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The use of multi-level modelling in risk research. A secondary analysis of a study of public perceptions of genetically modified food

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Abstract

Many studies have examined the relationship between various individual variables and people's perceptions of genetically modified (GM) food. A problem with this type of research is that contextual factors are completely ignored. This article explores the use of multi-level modelling in the field of risk research, by re-analysing a recent British study of public perceptions of GM food. As the study employed a multi-stage sampling strategy, it could be used to examine simultaneously the individual and spatial variation in trust and the acceptability of GM food. While the geographical variation in acceptability was largely due to compositional differences between the sampling points, a geographical variation in trust remained after controlling for individual differences. The analysis demonstrated that city-dwellers commonly have more trust in the regulation of GM food than other respondents. Next to being associated with a number of socio-demographic variables, both acceptability and trust were related strongly to voting intention. Moreover, the results suggest that there is a link between vulnerable groups, feelings of exclusion, and (dis)trust. The article is concluded by arguing that multi-level modelling provides new opportunities for simultaneously examining the individual and contextual basis of public perceptions of controversial risk issues.

KEY WORDS: multilevel modelling, GM food, trust, attitudes, risk perception

1. Introduction

Genetically modified (GM) food has become one of the most contentious risk issues in Britain in recent years. Although GM food is currently a divisive risk issue, it has not always elicited strong feelings. Surveys show that the general public felt relatively positive about biotechnology during the late 1980s and early 1990s (see, e.g., Tait, 1988; Zechendorf, 1994). The period between 1996 and 1999 can be seen as the watershed years for modern biotechnology (Gaskell and Bauer, 2001). In this period, a number of successive events dramatically changed public opinion. By the end of the decade public opinion had turned strongly against GM food, and consumer and NGO pressure made supermarkets remove GM products from their shelves (Simmons and Weldon, 2000). Moreover, trust in the regulation of risks, especially in the area of food production, was at an all-time low. Perhaps not surprisingly in the light of their previous experiences with

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various food scares, people have become increasingly suspicious about the ability of the government to regulate a complex new food technology such as GM food. The GM controversy shows that members of the general public have become key players in risk controversies of the day. It is a clear reminder that public acceptance and trust in (risk) regulation are of critical importance for the uptake of a new technology.

As consumers have become a decisive factor for policy making on the national as well as the international level (Grabner *et al.*, 2001), public attitudes towards (agricultural) biotechnology were studied intensively during the 1990s. Accurate knowledge of the factors influencing people's perceptions is essential in order to be able to effectively address fears and concerns expressed by the public (Siegrist, 2003). Most empirical studies have focussed on individual factors underlying people's perceptions of diverse applications of biotechnology. Some studies have investigated the relationship between various socio-demographic variables and attitudes towards GM food (see, e.g., Sparks *et al.*, 1994; Pardo *et al.*, 2002; Siegrist, 2003), while others have pointed to the importance of perceived risks and benefits (e.g., Sparks *et al.*, 1994; Frewer *et al.*, 1997), ethical considerations (e.g., Hoban *et al.*, 1992; Wagner *et al.*, 1997), trust (e.g., Siegrist, 1999), knowledge (e.g., Durant *et al.*, 1998; Hampel *et al.*, 2000), and people's wider views on science and technology (e.g., Midden *et al.*, 2002; Siegrist, 2003). Although these studies have contributed to a better understanding of the individual basis of public perceptions of this controversial risk case, quantitative risk perception research tends to ignore contextual factors. That is, the studied relationships are assumed to be the same, irrespective of differences in the wider (social) context.

Although it is now widely recognised that social, cultural, and institutional factors play an important role in the shaping of public attitudes, it has until recently been difficult to study contextual factors quantitatively in conjunction with individual variables. Standard statistical techniques, such as regression analysis or analysis of variance (ANOVA), only allow the inclusion of variables at one level. One possible solution is to use dummy variables representing specific contextual settings. However, this is a highly inefficient solution, especially when large numbers of observations are involved (Jones and Jørgerson, 2003). Recent developments in statistical modelling provide new opportunities for studying the connection between individuals and contextual settings. These types of models are differently known as *hierarchical linear models* (Bryk and Raudenbush, 1992), *random coefficient models* (Longford, 1993), or *multilevel models* (Goldstein, 2003). A great advantage of multilevel models is that they make it possible to move from a purely individualistic to a more comprehensive analysis of complex social issues.

