Elsevier Editorial System(tm) for Food Quality and Preference
Manuscript Draft

Manuscript Number: FQAP-D-11-00437R1

Title: Investigating individual preferences in rating and ranking conjoint experiments. A case study on semi-hard cheese

Article Type: Research Article

Keywords: Method comparison; Rating; Ranking; Conjoint; Self-explicated measures; Mixed Logit; Consumer segmentation; Cheese

Corresponding Author: Dr. Valérie Lengard Almli, PhD

Corresponding Author's Institution: Nofima AS

First Author: Valérie L Almli, MSc.

Order of Authors: Valérie L Almli, MSc.; Arnstein Øvrum, MSc.; Margrethe Hersleth, Ph.D.; Trygve Almøy, Ph.D.; Tormod Næs, Ph.D.

Abstract: Stated preference conjoint experiments and self-explicated measures based on rating and ranking approaches were conducted to investigate Norwegian consumers' choices among healthier and organically produced semi-hard cheeses. In the conjoint experiments, one group of participants (n=114) performed a rating task of eight cheeses whereas the other group (n=105) performed a ranking task of the same cheeses, all based on pictorial stimuli only. Then, all participants performed self-explicated rating and ranking evaluations of the cheese attributes. Conjoint rating data were analysed by mixed model ANOVA, while conjoint ranking data were analysed by mixed logit. The different approaches are compared in terms of data analysis methodologies, outcomes and practicalities for the experimenter as well as for the respondents. Rather than average population effects, focus is brought on individual preferences and consumer segmentation. Findings reveal that the two conjoint experiments lead to similar population effects and consumer segments. Consumers on average prefer cheeses of new (healthier) fat composition, organic production and lower price to cheeses of regular fat composition, conventional production and higher price. Two consumer segments are investigated. Consumers in the New fat segment are health-conscious, whereas consumers in the Regular fat segment are attracted by conventional cheese and lower prices. Self-explicated ratings of the cheese attributes corroborate these findings.

***Highlights (for review)**

Highlights

- Conjoint rating, conjoint ranking and direct attribute evaluations are compared
- A new approach to investigate individual preferences in mixed logit is proposed
- Results from conjoint approaches corroborate direct attribute ratings
- Health conscious consumers prefer healthier-fat cheese to low-fat cheese

Investigating individual preferences in rating and ranking conjoint experiments. A case study on semi-hard cheese

Valérie Lengard Almli[1,2*], Arnstein Øvrum[3], Margrethe Hersleth[1,2], Trygve Almøy[2] and Tormod Næs[1]

[1] Nofima AS, PO Box 210, 1431 Ås, Norway
[2] The Norwegian University of Life Sciences, Department of Chemistry, Biotechnology and Food Science, PO Box 5003, N-1432 Ås, Norway
[3] Norwegian Agricultural Economics Research Institute, PO Box 8024 Dep, 0030 Oslo, Norway

Abstract

Stated preference conjoint experiments and self-explicated measures based on rating and ranking approaches were conducted to investigate Norwegian consumers' choices among healthier and organically produced semi-hard cheeses. In the conjoint experiments, one group of participants (n=114) performed a rating task of eight cheeses whereas the other group (n=105) performed a ranking task of the same cheeses, all based on pictorial stimuli only. Then, all participants performed self-explicated rating and ranking evaluations of the cheese attributes. Conjoint rating data were analysed by mixed model ANOVA, while conjoint ranking data were analysed by mixed logit. The different approaches are compared in terms of data analysis methodologies, outcomes and practicalities for the experimenter as well as for the respondents. Rather than average population effects, focus is brought on individual preferences and consumer segmentation. Findings reveal that the two conjoint experiments lead to similar population effects and consumer segments. Consumers on average prefer cheeses of new (healthier) fat composition, organic production and lower price to cheeses of regular fat composition, conventional production and higher price. Two consumer segments are investigated. Consumers in the New fat segment are health-conscious, whereas consumers in the Regular fat segment are attracted by conventional cheese and lower prices. Self-explicated ratings of the cheese attributes corroborate these findings.

* Corresponding author. Tel: +47 64 97 03 05, Fax: +47 64 97 03 33,
E-mail: valerie.almli@nofima.no (V. Almli)

Keywords : Method comparison; Rating; Ranking; Conjoint; Self-explicated measures; Mixed Logit; Consumer segmentation; Cheese

1 Introduction

Experimental approaches are widely used to study consumer responses to food products. A first level of research on consumer experimental methods concerns the selection of a methodology, comparing for example experimental auctions to conjoint studies (Grunert et al., 2009; Sichtmann & Stingel, 2007), or combining such methods (Combris et al., 2009). A second level of research concerns possible options within one methodology. This paper addresses the latter by comparing an acceptance rating test to a preference ranking test in a conjoint study on generic unbranded semi-hard cheese. More specifically, focus is brought on modelling strategies with regard to the different nature of rating and ranking data. As preference heterogeneity is a very relevant and natural element of food choice research, described as "a key and permanent feature of food choices" (Combris et al., 2009), emphasis is made on studying inter-individual preference variations and consumer segmentation. Further, conjoint experiments may often be complex to design, time-consuming to perform and costly to carry-out (Sattler & Hensel-Börner, 2003). A second aspect of this paper is thus to compare conjoint approaches with self-explicated approaches, where the consumer is plainly asked about preference levels for a product's attributes (Sattler & Hensel-Börner, 2003).

1.1 Rating and ranking scales

Several rating and ranking scales have been developed and are commonly used in consumer testing (Hein et al., 2008). We will here focus on the types utilised in the present conjoint study: acceptance rating with a 9-point category scale ranging from 1 to 9, and preference ranking with no ties allowed (forced choice). In acceptance rating, consumers evaluate each product separately and rate these according to their degree of appreciation. Rating generates an indirect measure of product distances. In preference ranking, consumers order products according to their preferences from best to worst. Ranking involves performing a succession of product choices where the consumer is forced to discriminate between products, but no information regarding the degree of appreciation is obtained (Hein et al., 2008). Rating and ranking methods have previously been compared in a number of studies (Villanueva, Petenate

& Da Silva, 2005), often with a general focus on mean population results comparisons. In a comprehensive method comparison study, Hein et al. (2008) tested five common acceptance and preference methods based on rating and ranking approaches: 9-point hedonic scale, labelled affective magnitude scale, unstructured line scale, best–worst scaling and preference ranking. Their main finding is that all five methods lead to the same conclusions regarding the products, with slight performance differences observed in product discrimination power, ease of use and perceived accuracy in favour of the best-worst scaling method. However these authors worked with hedonic tests involving real food stimuli and the results may not necessarily generalise to other contexts, such as pictorial stimuli in a web-based survey. Further, their study neither investigated conjoint factors, nor compared the different methods in terms of consumer segmentation. These issues will be addressed in the present paper in the case of two rating and ranking approaches.

1.2 Self-explicated and conjoint approaches

Self-explicated approaches consist in testing consumer's attitudes or preferences for product attributes by directly asking about the attributes rather than presenting products. Such approaches are often seen in comparison to conjoint methods, which by using a complex design setup aim at collecting more reliable data than self-explicated measures. Among other, it is believed that conjoint methods increase the similarity to real choice situations and decrease the risk of collecting socially acceptable answers (Sattler et al., 2003). Sattler and Hensel-Börner (2003), however, report that studies that compare conjoint and self-explicated measures generally conclude that their performances are either equivalent, or different in favor of self-explicated measures. It is therefore interesting to study how these methods compare to each other when studying stated preferences for food choices.

1.3 Data analysis

Acceptance rating tests generate (nearly) continuous data, whereas preference ranking tests generate ordinal, discrete data. Accordingly, in conjoint experiments with rating scales the population effects from consumers' evaluations are typically analysed by mixed model ANOVA (ANalysis Of VAriance), that is to say an ANOVA model combining fixed and random effects and usually assuming normal distributions for the random parts (Næs, Brockhoff & Tomic, 2010a). In practice, ordinal measures can be approximated to continuous measures, such that ANOVA is also frequently used on ranking data even though this method is not designed for discrete data (Villanueva et al., 2005; Villanueva, Petenate & Da Silva, 2000). One must, in particular, be aware of the fact that the ranks are highly dependent on each other in small studies and the assumptions underlying standard ANOVA may be strongly violated. More appropriately, in the field of econometrics ranking data and other choice-based data are routinely analysed by so-called discrete choice models. Discrete choice models aim at understanding the behavioural process that leads to a consumer's choice (Train, 2009). The approach consists in modelling Utility, that is to say the net benefit a consumer obtains from selecting a specific product in a choice situation. These models emerged in the 1970s and have undergone a rapid development from the original fixed coefficients models such as multinomial logit, to the highly general and flexible mixed logit, also called Random Parameter Logit (Ortúzar, 2010). Mixed logit is an advanced discrete choice model where one may freely include random parameters of any distributions and correlations between random factors. This flexibility allows writing models that better match real-world situations. By including random parameters, mixed logit intrinsically models preference heterogeneity, i.e. inter-individual preference variations. Further, mixed logit acknowledges the fact that any food choice decision in the experiment, in this case any product ranking, may be dependent on the consumer's previous decisions. Even though discrete data is common in sensory and consumer science, there is no tradition in sensometrics for mixed logit, which was recently introduced to the field by Barreiro-Hurlé et al. (2008), Jaeger and Rose (2008) and Ortúzar (2010). We refer to the latter for a sound introduction to the mixed logit model and to Train (2009) for a comprehensive description.

