



# Who do UK consumers trust for information about nanotechnology?

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## ABSTRACT

This paper investigates UK consumers' trust in sixteen information sources, from government institutions to food handlers and media, to provide accurate information about the use of nanotechnology in food production and packaging. We elicit the perceived trust using a well-known choice-based stated preference technique, namely best-worst scaling. The results from the analysis of a scale-adjusted latent class model show considerable heterogeneity in consumers' perceptions of trust and choice variability. The findings from this study provide insights into the development of best practices and policies in risk communication and management for novel foods produced by nanotechnologies. More specifically, they highlight how targeted approaches can be used by policymakers responsible for disseminating information relating to novel technologies.

## 1. Introduction

Nanotechnology, which can be described as the creation and manipulation of materials at the nano (one-billionth) scale, is one of the emerging technologies that has attracted considerable attention within the food industry. This attention has stemmed from the technology's potential for developing innovative products and applications for food processing, preserving and packaging (FAO/WHO, 2013; Prasad et al., 2017; Chaudhry et al., 2017). Nanotechnology can, for example, be used for 'smart' packaging that has the capability to monitor the condition of foods during storage and transportation. As a result, it has the potential to extend shelf-life, enhance tastes and quality, reduce the need for preservatives, salt and fat, and improve the nutritional value of food (García et al., 2010; Chaudhry and Castle, 2011; Chaudhry et al., 2017). Not surprisingly, the food industries in a number of countries, including the USA, Australia, New Zealand, South Korea, Taiwan, China and Israel are exploring its use. However, for the most part, these developments are still at the research and market development, or near-market stage (Chaudhry and Castle, 2011; Food Standards Agency, 2016).

Although nanotechnology has a number of promising applications, its use in the food industry remains limited. This slow uptake is mainly due to a lack of information and uncertainties linked with its potential health and environmental impacts (Stampfli et al., 2010; Food Standards Agency, 2010; Anderson et al., 2012). This has significantly increased consumer concerns, especially over its effectiveness, long-term side effects, and ability to ensure safety (Lyndhurst, 2009; Gupta

et al., 2017), as well as how their impacts will be handled, and by whom (Gavelin et al., 2007; Food Standards Agency, 2010). There are also doubts in consumers' minds, which has, consequently, led to mistrust in the organisations and people involved in food production (Roosen et al., 2009; Nocella et al., 2014). This makes risk communication and management more difficult for policy-makers and other stakeholders (Ding et al., 2013). Therefore, it is important to understand the reactions of consumers towards nanotechnology and the levels of trust they have in institutions who provide information on the technology before it is more widely used in the food industry. Knowing public views of, and the preferences for, new technology will also help design communication strategies, such as awareness campaigns and other public policy messages targeting different consumer segments. This is particularly relevant given the contentious history of previous technologies, such as genetic modification (Bennett and Radford, 2017). Indeed, some of the controversies relating to genetically modified foods include the effect of consuming such foods might have on health and the environment, the role of government regulators, the objectivity of scientific research, and whether or not such food should be labelled. These have affected consumers' purchasing behaviour, as found in a review by Costa-Font et al. (2008).

There are many factors influencing how consumers might respond to the use of new nanotechnologies. These include, *inter alia*, media coverage, personal experiences with earlier novel technologies, general underlying attitudes, beliefs, knowledge and preferences. Among these factors, the level of trust a person has in the food system (producers, processors, retailers) and in the regulatory process watching over it, is

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likely to be important. In the case of the introduction of new technologies, trust is considered to be one of the key constructs (Anderson et al., 2012; Roosen et al., 2015; Gupta et al., 2017). In particular, when consumer knowledge and experience of a new technology are limited, consumers may rely heavily on the advice provided by experts. This serves as a mechanism to reduce the complexity of judging the risks and benefits of the new technology (Siegrist and Cvetkovich, 2000; Gupta et al., 2017). On the other hand, the lack of trust in institutions could impact adoption of new technologies and generate political resistance to policies (Hobbs and Goddard, 2015).

This paper investigates UK consumers' perceived levels of trust in information sources regarding the use of nanotechnology in food production and packaging using the best-worst scaling (BWS) technique. Specifically, this paper explores how trust perceptions vary with consumers' characteristics and the extent to which consumers make consistent choices in relation to the institutions that they believe are trustworthy (i.e., choice variability). Analysing heterogeneity in trust perceptions combined with the consistency of choices has been largely overlooked in trust studies.

The research also contributes to the literature by providing new empirical evidence on consumers' perceived trust in information sources about the technology. Moreover, to date, studies investigating institutional trust have focussed on a relatively small number of sources of information. For example, Lang and Hallman (2005) investigate trust in ten institutions; Coveney et al. (2012) focus on five institutions; Roosen et al. (2009) and Bieberstein et al. (2010) study trust in three institutions; Anderson et al. (2012) look into governmental agencies and scientists only; and Macoubrie (2006) focus on only government and regulatory agencies. By extending the analysis to sixteen sources of information including a wide range of institutions and individuals in the food chain, the research provides unique insights into trust in a much broader context. In terms of the policy implications, the research provides insights into how best to develop communication strategies targeting certain consumer segments with the aim of improving their food safety and risk behaviour.

## 2. Trust in information sources

Trust has been defined in various ways in the literature. While there is no consensus on its definition, it is generally considered as a multifaceted concept and analysed with the dimensions or factors that influence it. For example, from a socio-psychological perspective, Lewis and Weigert (1985) and Bradbury et al. (1999) analysed trust within three dimensions (or attributes): cognitive, affective, and behavioural. The cognitive dimension “involves a choice based on a reasoning about the available evidence and is based on a degree of cognitive familiarity with the object of trust” (Bradbury et al., 1999, p. 118). The affective dimension of the trust involves an emotional bond between the truster and trustee, implying the existence of a perception that the trustee shares important values with the truster (Lewis and Weigert, 1985). Damage to this kin, therefore, weakens the relationship. The behavioural dimension involves actions taken under the belief that others also take similar actions. Cvetkovich (1999) calls this latter dimension “shared values” or “trustworthy behaviour”. Although these dimensions are analytically separate, they are combined in actual human experience (Bradbury et al., 1999). For example, someone's behavioural display of trust may build up cognitive and affective trust in another. Other dimensions most commonly identified in the literature centre on competence, objectivity, fairness, consistency, empathy, honesty, and openness (Renn and Levine, 1991). Trustworthiness is influenced by how these dimensions are perceived by individuals. For example, willingness to disclose information (i.e., openness) and fairness can be interpreted as a means of demonstrating concern and care for others and, as a result, could influence the perceived trustworthiness (Peters et al., 1997).

In addition to the mentioned dimensions, trust is commonly

classified into broader categories. These include trust in regulatory systems (sometimes termed as institutional trust), trust in other people (generalised trust), trust developed over time due to interactions and experience (relational trust), and trust based on a rational evaluation of benefits and costs of (in)actions of trustee (calculative trust) (Roosen et al., 2015; Ding et al., 2015).<sup>1</sup> Depending on the conceptual treatments of trust, various approaches can be used for the analysis. For example, Poppe and Kjærnes (2003) and Chryssochoidis et al. (2009) analysed trust with the factors influencing it, such as perceived institutional characteristics, information characteristics, risk characteristics, individuals' socio-cultural characteristics, and the existence of similar values or prior attitudes regarding risks. In contrast, others analysed trust with its role in risk perceptions (e.g., Siegrist and Cvetkovich, 2000; Viklund, 2003) and technology acceptance (e.g., Lang and Hallman, 2005; Anderson et al., 2012).