There are various reasons for applying multi-level models instead of standard statistical techniques. Ignoring the multi-level or hierarchical nature of data may have implications for the validity of statistical inferences. For example, it is common practice to disaggregate higher-level variables to the lowest (usually individual) level of analysis. This approach may be problematic, because conventional statistical techniques (such as regression analysis or ANOVA) assume independence of observations. When the assumption of independence is not met, as is the case with clustered or hierarchical data, they will underestimate standard errors, which will lead to inflated confidence intervals (see, e.g., Hox, 1989). This means that one may find significant results when they are not actually there. Another problem with standard statistical techniques emerges when someone wants to compare different contextual settings (e.g., country, region, or community). In many cases the different (geographical) settings are compared by simply aggregating individual responses to the higher level of analysis. However, differences between settings do not necessarily reflect a contextual effect. They may also be due to compositional differences (Duncan *et al*., 1998). That is, variation between the different settings may well arise from the fact that they are composed of different (types of) people. Fitting a multi-level model circumvents the problems mentioned here. Multi-level modelling makes it possible to examine factors at the appropriate level of analysis. Furthermore, by explicitly recognising the hierarchical nature of a dataset, it provides more accurate and efficient estimates of model parameters (Goldstein, 2003).

While multi-level modelling has almost become synonymous with *multilevel regression analysis*, it actually has a variety of possible applications. For example, hierarchically structured data also occurs when individuals are measured on more than one occasion. *Repeated measures* can be considered as multilevel data, as (measurement) occasions are clustered within individuals (Goldstein, 2003). Closely related are so-called *event history models*. In this type of model periods are nested within individuals. Applying multi-level modelling to this data enables to simultaneously study individual and time-dependent factors. Similarly, hierarchical data occurs when different measurements are made for each individual. An example of a *multivariate response model* is given by Langford *et al*. (1999), who examined simultaneously people's responses to various psychometric attributes at the individual and risk level. For a more complete overview of different applications of multi-level modelling, see, e.g., Hox (1995), Snijders and Bosker (1999), or Goldstein (2003).

Traditionally, multi-level research has mainly been used in educational research (Nuttal *et al*., 1989; Goldstein *et al*., 1993) and epidemiology (Langford and Bentham, 1996; Duncan *et al*., 1998; Leyland and Goldstein, 2001; Haynes *et al*., 2003). These research fields deal routinely with datasets that have an evident hierarchical character (Hox, 1989). For example, students typically are clustered in classes within school, which themselves may be nested in educational authorities or boards, whilst patients with a particular disease are usually treated by different consultants in different hospitals. However, also other research fields deal with issues that have a multilevel or hierarchical character, and in recent years multi-level modelling is slowly finding its way to other research communities, such as organisational research (Griffin *et al*., 2001), environmental psychology (Guerin *et al*., 2001; Regoeczi, 2003), and risk research (Langford *et al*., 1999; Allum *et al*., 2002).

This article explores the use of multi-level modelling in the field of risk research by re-analyzing a recent British dataset on public perceptions of GM food. More specifically, the dataset is used to examine the individual and spatial variation in trust in and the acceptability of GM food. The following section gives a more detailed description of the study methodology, the resulting hierarchical nature of the collected data, and the specific multilevel regression model that is used to examine public perceptions of GM food.