Following the study of mean population effects, a study of preference heterogeneity is often required to identify trends within subgroups of the consumer sample. Various methods of consumer segmentation may be applied, such as clustering algorithms, visual segmentation based on Principal Component Analysis (PCA) (Almli et al., 2011) or fuzzy clustering (Johansen, Hersleth & Næs, 2010; Næs et al., 2010a; Westad, Hersleth & Lea, 2004). It is also possible to induce segments in a latent class model (Mueller et al., 2010; Hess et al., 2011) or in a clustering around latent variables model (Vigneau, Endrizzi & Qannari, 2011; Vigneau et al., 2001). Beyond the selection of a statistical approach, there are two main strategies to choose from when addressing clustering purposes: one may either create consumer groups of similar background such as gender, income, attitudes or purchase habits, or create consumer groups of similar product preferences. The first strategy is sometimes called a priori segmentation (Næs et al., 2010a) and is based on splitting the consumer group into segments according to consumer characteristics and analysing the group preferences separately or together in an ANOVA model. The second strategy is based on analysing the actual preference, liking or purchase intent data to create segments, then relating segments to consumer characteristics a posteriori. In the present paper the second strategy will be used. To perform consumer segmentation based on individual acceptance ratings, a multi-step approach introduced by Næs et al. (Endrizzi et al., 2011; Næs et al., 2010b) is applied. To perform consumer segmentation in the case of preference ranking, a new approach is presented based on individual model estimates from mixed logit and inspired by the method in Næs et al. (2010b). In both cases, segmentation will be done based on visual interpretation of PCA plots of the individual differences. The main advantage of such an approach is that one can decide on which segments or groups of consumers one is interested in studying. Another argument for such an approach is that using different automatic clustering methods can give quite different results, and also results which are difficult to interpret in terms of samples tested (see Endrizzi et al., 2014).

1.4 Objectives

The data presented in this paper are extracted from a large conjoint experiment conducted in Norway in 2009 investigating the effect of health information on consumers' diet choices (Øvrum et al., 2012). In the present paper, only the control group of participants who did not receive health information are utilised. In particular, the study investigates consumer's willingness to buy full fat vs. low fat cheese and cheese of regular fat composition vs. new fat composition, which includes a higher unsaturated fat/saturated fat ratio. The factor corresponding to a new, healthier fat composition is of major interest in this study and will guide the consumer segmentation. This innovation was not present yet on the Norwegian market at the time of the consumer experiment.

The objective of this study is threefold: (i) present and compare modelling strategies for studying population effects and preference heterogeneity in conjoint rating and ranking experiments, (ii) investigate consumers' stated preferences for various attributes in every day-use semi-hard cheese at population and segment levels and (iii) compare conjoint and self-explicated methods for eliciting consumers' acceptance.

2 Materials and methods

2.1 Consumer test

2.1.1 Cheese samples

Eight pictures of generic every day-use semi-hard cheese packages were generated according to a 2_{IV}^{4-1} fractional factorial design with variations in fat content (full fat vs. low fat), fat composition (regular vs. increased unsaturated fat/saturated fat ratio), sustainable production (conventional vs. organic) and price (NOK 42 vs. NOK 58 per 500 g) as presented in Table 1. In this experimental design each two-way interaction is confounded with another one (LowFat*NewFat + Organic*Price, NewFat*Organic + LowFat*Price and NewFat*Price + LowFat*Organic) but not with main effects.

For each factor combination, the picture included the cheese's price as well as symbols corresponding to factors organic production, low fat cheese and cheese with new fat composition (Figure 1). By contrast, the absence of these symbols indicated full fat content, regular fat composition and conventional production process, respectively. All three symbols were present on the Norwegian market at the time of the experiment. In the following, reference to the cheese samples will refer to the constructed photographs of cheese packages with varying prices and symbols.

<Table 1>, <Figure 1>

2.1.2 Consumers

A sample of 219 Norwegian consumers across the country participated in a web-based experiment. They were selected on the criteria that they eat semi-hard cheese at least once a week, are frequently responsible for food purchases for the household and do not work in the food or marketing sectors. Participants were potentially rewarded by the draw of three universal gift coupons for a value of NOK 1000 (approx. € 125). In a first step, the study consisted in either a rating or a ranking conjoint test on the eight cheeses presented in Table 1. The assignment of participants to one or the other test was done semi-randomly by the system, aiming at ensuring a balanced repartition according to gender, age, education and region of residence. Table 2 presents key socio-demographic indicators for the rating (n=114) and ranking (n=105) groups of consumers. The two groups present similar distributions in gender, age, household size and household income. Participants of university education and overweight participants are somewhat overrepresented in the ranking group compared to the rating group. The total sample (n=219) compares to national census data for the targeted age group (30-70 years old) in terms of gender composition and is slightly higher in mean age (Table 2).

<Table 2>

2.1.3 Test protocol

The same cheese pictures were used both in rating and ranking conjoint experiments (Table 1). For all participants, the survey started with a welcoming introduction and a brief presentation of the three symbols used on the cheese packagings to ensure a common interpretation of the conjoint factors. Then, for the rating group eight successive screens presenting the eight cheeses were shown in randomized balanced order. The consumers evaluated their Willingness To Buy (WTB) the cheeses on 9-point scales anchored with "I would definitely not purchase" and "I would definitely purchase". For the ranking group, a ranking test was organised in seven successive screens. A first screen presented all eight cheeses and participants were asked to click on the four items they would most probably purchase. The second screen showed these four selected cheeses and participants were asked to indicate the item they would most probably purchase among the four. The third and fourth screens showed the three (resp. two) remaining cheeses and participants were asked to indicate the item they would most probably purchase among the three (resp. two). Then, the procedure was repeated on the four rejected cheeses from the original eight. In the following, these conjoint experiments will be referred to as "conjoint rating" and "conjoint ranking".

Following the conjoint experiments, participants were questioned about the importance of factors fat content, fat composition, organic production and price in self-explicated measures (Sattler & Hensel-Börner, 2003). They first rated each factor on a 5-point likert scale anchored from "Very little importance" to "High importance", then ranked the same factors from the most to the least important one. In the following, these evaluations will be referred to as "self-explicated rating" and "self-explicated ranking". These direct measures of factor importance will be compared to the indirect measures obtained through the conjoint experiments. Finally, the participants filled in a questionnaire including behavioural and lifestyle items, attitudinal items from the Food Choice Questionnaire (Steptoe, Pollard & Wardle, 1995) and socio-demographic items.

2.2 Data analysis of conjoint rating

2.2.1. Mixed model ANOVA

A mixed model ANOVA was run to identify significant effects for the total group of consumers. This model includes low fat, new fat, organic, price and three interaction effects between conjoint factors as fixed factors, and consumer as random factor (see the confounding pattern of the experimental design in section 2.1.1 above). In addition, random interaction effects between consumer and the four conjoint factors and their interactions were included to account for individual preferences. The model is written:

Y = Mean + Consumer effect + Main effects for conjoint variables + 2-Way interactions between conjoint variables + 2-Way interactions between conjoint variables and Consumer + 3-Way interactions between Consumer and 2-way interactions of conjoint variables + random noise

More specifically,

$$\begin{aligned} y_{ijklmp} &= \mu+\tau_m+\alpha_i+\beta_j+\chi_k+\delta_l+(\alpha\beta)_{ij}+(\beta\chi)_{jk}+(\beta\delta)_{jl}+(\tau\alpha)_{mi}+(\tau\beta)_{mj}+(\tau\chi)_{mk}+(\tau\delta)_{ml} \\ &+(\alpha\beta\tau)_{ijm}+(\beta\chi\tau)_{jkm}+(\beta\delta\tau)_{jlm}+\varepsilon_{ijklmp} \end{aligned}$$ **(Eq. 1)**,

where μ is the intercept, τ is the consumer effect and α, β, χ and δ are the effects of factors low fat, new fat, organic and price. Further terms represent interactions and residuals (ε). Note that this model uses all available degrees of freedom for effects calculations and will therefore give a random error equal to zero. This model is interpreted in terms of mean acceptance in the total consumer sample. The model was run in Minitab 16 (Minitab Inc.).

2.2.2. Individual preferences and consumer segmentation

First, a reduced mixed model ANOVA was run almost identical to the former model but without interaction effects between consumer and conjoint factors, i.e. only the fixed effects and the main consumer effect were retained. The residual vector $\boldsymbol{\varepsilon}$ was rebuilt as a consumers x products (114x8) residual matrix. Note that the model for each individual is saturated, leading to a residuals matrix with column sums and row sums equal to zero (Endrizzi et al., 2011). Then, this matrix was used to extract consumer segments. It was chosen to define segments visually, corresponding to the distribution of consumers along a relevant principal component in PCA. These segments are directly interpretable with regard to the products projected on the PCA loadings plot. Finally, the consumer segments were characterised in terms of socio-demographics, attitudes and self-explicated responses with the help of a Partial Least Squares Discriminant Analysis (PLS-DA) regression model relating the segments to the questionnaire. Multivariate models were run in The Unscrambler X 10.1 (Camo Software AS). We refer to Almli et al. (2011), Endrizzi et al. (2011) and Hersleth et al. (2011) for similar approaches to modelling and consumer segmentation from rating-based conjoint analysis.

2.3 Data analysis of conjoint ranking

2.3.1. Mixed logit

The ranking data were first reshaped in the form of choice sets following the pattern presented in Table 3. For eight products, this gives seven choice sets of decreasing sizes from eight to two items, leading to a total of 35 data rows per consumer. It is to be noted that in mixed logit, the seven choice sets per consumer are modelled as dependent observations, i.e. correspond to *one* consumer. This is an advantage over for example rank-ordered logit, which treats each decomposed choice set as an independent observation.

<Table 3>

In the mixed logit model, the utility (i.e. the net benefit a consumer obtains from selecting a specific cheese) of cheese *j* for individual *m* in choice occasion *t* is written:

$$U_{mjt} = \boldsymbol{\beta'}_m \, \boldsymbol{x}_{mjt} + \varepsilon_{mjt} \qquad \textbf{(Eq. 2)}$$

where $\boldsymbol{\beta}_m$ is a vector of individual-specific parameters accounting for preference heterogeneity, $\boldsymbol{x}_{mjt}$ is a vector of conjoint factors (here: cheese attributes and interactions), and ε_{mjt} is a random error term which is assumed to be independent identically distributed (i.i.d.)

extreme value (Train, 2009). Further, it is assumed that the $\boldsymbol{\beta}_m$'s are random vectors representing the individuals while $\boldsymbol{\beta}_{mean}$ will be the random population mean, representing the mean of the distribution of $\boldsymbol{\beta}_m$. In this way, both the individual effects and the population average can be estimated.