Studies investigating trust in information sources show variation in the context and information sources included in their analysis. The context has varied from technological risks, such as genetic modification (Frewer et al., 1996), and nanotechnology (Siegrist et al., 2008; Bieberstein et al., 2010), to environmental issues (Maeda and Miyahara, 2003; Brewer and Ley, 2013). The number of institutions included in these studies has varied from government institutions to friends and family. While a number of studies focussed on trust in government authorities only (e.g., Poortinga and Pidgeon, 2003; Coveney et al., 2012), some included various other information sources. For example, Maeda and Miyahara (2003) investigated trust in industry, government, and citizens' groups, Siegrist and Cvetkovich (2000) and Coveney et al. (2012) focussed on media, government, friends, food industry and scientists, and Priest et al. (2003) included ten institutions varying from media to environmental groups and farmers.

As nanotechnology is an emergent technology, there are only limited studies on consumers' trust in information sources (for example, Lee and Scheufele, 2006; Siegrist et al., 2008; Bieberstein et al., 2010; Capon et al., 2015; Roosen et al., 2015). The types and number of institutions included in these studies, as well as the country focus are varied. For example, Bieberstein et al. (2010) investigated trust in the food industry, science and research, and governmental organisations in Germany. Capon et al. (2015) studied trust in health department, scientists, journalists, and politicians in Australia. Anderson et al. (2012) investigated trust in scientists and government agencies in the USA, and Macoubrie (2006) focussed on trust in the US Government only.

## 3. Methodology

The means by which the trust in different information sources is elicited and analysed in this paper differs from past trust analyses. Trust studies typically involve asking respondents multiple statements, such as ‘to what extent the following source can be trusted[...]’, on a Likert-type scale (e.g., strongly agree to strongly disagree). The responses to these statements are then analysed using descriptive statistical methods (e.g., finding mean scores or frequencies) (e.g., Viklund, 2003; Nocella et al., 2010) or factor analytic and principal components approaches (e.g., Bieberstein et al., 2010; Hartmann et al., 2015). The descriptive methods used in the trust studies generally involve calculating the mean of ‘trust’ rating scores respondents assign to each institution. Whereas, the factor analytic or principal component analysis approaches examine the pattern of correlations (or covariances) between the observed measures (e.g., rating responses to various statements) to explain the underlying constructs influencing the responses. In this

<sup>1</sup> An overview of different conceptual treatments of trust can be found in Hobbs and Goddard (2015), which is published in a special issue focussing on consumers and trust in this Journal.

**Table 1**  
Institutions used in the study.

Government institutions
Department for Environment, Food and Rural Affairs (Defra)
Food Standards Agency (FSA)
Department of Health (DoH)
Scientists
Food industry scientists
University scientists
Non-governmental organisations (NGOs)
Consumer organisations (e.g. Which?, National Consumer Federation, etc.)
Environmental groups (e.g. Greenpeace, Friends of the Earth, etc.)
Food handlers
Farmers/Growers
Supermarkets
High street butchers
Food manufacturers/processors
Media
TV/Radio: news programmes
TV/Radio: food and cooking programmes
Newspapers
Food magazines (e.g., Good Food magazine, Sainsbury's and Tesco's magazines)
Friends and family
Friends and family

study, we use the best-worst scaling (BWS) technique to elicit consumers' trust in sixteen institutions and people of information (see Table 1).<sup>2</sup>

The BWS technique involves asking respondents to identify an institution that they consider to be the 'most' trustworthy, and another institution that they consider is the 'least' trustworthy from a subset of information sources. They make repetitive choices from different subsets presented to them. The pair of institutions chosen in a set is the one which shows the maximum difference in the perceived level of trust.<sup>3</sup> The BWS technique has been found to give a better predictive performance (Rasmussen, 2009) and a better discrimination among items in terms of their underlying features, such as importance and trustworthiness, as compared to rating scales (Cohen and Orme, 2004). This has prompted us to consider this technique in this paper. More about the technique can be found in Erdem and Rigby (2013).

### 3.1. Survey design

The sixteen institutions that we are investigating in the BWS survey were chosen as a result of comprehensive literature review and expert opinion in the field. The reasons for having a diverse range of institutions were, *inter alia*: (i) to give a broader context and better understanding into consumers' trust in institutions involved in the entire food chain; (ii) to investigate whether there are any systematic differences in the level of trust consumers had in various subgroups (e.g., university vs. food industry scientists); (iii) to shed light into consumers' trust in, so far, under explored institutions (e.g., supermarkets), especially those involved in food scares in the past (e.g., butchers); and, (iv) to provide policy-makers with insights on the design of targeted policy and communication strategies for novel foods and technologies.

The BWS experimental design comprised of 300 versions (assigned randomly) so as to avoid any context and ordering-based biases. Each version included eight best-worst tasks. Each task included five institutions from which respondents were asked to identify one institution that they considered to be the most, and another institution that they

considered to be the least trustworthy.<sup>4</sup> The combination of five institutions in each choice set satisfies the optimal design characteristics: frequency balance, positional balance, orthogonality, and connectivity among tasks.<sup>5</sup> After ensuring a balanced design, best-worst tasks were randomised in each version, and respondents were assigned to each version randomly. An example of a BWS task is given in Fig. 1.

Before presenting the best-worst tasks in the survey, we asked all respondents whether or not they had heard about nanotechnology. We then explained the technology using a visual aid that described the relative nano size using familiar everyday objects (e.g., football). We also provided each respondent with information on the potential benefits and uncertainties of the technology, and brief information on the regulatory procedure in the UK for this technology. It was intentional to ask questions to ascertain respondent's knowledge about nanotechnology first, and to subsequently provide some basic information on the technology. Our piloting showed that respondents were unfamiliar with this relatively new technology, and therefore, providing information on the technology was necessary for respondents to be able to answer the best-worst questions. Importantly, every step was taken to ensure that this information on the potential benefits and uncertainties of the technology was accurate and balanced so as to avoid any biases in respondent's answers. The details of the supplementary materials are presented in the Appendix.

### 3.2. Analysis of trust

We analyse perceptions of trust in a number of institutions using choice models based on the random utility maximisation theory (Thurstone, 1927; Manski, 1977). At each BWS task, respondents identify a pair of institutions reflecting the maximum difference in trustworthiness (i.e., most and least trustworthy) from presented subset. In the choice model, it is assumed that an individual's underlying level of trust in institutions cannot be observed with certainty. All we observe are the choices made, which may include some inconsistencies across repeated choices because of, *inter alia*, limited cognitive ability, lack of attention, or changing preferences (Swait and Marley, 2013). Such uncertainty in the level of 'trust' can be accommodated by adding a stochastic component to the deterministic element of the model that drives individuals' choices. The model can be expressed as follows:

$$U_{int} = \beta X_{int} + \varepsilon_{int}, \quad (1)$$

where  $U_{int}$  is the level of trust individual  $i$  associates with the chosen pair of institutions  $n$  from  $J$  possible pairs;  $\beta$  is a vector of coefficients relating to the level of trust;  $X$  is a matrix denoting the characteristics of the pair of institutions chosen in choice occasion  $t$ ; and,  $\varepsilon_{int}$  is the stochastic component.<sup>6</sup>

In order to explore how the perceived trust varies across different consumer segments, we use a latent class (LC) modelling approach. The underlying theory of the LC model posits that individuals' choice behaviour depends on both observable attributes and unobserved latent heterogeneity. Individuals are allocated into a set of  $Q$  classes, which are not observable by the analyst. Consumers within each class are assumed to share the same level of trust, but differences exist between classes.

In addition to the heterogeneity in perceptions of trust, the model also accommodates for differences in choice variability. Choice

<sup>4</sup> Cohen and Orme (2004) suggest the gains in precision of the estimates are minimal when using more than five items in a choice set. Moreover, presenting a large number of items in a choice set may result in confusion and fatigue, which may in turn result in anomalous decision-making.

<sup>5</sup> More details on the BWS experimental design can be found in Campbell and Erdem (2015).

<sup>6</sup> As we presented five institutions at each BWS task, there are 20 combinations of best/worst pairs an individual can choose from in each BWS task.

<sup>2</sup> In the paper, we refer to these different groups as 'institutions'.

<sup>3</sup> The level of trust is elicited using consumers' perceptions, and thus present their beliefs rather than actual measures for the trust in institutions.