2. Method

2.1. PROCEDURE AND RESPONDENTS

Data for this study were collected between 19 July and 12 September 2003. The study was designed to gauge public attitudes to GM food in general, as well as to evaluate a national public debate on the commercialisation of agricultural biotechnology occurring during the summer of 2003 (Horlick-Jones *et al*., 2004; Poortinga and Pidgeon, 2004). The survey was administered in Britain by market research company MORI. A national quota sample of

1363 people aged 15 years and older was interviewed face-to-face in their own homes. The overall sample consisted of a core British sample of 1017 interviews, and two booster samples in Scotland and Wales of 151 and 195 interviews, respectively. The survey was run in 116 sampling points, which were randomly selected with a probability proportional to the size of their population. Interviewers approached addresses within the sampling points until they reached the quotas for gender, age, and work status. The quotas reflected the actual profile of each sampling point. A maximum of one interview per address was conducted. The booster samples were conducted in order to be able to compare public perceptions of GM food between England, Scotland, and Wales. Fifty-one percent of the sample was female and 49% was male. Thirty-four percent of the respondents were between 15 and 34 years old, 34% were aged between 35 and 54, and 32% were aged 55 or over (for more details, see Poortinga and Pidgeon, 2004).

2.2. THE MULTILEVEL REPRESSION MODEL

The previous section described the multi-stage sampling strategy that was utilised to collect the data for this study. As a result of this non-random sampling method the dataset has a clear multi-level structure: a sample from the higher level (sampling points) was followed by a sample from the lower level (individuals). The sampling points themselves are located in the three British countries (see Fig. 1). Although such a multi-stage sampling strategy is generally more economic than a random population sample, the hierarchical nature of the generated data should not be ignored. The assumption of independence may not be met as a result of geographical clustering. Although there may be some statistical problems associated with multi-stage sampling, it also provides new research opportunities. The geographical clustering of this dataset can be exploited to say something about the spatial variation in responses.

$$\left.\begin{aligned} y_{ij} &\sim N\left(XB, \sigma^2\right) \\ y_{ij} &= \beta_0 + \beta_1 x_{1ij} + \beta_2 x_{2j} + u_j + e_{ij} \\ u_j &\sim N\left(0, \sigma_u^2\right) \\ e_{ij} &\sim N\left(0, \sigma_e^2\right) \end{aligned}\right\} \tag{1}$$

A simple two-level *random-coefficient* regression model was constructed to analyse the data (see Equation 1), utilising the *MLwiN* multi-level software package (Rasbash *et al.*, 2002).[1] The model consists of j sampling points (level 2), with i respondents (level 1). A multi-level model is made up of a *fixed* part and a *random* part. The fixed part of the equation (β_0, β_1, and β_2) represents the mean regression line of the model. The random part is where the difference can be found with the conventional regression model. That is, the (random-coefficient) model allows the intercept to vary between the different sampling points. So next to a unique individual (level-1) contribution (which in a normal regression analysis is treated as unexplained variance), there is a separate level-2 contribution, which is common to all individuals in a particular sampling point. Both the sampling point

[1] The multilevel model described here may be extended to a more complex one that also allows the slopes of the regression lines to vary. This type of multi-level model that is known as a *random slope* model will not be discussed here.