More specifically, the cheese utility model in the present case may be written:

$$V_{mjt} = \beta_{1m}\, Lowfat_{mjt} + \beta_{2m}\, Newfat_{mjt} + \beta_{3m}\, Organic_{mjt} + \beta_{4m}\, Price_{mjt} \\ + \beta_{5m}\, (Lowfat*Newfat)_{mjt} + \beta_{6m}\, (Newfat*Organic)_{mjt} + \beta_{7m}\, (Newfat*Price)_{mjt} \qquad \textbf{(Eq. 3)}$$

where V_{mjt} is the explained part of U_{mjt} in Eq. 2 and where the interactions follow the experimental design's confounding pattern presented above (section 2.1.1). The mixed logit model used here assumes random parameters with normal distributions for all conjoint factors and two-way interactions. Thus, this model provides estimates of the mean ($\boldsymbol{\beta}_{mean}$) and the standard deviation of the random conjoint parameters and interactions. Note that the mean coefficients for the population effects may be seen as counterparts for the fixed factors in the mixed model ANOVA. Likewise, the individual effects ($\boldsymbol{\beta}_m$) correspond to the random interactions between the conjoint factors and the consumer effect in the mixed model ANOVA. These individual parameters will be discussed below. Further, the assumption of a random distribution for price in this model accommodates the expectation that different people prioritise price differently in comparison to other product properties. This assumption leads to a number of positive individual coefficient estimates for price, suggesting a preference for the higher price level relative to the lower price level for a number of participants. In practice, these may be interpreted as price indifferent consumers. The mixed logit models were run in Stata 11 (StataCorp LP) using the *mixlogit* add-on developed by Hole (2007).

2.3.3. Individual preferences and consumer segmentation

First, the matrix of individual parameter estimates $\boldsymbol{\beta}_m$ was extracted from the mixed logit model (Eq. 2). This matrix of individual estimates is comparable to the residuals matrix from the reduced mixed model ANOVA on the rating data in the sense that they both reflect individual variations from population effects. Then, the $\boldsymbol{\beta}_m$ matrix was submitted to a visual segmentation in PCA. These segments are directly interpretable with regard to the conjoint factors projected on the PCA loadings plot. Finally, the consumer segments were characterised in terms of socio-demographics, attitudes and self-explicated responses with the help of a PLS-DA regression model relating the classes to the questionnaire, following the same procedure as for conjoint rating data.

3 Results and discussion

3.1 Population effects

3.1.1 Main effects

The ANOVA results studying population effects of factors low fat, new fat, organic and price in conjoint rating of pictorial cheese-package stimuli are presented in Table 4. New fat, organic and price present significant effects (p-values<0.01), while factor low fat is not statistically significant at a 5% level. All effects are estimated positive except price, that is to say that consumers on average prefer new fat composition, organic production and lower price cheeses to regular fat composition, conventional production and higher price cheeses (Figure 2).

<Table 4>

<Figure 2>

A mixed logit model as described in section 2.3.1 was used to investigate population effects from conjoint ranking. Table 5 reports the mean coefficients and standard deviations for each factor. In this model, price was coded as a 0/1 binary variable like the other factors in order to allow coefficients comparisons. Similarly to the rating group, consumers in the ranking group prefer new fat, organic and lower price cheeses to regular fat, conventional production and higher price cheeses. Here again, factor low fat is not significant. Factor price shows the largest mean coefficient, but the model also reveals a large consumer interest for attribute new fat: consumers on average valued new fat nearly four times as much as low fat and twice as much as organic.

Conclusively, population effects are consistent between the two conjoint experiments, revealing in particular a large interest for low price and new fat and a poor interest for low fat. Former studies have shown that consumers are often not willing to compromise on taste for health benefits (Tuorila & Cardello, 2002; Verbeke, 2006). New-fat cheese may have come through as an attractive product to the consumers as its regular fat content may give positive sensory expectations, while at the same time its healthier fat quality (reduced saturated fat) may provide health benefits.

<Table5>

3.1.2 Interaction effects

None of the interaction effects are detected as statistically significant in the mixed model ANOVA from conjoint rating (Table 4), while one interaction is significant (*New fat * Price + Low fat * Organic*) and another one is nearly significant (*Low fat * New fat + Organic * Price)* in the mixed logit model from conjoint ranking (Table 5). The significant interaction coefficient is, however, smaller than the significant main effects coefficients. Unfortunately the specific identification of the interactions at play is not possible because of the confounding pattern of the design. In order to understand whether this difference in interaction sensitivity lies in the modelling methods or in the data sets, a mixed ANOVA using a continuous approximation of the eight product ranks and a mixed logit including parameter correlations instead of factor interactions were run on the conjoint ranking data (Train, 2009). Both these models also detect significant interactions/factor combinations in the ranking data. All this indicates that the ranking data contains some interaction information that is not present in the rating data.

3.2 Preference heterogeneity and consumer segmentation

3.2.3 New fat and Regular fat segments

In order to determine consumer segments based on individual preference patterns in the conjoint rating and ranking groups, PCA models were run on ANOVA residuals and mixed logit β_m estimates, respectively, according to the method descriptions in section 2.
The PCA bi-plot for conjoint rating includes consumers and products, and conjoint factors were added on the plot to ease interpretation (Figure 3a). The PCA bi-plot for conjoint ranking shows consumers as well as main effects and interactions of conjoint factors (Figure 3b). The results from these two PCAs are highly similar; in both models, each conjoint factor spans one dimension from PC1 to PC4 in the following order: price, new fat, organic and low fat. This order matches the relative importance of the factors at a population level indicated in

the ANOVA and mixed logit results above. Note however that this structure in PCA is clearer and shows higher calibration (fitted) and cross-validation variances (Martens and Næs, 1989) in the case of ranking than rating results, with 85% of explained variance restituted on the first two principal components for ranking data against 56% for rating data. Finally, for conjoint ranking PC5-PC7 span the variations of the three interactions, however these are negligible in comparison to the main effects.

Next, for each PCA model a visual consumer segmentation in two clusters was performed along PC2 on the scores plots, separating the consumers that are most favourable to new fat composition from those least favourable (Figures 3a and 3b). Here it was chosen to perform a visual segmentation along PC2 rather than PC1 because of the particular interest for factor new fat in this study. A visual segmentation easily allows for flexibility in targeting the analysis towards the objective of the study. Moreover there is no clear separation between the segments, indicating the strength of a visually-oriented approach. The consumer segments consist of 47 and 67 consumers for conjoint rating and of 59 and 46 consumers for conjoint ranking. In the following these segments are referred to as the “New fat” and “Regular fat” segments, respectively.

<Figure 3a and 3b next to each other>

3.2.3 Segments characteristics

To describe the consumer segments in terms of socio-demographics, attitudinal characteristics and self-explicated responses, identical approaches based on PLS-DA were used for conjoint rating and conjoint ranking data. In the PLS regressions, jack-knifing and uncertainty testing were used for variable selection and significance testing (Martens & Martens, 2000) and Cross-Validation (CV) was run with 10 random segments. As the questionnaire consisted of 46 items covering very different areas of the consumer background (with possibly little relation between them), a global PLS regression may have resulted in spurious variable selections. To avoid this problem, several models were attempted with different sets of predictor variables: (i) all questionnaire variables, (ii) socio-demographics variables only, (iii) attitudinal variables only and (iv) self-explicated rating/ranking evaluations only. In these models, category variables were recoded as binary or ordinal variables. Finally, a summary model was built on the significant variables from these former models.

The final PLS-DA models from conjoint rating (R^2=0.23, R^2_{CV}=0.20) and conjoint ranking (R^2=0.21, R^2_{CV}=0.18) are presented in Figures 4a and 4b. It should be mentioned that these R^2 values might be somewhat overoptimistic since the models are based on variable selection. The results reveal that consumers in the New fat segment typically gave high ratings/low ranks in self-explicated measures for the importance of fat type and the importance of fat content. In addition, consumers in the New fat segment from conjoint ranking typically gave a high rank (i.e. little importance) to factor price in self-explicated measures. These results are fully consistent with these consumers' belonging to the New fat segments. Further, these results show a good correspondence between the two conjoint approaches and self-explicated approaches.

Socio-demographic variables were not significant in submodels (i) and (ii) and do not appear in the final model. This highlights the relevance of a segmentation approach based on common preferences rather than common socio-demographic parameters, as the latter may not always be pertinent. Regarding behavioural and attitudinal characteristics, consumers in the New fat segments from both conjoint approaches may be described as health-conscious. However, the PLS-DA for rating reveals two significant variables only: having a healthy diet and being very physically active, whereas the PLS-DA for ranking reveals seven significant variables: having a healthy diet, importance to them that the food they eat on an ordinary day has a low fat content, is low in saturated fat, has few calories, helps them keep their weight, keeps them healthy and is good for the skin. These attitudinal statements may be related to the slight overrepresentation of overweight participants in the ranking group. A possible explanation for the lower number of significant variables in PLS-DA from conjoint rating is that these consumer segments may be less well-defined, due to a lower explained variance in PCA. Finally, by contrast to the New fat segments, the Regular fat segments include consumers that are less health-conscious, less physically active and more attracted by regular fat composition and full fat content products as well as by low prices. Conclusively, it seems that new-fat cheese appeals to existing consumers of low-fat cheese rather than attracts new consumer groups to the healthy market.

<Figure 4a and Figure 4b next to each other >

3.3 Comparison of self-explicated and conjoint evaluations of factor importance

Figure 5 (resp. 6) shows the results of self-explicated rating (resp. ranking) evaluations presented per conjoint consumer group and per consumer segment. Self-explicated rating results are highly consistent across conjoint conditions, showing the same patterns of factor importance between the two New fat segments, between the two Regular fat segments and between the two conjoint groups (Figure 5). Further, there is globally a good agreement between self-explicated rating and conjoint measures, corroborating the conclusions of Sattler and Hensel-Börner (2003). On average, consumers in the New fat segments rated fat composition and fat content in top positions, while consumers in the Regular fat segments rated price and fat content in the first positions. This is logical with their respective segment belongings. Note that the fact that fat content is highly rated in both segments may be due to the ambiguity of the self-explicated questions, which enquired about the importance of fat content in general without specifying a low or high level of fat content. Fat content may be important both to consumers interested in low fat and to consumers interested in full-fat cheeses even though they belong to different segments.