Consider the five organisations/people shown below. Please indicate which of the five you:

- Trust **MOST** to provide accurate information about nanotechnology and its use in food production and packaging
- Trust **LEAST** to provide accurate information about nanotechnology and its use in food production and packaging

Trust <b>most</b> on nanotechnology		Trust <b>least</b> on nano-technology
<input type="radio"/>	TV/radio: news programmes	<input type="radio"/>
<input type="radio"/>	Farmers/growers	<input type="radio"/>
<input type="radio"/>	Food manufacturers/processors	<input type="radio"/>
<input type="radio"/>	Food industry scientists	<input type="radio"/>
<input type="radio"/>	Newspapers	<input type="radio"/>

Fig. 1. Sample best-worst scaling task.

variability refers to how (in) consistent individuals are in their overall choices of ‘most’ and ‘least’ trustworthy institutions. Such variability in choices can be due to various factors, including uncertainty or confusion (Burke et al., 2010). For example, some respondents may be less certain about who can provide the most accurate information about nanotechnology or the technology itself. This model taking into account both heterogeneity of trust perceptions and choice variability is called the scale-adjusted latent class model (SALCM) proposed by Vermunt and Magidson (2005).

In this model, we investigate the choice variability via a scale parameter ( $\lambda$ ). This scale is related to the error term and reflects any non-deterministic behaviour from the viewpoint of researchers. It is inversely related to the standard deviation of the error term:  $\text{var}(\epsilon_{itn}) = \pi^2/6\lambda^2$ , where  $\pi$  is approximately equal to 3.14. This scale parameter is typically set to 1, but when it is believed that there are differences in respondents’ choice consistency or variation, it is better to estimate it. Similar interpretations of the scale parameter have been also made in the literature, for example in Burke et al. (2010), Magidson and Vermunt (2007), Campbell et al. (2011), Erdem and Thompson (2014), and Campbell et al. (2018). It has been highlighted that failing to account for differences in choice variability can lead to biased and incorrect results (Louviere, 2001; Magidson and Vermunt, 2007). For example, two consumer segments might exhibit different preferences for a product, but the observed differences may simply be due to the differences in how consistent the choices revealing preferences are made in each segment. Another reason for accommodating for differences in scales is to accommodate for the potential confounding between perceptions of trust and the variability or consistency in consumer choices, as suggested by Fiebig et al. (2010), Magidson and Vermunt (2007), and Louviere and Eagle (2006). However, we recognise that it is very difficult to separate scale heterogeneity from preference heterogeneity (see Hess and Train, 2017, for a recent discussion).

In the SALCM, the probability of pair  $n$  (among  $J$  alternatives) being chosen by individual  $i$  in choice occasion  $t$ , conditioning on preference class  $q$  and scale factor class  $s$  is:

$$P(itn|q,s) = \frac{\exp(\lambda_s \beta_q X_{it,n})}{\sum_{j=1}^{J=20} \exp(\lambda_s \beta_q X_{it,j})} \tag{2}$$

where  $\beta_q$  is a class-specific vector of coefficients and  $\lambda_s$  is a class-specific scale parameter that needs to be estimated. Again we use the scale parameter as a way of understanding choice variation or consistency, as described above. As individuals make a series of choices, the contribution of individual  $i$  to the likelihood function is the joint probability of the sequence of choices:  $\prod_{t=1}^{T=8} P_{itn|q,s}$ .

The class assignment of the individuals is not known to the analyst. However, following Swait (1994) and Boxall and Adamowicz (2002), an unobservable or latent membership likelihood function can be used

to classify individuals into one of the  $Q$  classes. The classification variables used in segmentations can be related to individuals’ characteristics, such as age and gender. We can then calculate the unconditional probability of membership in class  $q$  as the following:

$$P(q|c_q, \gamma_q, Z_i) = \frac{\exp(c_q + \gamma_q Z_i)}{\sum_{q=1}^Q \exp(c_q + \gamma_q Z_i)} \tag{3}$$

where  $c_q$  is a class-specific constant,  $Z_i$  is a vector of individuals’ characteristics (e.g., gender), and  $\gamma_q$  is a vector of parameters to be estimated. Replacing the  $q$  subscripts in Eq. (3) with  $s$  subscripts provides the equivalent unconditional probability expression for the scale classes.

Accounting for differences in preferences and choice variability (i.e., scale), the overall choice probability of the sequence of choices made by individual  $i$  can be expressed as the following:

$$P_i = \sum_{q=1}^Q P_q \sum_{s=1}^S P_s \left( \prod_{t=1}^{T=8} \frac{\exp(\lambda_s \beta_q X_{it,n})}{\sum_{j=1}^{J=20} \exp(\lambda_s \beta_q X_{it,j})} \right) \tag{4}$$

where  $P_s$  is the scale membership probability within a class  $s$ ,  $\lambda_s$  is scale parameter in scale-class  $s$ , and  $P_q$  is the class probability for trust perceptions. We normalised  $\lambda_1$  to 1 for identification purposes and estimated  $s-1$  scale-class specific  $\lambda$ ’s.

This model allows us to explain individuals’ perceptions of trust from their choice data and simultaneously show how their characteristics, such as gender, influence class membership. We then maximise the log-likelihood function,  $LL = \sum_{i=1}^{N=613} \ln P_i$ , with respect to the parameters to be estimated (i.e.,  $\beta_q, \lambda_s$ , and latent class unconditional probabilities) via Maximum Likelihood estimation, where  $N$  is the number of individuals. The analysis was performed using Latent GOLD Syntax version 4.5 (Vermunt and Magidson, 2015).

In order to make the interpretation of the estimated trust coefficients more intuitive and quantitatively comparable across  $q$  and  $s$  classes, we convert them to ratio-scaled probabilities that sum to 100, similar to Campbell and Erdem (2015). For institution  $k$  in class  $q$  and  $s$ , the conversion to a 0–100 point ratio scale is achieved as follows:

$$\Pr(x_k | q, s) = \left( \frac{\exp(\lambda_s \beta_{kq})}{\exp(\lambda_s \beta_{kq}) + L - 1} \right) \bigg/ \left( \sum_{k=1}^K \frac{\exp(\lambda_s \beta_{kq})}{\exp(\lambda_s \beta_{kq}) + L - 1} \right) \times 100, \tag{5}$$

where  $\beta_{kq}$  are zero-centred raw trust scores within each  $q$  class,  $L$  is the number of items shown per choice task, and  $k$  is the institutions. By doing so, we can say that an information source with a ratio-scaled score of 20 (out of 100) is twice as trustworthy as an information source with a score of 10. One can also treat these probabilities as ‘levels of trust’. As we have  $S$  subgroups having a different level of choice variability (scale) in each class, we need to multiply Eq. (5) by the sizes of the subgroups to find the ‘weighted’ levels of trust, which we refer to as scale-adjusted levels of trust.

### 3.3. Data collection and sample

A web-based best-worst scaling survey was administered to a sample of 613 consumers in the UK in 2010.<sup>7</sup> The respondents were recruited using a survey research company, who is compliant with ESOMAR regulations.<sup>8</sup> The characteristics of our survey respondents are presented in Table 2.

Half of the respondents were male, 37% were in full-time employment and 45% had education until at least 18 years-old (i.e., secondary and high school education). The average age was 42 years old and the median annual household income was just over £21,000. A comparison with the 2011 UK census data shows that the respondents in our study were similar to the general population with respect to age, gender, occupation, and employment status. Among the respondents, 40% of them had not heard about nanotechnology previously, which is similar to the level of knowledge in some other studies, such as Cobb and Macoubrie (2004), Vandermoere et al. (2010), and Capon et al. (2015).<sup>9</sup> Each of 613 respondents answered eight best-worst tasks, resulting in 4904 choice tasks (i.e., observations) for model estimation.<sup>10</sup>

## 4. Results

As part of our exploratory investigation, we analysed the choice data using latent class models with up to five classes for consumer perceptions, with and without accommodating for heterogeneity in standard deviation of utility over different choice situations (i.e., choice variability or consistency) across individuals. All models utilise effects-coding in which all coefficients sum to zero. The LC models accommodating for scale attain superior fits as compared to standard multinomial logit model (MNL).<sup>11</sup> Besides, the MNL model assumes that all consumers share the same perception of trust and exhibit the same degree of variability in their choices. As this is not realistic and the model did not perform as well as the LC model, we do not focus on the MNL model in the paper.<sup>12</sup> As for the selection of the best LC model explaining consumers' perceptions of trust, we observed that the model with three consumer perception classes and two choice variability classes was the best candidate. This was established using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are commonly used for model selection (Boxall and Adamowicz, 2002; Greene and Hensher, 2003). Therefore, we will focus on this model in this paper.

