapers Source other people Source radio Source television Source internet
Incentive	Personal ➔ Lack of self-efficacy ➔ Self-responsibility ➔ Innovativeness ➔ Perceived behavioural control Product-related ➔ SP attributes ➔ Label understanding ➔ Label trust ➔ Product trust Social ➔ Descriptive norm ➔ Injunctive norm ➔ Perceived benevolence ➔ Contribution condition ➔ Performance others ➔ Perceived honesty Economic ➔ Financial situation ➔ Economic situation		

Table 9: Variables in consumer segmentation model

3.4 Methodological framework

Our methodological framework consisted of two main steps: (i) reliability analyses and (ii) finite mixture model analysis.

First, we conducted reliability analyses to assess the adequacy of the measurement of the constructs under consideration. Most of the considered constructs were based upon existing literature and measured by three or more item scores. For these variables we used Cronbach α values to establish their reliability. In several cases, the constructs were measured by two item scores. Here, we also calculated, in addition to Cronbach α, also the correlation coefficient to inspect their reliability. Finally, in the cases of food-choice motives and the perception of sustainable food-product attributes, where we did not have strong a priori reasoning about the number of underlying constructs, we performed a principal components analysis to explore the underlying structure of these two topics.

Second, we applied a finite-mixture model approach to uncover consumer segments. Conceptually, we identified consumer segments based on the above-mentioned *willingness, preference,* and *incentive variables*, hereby accounting for the possibility that segment membership may depend on a set of covariates (Table 9). To derive the number of segments, we estimated nine alternative models, which allowed for one up to nine segments. We did not consider models with more than nine segments, as, in such models, the number of parameters

would become too large in relation to the total number of observations. To minimize the risk of sub-optimal solutions, we re-estimated each alternative model with fifty different starting values and retaining the best solution.

Third, we compared these models based on several criteria. First, the overall fit of the models was established by means of the Consistent Akaike's Information Criterion (CAIC) and the entropy R^2 value. The CAIC is designed to determine the best trade-off between model fit and parsimony. This is of interest, because the larger (smaller) the number of segments is, the smaller (larger) their sizes will be. The entropy R^2 value indicates how extreme the assignment probabilities of the individuals are divided across the segments. This is of interest, because the more likely an individual belongs to only one particular segment, the more distinct the segments are.

Subsequently, we inspected the segment profiles of each model. Doing so, we used Wald tests to investigate the contribution of each core variable and covariate towards the ability to discriminate between the segments in each of the seven models. If this appeared not to be the case, we removed those variables as segment indicator and, instead, used them as a background variable to further characterize the segments. In addition, we checked if there is empirical motivation to include one of the background variables as additional core variables or covariates in the model selection procedure. Accordingly, to our findings, we re-estimated the models.

Finally, we used expert opinion to check to what extent the alternative models lead to different conclusions about the segments. If such empirical findings were robust among the alternative models, we preferred, given the size of the dataset, the more parsimonious (in terms of the number of parameters) alternatives. As such, we prefer a smaller number of larger groups over a larger number of smaller groups, if the empirical findings do not substantially differ.

Following this procedure, we eventually selected a preferred model, which is based on both statistical tests and expert opinion. We believe that this strategy leads to the best trade-off between real-life data and managerial relevance.

3.5 Empirical results

3.5.1 Reliability analysis

All constructs in the dataset demonstrated high reliability, as indicated by Cronbach's α values exceeding .70. The two-item constructs also exhibited strong reliability, with all correlation coefficients surpassing .60. Furthermore, a principal components analysis was conducted, revealing the motives of sustainable-oriented food-choice. Specifically, the statements "*It is important to me that the food that I buy has been traded in a fair way, has been produced in an environmentally friendly way, has been produced with care for the public health"* reliably captured the underlying sustainability food-choice motive. We therefore included a sustainability food-choice motive as a construct in our empirical database. The other food-choice motives were not found to measure a smaller set of underlying constructs, and therefore entered our empirical database as single-item variables. In addition, a principal components analysis was conducted for *the perceived sustainable food-product attributes*. Based on our analysis, we have concluded that all the corresponding six items reliably measure an underlying construct that can be defined as sustainable food products attribute. A complete list of the item questions, constructs, and reliability measures are given in Annex B.

3.5.2 Finite mixture modelling

We started our finite-mixture model analysis (using Latent-GOLD 5.1, (Vermunt and Magidson 2016)), with a model that included all core variables of the segmentation base, and we included country of residence as a covariate to account for its uneven representation among the farmers.

We found that all alternative models had an excellent model fit in terms of the entropy R^2 (all values were above .95). So, models with a relatively small number of segments already have very distinctive segments. This suggests the use of models with a low number of segments, given their parsimony. In addition, we found lower CAIC values for models with larger number of segments. The minimum CAIC value across all models was found for the eight-segment model. So, the CAIC suggests the appropriateness of a model with a relatively large number of segments. We decided to continue our investigation by concentrating on the three-, four-, five-, and six- segment models, because we argue that these models are a defensible compromise between the outcomes of the CAIC and entropy R^2 value.

Subsequently, we investigated the segment profiles of each model alternative. It appeared that CSA-knowledge and market access could not discriminate between the segments in the considered models (as Wald tests showed), and therefore, we removed this variable from the core segmentation basis. In case of the three-segment model, we also found that label understanding (product -related incentive), and perceived benevolence (social incentive) could not discriminate between the three segments (see Table 9). Therefore, in the three-segment model, we removed these variables from the core segmentation basis, and considered them as further profiling variables. In addition, we found that scores for low prices (see Table 9, covariate "Motive cheap"), and habit formation (see Table 9, covariate "Habit formation") substantially differed among the segments in each of the alternative models. Therefore, we included them as covariates in our model. We re-estimated the three-, four-, five-, and six-segment models. The respective CAIC values and the R^2 entropy values are shown in Table 10. As Table 10 shows, the three-segment model showed the highest R^2 entropy and the lowest CAIC values.

Segment models	CAIC value	R^2
3- segments	**66492**	**.98**
4- segments	76167	.95
5- segments	74077	.96
6- segments	73558	.96

Table 10: CAIC and R^2 values of 3, 4, 5 and 6 segmentation models

In addition, expert opinion was used to compare the segment solutions with respect to insights in differences among the segments regarding lock-ins and leverages (which is the empirical context of our study). When comparing the three and four segment solutions, it was concluded that the four-segment solution does not give more insight in differences regarding barriers among segments. As compared to the four-segment solution, it was concluded that the five-segment solution does not give more insight in differences regarding barriers among. When comparing the five- and the six-segment solution, it was found that the six-segment solution would not lead to substantial different outcomes regarding the barriers than the five-segment solution. Therefore, the three-segment solution was established as the preferred model for our purpose, based upon statistical test outcomes and expert opinion.

To summarize, we found three consumer segments with distinct scores for lock-ins in the purchase of CSA produced foods, and for which segment membership is associated with *country of residence*, *habit formation*, and *low price* as a food-choice motive.

3.5.3 Profiling the segments

All segments are substantial in size. In descending order, their sizes are 48%, 44%, and 8%.

First, we look at the overall similarities of the segments, after which we turn our attention to the differences between the segments.

3.5.4 Profiling the three segments

All segments are substantial in size. In descending order, their sizes are 48%, 44%, and 8%. We discuss the profile of the segments through the lens of potential lock-ins that may exist in each of the segments, as this is the focus of the study.

3.5.5 Intention and stated preference

Inspection of the consumer segment profiles shows that all groups express a willing to pay a premium price for CSA products. However, in the experimental choice, the preference scores for CSA produced potatoes reveals the existence of a food-choice dilemma in one of the three segments (Segment 2, 44%). In this situation, the trade-off is between a higher price and a higher sustainability. We name the identified segments according to the presence or absence of the trade-off. The mean scores on stated intention and preferences per identified segment are presented in Table 11.