<Figure 5>

Self-explicated ranking results on the other hand are rather inconsistent across conjoint conditions, showing different patterns of factor importance between segments (Figure 6). Some inconsistencies can also be seen between self-explicated approaches by comparing Figures 5 and 6. For example, in the New fat segment for conjoint ranking fat content is rated in first position in self-explicated rating, but ranked in third position in self-explicated ranking. A possible explanation for these inconsistencies is that self-explicated ranking is the only one of the four approaches in the present study that did not enable ties between factors in the consumer test.

<Figure 6>

4 Method comparison discussion

4.1 Conjoint experimental setup and data analysis

The same fractional factorial design was used in both the rating and ranking conjoint experiments, allowing a method comparison based on stated preference measures of the same eight cheeses. While orthogonal designs are state-of-the-art in the context of linear models and still widely used in the context of stated choice models, Ortúzar (2010) and Jaeger & Rose (2008) argue that "orthogonality between attributes is not even a desired feature" in highly non-linear models such as mixed logit, and recommend the use of so-called efficient designs. The selected samples may therefore not have been optimal for mixed logit modelling. Further, multi-step approaches of equivalent complexity were chosen for the modelling of conjoint rating and conjoint ranking. The mixed model ANOVA approach on rating data may appear simpler in the sense that ANOVA is based on analysis of averages, which are intuitively appealing, and is a well-known, widely spread modelling method in sensometrics. Mixed logit is neither a standard tool in sensometrics nor in classical statistical software packages. Further, complex mixed logit models can require a large computation time due to the need for simulation algorithms (Ortúzar, 2010). However, computation time is seldom decisive in the scope of a consumer experiment.

In this paper a visual segmentation approach was used as the clustering algorithm that was originally attempted suggested clusters that did not show any interpretable trend in PCA. This may be due to the fact that in this case there is not clear separation between consumers. Segmenting consumers visually by help of PCA and using the experimenter's product and problem knowledge to define relevant classes is a simple approach which can sometimes be more sensible than standard algorithms (see also Endrizzi et al, 2014).

4.2 Results consistency in different approaches

4.2.1 Conjoint experiments

One of the results of this study is the overall equivalence of population effects obtained in rating and ranking approaches, corroborating conclusions from Hein et al. (2008) and extending these toward picture stimuli in conjoint experiments. It should be noted, however, that the present results show a higher sensitivity to interaction effects in the ranking experiment than in the rating experiment, and a generally higher structure in ranking data than in rating data. Yet it is not known whether the stronger structure that is obtained better reflects true consumer preferences or whether conjoint ranking might be forcing an artificial structure in the data. Villanueva et al. (2000 and 2005) observed that ranking scales have a high discriminating power on the condition that product differences are salient. In particular, the ranking protocol consisted in first performing a partition of the set of eight products into two groups. Thirty-four consumers out of 105 (32.4%) used the two levels of the price factor as a criterion for this dichotomy stage, leading to a high explained variance linked to price in PCA (64% explained variance on PC1, see Figure 3b). This reflects the fact that price is an important factor of product choice for these consumers. In addition, the numeric information for price may have been cognitively easier to process than the symbols representing qualitative factors (Rayner, 2009).

Further, the consumer segments derived from the rating/mixed ANOVA approach and from the ranking/mixed logit approach are similar in terms of self-explicated rating responses and attitudes, but here again the results from conjoint ranking show more structure and detect several additional significant characteristics to distinguish between segments.

From a global perspective, this study validates two unrelated multi-step modelling approaches: one based on a mixed model ANOVA and study of residuals from conjoint rating data, the other based on mixed logit and study of individual parameter estimates from conjoint ranking data. Such multi-step approaches are challenging to validate by internal statistical validation. By separately reaching the same conclusions, the two approaches serve as external validations for each other.

4.2.2 Self-explicated measures

The study of factor importance by self-explicated evaluations revealed that self-explicated rating globally gives consistent results with the conjoint experiments, while self-explicated ranking did not fully capture the same information. Possibly, self-explicated ranking elicited more mental deliberation from the consumers than self-explicated rating or conjoint experiments, which are monadic tasks. In a series of preference experiments on Chinese ideograms, paintings, jellybean flavours and apartments, Nordgren and Dijksterhuis (2009) found that deliberation leads to the inconsistent weighting of information, resulting in reduced preference consistency. Moreover, Lagerkvist (2013) compared attribute importance rankings for labelling of beef from two formats of best-worst scaling (BWS) with those from direct ranking. It was found that direct ranking showed poorer individual choice predictions than BWS, and poorer transitivity of attribute importance.

Further, as the evaluations obtained by self-explicated measures corroborate the conjoint results, one may wonder whether a comprehensive conjoint experiment is necessary. Sattler and Hensel-Börner (2003) reviewed 23 publications comparing self-explicated to conjoint approaches and conclude that despite theoretical advantages in conjoint experiments, their analysis “fails to confirm the superiority of conjoint measurement”. Nonetheless, our study highlights three assets of conjoint analysis: firstly, information about attributes combinations is revealed. Secondly, in conjoint analysis there is no possible ambiguity when interpreting preferred levels for important attributes. Thirdly, contrary to self-explicated ranking, conjoint ranking always allows the possibility of ties occurring between attributes - even if ties between products are not allowed.

4.3 Respondents’ experience: time usage and monotony

A study of the respondents’ time usage reveals that the conjoint rating test was less time-consuming to perform than the conjoint ranking test, with averages of 83 seconds (median: 76 seconds, Standard Deviation: 37) against 127 seconds (median: 116 seconds, S.D.: 54), respectively, after removal of extreme time values in each group (test time <10 seconds or >400 seconds). From a practical point of view, this difference in time usage is unexpected as both tests required nearly the same number of screens (one fewer for the ranking test) and mouse-clicks (one more for the ranking test). Based on time usage, it seems therefore that the rating task is simpler for the consumers than the ranking task. This corroborates Hein et al. (2008), whom in their study comparing five acceptance and preference methods report that preference ranking was identified by the consumers as “the least easy scale to use”. A possible explanation is that ranking requires making many comparative decisions between the cheeses and is thus more cognitively demanding than rating, which is a monadic task. Ranking may force consumers to establish a logical strategy while in rating consumers may rather answer by gut feeling. Finally, note that such time differences may possibly vanish or differ in acceptance tests involving tasting of products.

Further, it is possible that some respondents got bored or even annoyed during the conjoint rating experiment, as it consisted in a monotonous succession of nearly identical screens requiring nearly identical tasks where only the picture of the cheese varied. Whereas consumers in conjoint ranking saw from the first test screen that eight cheeses were to be ranked, consumers in conjoint rating may have gone from screen to screen wondering when the test would be ending, thus loosing focus and generating poorly structured data. An indication of this is the presence of several consumers that did not fit well into the PCA model for conjoint rating and a generally poorer structure in the rating data than in the ranking data. It may be advisable in the future to inform consumers in a monadic (web-)experiment about the number of items that they will be evaluating. In contrast to conjoint rating respondents, the respondents performing conjoint ranking may have remained better focused on the task throughout the test as it consisted in the succession of varied screens requiring varied tasks ("select four out of eight cheeses", "select one out of three cheeses"…). Finally, Hein et al. (2008) report that consumers "were more confident that they had provided accurate information" in preference ranking than in hedonic rating, probably due to the simultaneous presentation of samples instead of a monadic one.

5 Conclusion

This study compared conjoint experiments and self-explicated measures based on rating and ranking approaches in consumer testing of cheese attributes. The data from rating and ranking conjoint experiments were modelled with two parallel multi-step approaches respecting the different nature of the data. Thus, rating data were analysed by a combination of mixed model ANOVA, PCA and PLS-DA, while ranking data were analysed by a combination of mixed logit, PCA and PLS-DA in a new approach. Findings show that the two methods give similar conclusions both in terms of population effects and consumer segments. On average, consumers favour cheese of new (healthier) fat composition, organic production and lower price to cheese of regular fat composition, conventional production and higher price. The consumer segmentation from conjoint ranking data reveals that consumers attracted by new fat composition are described as health-conscious consumers who follow a healthy diet, consume low-fat and low-calorie products and products that keep them healthy. The consumer segmentation from conjoint rating data corroborates these results by indicating consumers who follow a healthy diet and are particularly physically active. It seems therefore that new-fat cheese may especially appeal to already health-conscious consumers. Seen from the respondents' point of view, the conjoint ranking test is significantly more time consuming than the conjoint rating test but may be perceived as less monotonous and generates more structured data. Further, self-explicated ratings of the cheese attributes corroborate the conjoint approaches, while self-explicated rankings differ from the three other approaches.

Future research may further investigate modelling of individual preferences in conjoint experiments, for example in choice-based conjoint. Finally, hedonic and revealed preference studies may be conducted to better measure the potential of healthier semi-hard cheese on the Norwegian market.

Acknowledgements

This study was supported by TRUEFOOD (Traditional United Europe Food), an Integrated Project financed by the European Commission under the Sixth Framework Programme (Contract nº FOOD-CT-2006-016264) and "Quality labelling and consumer responses in the Norwegian food sector" (Research Council of Norway, Contract nr. 178200/110). The information in this document reflects only the authors' views and the Community is not liable for any use that may be made of the information contained therein.

References

Almli, V. L., Næs, T., Sulmont-Rossé, C., Enderli, G., Issanchou, S., & Hersleth, M. (2011). Consumers' acceptance of innovations in traditional cheese. A comparative study in France and Norway. *Appetite*, *57*, 110-120.

Barreiro-Hurlé, J., Colombo, S., & Cantos-Villar, E. (2008). Is there a market for functional wines? Consumer preferences and willingness to pay for resveratrol-enriched red wine. *Food Quality and Preference*, *19*(4), 360-371, doi: 10.1016/j.foodqual.2007.11.004.