### 4.1. Estimation results

The results of our analysis are presented in Table 3. According to the results, we observe differences in choice consistency among subsets of respondents, which we called 'choice variability' earlier. This is denoted by the significant scale parameter,  $\lambda_2$ . We observe two subgroups within each latent class showing differences in the choice variability: one that accounts for the majority of consumers (75%) who have made relatively

<sup>7</sup> We recognise that consumer perceptions might have changed since the data collection. In fact, this is an issue in any consumer research investigating perceptions. Some factors could potentially influence this, such as news in the media, availability of nanofoods at the market, or whether the government makes a critical announcement about the technology. In the UK, none of these have happened since 2010. Thus, our research questions are still relevant as nanotechnology is still categorised as a novel technology by the FSA.

<sup>8</sup> See <http://esomar.org> for further details on the ESOMAR regulations.

<sup>9</sup> In these studies, the proportion of participants that heard nothing about nanotechnology were 52%, 40%, and 30%, respectively.

<sup>10</sup> More about the study can be found in Campbell and Erdem (2015).

<sup>11</sup> The improvement in model fit is measured by an increase in log-likelihood value and decreases in AIC and BIC values. We find that the scale-adjusted LC model had a higher log-likelihood value (by 1100 units) and lower AIC (by 2138) and BIC (by 1889) values, as compared to a standard MNL model. Thus, there is little statistical support for the MNL model.

<sup>12</sup> The MNL results are available upon request from the author.

**Table 2**

Characteristics of survey respondents.

	Sample (2010)	UK Census (2011)
Male	50%	49%
Age (in years)	42	39
Median annual income (£)	£21,400	£26,200
Occupation		
Student	9%	9%
Full-time employed	37%	38%
Part-time employed	13%	14%
Unemployed	22%	15%
Self-employed	3%	10%
Retired	15%	14%
Education		
No qualification	8%	23%
Secondary	21%	29%
High School	24%	12%
Degree (MSc, PhD)	32%	27%
Vocational	16%	9%
How much have you heard about nanotechnology?		
Heard a lot	9%	
Heard some	22%	
Heard little	29%	
Nothing at all	38%	
Not sure	2%	

consistent choices (i.e., smaller variance); and another subgroup (25%) whose choices were associated with almost 69 times more variance (i.e.,  $\lambda_1^2 / \lambda_2^2 = 1 / 0.12^2 = 69$ ). The trust coefficients presented in Table 3 are for the first subgroup whose scale is fixed at 1 for identification purposes. For those presenting high choice variability, the trust coefficients can be obtained by multiplying by the scale belonging to this group (i.e.,  $\lambda_2$ ).<sup>13</sup>

Looking at Table 3, we see that consumers perceive the sixteen information sources differently and allocate different levels of trust towards them. This is not surprising, given the current evidence in the literature (e.g., Nocella et al., 2014). Some of these differences could also be due to different error variances (scales) over different choice situations that we found in our analysis. More specifically, we find three consumer segments, each having different perceptions of trust, and two subgroups within each segment having different choice variability.

All else being equal, Class-1 accounts for almost half of the sample (49%), Class-2 accounts for 30%, and Class-3 accounts for 21% of the sample. In terms of the characteristics of these classes, we observe that gender, age, employment and education all have an effect on the class membership probabilities.<sup>14</sup> With respect to gender, we observe that consumers in Class-1 are more likely to be female, however, differences in the likelihood of gender composition of Class-2 and Class-3 are not statistically significant. This implies that while trust is important for the evaluation of nanotechnology, females and males assign different levels of trust to institutions. These gender differences in perceptions have also been found in other studies, such as Buchan et al. (2008), Bieberstein et al. (2010) and Vandermoere et al. (2010). In regards to education level, we see that Class-1 is more likely to be comprised of consumers who have acquired up-to a high school degree, whereas Class-2 is more likely to be made up of those with a higher level of education. Education levels are not a significant determinant for the smallest consumer segment, Class-3. As for the age categories of these classes, Class-1 is more likely to include consumers who are aged less

<sup>13</sup> Multiplication of the estimates with a constant does not change the relative interpretation of the estimates.

<sup>14</sup> We note that the model included other socio-economic characteristics, such as employment status, income, ethnicity, and occupation. However, they were not significant in explaining the class membership. For this reason, we do not include them here. Due to the endogeneity issue, we did not include responses to attitudinal questions.

**Table 3**  
Estimation results of the scale-adjusted latent class model.

Institutions	Class-1 (49%)			Class-2 (30%)			Class-3 (21%)		
	Coeff.	St. er.	Scale adjusted level of trust (%)	Coeff.	St. er.	Scale adjusted level of trust (%)	Coeff.	St. er.	Scale adjusted level of trust (%)
<i>Government institutions</i>									
Defra	2.18**	0.12	13.14	1.92***	0.18	11.88	0.82***	0.26	8.39
FSA	2.85***	0.12	15.23	3.18***	0.19	15.73	0.87***	0.28	8.59
DoH	2.14***	0.12	12.98	2.44***	0.17	13.75	0.39**	0.26	6.61
<i>Scientists</i>									
Food industry scientists	2.14***	0.12	12.96	1.39***	0.18	9.75	-0.73***	0.20	3.43
University scientists	1.61***	0.11	10.86	1.71***	0.16	11.05	1.29***	0.22	10.56
<i>Non-governmental organisations</i>									
Consumer organisations	0.52***	0.12	6.44	1.96***	0.19	12.03	1.96***	0.22	13.67
Environmental groups	-0.82***	0.16	3.05	-0.92***	0.29	2.86	1.80***	0.23	12.95
<i>Food handlers</i>									
Food manufacturers/processors	-0.33**	0.16	3.97	-2.13***	0.15	1.71	-2.51***	0.24	1.58
Farmers/Growers	0.07*	0.11	4.99	-1.43***	0.17	2.25	0.31**	0.22	6.27
Supermarkets	-1.33**	0.10	2.38	-1.81***	0.14	1.92	-1.87***	0.21	1.98
High street butchers	-0.54**	0.15	3.51	-1.76***	0.18	1.96	0.32**	0.22	6.27
<i>Media</i>									
TV/Radio: news programmes	-1.53**	0.11	2.16	-0.33**	0.16	3.92	-0.37**	0.21	4.21
TV/Radio: food and cooking programmes	-1.36**	0.11	2.33	-0.57***	0.14	3.43	-0.43***	0.19	4.08
Newspapers	-2.60***	0.12	1.49	-1.45***	0.18	2.23	-1.29***	0.20	2.56
Food magazines	-1.12**	0.10	0.10	-0.54***	0.14	3.49	-0.35**	0.14	4.23
<i>Friends and family</i>									
Friends and family	-1.86***	0.11	1.90	-1.66***	0.15	2.04	-0.21*	0.24	4.60
<i>Class membership</i>									
Intercept	0.44**	0.19		-0.24**	0.23		-0.20*	0.19	
Male (= 1, yes)	-0.50**	0.16		0.28*	0.18		0.21*	0.17	
Have at least high school degree (= 1, yes)	-0.30**	0.15		0.31**	0.17		-0.01*	0.17	
Less than 30 years old (= 1, yes)	0.58***	0.13		-0.19*	0.15		-0.39**	0.16	
Between 30 and 60 years old (= 1, yes)	-0.27**	0.14		0.26**	0.15		0.02*	0.16	
Over 60 years old (= 1, yes)	-0.31***	0.11		-0.06*	0.12		0.37***	0.12	
Log-likelihood									
Scale, $\lambda_e$									
Number of respondents									

$\lambda_1 = 1$  (75%),  $\lambda_2 = 0.12$  (25%) s.e = 0.03  
- 11327.93

613

Coefficients are effects-coded (i.e., they sum to 0), rather than dummy-coded with a baseline category.