Sustainable Buyers (SB) (48%). This segment is extremely outspoken in their preference for CSA potatoes. No matter what the prices of the CSA and non-CSA potatoes are, they will always prefer the CSA variant, although it can be observed that their preference for the CSA potatoes is lower if the price is higher than the non-CSA variant (although this score is still above the midpoint of the scale).

Price-Sensitive Buyers (PSB) (44%). The preference of this segment for CSA potatoes follows the price differences. If they have to pay a premium price for CSA potatoes, they prefer non-CSA potatoes; if the non-CSA potatoes are on discount, they prefer non-CSA potatoes; if the prices are equal, they prefer CSA potatoes; if CSA potatoes have a lower price, they prefer CSA potatoes.

Non-Sustainable Buyers (NSB) (8%). In none of the four choice situations, this segment prefers CSA potatoes, i.e., the consumers in this segment always opt for the non-CSA variant.

	Segment 1: SB	s.e.	Segment 2: PSB	s.e.	Segment 3: NSB	s.e.
Segment size	48%		44%		8%	
Stated intention						
Willingness to pay premium	5.99	0.04	5.24	0.06	5.26	0.14
Stated preference						
Preference equal price	7.00	0.00	5.20	0.08	1.00	0.01
Preference CSA subsidy	7.00	0.00	5.71	0.07	1.04	0.02
Preference regular discount	6.72	0.03	3.46	0.09	1.00	0.01
Preference CSA higher price	5.21	0.09	3.07	0.09	1.00	0.01

s.e. – standard error
where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale with 'absolutely not the CSA-product' and 'absolutely the CSA product' at the, respectively, left, and right extremes.

Table 11: Mean scores and percentages of the 3-segment model

Figure 2 shows a graphical presentation of the scores of core variables in the scale of [1;7] of the three consumer segments.

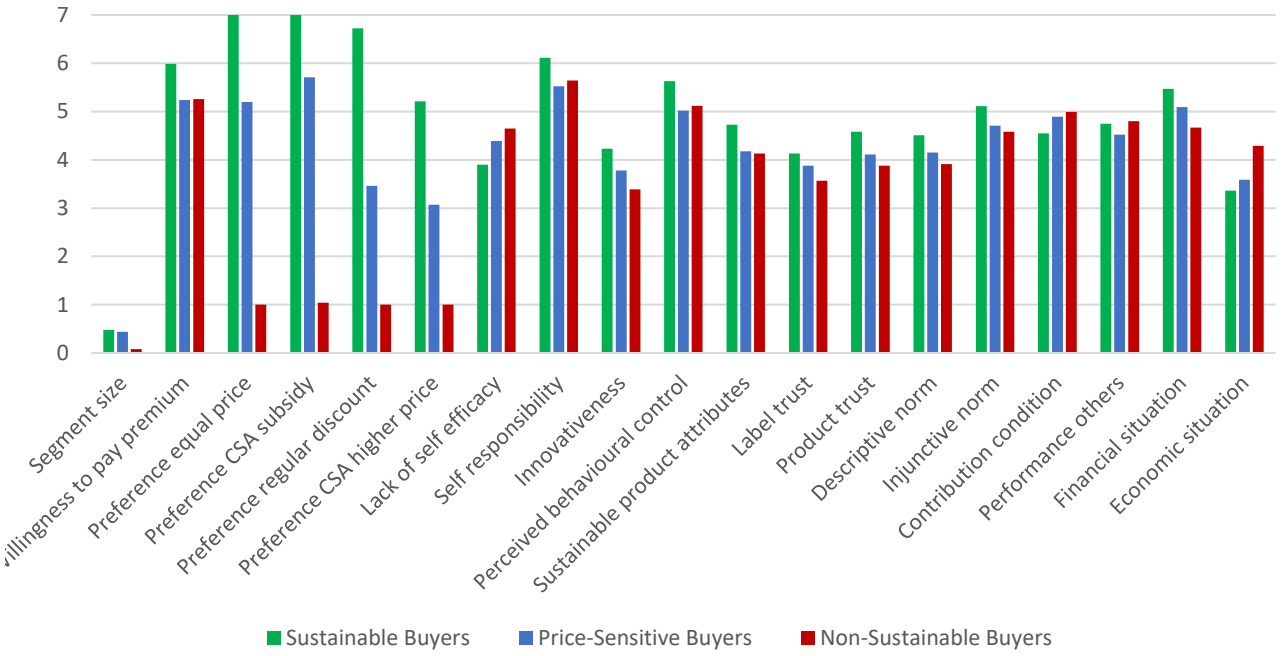

Figure 2: Core variable scores in the scale of [1;7] per consumer segment

3.5.6 Personal factors

Table 12 shows the mean scores on statements related to personal factors. All segments state that they have a responsibility to contribute to a higher sustainability standard of the food system. All segments also state that if it would be up to them, they would buy pro-sustainable food products (perceived behavioural control). Both price-sensitive and non-sustainable buyers believe that even if they purchase sustainable products, it will not make a difference for a more sustainable food system (lack of self-efficacy), whereas the sustainable buyers do believe that their purchasing

behaviour creates an impact. Sustainable buyers enjoy trying out new food products, whereas price-sensitive buyers and non-sustainable buyers do not.

	Segment 1: SB	s.e.	Segment 2: PSB	s.e.	Segment 3: NSB	s.e.
Segment size	48%	0.01	44%	0.01	8%	0.01
Lack of self-efficacy	3.90	0.07	4.39	0.07	4.65	0.17
Self-responsibility	6.11	0.04	5.52	0.06	5.64	0.12
Innovativeness	4.23	0.05	3.78	0.06	3.39	0.15
Perceived behavioural control	5.63	0.04	5.02	0.05	5.12	0.13

s.e. – standard error
where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale.

Table 12: Mean scores on personal factors

3.5.7 Product-related factors

Table 13 provides the scores on product related factors. Sustainable and price-sensitive buyers think that sustainable products are at a higher standard in comparison to non-sustainable products, whereas non-sustainable buyers are neutral in this respect. Only sustainable buyers trust information from product labels; price-sensitive and non-sustainable buyers do not trust this information. In addition, both sustainable and price-sensitive buyers trust the claims that sustainable products make about their pro-environmental contributions, whereas the non-sustainable buyers do not.

	Segment 1: SB	s.e.	Segment 2: PSB	s.e.	Segment 3: NSB	s.e.
Segment size	48%	0.01	44%	0.01	8%	0.01
Sustainable product attributes	4.73	0.04	4.18	0.05	4.13	0.14
Label trust	4.13	0.05	3.88	0.06	3.57	0.15
Product trust	4.58	0.05	4.11	0.06	3.88	0.15

s.e. – standard error
where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale.

Table 13: Mean scores on product-related factors

3.5.8 Social factors

Table 14 presents the outcomes of the social factor scores. Sustainable buyers most frequently encounter similar others who buy sustainable products, followed by price-sensitive buyers, and finally non-sustainable buyers (i.e., the respective ratings on descriptive norm). All segments believe that sustainable purchasing is approved by the significant others (injunctive norm). In addition, all segments think that they do more for a sustainable environment than the other food-system actors, including farmers (performance others), and state that they are only willing to

contribute to a more sustainable environment if the other actors make a fair share (contribution condition).

	Segment 1: SB	s.e.	Segment 2: PSB	s.e.	Segment 3: NSB	s.e.
Segment size	48%	0.01	44%	0.01	8%	0.01
Descriptive norm	4.51	0.05	4.15	0.05	3.91	0.14
Injunctive norm	5.11	0.05	4.71	0.05	4.58	0.14
Contribution condition	4.55	0.08	4.89	0.07	4.99	0.15
Performance others	4.75	0.05	4.52	0.05	4.80	0.14

s.e. – standard error
where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale.