Combris, P., Bazoche, P., Giraud-Heraud, E., & Issanchou, S. (2009). Food choices: What do we learn from combining sensory and economic experiments? *Food Quality and Preference*, *20*(8), 550-557, doi: 10.1016/j.foodqual.2009.05.003.

Endrizzi, I., Gasperi, F., Rødbotten, M., & Næs, T. (2014). Interpretation, validation and segmentation of preference mapping models. Food Quality and Preference, 32, Part C(0), 198-209, doi: http://dx.doi.org/10.1016/j.foodqual.2013.10.002.

Endrizzi, I., Menichelli, E., Johansen, S. B., Olsen, N. V., & Næs, T. (2011). Handling of individual differences in rating-based conjoint analysis. *Food Quality and Preference*, *22*(3), 241-254, doi: 10.1016/j.foodqual.2010.10.005.

Grunert, K. G., Juhl, H. J., Esbjerg, L., Jensen, B. B., Bech-Larsen, T., Brunso, K., & Madsen, C. O. (2009). Comparing methods for measuring consumer willingness to pay for a basic and an improved ready made soup product. *Food Quality and Preference*, *20*(8), 607-619, doi: 10.1016/j.foodqual.2009.07.006.

Hein, K. A., Jaeger, S. R., Carr, B. T., & Delahunty, C. M. (2008). Comparison of five common acceptance and preference methods. *Food Quality and Preference*, *19*(7), 651-661.

Hersleth, M., Lengard, V., Verbeke, W., Guerrero, L., & Næs, T. (2011). Consumers' acceptance of innovations in dry-cured ham Impact of reduced salt content, prolonged aging time and new origin. *Food Quality and Preference*, *22*(1), 31-41, doi: 10.1016/j.foodqual.2010.07.002.

Hess, S., Ben-Akiva, M., Gopinath, D., & Walker, J. (2011). Advantages of latent class over continuous mixture of Logit models. http://www.stephanehess.me.uk/papers/Hess_Ben-Akiva_Gopinath_Walker_May_2011.pdf.

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *The Stata Journal*, *7*, 388-401.

Jaeger, S. R., & Rose, J. M. (2008). Stated choice experimentation, contextual influences and food choice: A case study. *Food Quality and Preference*, *19*(6), 539-564, doi: 10.1016/j.foodqual.2008.02.005.

Johansen, S. B., Hersleth, M., & Næs, T. (2010). A new approach to product set selection and segmentation in preference mapping. *Food Quality and Preference*, *21*(2), 188-196, doi: 10.1016/j.foodqual.2009.05.007.

Kozak, M., & Cliff, M. A. (2013). Systematic Comparison of Hedonic Ranking and Rating Methods Demonstrates Few Practical Differences. Journal of Food Science, 78(8), S1257-S1263, doi: 10.1111/1750-3841.12173.

Lagerkvist, C. J. (2013). Consumer preferences for food labelling attributes: Comparing direct ranking and best–worst scaling for measurement of attribute importance, preference intensity and attribute dominance. Food Quality and Preference, 29(2), 77-88, doi: http://dx.doi.org/10.1016/j.foodqual.2013.02.005.

Martens, H., & Martens, M. (2000). Modified Jack-knife estimation of parameter uncertainty in bilinear modelling by partial least squares regression (PLSR). *Food Quality and Preference*, *11*(1-2), 5-16.

Mueller, S., Lockshin, L., Saltman, Y., & Blanford, J. (2010). Message on a bottle: The relative influence of wine back label information on wine choice. *Food Quality and Preference*, *21*(1), 22-32, doi: 10.1016/j.foodqual.2009.07.004.

Nordgren, L. F., & Dijksterhuis, A. P. (2009). The Devil Is in the Deliberation: Thinking Too Much Reduces Preference Consistency. *Journal of Consumer Research*, *36*(1), 39-46, doi: 10.1086/596306.

Næs, T., Brockhoff, P., & Tomic, O. (2010a). *Statistics for sensory and consumer science*, Wiley, Chichester, UK.

Næs, T., Lengard, V., Johansen, S. B., & Hersleth, M. (2010b). Alternative methods for combining design variables and consumer preference with information about attitudes and demographics in conjoint analysis. *Food Quality and Preference*, *21*(4), 368-378, doi: 10.1016/j.foodqual.2009.09.004.

Ortúzar, J. D. D. (2010). Estimating individual preferences with flexible discrete-choice-models. *Food Quality and Preference*, *21*(3), 262-269, doi: 10.1016/j.foodqual.2009.09.006.

Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. The Quarterly Journal of Experimental Psychology, 62(8), 1457-1506, doi: 10.1080/17470210902816461.

Sattler, H., & Hensel-Börner, S. (2003). A comparison of conjoint measurement with self-explicated approaches, in *Conjoint Measurement: Methods and Applications* edited by Gustafsson, A., Herrmann, A. & Huber, F., pp. 147-159, Springer, p.147-159, Berlin.

Sichtmann, C., & Stingel, S. (2007). Limit conjoint analysis and Vickrey auction as methods to elicit consumers' willingness-to-pay - An empirical comparison. *European Journal of Marketing*, *41*, 1359-1374, doi: 10.1108/03090560710821215.

Steptoe, A., Pollard, T. M., & Wardle, J. (1995). Development of a measure of the motives underlying the selection of food: the Food Choice Questionnaire. *Appetite*, *25*(3), 267-284, doi: 10.1006/appe.1995.0061.

Train, K. (2009). *Discrete Choice Methods with Simulation*, Cambridge University Press, 2003. Second edition, 2009.

Tuorila, H., & Cardello, A. V. (2002). Consumer responses to an off-flavor in juice in the presence of specific health claims. *Food Quality and Preference*, *13*(7-8), 561-569, doi: Pii s0950-3293(01)00076-3
10.1016/s0950-3293(01)00076-3.
Verbeke, W. (2006). Functional foods: Consumer willingness to compromise on taste for health? *Food Quality and Preference*, *17*(1-2), 126-131, doi: 10.1016/j.foodqual.2005.03.003.
Vigneau, E., Endrizzi, I., & Qannari, E. M. (2011). Finding and explaining clusters of consumers using the CLV approach. *Food Quality and Preference*, *22*(8), 705-713, doi: 10.1016/j.foodqual.2011.01.004.
Vigneau, E., Qannari, E. M., Punter, P. H., & Knoops, S. (2001). Segmentation of a panel of consumers using clustering of variables around latent directions of preference. *Food Quality and Preference*, *12*(5-7), 359-363, doi: 10.1016/s0950-3293(01)00025-8.
Villanueva, N. D. M., Petenate, A. J., & Da Silva, M. (2000). Performance of three affective methods and diagnosis of the ANOVA model. *Food Quality and Preference*, *11*(5), 363-370.
Villanueva, N. D. M., Petenate, A. J., & Da Silva, M. (2005). Performance of the hybrid hedonic scale as compared to the traditional hedonic, self-adjusting and ranking scales. *Food Quality and Preference*, *16*(8), 691-703, doi: 10.1016/j.foodqual.2005.03.013.
Westad, F., Hersleth, M., & Lea, P. (2004). Strategies for consumer segmentation with applications on preference data. *Food Quality and Preference*, *15*(7-8), 681-687.
Øvrum, A., Alfnes, F., Almli, V. L., & Rickertsen, K. (2012). Health information and diet choices: results from a cheese experiment. Food Policy, 37, 520–529.

Tables

Table 1. Fractional factorial design used in the conjoint experiments

Cheese	**Code**	**Low fat**	**New fat type**	**Organic**	**Price (NOK/500g.)**
1	1000	Yes	No	No	42
2	1011	Yes	No	Yes	58
3	0001	No	No	No	58
4	0010	No	No	Yes	42
5	1101	Yes	Yes	No	58
6	1110	Yes	Yes	Yes	42
7	0100	No	Yes	No	42
8	0111	No	Yes	Yes	58

Table 2. Selected socio-demographic characteristics of the consumer groups

	Rating group n=114	**Ranking group** n=105	**Total sample** n=219	**National census data per 01.01.2011**
Gender (%)				
Female	52.2	49.5	50.9	50.9%[1]
Male	47.8	50.5	49.1	49.1%[1]
Age (%)				
30-39	20.3	23.8	22.0	26.4%
40-59	44.3	40.9	42.7	51.9%
60-70	35.4	35.3	35.3	21.7%
Mean in years (S.D.)	51.3 (11.2)	51.1 (12.3)	51.2 (11.8)	48.6 (n/a) [1]
BMI (%)				
< 18.5 (underweight)	0.9	0	0.5	(n/a)
18.5-24.9 (normal weight)	47.8	38	43.1	(n/a)
25-30 (overweight)	34.5	44.8	39.4	(n/a)
>30-34.9 (obese)	16.8	17.1	17.0	(n/a)
Household size				
Mean (S.D.)	2.5 (1.4)	2.5 (1.3)	2.5 (1.4)	2.2 (n/a) [2]
Education (%)				
Secondary school or lower	2.6	0.9	1.8	
High school	31.9	24.8	28.4	
University	65.5	74.3	69.7	
Household income in kNOK/year (S.D.)	640 (241)	670 (250)	655 (246)	617.1 (n/a) [3]

Source of national census data: Statistics Norway, www.ssb.no.
[1] Age group 30-70 years old specifically.
[2] All age groups confounded.
[3] Data from 2009 and all age groups confounded.