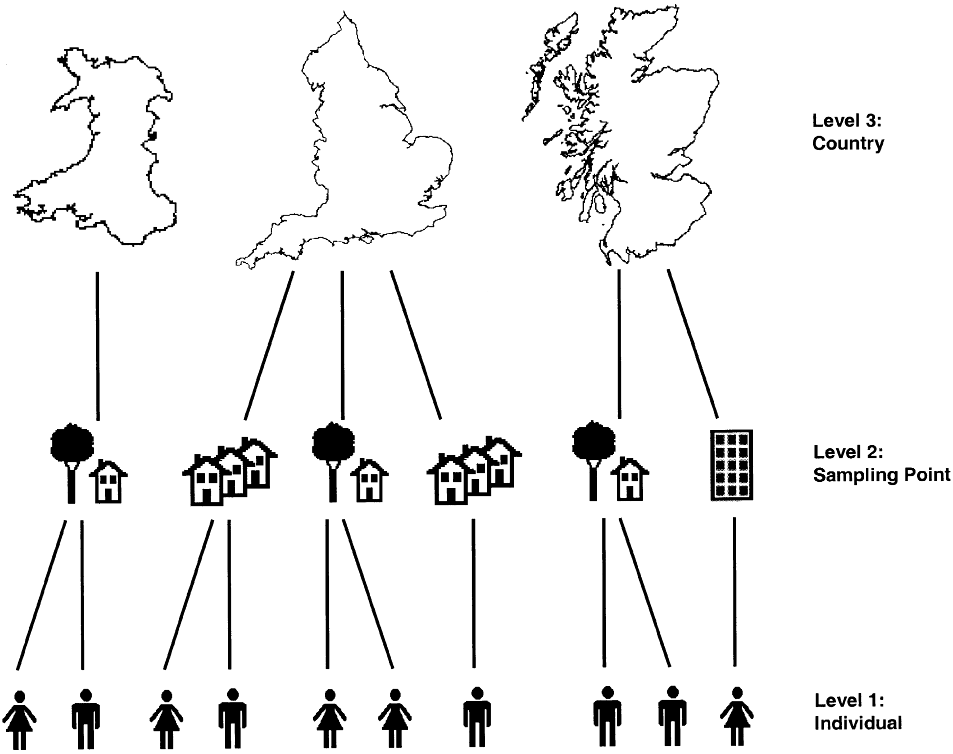

Fig. 1. The multilevel structure of respondents clustered in sampling points that themselves are nested in three British countries.

residual (u_j) and the individual residual (e_{ij}) are random quantities whose means are zero and are assumed to follow a normal distribution. Their variances can be estimated by σ^2_u and σ^2_e, respectively. The multi-level regression model can be used to investigate whether the multi-staged sampling strategy creates a *design effect*. A design effect exists when a significant part of the overall variation can be found at the sampling-point level, and is also known as the *intra-class correlation*. The intra-class correlation gives an indication of the similarity of the observations within the different sampling points. As the individual and sampling-point contributions are separated, the model can be used to simultaneously examine the relationship between various individual and sampling-point variables on the one hand, and the response variable on the other. Equation 1 shows the situation with one individual (x_{1ij}) and one sampling-point (x_{2j}) explanatory variable. A more elaborate (statistical) discussion of the multi-level methodology can be found in, e.g., Hox (1995), Snijders and Bosker (1999), and Goldstein (2003).

2.3. DEPENDENT VARIABLES

The dataset was used to fit two multi-level regression models. The dependent variable of the first model was the acceptability of GM food. *Acceptability of GM Food* was measured with two items. First, respondents were asked to indicate the extent to which they thought that GM food is acceptable on a scale ranging from 1: "very unacceptable", to 5: "very acceptable". Second, they were asked to weigh the risks and benefits of GM food on a 5-point scale with the following response options: 1: "the risks far outweigh the benefits", 2: "the risks slightly outweigh the benefits", 3: "the risks and the benefits are about the same", 4: "the benefits slightly outweigh the risks", 5: "the benefits far outweigh the risks". The two items had a high internal consistency (Cronbach's α=0.84), and were used to construct a single acceptability scale. The dependent variable of the second model was trust in risk regulation. *Trust in risk regulation* was measured with the items "I feel confident that the British government adequately regulates GM food" and "I am confident that the development of GM Crops is being carefully regulated". Both statements were answered on a 5-point scale from 1: "totally disagree" to 5: "totally agree". The reliability of the two items was sufficient to construct a single trust in risk regulation scale (Cronbach's α=0.69). Both the acceptability scale (M=2.58; SD=1.10, Skewness=0.05; Kurtosis=−0.87) and the trust in risk regulation scale (M=2.63; SD=0.98, Skewness=0.05; Kurtosis=−0.74) were assumed to have a normal distribution (see Equation 1).