Table 14: Mean scores on social factors

3.5.9 Economic factors

Mean scores on the economic factors are given in Table 15. All segments indicate that their financial situation is sound (financial situation). As compared to sustainable and price-sensitive buyers, the non-sustainable buyers indicate that the current economic situation forces them to cut back on their expenditures on sustainable products (economic situation).

	Segment 1: SB	s.e.	Segment 2: PSB	s.e.	Segment 3: NSB	s.e.
Segment size	48%	0.01	44%	0.01	8%	0.01
Financial situation	5.47	0.05	5.09	0.07	4.67	0.16
Economic situation	3.36	0.08	3.59	0.08	4.29	0.20

s.e. – standard error
where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale.

Table 15: Mean scores on economic factors

3.5.10 Further profiling

We further characterize each of the segments by looking at the means of the background variables, and by the distribution of the consumers over the segments for the background variables in the study. Indeed, if the percentage of consumers that show particular scoring patterns are over- or underrepresented (with respect to segment size) in one of the segments, this may help to further profile the segments. Here, we discuss several key characteristics of the segments. A complete table of all background variables is given in Annex B.

In Table 16, we give mean scores for a number of characterizing background variables. All segments would like to be informed about the pro-sustainability activities of the other actors in the food-supply chain (information interest). However, at the same time, none of the segments believe that these other actors are honest about their pro-sustainability activities (perceived honesty).

	Segment 1: SB	Segment 2: PSB	Segment 3: NSB
Segment size	48%	44%	8%
Information interest	5.67	5.27	5.10
Perceived honesty	3.75	3.74	3.57

where: SB is Sustainable Buyers, PSB is Price Sensitive Buyers, NSB is Non-Sustainable Buyers,
The preference variables are measures with a seven-point scale.

Table 16: Mean scores background variables

Table 17 presents the distribution of the total sample across segments. As shown in the distribution data (Table 17), German, Dutch, and Italian consumers are over-represented in the sustainability segment, that Danish and Greek consumers are over-represented in the price-sensitivity segment, and that Slovenian consumers are over-represented in the non-sustainability segment. In addition, consumers that consider a low price very important (Motive cheap) and live in large households (Number household persons) with many children (Number household children) are underrepresented in the sustainability segment. Consumers with only primary school (education), that live in large households with many children, and that find a low price very important are overrepresented in the price-sensitive segment. Finally, lower income groups are overrepresented in the price-sensitive consumer segment, and higher income groups are overrepresented in the sustainable consumer segment (Segment 1).

	Segment 1: SB	Segment 2: PSB	Segment 3: NSB	Total
Segment Size	**48%**	**44%**	**8%**	100
Residence				
DK	44	54	2	100
DE	62	37	2	100
NL	53	47	0	100
LT	43	46	11	100
ES	47	47	6	100
SI	46	41	13	100
GR	41	59	0	100
IT	60	40	0	100
Other residence	55	45	0	100
Residence unknown	0	100	0	100
Education				
No training completed	100	0	0	100
Primary school	19	81	0	100
Secondary school	43	44	13	100
Vocational training	46	47	8	100
Bachelor degree	47	43	10	100
Master's degree	52	44	5	100
Doctorate degree	50	47	3	100
Something else, namely	49	38	13	100
Number household persons				
One person	55	37	8	100
Two persons	50	43	7	100
Three persons	45	45	10	100
Four persons	47	47	6	100
Five persons	43	46	11	100
Six or more persons	29	57	14	100

Number household children				
None	50	42	8	100
One child	46	45	9	100
Two children	48	45	6	100
Three children	43	49	8	100
Four children	27	50	23	100
Five or more children	33	67	0	100
Income				
No income	11	79	10	100
EUR 500 or less	44	51	5	100
EUR 501 to EUR 1000	36	43	21	100
EUR 1001 to EUR 1500	42	37	21	100
EUR 1501 to EUR 2000	57	35	8	100
EUR 2001 to EUR 2500	53	42	4	100
EUR 2501 to EUR 3000	56	38	6	100
EUR 3001 to EUR 3500	45	45	10	100
EUR 3501 to EUR 4000	41	51	8	100
EUR 4001 to EUR 4500	44	56	0	100
EUR 4501 to EUR 5000	62	34	4	100
EUR 5001 to EUR 7500	54	43	2	100
EUR 7501 or more	44	52	4	100
I really don't know	26	71	3	100
I'd rather not say	47	46	7	100
Motive cheap				
Lowest importance (1 – 3)	59	32	9	100
Neutral importance (4 – 4)	54	38	7	100
Importance (5 – 5)	54	39	7	100
High importance (6 – 6)	35	56	9	100
Highest importance (7 – 7)	37	55	8	100

Table 17: Distribution (%) of the total sample across consumer segments

Finally, all segments were found to be accessible through both traditional and modern media channels (the source variables in Annex B).

3.6 Discussion

Our study reveals a clear segmentation structure consisting of three segments of consumers with distinct profiles that combine similar perceptions of sustainable food products. These segments are named sustainable buyers (48%), price-sensitive buyers (44%), and non-sustainable buyers (8%).

One of the three segments (the price-sensitive segment) shows a trade-off between personal benefits (equal or lower price) and positive externalities (higher sustainability level). This empirical finding is in line with the self-other trade-off challenge that has been identified in White et al. (2019). Consumer decisions regarding environmentally friendly, or, in our study, climate-smart food products often present a dilemma where individuals must balance the interests of others, such as a sustainable food-supply chain, with their own motives, such as seeking lower prices. These interests can conflict, and thus may form a dilemma (Van Doorn and Verhoef 2011). For this price-sensitive segment, which accounts for 44% of the sample population, the price mechanism can be used as a lever to stimulate more pro-environmental behaviour.

A key barrier, at the personal factor level, among the segments of price-sensitive (44%) and non-sustainable buyers (8%) is that they do not believe that they can make the food-supply chain more sustainable with their purchasing behaviour. This barrier relates to the challenge of a long-time horizon, as identified in White et al. (2019). This challenge implies that sustainable behaviours often

require a long-time horizon for outcomes to be realized. In addition, we argue that it is not only the long-time horizon of the results of actions that may be challenging, but also to the long length of the food supply chain. Indeed, the results of sustainable buying behaviour, may not be observed by the consumer, as its impact takes place at a location in the food-supply chain that is unknown, or very remote, to the consumer. In White et al. (2019), it is suggested that, for example, the use visual images may help to increase tangibility among consumers in this respect. Promoting, for example, CSA products by emphasizing its innovativeness may not be a promising lever, because it is expected that only the segment of sustainable buyers will respond to this promotional instrument, and these consumers are already inclined to purchase sustainable products.

At the product-related level, we found a barrier in the lack of trust in the information that is communicated through labelling, as both the price-sensitive and non-sustainable buyers do not believe this type of message. Consumers cannot directly observe more sustainability when they buy pro-sustainable products. Instead, they have to believe that the production indeed complies with the conditions promised by the label. This implies that consumers have to trust that the other actors in the food-supply chain. As a result, consumer trust in label claims depends on label ownership and management. This gives guidelines to tackle this barrier.

There are several potential barriers at the social level. First, all consumer segments have a low level of trust in the honesty of the other actors in the food-supply chain regarding their pro-sustainable activities. Second, all segments believe that they do more for a sustainable environment, than the other actors in the food chain. These barriers are related to the challenge of collective action (see, White et al. 2019). More climate-smart behaviours often require collective action, which implies that a large group of individuals must undertake pro-environmental behaviours for the benefits to be fully realized. If consumers are not aware of this interplay, or do not trust the commitment of other actors, it may hamper their willingness to deliver their share in the collective action. In our empirical analysis, we also found that all segments indicate that they are only willing to contribute to a higher sustainability standard, if the other actor also make a fair share. A possible lever may be to involve a trusted authority (i.e., an NGO or an EU public authority) in the collective action that monitors the behaviour changes of the food-chain actors.