Table 3. Reshaping ranking data of *t* products into choice sets for analysis with discrete choice models. Example for ranking order 4;2;6; … t-1;t

Choice set 1		**Choice set 2**		**Choice set 3**		**…**	**Choice set t-1**	
Sample	Y	Sample	Y	Sample	Y	…	Sample	Y
1	0	1	0	1	0	…	t-1	1
2	0	2	1	3	0	…	t	0
3	0	3	0	5	0	…		
4	1	5	0	6	1	…		
5	0	6	0	…	0	…		
6	0	…	0	t	0			
…	0	t	0					
t	0							

Table 4. Mixed model ANOVA on conjoint rating data

Sources of variation	**D.F.**	**SS**	**F-value**	**p-value**
Low fat	1	8.685	3.54	0.063
New fat	1	58.510	21.05	0.000
Organic	1	14.001	7.35	0.008
Price	1	64.747	24.08	0.000
Low fat*New fat + Organic*Price	1	0.580	0.51	0.477
New fat*Organic + Low fat*Price	1	0.010	0.01	0.920
New fat*Price + Low fat*Organic	1	0.317	0.39	0.532
All consumer effects (main effect and interactions)	904	4046.149		
Error	0			
Total	911	4192.999		
R-Square: n/a				

Table 5. Mixed logit model on conjoint ranking data

Factors	Coefficient	z	p-value
Mean			
Low fat	0.185	1.52	0.127
New fat	0.778	5.12	0.000
Organic	0.454	3.59	0.000
Price	-1.600	-6.53	0.000
Lowf*Newf+Organic*Price	-0.178	-1.85	0.064
Newf*Organic+Newf*Price	-0.149	-1.59	0.112
Newf*Price+Lowf*Organic	0.376	3.84	0.000
Standard deviation			
Low fat	0.775	4.09	0.000
New fat	1.088	5.58	0.000
Organic	0.786	4.19	0.000
Price	1.712	6.64	0.000
Lowf*Newf+Organic*Price	0.278	0.86	0.390
Newf*Organic+Newf*Price	0.010	0.03	0.974
Newf*Price+Lowf*Organic	0.006	0.04	0.971

Number of choice observations: 735
Number of consumers: 105
Log likelihood at convergence: -989.040

Figure captions

Figure 1. Picture of cheese sample 1110 (Table 1): low fat (keyhole symbol to the left), new fat type (LHL symbol in the middle), organically produced (Debio symbol to the right) and low price (NOK 42).

Figure 2. Main effects of the four factors in conjoint rating

Figure 3. PCA bi-plots on (a) ANOVA residuals from conjoint rating and (b) individual mixed logit parameter estimates from conjoint ranking. □ Consumers in the Regular fat segment, ○ Consumers in the New fat segment

Figure 4. Correlation loadings from PLS-DA models in (a) conjoint rating and (b) conjoint ranking

Figure 5. Self-explicated rating of factors across conjoint groups and consumer segments

Figure 6. Self-explicated ranking of factors across conjoint groups and consumer segments

Figure 1

Click here to download high resolution image

Figure 2
Click here to download high resolution image

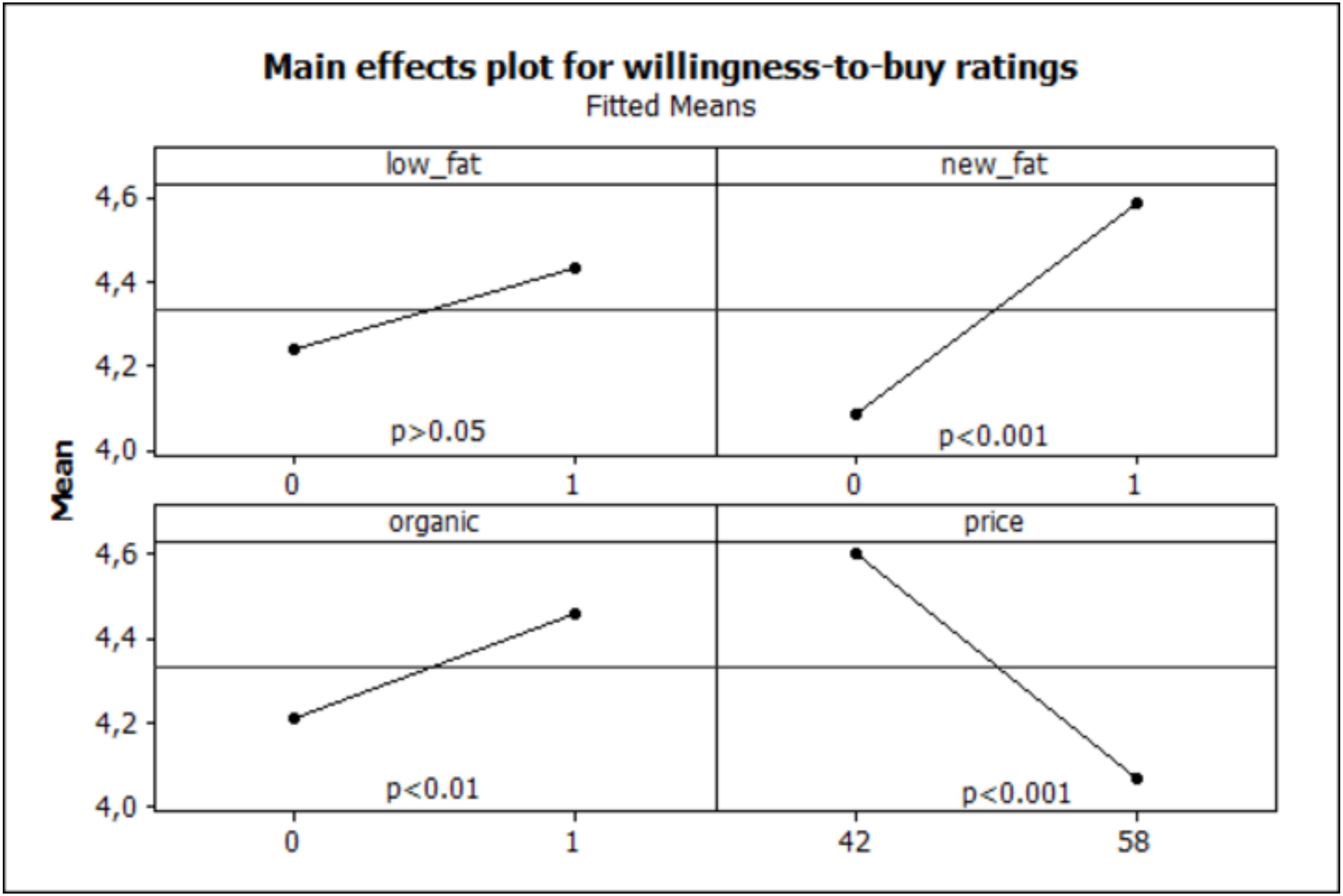
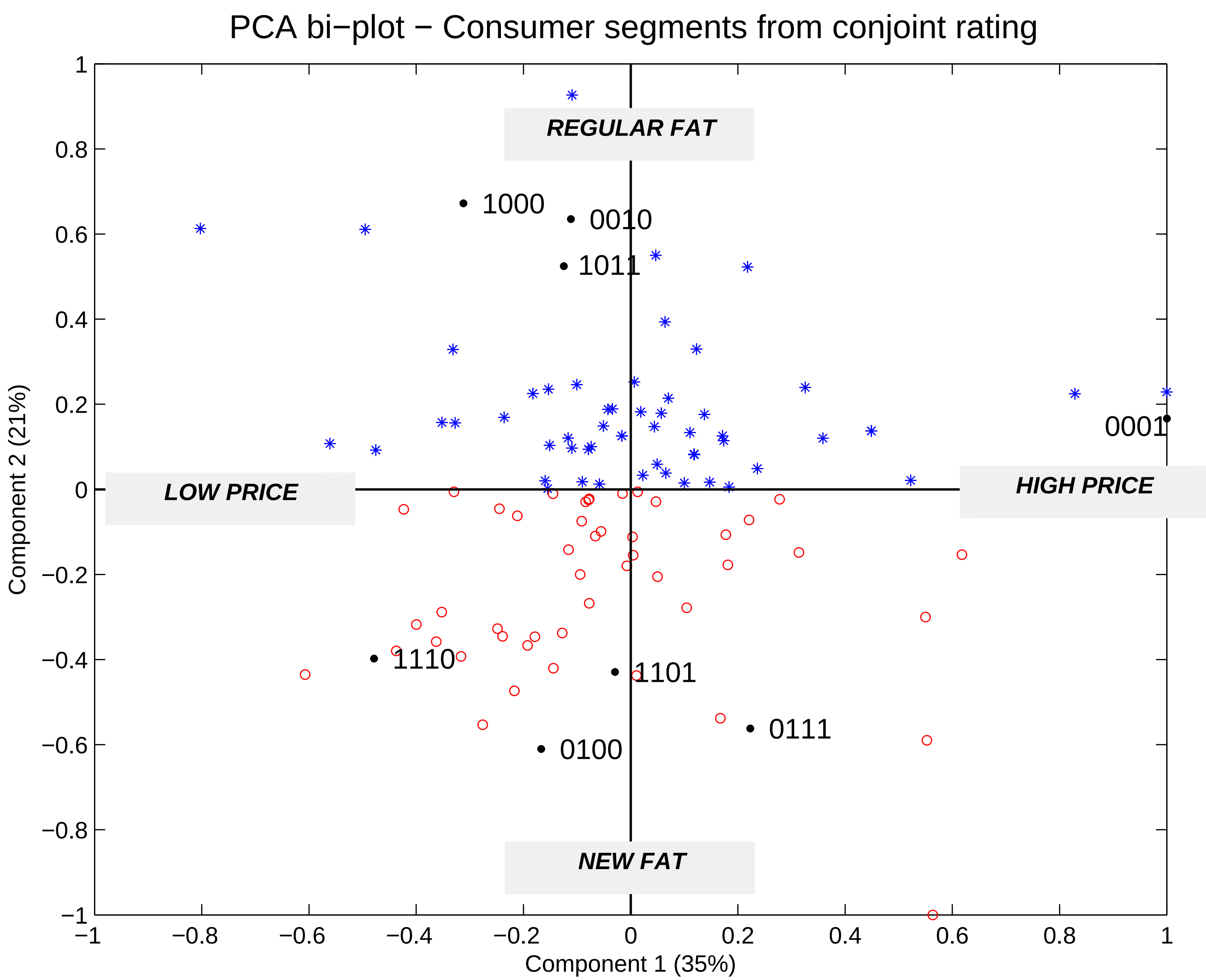


Figure 3a



PCA bi−plot − Consumer segments from conjoint rating
REGULAR FAT
LOW PRICE
HIGH PRICE
NEW FAT
1000
0010
1011
0001
1110
1101
0111
0100
Component 1 (35%)
Component 2 (21%)