2.4. INDEPENDENT VARIABLES

Various socio-demographic variables were used in the two analyses: gender (female, male), age (15–34, 35–54, 55+), level of income (low, average, and high income, and refused income)[2], level of education (no formal education, GCSE: General Certificate of Secondary Education, NVQ: National Vocational Qualification, A level: Advanced Level secondary education/ high school education, University degree or higher), social class (AB: professional, managerial, and technical occupations, C1: non-manual skilled occupations, C2: manual skilled occupations, DE: unskilled and partly-skilled occupations), ethnicity (white, Asian, other ethnicity), household composition (children, no children), and employment status (unemployed versus not unemployed). Other level-1 explanatory variables included people's voting intention (Labour, Conservative, Liberal Democrats, the Green Party, other, and "will not vote")[3], and feelings of exclusion (less say versus not less say)[4].

Two explanatory variables were included at the sampling-point level. The first was 'area type', reflecting whether the sample was taken in a city, suburb, or the countryside[5]. Second, two separate dummy variables were created to represent the British countries

[2] Low: <£11,500 gross per annum, Average: £11,500 to £30,000, high: ⩾£30,000. Thirty-six percent of the sample refused to give their income. This group was included as a separate category.

[3] People were asked: "How would you vote if there were a general election tomorrow?".

[4] People were asked to finish the question "In general, compared to other people in your local community, do you feel that on national issues you have …". They could choose between "more say than them", "less say than them", and "no difference". In this study the respondents choosing "less say to them" were compared to the other responses.

[5] People were asked: "Which of these best describe the area where you live most of the time". The response categories were: "In the middle of a town or city", "In a suburb", "on the edge of the countryside", and "In the middle of the countryside". The latter two were collapsed into one category. Sampling points with more than 50% responses in one of the three categories were characterised as "city", "suburb", or "countryside". The area type of nine sampling points could not be ascertained in this way.

Scotland and Wales, with England as the reference group. Note that the countries are not modelled as a separate level (cf., Fig. 1) because there are not enough observations.

3. Results

Table 1 and Table 2 show the fixed and random parameters of the first *acceptability model*, respectively. The fixed part of the model can be interpreted as a normal regression analysis. Table 1 presents the unstandardised regression coefficients and the standard errors of the level-1 and level-2 predictors of the final model. The acceptability of GM food varied across a number of socio-demographic groups. Male respondents found GM food more acceptable than female respondents. Respondents aged 55 and over found GM food less acceptable than the reference group of respondent aged between 15 and 34. Moreover, people with a first or higher degree ("degree or higher") found GM food less acceptable than people with a different level of education. The results also show that there was a strong link between people's voting intention and their views on the acceptability of GM food. It appeared that people who had the intention to vote Labour were more in favour, while people with the intention to vote for the Green Party were less in favour of GM food. The model also suggests that income, social class, and ethnicity, as well as feelings of exclusion, household composition, and work status are unrelated to the acceptability of GM food. Moreover, no relationship was found between the level-2 variables (i.e., area type and country) and the acceptability of GM food.

Table 2 shows that there is significant variation in the acceptability of GM food at both the individual and the sampling point level when no predictors are included (the null model). Although the acceptability of GM food varied significantly across the different sampling points, it represented only a small proportion (7%) of the total variance (0.089/(0.089+1.172)). The intra-class correlation could be largely attributed to differences in the (socio-demographic) composition of the different sampling points. Adding the individual (level 1) variables to the model reduced the intra-class correlation to 0.05. Table 2 shows that the variation between the sampling points is substantially reduced, especially in comparison to its standard error. Although no specific relationships were found between the level-2 variables and the acceptability of GM food, they rendered the remaining variance at the sampling-point level non-significant.