The current economic situation hampers non-sustainable buyers to purchase sustainable products. Again, the price mechanism may seem to be a mechanism to stimulate their pro-sustainable behaviour. However, note that this segment did not prefer CSA-produced potatoes, even if the price was lower than the non-CSA alternative. So, the economic situation can only partially explain the unwillingness of this segment to shift towards more sustainable buying.

In the empirical analysis, we demonstrated that the identified segments are identifiable, accessible, and substantial in size. Other determinants of segmentation effectiveness include stability, responsiveness, and actionability. The stability of the food-choice segments depends on the stability of their identifiers. Eating patterns can be directly related to personal value systems, which are generally stable as they are central to people's self-concept. So, the found segments are probably stable enough for the implementation and evaluation of an intervention strategy. Whether or not the segmentation will perform well on responsiveness and actionability depends on the specific goal of the policy makers or other stakeholders. For example, sustainable buyers are likely to respond to new food products, whereas price-sensitive buyers are probably more responding to price intervention. The most challenging consumers are the non-sustainable buyers, as they are not expected to respond to such intervening activities. For this segment, it is recommended to try to increase their trust in the economic outlook and the sustainable activities of others in the food-supply. This calls for the intervention by mean of a communication campaign, which is possible, because this segment is accessible, as our findings reveal.

4. Overall discussion and conclusion

The aim of this study was to segment the farmer and consumer population based on individual, systemic and policy decision making factors to identify groups of farmers and consumers with similar characteristics with regards to their decision to adopt CSA practices and purchase environmentally friendly products respectively. To explore this, we employed a segmentation modelling approach to examine whether all consumers and farmers encounter identical obstacles in relation to climate-smart agricultural practices and products, or if distinct consumer and/or farmer segments exist, each experiencing unique lock-ins.

In our empirical analysis, we used data from two surveys: one targeting consumers and the other on farmers. These surveys included questions and statements aimed at identifying factors that could contribute to the emergence of lock-in situations. By employing such approach, we derived separate segmentation structures for consumers and farmers. The segmentation allowed us to gain a comprehensive understanding of the unique dynamics and potential barriers within each group.

In both segmentations, we classified the factors that may cause a lock-in situation into the categories personal, production, social, and economic factors. In comparison to the consumer segmentation, the farmer segmentation structure has one additional category that is institutional factors (which is not a relevant category for consumers that purchase food products). These categorizations may help public-policy makers and other stakeholders to develop effective intervention strategies that aim to deal with unwanted lock-ins among consumers and farmers.

We found empirical evidence for possible lock-in factors that are the same for all farmers and consumers, and we found empirical evidence for lock-in factors that occur in specific groups of consumers or farmers. Moreover, empirical evidence showed that, potentially, there exist lock-ins in all categories.

Our data analysis presents the overall findings regarding factors that may lead to lock-ins among consumers and farmers. For the ease of exposition, we characterize each factor in the form of a statement. These statements reflect the quantitative results from the empirical analyses (Table 13).

The empirical findings shed light on the factors relating to the willingness of both farmers and consumers to engage in sustainable practices. These factors indicate that for both parties, a condition for contributing to sustainability is the expectation that others should also contribute fairly. Moreover, there exists a shared belief among farmers and consumers that they personally contribute more than others do. Additionally, a significant majority of farmers and all consumers express doubts regarding the sincerity or honesty of others' contributions. These observations collectively underscore the challenges associated with achieving collective action in the context of sustainability (see, White et al. 2019). More sustainable behaviours often require collective action, which implies that a large group of individuals must undertake pro-environmental behaviours for the benefits to be fully realized. If farmers and consumers are not aware of this interplay, or do not trust the commitment of the other actors, it may hamper their willingness to deliver their share in the collective action. A possible lever may be to involve a trusted authority (i.e., an NGO or an EU public authority) in the collective action that monitors the behavioural changes of the food-chain actors.

All in all, most lock-ins can be found among farmer (in comparison to consumers), but if it comes down to the challenge of collective action, both farmers and consumers show the same type of lock-ins.

Farmers	Consumers
Statements (segments (%) of the sample population)	
Production-related	
"I have not much experience with climate-smart initiatives" (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	"I do not trust the information of labels on food products." (PSB (44%), NSB (8%))
Personal	
"The use of climate-smart initiatives is beyond my control." (*CSA*-NU (13%))	"The impact of my sustainable buying behavior is too small to make a difference." (PSB (44%), NSB (8%))
Social	
"We, farmers, do more for sustainability than all others, including consumers." (All segments (100%))	"We, consumers, do more for sustainability than all others, including farmers." (All segments (100%))
"I'm only willing to contribute to more sustainability if others also make a fair share." (All segments (100%))	"I'm only willing to contribute to more sustainability if others also make a fair share." (All segments (100%))
"I do not believe that groups in society, other than farmers, are honest about their contributions to more sustainability." (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	"I do not believe that groups in society, other than farmers, are honest about their contributions to more sustainability." (All segments (100%))
"Business partners and consumers are not willing to pay a fair price for CSA-based products." (All segments (100%))	
"Farmers, who are similar to me, do not use CSA initiatives." (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	
"People, who are important to me, do not approve the use of CSA initiatives." (CSA-NU (13%))	
Economical	
"My financial situation is difficult." (CSA-SB (28%), CSA-NU (13%))	"The current economic situation makes it more difficult for me to buy food products." (NSB (8%))
"It is not easy for me to buy inputs and sell outputs of my farm." (CB (34%), SB (28%), NU (13%))	
Institutional	
"It is difficult for me to get needed certifications for CSA initiatives." (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	
"It is difficult for me to get governmental support for CSA initiatives." (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	
"It is difficult for me to get loans for my farm." (CSA-CB (34%), CSA-SB (28%), CSA-NU (13%))	

where: CSA-CB is CSA cautious expectation farmers, CSA-SB is CSA high expectation farmers, CSA-U is CSA users, CSA-NU is CSA non-users, SB is sustainable buyers, PSB is price-sensitive buyers, and NSB is non-sustainable buyers.

Table 18: Overview of empirical evidence about lock-in creating factors among farmers and consumers

5. Next steps towards fair value propositions

The deliverable 4.1 has two consecutive parts: market segmentations and fair value propositions. Based on the farmer and consumer segments identified in section 2 and Section 3 in this study, we will develop fair value propositions.

Value propositions are integral components of business models, encompassing the benefits that a product or service offers to potential customers (B2B or B2C). These benefits ideally exceed the market price, compelling customers to make a purchase. Values can stem from various aspects, such as product quality, including factors like taste, nutritional value, and user-friendliness, as well as considerations of the climate impact. Additionally, fairness within the supply chain can create value for customers. The follow-up study objective is, therefore, to describe fair value propositions for climate-smart agriculture, harnessing the value that farmers, other chain actors, and consumers attribute to fairness.

An indication of the potential value of fairness follows from the results of farmer and consumer market segmentation, where both farmers and consumers said to be willing to contribute to CSA more when fair contribution of others is ensured (Table 13). Different consumer segments attach different value to fairness and therefore warrant a different value proposition. On the other hand, the value propositions are also intrinsically linked to the different types of farmers. The value that farmers attach to e.g., protection of the environment, or risk avoidance may resonate in the design of value propositions. There may be a segment of farmers who value the exchange of knowledge in the chain. From the farmers segmentation it becomes clear that increased transparency about the contribution of each of the actors is important for the perception of fairness. Hence, increased transparency does not only create value for consumers, but also for farmers. The value propositions that will be identified, ideally connect the value that customers (consumers of firms in B2B chains) attach to fairness in CSA with the value that farmers attach to fairness in CSA.