Figure 3b

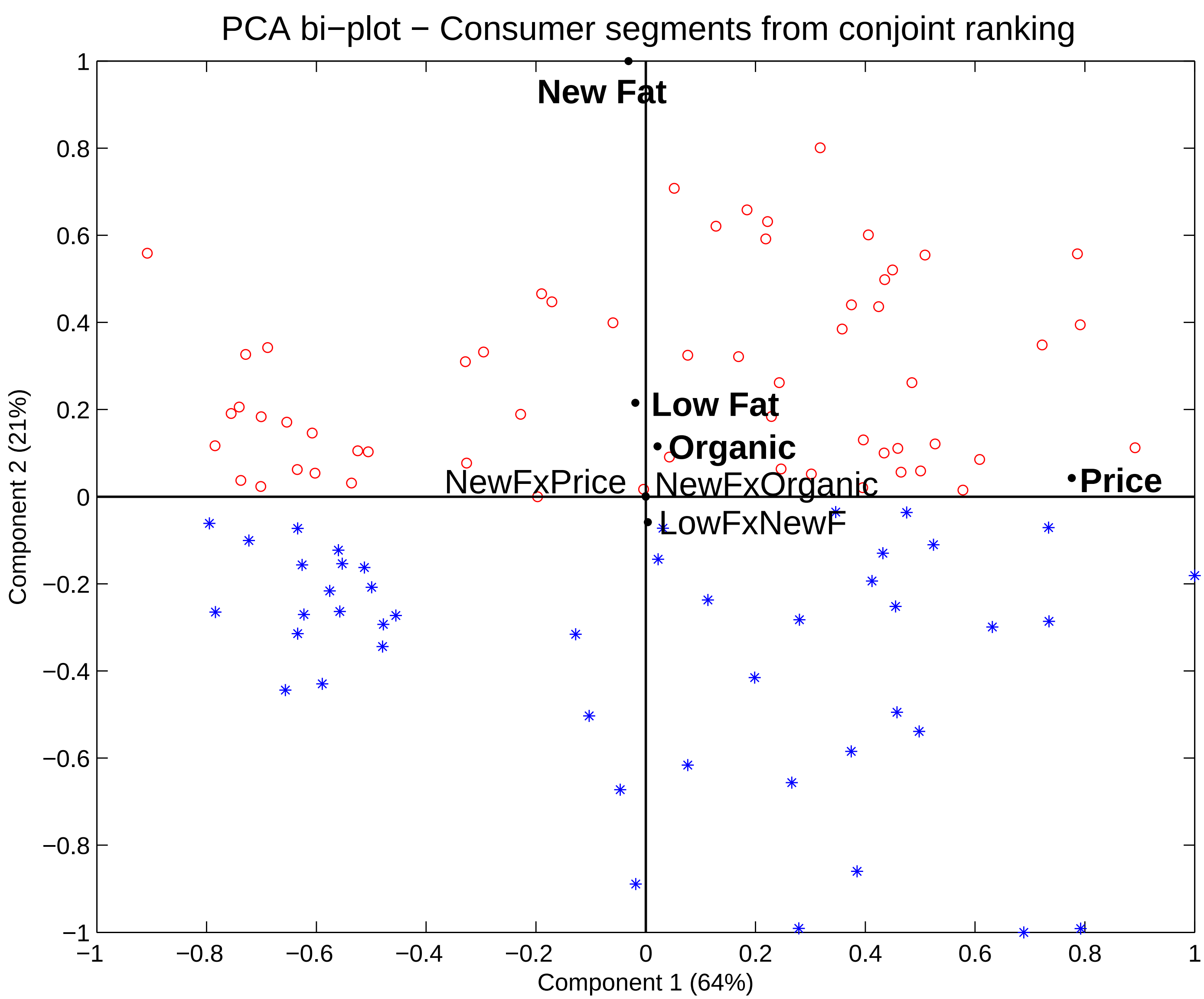
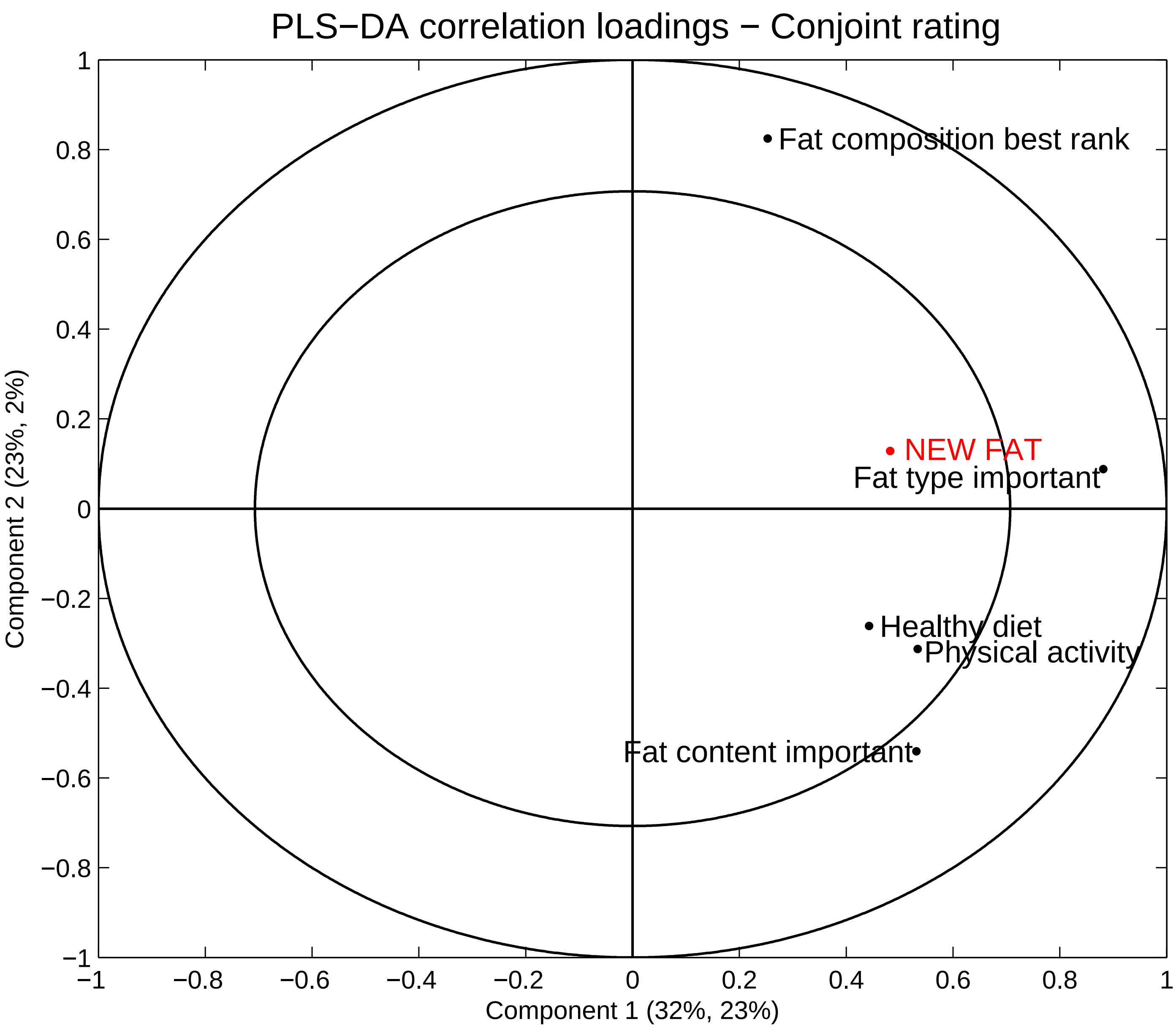

PCA bi−plot − Consumer segments from conjoint ranking
New Fat
Low Fat
Organic
Price
NewFxPrice
NewFxOrganic
LowFxNewF
Component 1 (64%)
Component 2 (21%)
−1
−0.8
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
0.8
1

Figure 4a



PLS−DA correlation loadings − Conjoint rating
Fat composition best rank
NEW FAT
Fat type important
Healthy diet
Physical activity
Fat content important
Component 1 (32%, 23%)
Component 2 (23%, 2%)
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1
−1
−0.8
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
0.8
1