Insignificant class membership variables (i.e., employment status, income, ethnicity, and occupation) are not shown for space considerations.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

than 30 years, Class-2 is more likely to be comprised of consumers aged between 30 and 60 years, and Class-3 is more likely to include consumers aged over 60 years.

In terms of trust perceptions, in general, all consumers in all three classes regard government institutions (i.e., Defra, FSA, and DoH), university scientists and consumer organisations trustworthy about providing accurate information on nanotechnology, as indicated by the significant and positive coefficients. As [Nocella et al. \(2014\)](#) also found in their trust analysis, consumers tend to have more trust in information sources that are closer to the 'public' interest or at least not bringing vested interests. On the other hand, consumers perceive food manufacturers/growers, supermarkets, media outlets and friends and family untrustworthy, as seen from the significant and negative coefficients. This is most likely to be related to 'relational' and 'calculative' trust that we discussed in Section 2.

Despite the similarities between the three perception classes, there are some significant differences in trust perceptions towards four institutions, namely, food industry scientists, environmental groups, farmers/growers, and high street butchers. While consumers in Class-1 and Class-2 regard both food and university scientists trustworthy, the smallest consumer segment, Class-3, consider only university scientists trustworthy. Class-3 also differs from the other two consumer segments in the way that they perceive environmental groups, farmers/growers and high street butchers trustworthy. This is apparent from the positive and significant coefficient for these two institutions in Class-3, as opposed to that observed in the other two classes.

According to scale-adjusted probabilities, we find that, on average, Class-1 and Class-2 allocate nearly twice as much trust to the three government institutions (c.42%) compared to Class-3 (c.24%). Of these government institutions, FSA is, relatively speaking, regarded as a more trustworthy source than Defra and DoH in all three consumer segments. High trust in government institutions contradicts with findings from some other studies, including [Lang and Hallman \(2005\)](#) and [Bieberstein et al. \(2010\)](#). However, [Macoubrie \(2006\)](#) and [Krishna and Qaim \(2008\)](#) argue that trust in government institutions depends on information about their role in nano-production. Such differences in findings are not surprising and might be due to a number of reasons. These include cultural differences, the level of knowledge, information individuals receive on the technology and its long-term health effects, the role of government in regulating the use of nanotechnology in food industry, as well as how government institutions are perceived by consumers (e.g., transparent, competent, benevolence).

We also remark that both university (10.86%) and food industry scientists (12.96%) are perceived to be as highly trustworthy as government institutions (c.13–15%) in the largest consumer segment, Class-1. This is, however, different for other segments: Class-2 regards only university scientists (11.05%) and consumer organisations (12.03%) on a par with government institutions (c.12–16%), whereas Class-3 find university scientists (10.56%), consumer (13.67%) and environmental (12.95%) organisations more trustworthy than government institutions (c.7–9%). Consumers in all classes trust consumer organisations more than environmental organisation. The difference in perceived trust between these two organisations is more apparent particularly in Class-2 (12.03% vs 2.86%) compared to Class-1 (6.44% vs 3.05) and Class-3 (13.67% vs 12.95%). As can be seen, Class-3 allocates approximately four times more trust to the environmental groups (12.95%) as compared to Class-1 (3.05%) and Class-2 (2.86%).

Another interesting comparison concerns how consumers perceive food handlers. While differences between the level of trust allocated to four food handlers are quite small in Class-1 and Class-2, they are more prominent in Class-3. Specifically, farmers/growers (6.27%) and high street butchers (6.27%) in Class-3 are perceived to be approximately three times more trustworthy than food manufacturers/processors (1.58%) and supermarkets (1.98%) in the same class. A similar finding regarding consumers' high trust in farmers was found in a study by [Henderson et al. \(2011\)](#). They considered this finding might be due to

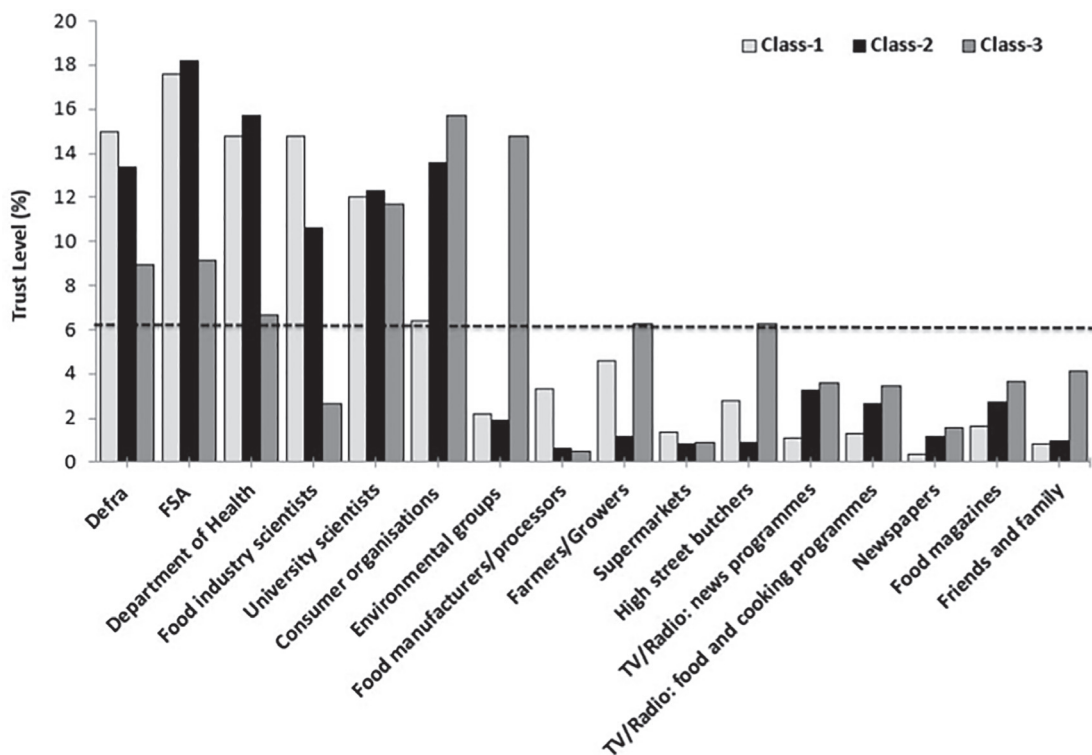
the result of lower levels of food importation alongside of limited exposure to food scares in an Australian context. Such differences in perceived levels of trust in food handlers is found to be quite small in the other two consumer classes.

The results also show that in the context of providing accurate information about the technology, the media attains relatively low levels of trust. This is especially prominent in Class-1 where the smallest trust share is 0.10% allocated to food magazines, and the highest is around 2.33% allocated to tv/radio, which is on a par with supermarkets (2.38%) in the same class. Such low levels of trust in media is consistent with other studies investigating trust in nanotechnology ([Capon et al., 2015](#)) and other technological risks, such as genetic engineering of food and cloning ([Hunt and Frewer, 2001](#); [Lang and Hallman, 2005](#)). Class-2 and Class-3, on the other hand, perceive media outlets relatively more trustworthy relative to Class-1 does. As for friends and family, Class-3 (4.60%) attains at least twice as much trust as Class-1 (1.90%) and Class-2 (2.04%) present. The relatively high trust in friends and family in Class-3 might be explained by their low sensitivity to risk perception and reliance on their social network, as also found in [Mazzocchi et al. \(2008\)](#).