The literature on fairness distinguishes four dimensions of fairness, that together form the complex construct of fairness (Andrés-Martínez et al., 2013, Colquitt, 2001, Katyal et al., 2019):

1. Distributive fairness,
2. Procedural fairness,
3. Informational fairness,
4. interpersonal fairness.

The literature has identified several established norms for each of these fairness dimensions. In terms of distributional fairness, the norms include equity, equality, and need. Procedural fairness norms encompass consistency, bias suppression, accuracy, correctability, representativeness, and ethicality (Suh, 2005, Zaefarian et al., 2016). Informational fairness is characterized by norms such as bilateral communication, explanation, and knowledgeability. Finally, interpersonal fairness is exemplified by the norm of courtesy, which encompasses qualities such as politeness, dignity, respect, and the avoidance of improper behaviour (Colquitt 2001). For example, applying the norm of equity to distributional fairness would imply that each actor in the chain is awarded a revenue in accordance with its costs or effort of CSA. Regarding procedural fairness, the way that contracts are designed and enforced is important; and the occurrence of unfair trading practices may seriously hamper fairness perceptions.

Fair value propositions that promote the advancement of climate-smart agriculture can be derived from the various dimensions and conceptual elements of fairness. Figure 3 provides an initial overview of these dimensions along with some examples of fair value propositions. To further explore fair value propositions in the context of climate-smart agriculture, a comprehensive literature survey will be conducted. The identified fair value propositions will be categorized based on the climate-smart practices they address, the dimensions of fairness, and the associated norms. To evaluate the potential of these value propositions, the study will leverage the findings from the farmer and consumer segmentation analysis. This qualitative link will help establish the connection between the characteristics of different farmer and consumer segments and the value they place on various value propositions.

Figure 3 Examples of fair value propositions at four dimensions of fairness

The variables and constructs presented in Figure 3 needs to be expanded towards a comprehensive framework, which will be tested and validated through empirical study, i.e. multi-actor co-creating workshops and stakeholder interviews. These empirical results are expected to raise mutual understanding among stakeholders about their perception of which values meet which fairness criteria.

6. References

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Annex A: Variables in the farmer dataset

Variable	Measures
Construct variables	
Stated intention (N= 716; Chr. α= .92)	1. I plan to adopt a climate-smart practice or technology. 2. I intend to use a climate-smart practice or technology over the next five years. 3. I will regularly try to apply a climate-smart practice or technology in the near future
Behavioural control (N= 716; Chr. α= .81)	I have the ability to implement a climate-smart agriculture practice/technology; If it were entirely up to me, I am confident that I will adopt a climate-smart agriculture practice/technology; I have resources, time and willingness to apply a climate-smart agriculture practice /technology on my farming activities
Self-responsibility (N= 687; Chr. α= .84)	As a farmer it is my responsibility to contribute to [better environment, better animal welfare, better public health, more jobs for people in my local area, fair priced products]
Technologies perceived usefulness (N= 716; Chr. α= .92)	If I am going to adopt the climate-smart agriculture practice/technology, I think that it will: [lower production costs, increase productivity, reduce workload; be useful for farm operations]
Perceived ease of use (N= 716; Chr. α= .93)	If I am going to adopt the climate-smart agriculture practice/technology, I think that it will: [be easy to learn; be easy to control; be easy to understand how it is used]
Perceived compatibility (N= 716; Chr. α= .84, r=.72)	If I am going to adopt the climate-smart agriculture practice/technology, I think that it will: [suit in the way I like to work, be consistent with the goals I find relevant]
Financial situation (N= 630 ; Chr. α= .82; r=.70)	1.My financial resources are sufficient; 2. I can get by with the income of my household]
Access to market (N= 671; Chr. α= .71)	It is easy for me to: [access the input markets for my agricultural production, sell my products on the internet, reach a physical marketplace to sell my products]
Market prices/willingness to pay (N= 667; Chr. α= .78; r=.64)	[1. It is easy to find business buyers (for instance, wholesalers, retailers) who are willing to pay fair prices for climate-smart agricultural production; 2. Consumers are willing to pay fair prices for climate-smart agricultural production]
Descriptive norm (N= 648; Chr. α= .86; r=.76)	1. Farmers similar to me mostly use a climate-smart agriculture practice or technology 2. Farmers in my surroundings apply a climate-smart agriculture practice or technology
Perceived equity (N= 648; Chr. α= .93)	I only want to contribute to a better environment, animal welfare, public health, and fair trade, if I surely know that the following groups also make a fair contribution [farmers other than myself, supermarkets, food industry (such as dairy companies, fruit and vegetable processors, and meat industries), consumers, governments]
Perceived contribution (N= 648; Chr. α= .89)	Farmers do more for a better environment, animal welfare, public health, and fair trade, than the following groups [supermarkets, food industry (such as dairy companies, fruit and vegetable processors, and meat industries), consumers, governments]

Perceived honesty (N= 648; Chr. α= .81)	I believe that the following groups are honest about their contributions to a better environment, animal welfare, public health, and fair trade: [farmers other than myself, supermarkets, food industry (such as dairy companies, fruit and vegetable processors, and meat industries), consumers, governments]
Injunctive norm (N= 648; Chr. α= .78, r=.66)	1. People, who are important to me, would approve the use of a climate-smart practice or technology 2. People, whose opinion I value, think that I should apply a climate-smart agriculture practice or technology
Policies and regulations (N= 671; Chr. α= .79; r=.66)	[1. Governmental financial support (schemes, tax reduction, subsidies) to climate-smart agriculture is adequate; 2. Existing policies and regulations to support adoption of climate-smart agriculture are adequate]
Certification (N= 671; Chr. α= .84)	A certification for climate-smart agriculture practices and technologies is: [always available, easy to get, cheap to get]
Access to credit (N= 671; Chr. α= .80; r=.67)	[Getting access to a loan to support my financial needs is easy; The bureaucracy surrounding receiving a loan is transparent]
Economic farming motives (N= 687; Chr. α= .80)	It is important to me that running my farm business: [has low production costs, produces the highest quality products, has a low labour need, results in high yields, results in a high income, is good for the employment in my rural area]
Non-economic farming motives (N= 687; Chr. α= .83)	It is important to me that running my farm business: [produces in an environmentally friendly way, produces with care for animal welfare, produces fairly priced products, produces with care for public health, maintains the tradition of my family]
Nominal	
Knowledge (N= 716)	Have you heard of the term climate-smart agriculture practice or technology before?
Past behaviour (N= 631)	Have you used a climate-smart agriculture practice or technology in the last five years?
Participation in a cooperative (N= 711)	Do you belong to a farmers' cooperative?
Ownership status (N= 711)	What is the ownership status of your farm The largest percentage of land I use for my farming activities is [privately owned, rented]
Annual total household income (N= 711)	less than 10.000 EUR/between 10.001 and 25.000 EUR/ between 25.001 and 50.000 EUR/ between 50.001 and 75.000 EUR/ between 75.001 and 100.000 EUR/ more than 100.000 EUR
Highest education level (N= 711)	No training was completed, primary school, secondary school, vocational training/degree in agriculture, bachelor's degree, master's degree or higher]
Years of experience in farming (N=711)	For how long have you been working in farming? [<5, 5-10, 11-15, 16-20, >20]
Farm size/Total area cultivated (N= 711)	2ha, 2-10 ha, 11-50 ha, 51-100 ha, 101-200 ha, 201-500 ha, >500
Production type (N= 711)	What is your main production system? [Arable crops, open field vegetables, orchards, vineyards, livestock, mixed farming]
Gender (N= 711)	What is your gender? [male, female, I would rather not say, other, namely:]
Age (N= 710)	What is your age? [below20, 20-29, 30-39, 40-49, 50-59, 60above]
Number of persons in household	Number of persons in my household are: [One person…six or more persons]