Trust in the regulation of GM food was modelled using the same predictors as the acceptability model. Table 3 and Table 4 present the fixed and random parts of the trust model, respectively. Table 3 gives the unstandardised regression coefficients and the standard errors of the level 1 and level 2 predictors of the final model. It appeared that respondents aged between 35 and 54 as well as respondents of 55 years and older have less trust in the regulation of GM food than the reference group of respondents aged between 15 and 34. The table also shows that people with a low income generally have less trust in risk regulation than people with an average income. Trust in risk regulation is, like the acceptability of GM food, strongly related to voting intention. Whereas the intention to vote Labour is associated with higher levels of trust, the intention to vote for the Green Party is associated with lower levels of trust in the regulation of GM food. Moreover, people who feel excluded (i.e., people who feel that they have less say about national issues than other people) tended to have less trust in the regulation of GM food. The analysis also shows that gender, education, social class, ethnicity, household status, and work status were not related to trust in the regulation of GM food. Trust was related to the type

Table 1. Fixed parameters of the acceptability model.

Fixed Parameters	*B*	*SE*	*p*
Intercept	2.83	0.17	<.001
Level 1 variables			
Gender (Female)			
Male	+0.30	0.08	<.001
Age (Age 15–34)			
Age 35–54	−0.16	0.10	
Age 55+	−0.26	0.12	<.05
Income (Average)			
Low income	−0.13	0.12	
High income	−0.12	0.10	
Refused income	−0.11	0.12	
Education (GCSE)			
No formal education	−0.13	0.12	
NVQ/Vocational	−0.03	0.14	
A Level	−0.11	0.12	
Degree or higher	−0.27	0.12	<.05
Social Class (AB)			
C1	−0.06	0.11	
C2	−0.22	0.13	
DE	−0.14	0.14	
Ethnicity (White)			
Asian	−0.22	0.24	
Other ethnicity	−0.01	0.28	
Voting Intention (Other)			
Labour	+0.32	0.11	<.01
Conservatives	+0.07	0.12	
Liberal Democrats	+0.07	0.13	
Green Party	−0.73	0.27	<.01
Will not vote	+0.21	0.12	
Feelings of Exclusion (Not less say)			
Less say	+0.03	0.11	
Household Composition (No Children)			
Children	−0.01	0.09	
Work Status (Employed)			
Unemployed	−0.01	0.16	

Table 1. (*continued*).

Fixed Parameters	*B*	*SE*	*p*
Level 2 variables			
Area (Suburb)			
City	+0.07	0.11	
Countryside	−0.01	0.10	
Country (England)			
Wales	−0.12	0.12	
Scotland	−0.10	0.12	

Note: B=Regression coefficients; SE=Standard errors; Reference groups are given in brackets.

of area the sample was conducted in. People living in the middle of a city had in general more trust in the regulation of GM food than people living in suburbs. English, Scottish, and Welsh respondents did not differentially trust the regulation of GM food.

Table 4 shows that trust varied substantially across individuals and sampling points. It appeared that there was a considerable design effect associated with trust in the regulation of GM food, as about 13% of the total variance occurred at the sampling-point level (0.121/(0.121+0.832)). Although the intra-class correlation was somewhat reduced after adding the level-1 variables, a (highly) significant 10% of the overall variation could still be attributed to differences between the sampling points. Even if adding the two level-2 variables further reduced the sampling-point variation, the spatial variation in trust remained significant.

4. Conclusions

This article explored the use of multi-level modelling in the field of risk research. A recent British study of public attitudes towards GM food was analyzed to illustrate how multi-level modelling can be used to analyse hierarchical datasets. The data of this study had a clear hierarchical structure, as respondents were clustered in a number of randomly selected sampling points. Two multi-level regression models were constructed in order to explore the individual and spatial variation in the acceptability of GM food and the regulation of GM food, respectively.

This study demonstrated that the multi-stage sampling strategy, which is often used by market research companies, could produce significant design-effects. The first model showed that, without any explanatory variables, a significant but moderate proportion of the variation in the acceptability of GM food could be found at the sampling-point level.

Table 2. Random parameters of the acceptability model.

Random Parameters	σ^2_u	σ^2_e
Null model	0.089 (0.028)**	1.172 (0.052)***
Level 1 variables	0.057 (0.027)*	1.075 (0.055)***
Level 2 variables	0.040 (0.025)	1.089 (0.058)***

Note: * $p<.05$; ** $p<.01$; *** $p<.001$; Standard errors are given in brackets.