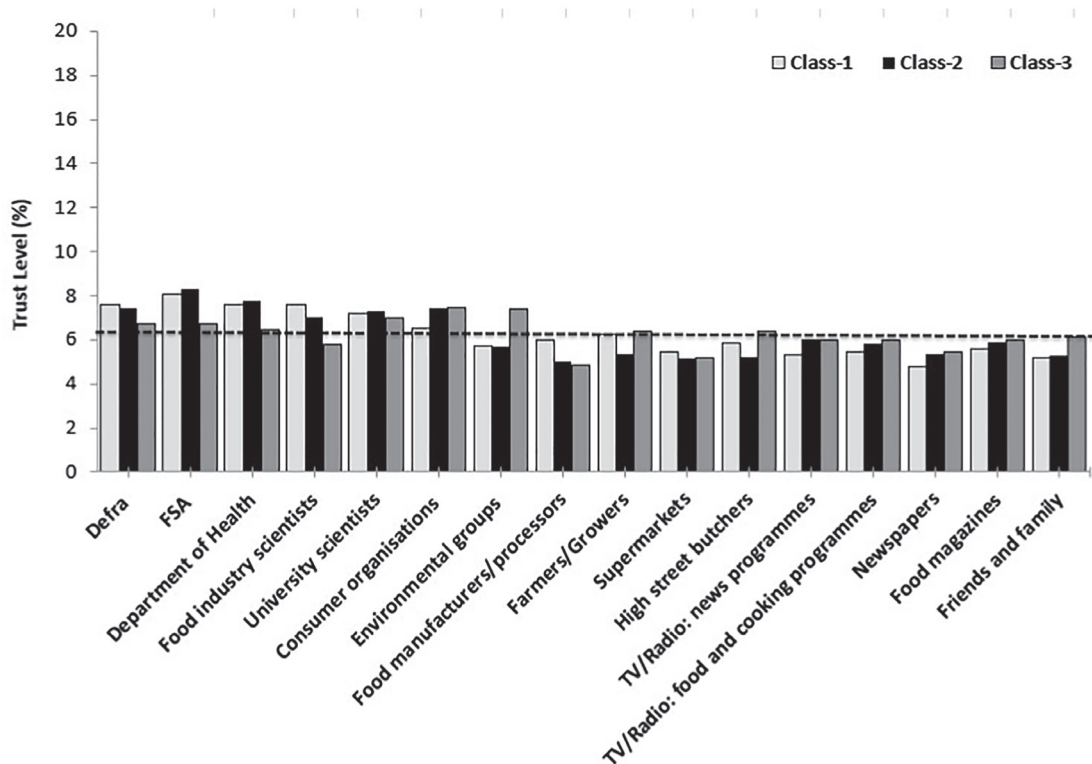
In addition to the weighted trust levels presented in [Table 3](#), we also plot the unconditional distribution of level of trust for two consumer subgroups presenting different choice variability in [Fig. 2](#). The dotted lines on the plots present a level when all sources were assumed to be equally trustworthy (i.e.,  $100/16 = 6.25\%$ ). The top figure, [Fig. 2\(a\)](#), presents the trust allocation for consumers who are more consistent in their choices in best-worst tasks (i.e., low variance or higher scale,  $\lambda_1 = 1$ ). The bottom figure, [Fig. 2\(b\)](#), on the other hand, presents trust shares allocated by consumers making less consistent choices (i.e., high variance or low scale,  $\lambda_2 = 0.12$ ). When respondents make less consistent choices, we see that the level of trust in all institutions become similar. Such choice behaviour might be due to various reasons, such as unfamiliarity with the subject or inattention to the survey questions (e.g., [Carlsson, 2011](#); [Malone and Lusk, 2018](#)). While these could lead to random, and thus inconsistent choices as shown in [Fig. 2\(b\)](#), it may also be the case where participants had genuinely equal levels of trust in these institutions. This highlights the issue of confounding between such choice behaviour and perception heterogeneity. However, when consumers make consistent choices, the level of trust allocated to institutions become more differentiated and follow a pattern as shown in [Fig. 2\(a\)](#), which is aligned with the scale-adjusted level of trust mentioned earlier in this section. As the study was not designed to identify the reasons behind inconsistent choices, we cannot say that inconsistent choices were made randomly. Further research is needed to explain the reasons behind such behaviour. Finding different patterns of trust distributions emphasises the importance of taking into account choice variability when analysing perceptions of trust.

## 5. Policy implications

It is important for policy-makers and other stakeholders in the food chain to understand consumers' views on nanotechnology and whom they perceive trustworthy regarding providing accurate information about this new technology. Having such insights would help policy-makers address any controversies associated with this technology before it is widely used in the food production and packaging. As observed in previous food technologies, such as genetic modification, controversies relating to a new technology can influence consumers' purchasing and consumption behaviour. In turn, this might influence the future of the technology in the market. For example, one possible situation would be where consumers doubt information relating the technology unless the information comes from a source that they deem trustworthy. In such cases, the most feasible thing to do is to provide accurate and balanced information to consumers via the source that they trust and more likely to engage with. This is also relevant in cases where consumers have unsafe food handling practices resulting in



(a) (For consumers with more certain choices,  $\lambda_1=1$ )



(b) (For consumers with less certain choices,  $\lambda_2=0.12$ )

Fig. 2. Unconditional distribution of level of ‘trust’ (%).

foodborne cases. For example, in the cases where nanotechnology is used in food packaging to extend the shelf-life of food products, consumers might underestimate their role in ensuring food safety and put all responsibility on the technology, rather than on their food handling

practices. Such behaviour might also result in foodborne cases due to mishandling of foods. As a result, it is important to inform consumers about the use of the technology and expectations in terms of safe food handling. As it is important to accommodate different consumer groups



in public policy messages (Mazzocchi et al., 2008; Ding et al., 2015), how to deliver such messages to different segments of consumers are equally important, as we found in this research. One way to deliver public health messages is via a trusting source. However, as we find in this study, not all consumers perceive institutions equally trustworthy. Thus, it is important to involve different institutions and individuals in the food chain in communication strategies relating to nanotechnologies. Doing so means that public policy messaging will be effective in reaching different consumer groups.

Indeed, although our results reveal that the majority of the participants trust the government institutions the most, there is a minority group (that is made up of older consumers) who find university scientists, NGOs, farmers, butchers, and friends and family more trustworthy compared to government institutions. Results from this study signal that communication strategies targeting different consumer groups is likely to be more effective when the information is delivered via the sources consumers regarded the most trustworthy. Such targeted approaches are expected to increase awareness and decrease ambiguity among different consumer groups about the technology. This might then lead to better informed choices and safer practices regarding the new technology and, ultimately, could influence the acceptance of the technology among consumers. Targeted approaches and tailored communication strategies could also be useful in situations where information campaigns involve changing risky food handling behaviours, such as the “don’t wash raw chicken” campaign and ‘use by’ date campaigns in the UK.<sup>15</sup> The use by date campaign targeted high risk group people (i.e., people over 60 years of age) to reduce the risk of food poisoning from listeria. The Food Standards Agency worked with general practitioners, pharmacies and a range of community groups across the UK, especially in areas with large populations of older adults, to raise the awareness of the risks of getting Listeria, importance of ‘use by’ date, and safe food storage conditions. Our findings can be utilised to design similar information campaigns regarding the use technology, such as smart packages and safe food handling practices among certain consumer groups.

## 6. Concluding remarks

This paper investigates UK consumers’ trust in sixteen institutions who may provide information about the use of nanotechnology in food production and packaging. It aims to identify differences in consumers’ perceived trust and distinguish the degree of consistency in their choices. By doing so, it contributes to the empirical literature in two main ways: (i) by investigating trust in a large number of institutions, some of which were overlooked in the previous literature, and (ii) by explaining how the perception of trust in sixteen institutions varies with individuals’ characteristics and choice variability or consistency.