(N= 711)	
Residence (N= 716)	Where do you currently live?
Single-item variables, continuous	
Risk tolerance (N= 687)	When I take decisions concerning my farming business [I prefer certainty over uncertainty, I avoid risks in my investments, I like to take financial risks]
Economic situation (N=631)	Because of the economic situation, I invest less in my farm than I used to do
Information use (N= 634)	To what extent are you going to use the following sources of information? [agricultural advisor, trade events and fares on agriculture, training courses, internet/social media (for example Facebook or Twitter), family and friends, mass media (for example, physical or online newspapers, radio, television, magazines), farmer associations, other farmers, other source]
Extension and advisory services (N= 634)	To what extent did you make use of the following sources for your agricultural training or advice in the last five years? [farmer trainings, farm visits, field demonstrations, field/farmers days, workshops/open discussions, advisory services, other]

Annex B: Variables in the consumer segmentation model

Variable	Measures
Construct variables	
Willingness to pay a premium (N= 1443; Chr. α= .91)	I am willing to pay extra money for food products that contribute to ➔ a better environment, ➔ a better animal welfare, ➔ fair trade, ➔ a better public health
Willingness to buy (N= 1399; Chr. α= .87)	1. I am willing to purchase environmentally friendly products. 2. I buy environmentally friendly products if I can. 3. I enjoy buying environmentally friendly products
Lack of self-efficacy (N= 1421; Chr. α= .97)	Even if I buy environmentally friendly food products, my contributions will be too small for: [a better environment, a better animal welfare, a contribution to fair trade, a better public health]
Self-responsibility (N= 1421; Chr. α= .93)	As a consumer, it is my responsibility to contribute to a [better environment, better animal welfare, better public health, fair trade]
Innovativeness (N= 1421 ; Chr. α= .76)	1. I am eager to buy new products as soon as they come out. 2. Others often ask me for advice about new food products. 3. I enjoy the novelty of trying out new food products]
Perceived behavioural control (N= 1310; Chr. α= .73)	1. I am able to buy environmentally friendly food products. 2. If it is entirely up to me, I will buy environmentally friendly food products. 3. I have the resources, time and willingness to purchase environmentally friendly food products.
Sustainable food-choice motive (N= 1443; Chr. α= .83)	It is important to me that the food that I buy ➔ has been traded in a fair way, ➔ has been produced in an environmentally friendly way, ➔ has been produced with care for the public health
Habit formation (N= 1443; Chr. α= .88)	I am used to buy food products that contribute to ➔ a better climate,

	➔ a better animal welfare, ➔ fair trade, ➔ a better public health
Sustainable product attributes (N= 1439; Chr. α= .86)	As compared to regular produced products, products with food labels that indicate that they are environmentally friendly have: ➔ a better value for money, ➔ a reasonable price, ➔ a better product quality, ➔ more appeal, ➔ a better taste, ➔ a higher nutritional value
Label understanding (N= 1310; Chr. α= .80) **Correlation**: .66	The information on food labels that indicate that the food products are environmentally friendly are ➔ informative, ➔ easy to understand
Label trust (N= 1310; Chr. α= .94) **Correlation**: .89	The information on food labels that indicate that the food products are environmentally friendly are ➔ trustworthy, ➔ realistic
Product trust (N= 1310; Chr. α= .93)	1. I feel that environmentally friendly products' environmental claims are generally trustworthy. 2. I feel that environmentally friendly products' environmental reputation is generally reliable. 3. Environmentally friendly products keep promises and commitments for environmental protection.
Descriptive norm (N= 1294; Chr. α= .70) **Correlation**: .54	1. People in my surroundings often buy environmentally friendly food products 2. People who are similar to me often buy environmentally friendly products
Injunctive norm (N= 12941; Chr. α= .71) **Correlation**: .55	1. People, who are important to me, approve if I buy environmentally friendly food products 2. People, who's opinion I value, believe that I should buy environmentally friendly products
Perceived benevolence others (N= 1270; Chr. α= .81)	Though circumstances may change, I believe that the following groups remain willing to contribute to a better environment, animal welfare, public health, and fair trade: ➔ supermarkets, ➔ food industry (such as dairy companies, fruit and vegetable processors, and meat industries), ➔ governments, ➔ farmers, ➔ consumers (other than myself)
Perceived equity (N= 1270; Chr. α= .97)	I only want to contribute to a better environment, animal welfare, public health, and fair trade, if I surely know that the following groups also make a fair contribution ➔ other consumers, ➔ supermarkets, ➔ food industry (such as dairy companies, fruit and vegetable processors, and meat industries), ➔ farmers, ➔ governments
Perceived contribution (N= 1262; Chr. α= .85)	Consumers do more for a better environment, animal welfare, public health, and fair trade, than the following groups [supermarkets, food industry (such as dairy companies, fruit and vegetable processors, and meat industries), farmers, governments]
Perceived honesty (N= 1242; Chr. α= .83)	I believe that the following groups are honest about their contributions to a better environment, animal welfare, public health, and fair trade: ➔ consumers other than myself, ➔ supermarkets, ➔ food industry (such as dairy companies, fruit and vegetable processors, and meat industries), ➔ farmers, ➔ governments

Financial situation (N= 1223; Chr. α= .87) **Correlation**: .78	My financial resources are sufficient, I can get by with the income of my household.
Access to market (N= 1439; Chr. α= .72) **Correlation**: .56	1. Sometimes I do not know where environmentally friendly food products can be found. 2. Environmentally friendly food products are not readily available at the stores where I do my shopping.
Tangibility (N= 1242; Chr. α= .95)	I want to be kept up to date about the contributions of the following groups to a better climate, better animal welfare, better public health, or fair trade [supermarkets; food industry (such as dairy compagnies, fruit and vegetable processors, and meat industries); governments, farmers, other consumers]
Nominal and/or dichotomous	
Knowledge (N= 1439)	Have you heard of the term climate-smart practice or technology?
Number of persons in household (N= 1219)	Number of persons in my household are: [One person…six or more persons]
Number of children in household (N= 1219)	Number of persons in my household are: [No children…five or more children]
Agglomeration (N= 1219)	In what type of area do you live?
Monthly net household income (N= 1219)	➔ less than 10.000 EUR ➔ between 10.001 and 25.000 EUR ➔ between 25.001 and 50.000 EUR ➔ between 50.001 and 75.000 EUR ➔ between 75.001 and 100.000 EUR ➔ more than 100.000 EUR
Gender (N= 1219)	What is your gender? ➔ male, ➔ female, ➔ I would rather not say, ➔ other, namely
Highest education level (N= 1219)	➔ No training was completed, ➔ primary school, ➔ secondary school, ➔ vocational training/degree in agriculture, ➔ Bachelor's degree, ➔ master's degree or higher
Employment (N= 1219)	I am [full-time employed (30 hours per week or more), part-time employed (less than 30 hours per week), retired, unemployed]
Residence (N= 1439)	In what country do you currently live?
Single-item variables, continuous	
Stated preference (N= 1439)	Which vegetable type would you prefer? ➔ equal prices, ➔ sustainable higher price, ➔ regular on discount, ➔ sustainable with subsidy
Health food-choice motive (N= 1439)	It is important to me that the food that I buy is healthy
No additives food-choice motive (N= 1439)	It is important to me that the food that I buy contains few or no artificial additives
Cheap food-choice motive (N= 1439)	It is important to me that the food that I buy is cheap
Appearance food-choice motive (N= 1439)	It is important to me that the food that I buy looks nice

Nutritious food-choice motive (N= 1439)	It is important to me that the food that I buy is nutritious
Economic situation (N= 1219)	Because of inflation, I spend less money on food products than I used to do
Information use (N= 1234)	Suppose that you have a question about environmentally friendly food products. To what extent are you going to use one of the following sources of information? [Social media (for example Facebook or Twitter), Family and friends, Physical or online newspapers, People I know, Radio, Television, Internet (for example, google or governmental websites), other sources]
Age (N= 1211)	Derived from "what is your year of birth"?