Figure 4b

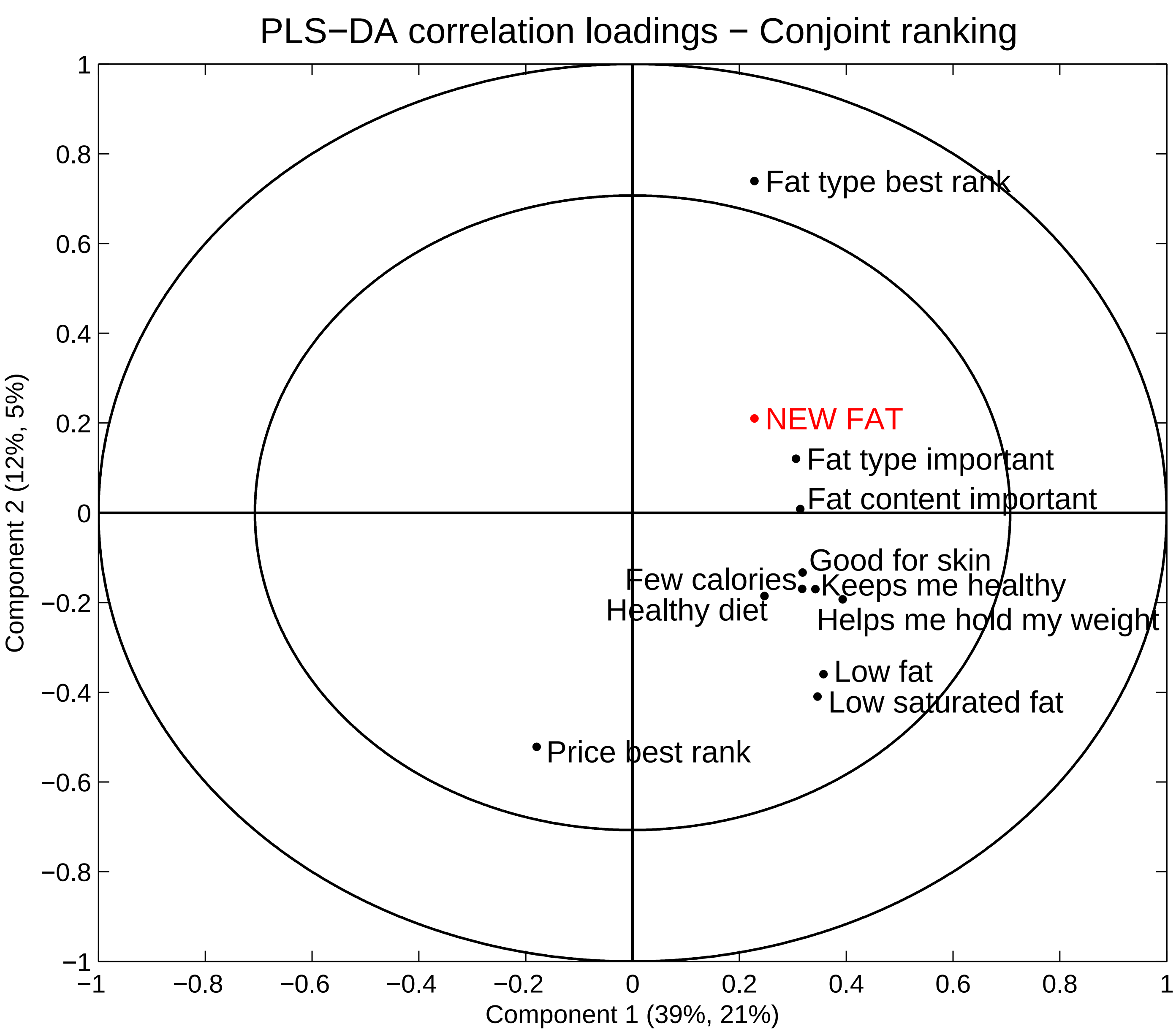

PLS−DA correlation loadings − Conjoint ranking
Fat type best rank
NEW FAT
Fat type important
Fat content important
Good for skin
Few calories
Keeps me healthy
Healthy diet
Helps me hold my weight
Low fat
Low saturated fat
Price best rank
Component 1 (39%, 21%)
Component 2 (12%, 5%)
−1
−0.8
−0.6
−0.4
−0.2
0
0.2
0.4
0.6
0.8
1

Figure 5

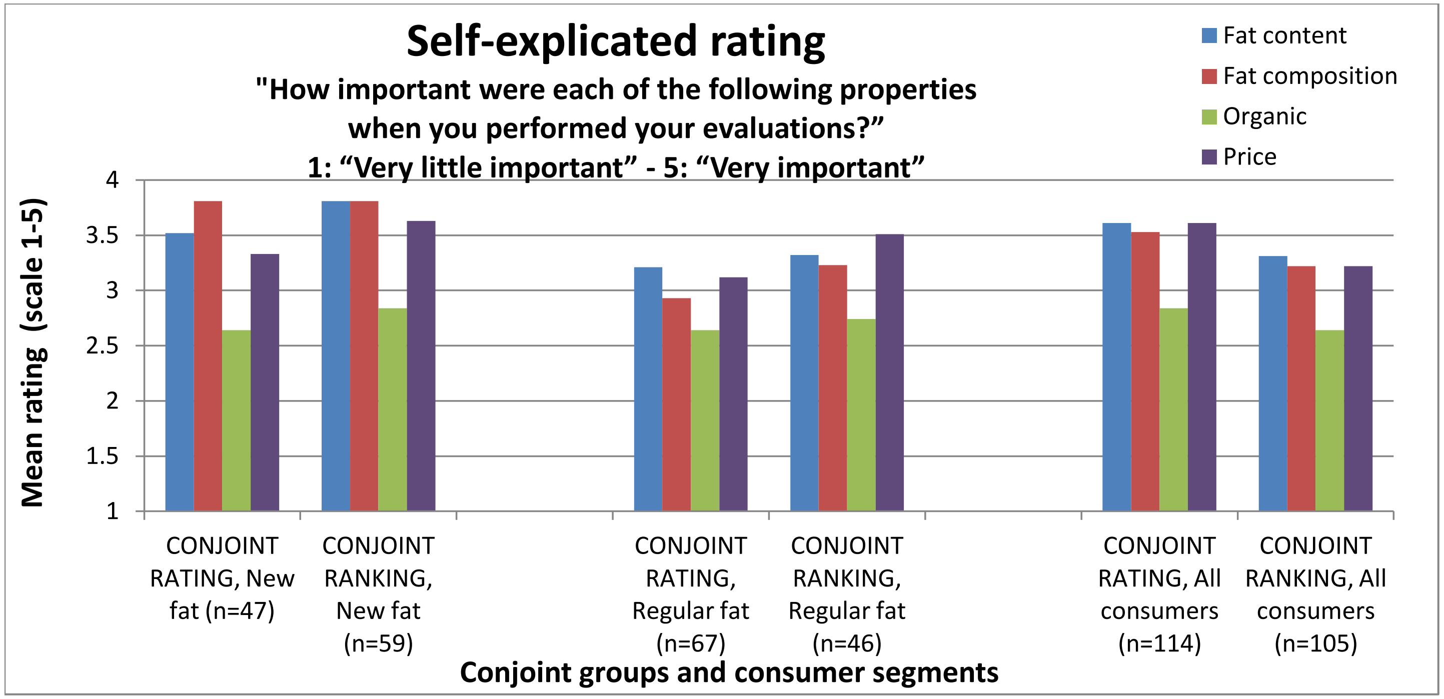
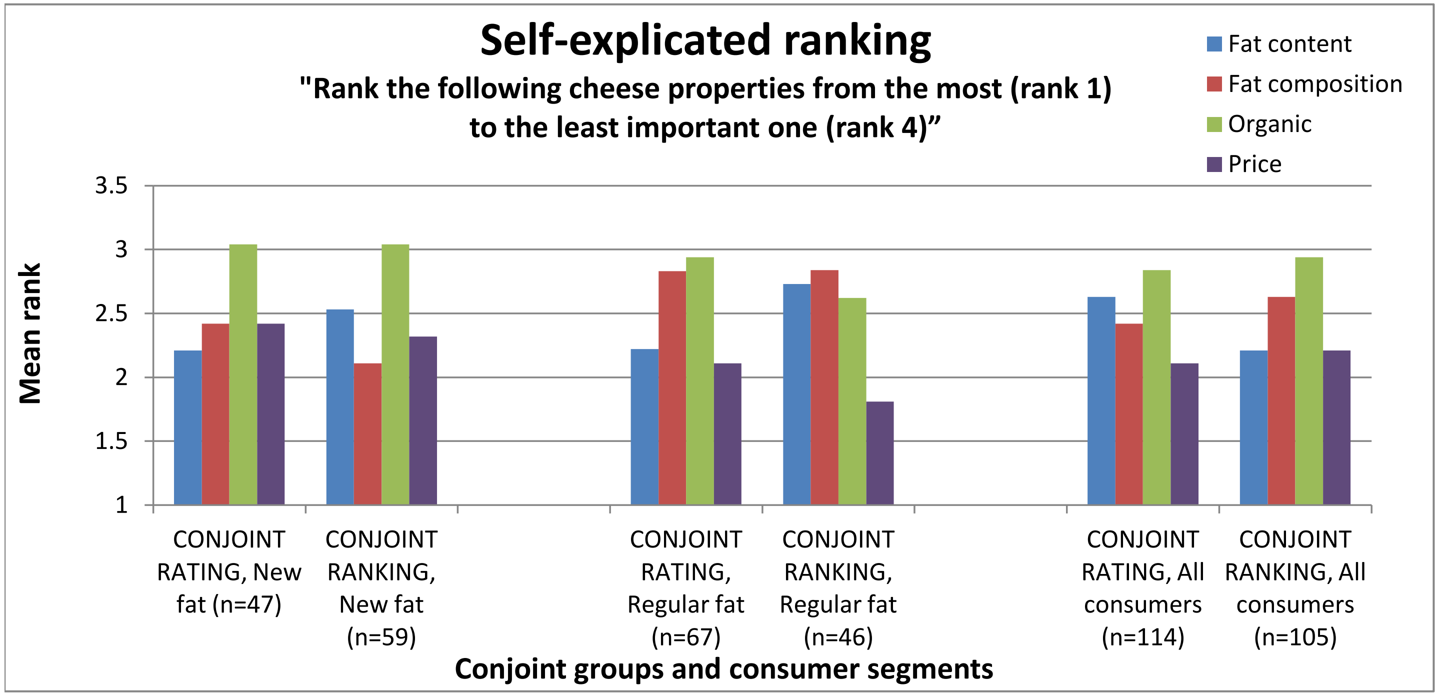

Self-explicated rating
"How important were each of the following properties
when you performed your evaluations?”
1: “Very little important” - 5: “Very important”
Fat content
Fat composition
Organic
Price
Mean rating (scale 1-5)
4
3.5
3
2.5
2
1.5
1
CONJOINT RATING, New fat (n=47)
CONJOINT RANKING, New fat (n=59)
CONJOINT RATING, Regular fat (n=67)
CONJOINT RANKING, Regular fat (n=46)
CONJOINT RATING, All consumers (n=114)
CONJOINT RANKING, All consumers (n=105)
Conjoint groups and consumer segments

Figure 6



Self-explicated ranking
"Rank the following cheese properties from the most (rank 1) to the least important one (rank 4)"
Fat content
Fat composition
Organic
Price
Mean rank
3.5
3
2.5
2
1.5
1
CONJOINT RATING, New fat (n=47)
CONJOINT RANKING, New fat (n=59)
CONJOINT RATING, Regular fat (n=67)
CONJOINT RANKING, Regular fat (n=46)
CONJOINT RATING, All consumers (n=114)
CONJOINT RANKING, All consumers (n=105)
Conjoint groups and consumer segments