Using a latent class modelling approach, we identified three different consumer groups, each of which was composed of two subgroups in terms of the level of variation in their choices. The first consumer group made up the majority of the sample (49%) and were more likely to be younger, female and to have attained higher than a high school education. This group perceived government institutions and scientists to be the most likely to provide trustworthy information on nanotechnology. While Class 2 (30%) also considered government institutions and scientists as highly trustworthy, they also deemed consumer organisations as equally trustworthy. This group was found to be comprised of consumers who acquired less than a high school education and aged between 30 and 60 years. The smallest consumer group (21%), however, was observed to be more likely to be aged over 60 years and to place least trust in government institutions. Instead, they regarded university scientists, NGOs, farmers, butchers, media,

and friends and family relatively more trustworthy.

Our research also identifies areas for future research. As with all empirical trust studies, the results are a product of, and limited by, the institutions included, and those excluded. The number of institutions used in the survey design was bound by the need to make the choice tasks intuitive and cognitively manageable for the general public. While more tasks offer the prospect of more efficient trust estimates, this must be balanced with the increased risk of choice inconsistency due to increased task complexity, fatigue and associated imprecision in estimation. We recommend researchers to extend this line of research to investigate the underlying reasons for inconsistent choices. Another extension of this research should investigate whether individuals perceive an institution trustworthy due to the dimensions of trust relevant to the context, such as perceived competence and transparency. Despite these limitations and the need for further research, our findings provide insight into the development of best practices and policies in risk communication and management for novel foods produced by nanotechnologies and have policy implications.

## Declarations of interest

None.

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## Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.foodpol.2018.04.008>.

## References

- Anderson, A.A., Scheufele, D.A., Brossard, D., Corley, E.A., 2012. The role of media and deference to scientific authority in cultivating trust in sources of information about emerging technologies. *Int. J. Public Opin. Res.* 24, 225–237.
- Bennett, D., Radford, T., 2017. Public perceptions of nanotechnologies: lessons from genetically modified foods. *Nanotechnol. Food* 60–80.
- Bieberstein, A., Vandermoere, F., Roosen, J., Blanchemanche, S., Marette, S., 2010. Revisiting social trust with regard to gendered perception of new food technologies: the case of nanofood. In: 1st Joint EAAE/AEAE Seminar: The Economics of Food, Food Choice and Health, Munich, Germany.
- Boxall, P.C., Adamowicz, W.L., 2002. Understanding heterogeneous preferences in random utility models: a latent class approach. *Environ. Resour. Econ.* 23 (4), 421–446.
- Bradbury, J.A., Branch, K.M., Focht, W., Lofstedt, R.E., Cvetkovich, G., 1999. Trust and Public Participation in Risk Policy Issues. Technical Report. Pacific Northwest National Laboratory (PNNL), Richland, WA (US).
- Brewer, P.R., Ley, B.L., 2013. Whose science do you believe? Explaining trust in sources of scientific information about the environment. *Sci. Commun.* 35 (1), 115–137.
- Buchan, N.R., Croson, R.T., Solnick, S., 2008. Trust and gender: an examination of behavior and beliefs in the investment game. *J. Econ. Behav. Organ.* 68 (3–4), 466–476.
- Burke, P.F., Burton, C., Huybers, T., Islam, T., Louviere, J.J., Wise, C., 2010. The scale-adjusted latent class model: application to museum visitation. *Tourism Anal.* 15 (2), 147–165.
- Campbell, D., Erdem, S., 2015. Position bias in best-worst scaling surveys: a case study on trust in institutions. *Am. J. Agric. Econ.* 97, 526–545. < <http://ajae.oxfordjournals.org/content/early/2015/01/20/ajae.aau112.abstract> > .
- Campbell, D., Hensher, D.A., Scarpa, R., 2011. Non-attendance to attributes in environmental choice analysis: a latent class specification. *J. Environ. Planning Manage.* 54 (8), 1061–1076.
- Campbell, D., Mørkbak, M.R., Olsen, S.B., 2018. The link between response time and preference, variance and processing heterogeneity in stated choice experiments. *J. Environ. Econ. Manage.* 88, 18–34. < <http://www.sciencedirect.com/science/>

<sup>15</sup> [www.food.gov.uk/news-updates/campaigns/campylobacter/fsw-2014](http://www.food.gov.uk/news-updates/campaigns/campylobacter/fsw-2014) and [www.food.gov.uk/news/pressreleases/2009/jun/olderpeople](http://www.food.gov.uk/news/pressreleases/2009/jun/olderpeople).