Annex C The mean scores of the core variables in the consumer segmentation model

	Segment 1	s.e.	Segment 2	s.e.	Segment 3	s.e.
	Sustainable buyers		**Price-sensitive buyers**		**Non-sustainable buyers**	
Segment size	0.48	.01	0.44	.01	0.08	.01
Willingness to pay premium	5.99	.04	5.24	.06	5.26	.14
Preference equal price	7.00	.00	5.20	.08	1.00	.01
Preference CSA subsidy	7.00	.00	5.71	.07	1.04	.02
Preference regular discount	6.72	.03	3.46	.09	1.00	.01
Preference CSA higher price	5.21	.09	3.07	.09	1.00	.01
Lack of self-efficacy	3.90	.07	4.39	.07	4.65	.17
Self-responsibility	6.11	.04	5.52	.06	5.64	.12
Innovativeness	4.23	.05	3.78	.06	3.39	.15
Perceived behavioural control	5.63	.04	5.02	.05	5.12	.13
SP attributes	4.73	.04	4.18	.05	4.13	.14
Label trust	4.13	.05	3.88	.06	3.57	.15
Product trust	4.58	.05	4.11	.06	3.88	.15
Descriptive norm	4.51	.05	4.15	.05	3.91	.14
Injunctive norm	5.11	.05	4.71	.05	4.58	.14
Contribution condition	4.55	.08	4.89	.07	4.99	.15
Performance others	4.75	.05	4.52	.05	4.80	.14
Financial situation	5.47	.05	5.09	.07	4.67	.16
Economic situation	3.36	.08	3.59	.08	4.29	.20

Annex D: Distribution of the background characteristics across the consumer segments

	Segment 1	Segment 2	Segment 3	Total
	Sustainable buyers	**Price-sensitive buyers**	**Non-sustainable buyers**	
Segment size	0.48	0.44	0.08	1
Indicators				
Willingness to pay premium				
1 - 4.77	0.15	0.72	0.13	1
5 - 5.5	0.46	0.46	0.07	1
5.75 - 6	0.50	0.41	0.09	1
6.25 - 6.5	0.62	0.34	0.04	1
6.75 - 7	0.70	0.25	0.05	1
Preference equal price				
1 - 4	0.00	0.65	0.35	1
5 - 6	0.00	1.00	0.00	1
7 - 7	0.78	0.22	0.00	1
Preference CSA subsidy				
1 - 5	0.00	0.65	0.35	1
6 - 6	0.00	1.00	0.00	1
7 - 7	0.71	0.29	0.00	1
Preference regular discount				

1 - 1	0.00	0.59	0.41	1
2 - 4	0.01	0.99	0.00	1
5 - 6	0.47	0.53	0.00	1
7 - 7	0.91	0.09	0.00	1
Preference CSA higher price				
1 - 1	0.23	0.51	0.26	1
2 - 2	0.25	0.75	0.00	1
3 - 5	0.40	0.60	0.00	1
6 - 6	0.60	0.40	0.00	1
7 - 7	0.90	0.10	0.00	1
Lack of self-efficacy				
1 - 2	0.62	0.32	0.06	1
2.25 - 3.75	0.53	0.43	0.04	1
4 - 4.75	0.41	0.51	0.09	1
5 - 5.75	0.47	0.44	0.09	1
6 - 7	0.39	0.50	0.11	1
Self-responsibility				
1 - 5	0.30	0.60	0.10	1
5.25 - 5.75	0.44	0.48	0.09	1
6 - 6	0.47	0.44	0.08	1
6.25 - 6.75	0.59	0.32	0.09	1
7 - 7	0.64	0.30	0.05	1
Innovativeness				
1 - 2.67	0.36	0.49	0.15	1
3 - 3.67	0.40	0.52	0.08	1
4 - 4.33	0.50	0.43	0.06	1
4.67 - 5	0.55	0.39	0.06	1
5.33 - 7	0.62	0.33	0.05	1
Perceived behavioural control				
1 - 4.33	0.31	0.61	0.07	1
4.67 - 5	0.36	0.55	0.09	1
5.33 - 5.67	0.52	0.39	0.10	1
6 - 6	0.50	0.42	0.08	1
6.33 - 7	0.73	0.23	0.05	1
SP attributes				
1 - 3.67	0.30	0.58	0.12	1
3.83 - 4.17	0.43	0.49	0.08	1
4.33 - 4.67	0.50	0.45	0.05	1
4.83 - 5.33	0.55	0.39	0.06	1
5.5 - 7	0.64	0.28	0.08	1
Label trust				
1 - 2.5	0.40	0.48	0.12	1
3 - 3.5	0.45	0.45	0.11	1
4 - 4	0.48	0.46	0.06	1
4.5 - 5	0.53	0.41	0.06	1
5.5 - 7	0.55	0.39	0.06	1
Product trust				
1 - 3	0.37	0.49	0.13	1
3.33 - 4	0.40	0.54	0.07	1
4.33 - 4.67	0.55	0.38	0.07	1
5 - 5.33	0.51	0.43	0.06	1
5.67 - 7	0.62	0.31	0.07	1
Descriptive norm				
1 - 3	0.35	0.54	0.12	1
3.5 - 4	0.46	0.45	0.08	1
4.5 - 4.5	0.48	0.44	0.08	1
5 - 5	0.49	0.44	0.07	1
5.5 - 7	0.62	0.33	0.05	1
Injunctive norm				
1 - 3.5	0.32	0.57	0.11	1

4 - 4.5	0.42	0.49	0.09	1
5 - 5	0.51	0.43	0.07	1
5.5 - 5.5	0.55	0.40	0.06	1
6 - 7	0.57	0.36	0.08	1
Contribution condition				
1 - 2.8	0.63	0.33	0.04	1
3 - 4.8	0.46	0.45	0.09	1
5 - 5.6	0.35	0.55	0.10	1
5.8 - 6	0.44	0.46	0.10	1
6.2 - 7	0.54	0.40	0.06	1
Performance others				
1 - 3.75	0.43	0.48	0.08	1
4 - 4.25	0.46	0.48	0.07	1
4.5 - 5	0.48	0.46	0.06	1
5.25 - 5.75	0.52	0.40	0.08	1
6 - 7	0.52	0.36	0.12	1
Financial situation				
1 - 4	0.36	0.50	0.13	1
4.5 - 5	0.46	0.44	0.11	1
5.5 - 5.5	0.57	0.39	0.04	1
6 - 6	0.51	0.44	0.06	1
6.5 - 7	0.57	0.39	0.05	1
Economic situation				
1 - 1	0.56	0.38	0.06	1
2 - 2	0.50	0.45	0.05	1
3 - 4	0.43	0.50	0.07	1
5 - 5	0.52	0.40	0.08	1
6 - 7	0.41	0.45	0.14	1
Covariates				
Market access <I>				
1 - 2.5	0.56	0.38	0.06	1
3 - 3.5	0.44	0.51	0.05	1
4 - 4.5	0.44	0.46	0.09	1
5 - 5	0.51	0.39	0.10	1
5.5 - 7	0.46	0.44	0.09	1
CSA knowledge <I>				
Yes, I have	0.49	0.43	0.08	1
No, I have not	0.47	0.45	0.08	1
Information interest <I>				
1 - 4.4	0.36	0.54	0.09	1
4.6 - 5.4	0.42	0.49	0.09	1
5.6 - 5.8	0.50	0.41	0.09	1
6 - 6.2	0.51	0.41	0.08	1
6.4 - 7	0.61	0.34	0.05	1
Residence				
Dk	0.44	0.54	0.02	1
De	0.62	0.37	0.02	1
NL	0.53	0.47	0.00	1
Lt	0.43	0.46	0.11	1
Es	0.47	0.47	0.06	1
Si	0.46	0.41	0.13	1
Gr	0.41	0.59	0.00	1
It	0.60	0.40	0.00	1
Other residence	0.55	0.45	0.00	1
Residence unknown	0.00	1.00	0.00	1
Gender<I>				
Male	0.42	0.50	0.08	1
Female	0.52	0.41	0.08	1
Other, namely	0.20	0.60	0.20	1
I would rather not say	0.42	0.42	0.17	1