Table 3. Fixed parameters of the trust model.

Fixed Parameters	*B*	*SE*	*p*
Intercept	2.66	0.15	<.001
Level 1 variables			
Gender (Female)			
Male	+0.04	0.06	
Age (Age 15–34)			
Age 35–54	−0.22	0.08	<.01
Age 55+	−0.30	0.10	<.01
Income (Average)			
Low income	−0.20	0.09	<.05
High income	−0.02	0.09	
Refused income	−0.12	0.09	
Education (GCSE)			
No formal education	−0.07	0.09	
NVQ/Vocational	−0.20	0.12	
A Level	−0.02	0.10	
Degree or higher	−0.10	0.10	
Social Class (AB)			
C1	−0.04	0.09	
C2	−0.14	0.11	
DE	−0.03	0.11	
Ethnicity (White)			
Asian	−0.05	0.21	
Other ethnicity	−0.02	0.22	
Voting Intention (Other)			
Labour	+0.41	0.09	<.001
Conservatives	−0.17	0.09	
Liberal Democrats	−0.17	0.11	
Green Party	−0.65	0.22	<.01
Will not vote	+0.14	0.10	
Feelings of Exclusion (Not less say)			
Less say	−0.16	0.08	<.05
Household Composition (No Children)			
Children	−0.02	0.08	
Work Status (Employed)			
Unemployed	−0.07	0.12	

Table 3. (*continued*).

Fixed Parameters	*B*	*SE*	*p*
Level 2 variables			
Area (Suburb)			
City	+0.20	0.10	<.05
Countryside	−0.08	0.09	
Country (England)			
Wales	−0.15	0.11	
Scotland	−0.00	0.11	

Note: B=Regression coefficients; SE=Standard errors; Reference groups are given in brackets.

However, the variation between sampling points could largely be attributed to compositional differences. Controlling for the various level-1 variables substantially reduced the variation between sampling points. These findings suggest that an ordinary regression analysis would suffice for examining the determinants of the acceptability of GM food at the individual level. As the intra-class correlation is small, the risk of type I errors would only slightly increase (see, e.g., Hox, 1989). Similarly, a substantial proportion of the variation in trust in the regulation of GM food could be found at the sampling-point level. However, with regard to the trust the level-2 variation is not caused by compositional differences. The variation between sampling points remained after adding the individual variables to the model. These results can be interpreted in a number of different ways. On the one hand, they show that there is a considerable design effect associated with the sampling strategy of this study. Ignoring the multi-level nature of this particular dataset could potentially lead to largely inflated alpha levels. As a result, one could find spurious relationships with regard to trust in the regulation of GM food. At the same time, the results show that (geographical) location is important for trust in the regulation of GM food. In other words, people living in the same area are more similar to one another than to (arbitrary) other people. The analysis demonstrated that city-dwellers commonly have more trust in the regulation of GM food than other respondents. The fact that the sampling-point variation in trust remained significant after the inclusion of level-2 variables indicates that trust is also related to other unidentified factors. Obviously, more research is needed to examine which factors contribute to the spatial variation in trust.

This study also identified a number of interesting relationships between a number of individual variables and people's perceptions of GM food. As described before, multi-level modelling is appropriate here, as especially the trust model had large intra-class

Table 4. Random parameters of the trust model.

Random Parameters (Trust)	σ^2_u	σ^2_e
Null model	0.121 (0.027)***	0.832 (0.035)***
Level 1 variables	0.083 (0.024)***	0.760 (0.037)***
Level 2 variables	0.063 (0.021)**	0.753 (0.038)***

Note: ** p<.01; *** p<.001; Standard errors are given in brackets.