- article/pii/S0095069617307349 > .
- Capon, A., Gillespie, J., Rolfe, M., Smith, W., 2015. Perceptions of risk from nanotechnologies and trust in stakeholders: a cross sectional study of public, academic government and business attitudes. *BMC Public Health* 15, 424.
- Carlsson, F., 2011. Non-market Valuation: Stated Preference Methods. *The Oxford Handbook of the Economics of Food Consumption and Policy*, p. 181.
- Chaudhry, Q., Castle, L., 2011. Food applications of nanotechnologies: an overview of opportunities and challenges for developing countries. *Trends Food Sci. Technol.* 22 (11), 595–603.
- Chaudhry, Q., Castle, L., Watkins, R., 2017. *Nanotechnol. Food* 42, 9–12.
- Chrysoschoidis, G., Strada, A., Krystallis, A., 2009. Public trust in institutions and information sources regarding risk management and communication: towards integrating extant knowledge. *J. Risk Res.* 12 (2), 137–185.
- Cobb, M.D., Macoubrie, J., 2004. Public perceptions about nanotechnology: risks, benefits and trust. *J. Nanopart. Res.* 6, 395–405.
- Cohen, S., Orme, B., 2004. What's your preference? *Market. Res.* 16, 32–37.
- Costa-Font, M., Gil, J.M., Traill, W.B., 2008. Consumer acceptance, valuation of and attitudes towards genetically modified food: review and implications for food policy. *Food Policy* 33 (2), 99–111.
- Coveney, J., Mamerow, L., Taylor, A., Henderson, J., Myer, S., Ward, P., 2012. Comparative examination of trust during times of a food scandal in Europe and Australia. *Food Public Health* 2 (6), 202–212.
- Cvetkovich, G., 1999. The attribution of social trust. *Social Trust and the Management of Risk Earthscan*, London pp. 53–61.
- Ding, Y., Veeman, M.M., Adamowicz, W.L., 2013. The influence of trust on consumer behavior: an application to recurring food risks in Canada. *J. Econ. Behav. Organ.* 92 (0), 214–223.
- Ding, Y., Veeman, M.M., Adamowicz, W.L., 2015. Functional food choices: impacts of trust and health control beliefs on Canadian consumers? *Choices of canola oil. Food Policy* 52, 92–98.
- Erdem, S., Rigby, D., 2013. Investigating heterogeneity in the characterisation of risks using best worst scaling. *Risk Anal.* 33 (9), 1728–1748.
- Erdem, S., Thompson, C., 2014. Prioritising health service innovation investments using public preferences: a discrete choice experiment. *BMC Health Serv. Res.* 14, 1–14.
- FAO/WHO, 2013. State of the Art on the Initiatives and Activities Relevant to Risk Assessment and Risk Management of Nanotechnologies in the Food and Agriculture Sectors: FAO/WHO Technical Paper. Technical Report.
- Fiebig, D.G., Keane, M.P., Louviere, J., Wasi, N., 2010. The generalized multinomial logit model: accounting for scale and coefficient heterogeneity. *Market. Sci.* 29 (3), 393–421.
- Food Standards Agency, 2010. FSA Citizens Forums: Nanotechnology and Food: TNS-BMRB Report. Technical Report JN 219186 (accessed: 9/02/2015).
- Food Standards Agency, 2016. Nanotechnology-enabled Foods and Food Contact Materials on the UK Market. Technical Report. < <https://www.food.gov.uk/science/novel/nano/monitoring> > (accessed: 9/02/2016).
- Frewer, L.J., Howard, C., Hedderley, D., Shepherd, R., 1996. What determines trust in information about food-related risks? Underlying psychological constructs. *Risk Anal.* 16 (4), 473–486.
- García, M., Forbe, T., Gonzalez, E., 2010. Potential applications of nanotechnology in the agro-food sector. *Food Sci. Technol. (Campinas)* 30 (3), 573–581.
- Gavelin, K., Wilson, R., Doubleday, R., 2007. Democratic Technologies: The Final Report of the Nanotechnology Engagement Group (NEG). Technical Report.
- Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis; contrasts with mixed logit. *Transp. Res. Part B* 37, 681–698.
- Gupta, N., Frewer, L., Fischer, A., 2017. Acceptance of agri-food nanotechnology: insights from the evolution of food technology, novel foods and the psychology of novel food acceptance and evidence from present research. *Nanotechnol. Food* 39–59.
- Hartmann, M., Klink, J., Simons, J., 2015. Cause related marketing in the german retail sector: exploring the role of consumers' trust. *Food Policy* 52, 108–114.
- Henderson, J., Coveney, J., Ward, P.R., Taylor, A.W., 2011. Farmers are the most trusted part of the Australian food chain: results from a national survey of consumers. *Aust. N. Z. J. Public Health* 35 (4), 319–324. <http://dx.doi.org/10.1111/j.1753-6405.2011.00725.x>.
- Hess, S., Train, K., 2017. Correlation and scale in mixed logit models. *J. Choice Model.* 23, 1–8.
- Hobbs, J.E., Goddard, E., 2015. Consumers and trust. *Food Policy* 52 (April), 71–74.
- Hunt, S., Frewer, L.J., 2001. Trust in sources of information about genetically modified food risks in the UK. *Br. Food J.* 103 (1), 46–62.
- Krishna, V.V., Qaim, M., 2008. Consumer attitudes toward GM food and pesticide residues in India. *Appl. Econ. Perspect. Policy* 30 (2), 233–251.
- Lang, J.T., Hallman, W.K., 2005. Who does the public trust? The case of genetically modified food in the United States. *Risk Anal.* 25 (5), 1241–1252.
- Lee, C.-J., Scheufele, D.A., 2006. The influence of knowledge and deference toward scientific authority: a media effects model for public attitudes toward nanotechnology. *Journalism Mass Commun. Quart.* 83 (4), 819–834.
- Lewis, J.D., Weigert, A., 1985. Trust as a social reality. *Soc. Forces* 63 (4), 967–985.
- Louviere, J., Eagle, T., 2006. Confound it! that pesky little scale constant messes up our convenient assumptions. In: *Proceedings of the Sawtooth Software Conference*, pp. 211–228.
- Louviere, J.J., 2001. What if consumer experiments impact variances as well as means? Response variability as a behavioral phenomenon. *J. Consum. Res.* 28 (3), 506–511.
- Lyndhurst, B., 2009. An Evidence Review of Public Attitudes to Emerging Food Technologies. Technical Report. Social Science Research Unit Food Standard Agency.
- Macoubrie, J., 2006. Nanotechnology: public concerns, reasoning and trust in government. *Public Understand. Sci.* 15 (2), 221–241.
- Maeda, Y., Miyahara, M., 2003. Determinants of trust in industry, government, and citizen's groups in Japan. *Risk Anal.* 23 (2), 303–310.
- Magidson, J., Vermunt, J.K., 2007. Removing the scale factor confound in multinomial logit choice models to obtain better estimates of preference. In: *Sawtooth Software Conference*.
- Malone, T., Lusk, J.L., 2018. Consequences of participant inattention with an application to carbon taxes for meat products. *Ecol. Econ.* 145, 218–230.
- Manski, C.F., 1977. The structure of random utility models. *Theor. Decis.* 8, 229–254.
- Mazzocchi, M., Lobb, A., Bruce-Trail, W., Cavicchi, A., 2008. Food scares and trust: a European study. *J. Agric. Econ.* 59 (1), 2–24. <http://dx.doi.org/10.1111/j.1477-9552.2007.00142.x>.
- Nocella, G., Hubbard, L., Scarpa, R., 2010. Farm animal welfare, consumer willingness to pay, and trust: results of a cross-national survey. *Appl. Econ. Perspect. Policy* 32 (2), 275–297.
- Nocella, G., Romano, D., Stefani, G., 2014. Consumers' attitudes, trust and willingness to pay for food information. *Int. J. Consum. Stud.* 38 (2), 153–165.
- Peters, R.G., Covello, V.T., McCallum, D.B., 1997. The determinants of trust and credibility in environmental risk communication. *Risk Anal.* 17 (1), 43–54.
- Poortinga, W., Pidgeon, N.F., 2003. Exploring the dimensionality of trust in risk regulation. *Risk Anal.* 23, 961–972. <http://dx.doi.org/10.1111/1539-6924.00373>.
- Poppe, C., Kjærnes, U., 2003. Trust in Food in Europe: A Comparative Analysis. Technical Report. National Institute For Consumer Research.
- Prasad, R., Bhattacharyya, A., Nguyen, Q.D., 2017. Nanotechnology in sustainable agriculture: recent developments, challenges, and perspectives. *Front. Microbiol.* 8, 1014.
- Priest, S.H., Bonfadelli, H., Rusanen, M., 2003. The 'trust gap' hypothesis: predicting support for biotechnology across national cultures as a function of trust in actors. *Risk Anal.* 23 (4), 751–766.
- Rasmussen, J., 2009. Situational Judgment Test Responding: Best and Worst or Rate each Response (Ph.D. Thesis).
- Renn, O., Levine, D., 1991. Credibility and Trust in Risk Communication. Springer pp. 175–218 (Chapter 9).
- Roosen, J., Bieberstein, A., Blanchemanche, S., Goddard, E., Marette, S., Vandermoere, F., 2015. Trust and willingness to pay for nanotechnology food. *Food Policy* 52, 75–83.
- Roosen, J., Marette, S., Blanchemanche, S., Verger, P., 2009. Does health information matter for modifying consumption? A field experiment measuring the impact of risk information on fish consumption. *Appl. Econ. Perspect. Policy* 31 (1), 2–20.
- Siegrist, M., Cousin, M.-E., Frei, M., 2008. Biased confidence in risk assessment studies. *Hum. Ecol. Risk Assess.: Int. J.* 14 (6), 1226–1234.
- Siegrist, M., Cvetkovich, G., 2000. Perception of hazards: the role of social trust and knowledge. *Risk Anal.* 20, 713–720.
- Stampfli, N., Siegrist, M., Kastenholz, H., 2010. Acceptance of nanotechnology in food and food packaging: a path model analysis. *J. Risk Res.* 13 (3), 353–365.
- Swait, J., 1994. A structural equation model of latent segmentation and product choice for cross-sectional revealed preference choice data. *J. Retail. Consum. Serv.* 1 (2), 77–89.
- Swait, J., Marley, A., 2013. Probabilistic choice (models) as a result of balancing multiple goals. *J. Math. Psychol.* 57 (1), 1–14.
- Thurstone, L.L., 1927. A law of comparative judgement. *Psychol. Rev.* 34, 278–286.
- Vandermoere, F., Blanchemanche, S., Bieberstein, A., Marette, S., Roosen, J., 2010. The morality of attitudes toward nanotechnology: about God, techno-scientific progress, and interfering with nature. *J. Nanopart. Res.* 12 (2), 373–381.
- Vermunt, J.K., Magidson, J., 2005. Technical Guide for Latent Gold 4.0: Basic and Advanced. Belmont Massachusetts: Statistical Innovations Inc.
- Vermunt, J.K., Magidson, J., 2015. Lg-syntax? User's Guide: Manual for Latent Gold® 5.0 Syntax Module.
- Viklund, M., 2003. Trust and risk perception in western Europe: a cross-national study. *Risk Anal.* 23 (4), 727–738.