Age <I>				
19 - 35	0.43	0.52	0.05	1
36 - 46	0.54	0.38	0.08	1
47 - 55	0.50	0.44	0.06	1
56 - 64	0.52	0.40	0.08	1
65 - 94	0.42	0.44	0.13	1
.	0.25	0.75	0.00	1
Education <I>				
No training completed	1.00	0.00	0.00	1
Primary school	0.19	0.81	0.00	1
Secondary school	0.43	0.44	0.13	1
Vocational training	0.46	0.47	0.08	1
Bachelor's degree	0.47	0.43	0.10	1
Master's degree	0.52	0.44	0.05	1
Doctorate degree	0.50	0.47	0.03	1
Something else, namely	0.49	0.38	0.13	1
Employment <I>				
Full-time employed (30 hours per week or more)	0.49	0.44	0.07	1
Part-time employed (less than 30 hours per week)	0.49	0.48	0.04	1
Retired	0.44	0.41	0.15	1
Unemployed	0.48	0.48	0.04	1
Number household persons <I>				
One person	0.55	0.37	0.08	1
Two persons	0.50	0.43	0.07	1
Three persons	0.45	0.45	0.10	1
Four persons	0.47	0.47	0.06	1
Five persons	0.43	0.46	0.11	1
Six or more persons	0.29	0.57	0.14	1
Number household children <I>				
None	0.50	0.42	0.08	1
One child	0.46	0.45	0.09	1
Two children	0.48	0.45	0.06	1
Three children	0.43	0.49	0.08	1
Four children	0.27	0.50	0.23	1
Five or more children	0.33	0.67	0.00	1
Agglomeration<I>				
Urban area	0.52	0.43	0.06	1
Suburban area	0.44	0.44	0.11	1
Small village or rural area	0.45	0.45	0.09	1
Income<I>				
No income	0.11	0.79	0.10	1
EUR 500 or less	0.44	0.51	0.05	1
EUR 501 to EUR 1000	0.36	0.43	0.21	1
EUR 1001 to EUR 1500	0.42	0.37	0.21	1
EUR 1501 to EUR 2000	0.57	0.35	0.08	1
EUR 2001 to EUR 2500	0.53	0.42	0.04	1
EUR 2501 to EUR 3000	0.56	0.38	0.06	1
EUR 3001 to EUR 3500	0.45	0.45	0.10	1
EUR 3501 to EUR 4000	0.41	0.51	0.08	1
EUR 4001 to EUR 4500	0.44	0.56	0.00	1
EUR 4501 to EUR 5000	0.62	0.34	0.04	1
EUR 5001 to EUR 7500	0.54	0.43	0.02	1
EUR 7501 or more	0.44	0.52	0.04	1
I really don't know	0.26	0.71	0.03	1
I'd rather not say	0.47	0.46	0.07	1
Motive sustainable <I>				
1 - 5.33	0.26	0.66	0.08	1
5.67 - 5.67	0.44	0.48	0.08	1

6 - 6.33	0.49	0.43	0.08	1
6.67 - 6.67	0.52	0.40	0.08	1
7 - 7	0.66	0.26	0.08	1
Motive health <I>				
1 - 5	0.39	0.54	0.07	1
6 - 6	0.42	0.50	0.08	1
7 - 7	0.55	0.37	0.08	1
Motive no additives <I>				
1 - 5	0.40	0.54	0.06	1
6 - 6	0.44	0.47	0.08	1
7 - 7	0.55	0.36	0.09	1
Motive appearance <I>				
1 - 3	0.53	0.38	0.09	1
4 - 4	0.57	0.36	0.07	1
5 - 5	0.45	0.47	0.08	1
6 - 7	0.40	0.51	0.08	1
Motive nutritious <I>				
1 - 5	0.39	0.53	0.08	1
6 - 6	0.47	0.46	0.08	1
7 - 7	0.55	0.36	0.08	1
Source social media <I>				
1 - 1	0.49	0.43	0.08	1
2 - 2	0.54	0.41	0.05	1
3 - 4	0.41	0.49	0.10	1
5 - 5	0.45	0.45	0.10	1
6 - 7	0.50	0.43	0.07	1
Source family friends <I>				
1 - 4	0.50	0.44	0.06	1
5 - 5	0.47	0.47	0.06	1
6 - 6	0.47	0.42	0.10	1
7 - 7	0.50	0.39	0.10	1
Source newspapers <I>				
1 - 3	0.42	0.47	0.11	1
4 - 4	0.44	0.48	0.09	1
5 - 5	0.47	0.44	0.09	1
6 - 7	0.56	0.40	0.04	1
Source other people <I>				
1 - 4	0.44	0.49	0.07	1
5 - 5	0.48	0.46	0.06	1
6 - 6	0.50	0.39	0.11	1
7 - 7	0.53	0.39	0.09	1
Source radio <I>				
1 - 2	0.44	0.45	0.10	1
3 - 3	0.50	0.44	0.07	1
4 - 4	0.43	0.51	0.06	1
5 - 5	0.54	0.38	0.08	1
6 - 7	0.47	0.46	0.07	1
Source television <I>				
1 - 2	0.44	0.45	0.11	1
3 - 3	0.52	0.42	0.06	1
4 - 4	0.50	0.44	0.05	1
5 - 5	0.48	0.44	0.08	1
6 - 7	0.50	0.44	0.06	1
Source internet <I>				
1 - 4	0.34	0.48	0.19	1
5 - 5	0.48	0.46	0.07	1
6 - 6	0.53	0.42	0.05	1
7 - 7	0.53	0.41	0.05	1
Motive cheap				
1 - 3	0.59	0.32	0.09	1

4 - 4	0.54	0.38	0.07	1
5 - 5	0.54	0.39	0.07	1
6 - 6	0.35	0.56	0.09	1
7 - 7	0.37	0.55	0.08	1
Habit formation				
1 - 4.75	0.26	0.68	0.06	1
5 - 5.5	0.40	0.52	0.08	1
5.75 - 5.75	0.56	0.36	0.08	1
6 - 6.5	0.53	0.39	0.09	1
6.75 - 7	0.67	0.24	0.09	1
Label understanding <I>				
1 - 3	0.48	0.44	0.07	1
3.5 - 4	0.43	0.49	0.08	1
4.5 - 4.5	0.41	0.50	0.10	1
5 - 5	0.50	0.45	0.06	1
5.5 - 7	0.55	0.35	0.10	1
Perceived benevolence <I>				
1 - 3	0.47	0.39	0.14	1
3.2 - 3.8	0.52	0.42	0.06	1
4 - 4.4	0.46	0.47	0.08	1
4.6 - 5	0.51	0.43	0.06	1
5.2 - 7	0.46	0.48	0.06	1
Perceived honesty <I>				
1 - 2.8	0.46	0.42	0.11	1
3 - 3.4	0.48	0.45	0.07	1
3.6 - 4	0.50	0.44	0.06	1
4.2 - 4.6	0.47	0.45	0.08	1
4.8 - 7	0.50	0.43	0.08	1