correlations. As multi-level modelling takes the clustering of the data explicitly into account, the analyses provide more accurate and conservative parameter estimates than standard statistical techniques. This study demonstrates that women are less supportive of GM food than are men. These findings are in line with other studies, which show that women generally express higher levels of concern about technology and the environment than do men (see, e.g., Davidson and Freudenburg, 1996). Moreover, this study indicates that older respondents are less supportive of GM food than are younger respondents. Similar relationships were found in a number of previous studies of public perceptions of agricultural biotechnology (e.g., Sparks *et al*., 1994). In contrast to earlier studies (e.g., Gaskell and Bauer, 2001), the present study found that people with a high level of education (degree or higher) were more opposed to GM food than the other educational groups. Like for acceptability, an age effect was found for trust in the regulation of GM food. Older respondents generally had less trust in the regulation of GM food than did younger ones. Respondents with a low income, as well as people who felt excluded from political decision-making, have less trust in the regulation of GM food. Although it is not clear whether this effect is specific to the GM food issue or whether it reflects a more general pattern in distrust in government (cf., Poortinga and Pidgeon, 2003), this study suggests that there is a link between vulnerable and/or marginalized groups, feelings of exclusion and trust. As argued by Bickerstaff *et al*. (under review) spatial and structural (social, economic, and political) distance to central policy-making is crucial for the understanding people's responses to risk and risk management practices. The lack of effective political powers to influence decisions may express itself in distrust of the decision-makers. The finding supports this idea that city dwellers (which in this study are mainly from London) are generally more trusting than the other respondents. Perhaps in contrast to this hypothesis, social class as well as ethnicity were unrelated to both trust and acceptability. In the future, multi-level modelling could be used for a more comprehensive analysis of vulnerable groups and communities, experienced exclusion, and people's responses to risk, trust, and involvement in decision-making. A further interesting result of this study is that both acceptability and trust are related strongly to voting intention. Labour voters find GM food more acceptable than other respondents and also trust the (Labour) government more to regulate GM food, while voting for the Green party is associated with greater opposition to and distrust in the regulation of GM food. While, as mentioned earlier, these perceptions may reflect a more general attitude towards the current (Labour) government, it also shows that GM food is a highly politicised issue.

In conclusion, this article has illustrated how multi-level modelling can be used in risk research, by re-analyzing a recent British study of public perceptions of GM food. Even if the study was not designed specifically for the purpose, it provided an opportunity to examine individual differences and geographical variation in the perception data. This study has demonstrated that multi-level modelling could be very useful for risk researchers as well as policy makers. For example, the analysis not only showed in what way different (groups of) people differ in their perceptions of GM food, it also shows *where* they are concentrated. For example, city-dwellers commonly have more trust in the regulation of GM food than other respondents. This suggests that, with respect to trust, more work needs to be done in the suburbs and countryside than in the major cities.

While multi-level modelling is a powerful method for examining the individual and contextual bases of public perceptions, it has only been used in a couple of risk studies (Langford *et al*., 1999; Allum *et al*., 2002). Multi-level modelling may be particularly useful for examining risk controversies with a clear geographical component such as siting issues, especially where risks are distributed unevenly across (geographically clustered) social groups. However, the attraction of multi-level modelling lies in its generality and flexibility, and is not restricted to spatial analyses. Context could also be seen in terms of social, administrative, temporal, or institutional settings (Duncan *et al*., 1998). For example, other useful applications would be in longitudinal or 'tracking' research, in order to determine the importance of time-specific contextual variables (e.g., media coverage) for the temporal variation in people's perceptions. Moreover, multi-level modelling is not limited to the simple two-level random coefficient model presented in this paper. Good overviews of other applications and more complex designs are given by, e.g., Duncan *et al.* (1998) and Leyland and Goldstein (2001). As a final caveat, multi-level models should be applied carefully and thoughtfully, as they are not suitable for all research questions or datasets. Certain datasets and/or research questions simply do not lend themselves for multi-level modelling. This study showed that it is not needed in situations with little structural complexity (Goldstein, 2003). Moreover, like any other research method, multi-level modelling has its limitations (see, e.g., Duncan *et al*., 1998; Jones and Jørgerson, 2003). However, provided that they are based on well-grounded theories and suitable research designs, multi-level modelling offers new opportunities to study the complex nature of public perceptions of a controversial risk issue such as GM food.

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