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Willingness to pay for reduction in air pollution: a multilevel analysis

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Abstract This paper presents the multilevel model approach to analyzing contingent valuation surveys of individuals' willingness to pay for reductions in the level of air pollution. It is likely that individuals living in the same area are exposed to the same level of air pollution, and accordingly these individuals' valuations of a reduction may be correlated. Thus, the data have a hierarchical structure with individuals clustered within regions, and this structure violates the general assumption of independence among observations. Multilevel models allow for this type of data structure. In this paper we analyze individuals' stated willingness to pay in an open-ended contingent valuation survey for a reduction in the local level of air pollution in Sweden. The results suggest that most variations are among individuals. However, our results indicate that there are also variations at higher levels, which may be explained by homogeneous preferences for a reduction in air pollution among individuals living in the same household or region with a similar level of air pollution.

Key words Air pollution · Contingent valuation · Multilevel models

1 Introduction

Measuring the welfare impact of reductions in air pollution using contingent valuation (CV)[1] surveys has been a frequently researched area (examples of recent studies are those of Alberini et al. 1997a, Carlsson and Johansson-Stenman 1999, and Halvorsen 1996). Individuals' willingness to pay (WTP) for a specific reduction in air pollution is strongly related to general health risks and the impact of the current level of air pollution on the environment. Accordingly, we expect individuals who live in the same region to have more similar valuations of a specific reduction in the level of air pollution than the valuations of the same reduction expressed by individuals who live in another region with a different level of air pollution. Thus, the variations in the valuation of a specific reduction

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[1] For a general overview on the CV method see, for example, Mitchell and Carson (1989); and for a critical assessment see Diamond and Hausman (1994).

are due to variations among both individuals and regions. Consequently, there is a hierarchical structure of the data where individuals are clustered into geographical regions. This structure, in which a correlation in valuations exists among individuals who live in the same region, invalidates the assumption that observations are independent as required by most econometric models. When analyzing data that fall into hierarchical structures, it is appropriate to use multilevel models that allow clustering of observations.[2]

The variations can be estimated by incorporating dummy variables for each geographical region (i.e., a fixed effect approach) or by assuming that the variations among regions are random (i.e., a random effect approach). Generally, a random effect approach is preferable for analysis of CV data on air pollution because the results from the fixed effect approach can be generalized only to the geographical regions included in the survey. Furthermore, as each region is explained by a dummy variable, the fixed effect approach is inefficient if there are many more variables to be estimated. We extend our discussion of this issue in section 2.

There are two advantages to recognizing the hierarchical structure of the data in an econometric model. First, the multilevel model allows correlation of the valuation of respondents who live in the same area. The confidence intervals of the coefficients may thereby be calculated correctly. Thus, we can study the impact of different variables on the valuation based on correctly calculated confidence intervals; and, accordingly, significance tests of coefficients are accurate. Second, the multilevel model partitions the unexplained variance to appropriate levels, and we can thereby assess the variations in valuation among regions as well as among individuals (Goldstein 1995). For policy purposes, it is of interest to study whether there is a substantial variation in the valuation of a reduction among regions, as it may indicate that it is not possible to transfer valuations among regions (at least not easily). Furthermore, if there are substantial variations among regions in the valuation, the use of fixed shadow values of emissions may result in nonoptimal environmental policies.

The objectives of this paper are to present the multilevel model approach in the context of analyzing data from a CV survey on a reduction in the level of air pollution and to analyze an open-ended CV survey in Sweden asking for respondents' WTP for a 50% reduction in the local level of air pollution by using the multilevel model framework. The use of an open-ended CV survey may seem somewhat controversial. A number of studies have found significant differences in estimated WTP between the open-ended and closed-ended formats (e.g., Kriström 1993). However, Halvorsen and Sælensminde (1998) pointed out that the differences between open-ended and closed-ended format may largely be due to the sensitivity of discrete responses to assumptions made about the random utility. We believe that the recommendation of the use of closed-ended question

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[2] It should be noted that a panel data model is a specific type of multilevel model because it, inter alia, is restricted to two levels. This type of two-level model has been applied to CV responses (e.g., Alberini et al. 1997b).

of the National Oceanic and Atmospheric Administration (NOAA) panel is premature, and that future research is needed.

The rest of the paper is organized in the following fashion. In section 2 we discuss the multilevel approach in the context of analyzing a CV survey on a reduction in the level of air pollution. Section 3 presents the results from the analysis of an open-ended CV study on a 50% reduction of local air pollution in Sweden. Finally, in section 4 we discuss our findings and present suggestions for future research.

2 Multilevel models

Multilevel models have frequently been applied in several areas, such as education and social research (e.g., Goldstein 1987), geography (e.g., Jones 1991), and health economics (e.g., Duncan et al. 1996; Scott and Shiell 1997) to allow for hierarchically structured data. However, we are aware of only three studies in environmental economics—those of Langford et al. (1998a,b) and Langford and Bateman (1999)—that use a multilevel model approach explicitly. Langford et al. (1998b) considered individuals' responses to an open-ended contingent valuation question to be clustered according to whether they participate in the program. Langford et al. (1998a) and Langford and Bateman (1999) considered individuals' responses to a binary valuation question to be clustered according to the bid level. In these three studies the hierarchical structure is a result of the questionnaire rather than the clustering of individuals based on geographical regions, which is the focus in this paper.

Let us first concentrate on an open-ended CV survey, where individuals have stated their WTP for a reduction in the level of air pollution. Let us, for simplicity, assume that WTP can be both positive and negative. It could be argued, however, that disutility derived from the activities that reduce the level of air pollution may exceed the utility derived from better air quality, and this would then justify a negative WTP. At the end of this section we discuss the case where individuals state nonnegative WTP for a reduction in the level of air pollution, where zero responses represent individuals not interested in reduction, and a positive WTP expresses individuals interested in reduction. We model this by a sample selection approach, where we model the binary choice of stating a positive WTP and individuals stating positive WTP separately. Thus, we include a discussion on binary models in a multilevel setting at the end of this section.

An analysis of open-ended CV data using an Ordinary Least Squares (OLS) regression, which ignores the hierarchical structure, is of the form

$$WTP_i = \alpha + \beta' x_i + \varepsilon_i \tag{1}$$

where α and β are parameters to be estimated, and x_i is a vector of variables describing personal characteristics of respondent i. This model assumes, among other things, independence among observations. The existence of correlation between the error terms results in an underestimation of standard errors. In our case we have spatial correlation, although the effect of the problem is similar to

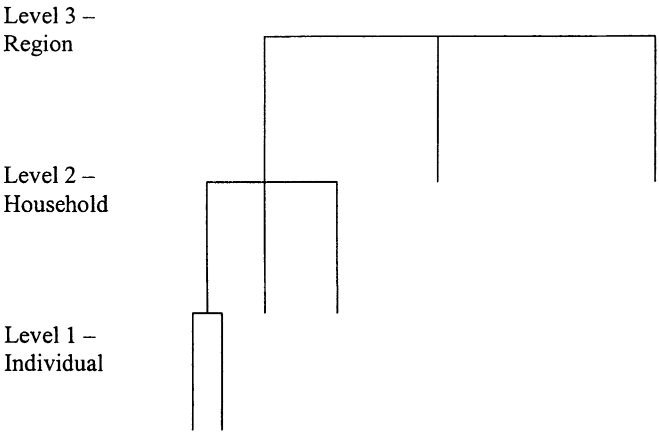

Fig. 1. Example of a three-level structure

correlation over time (i.e., the problem of autocorrelation). Furthermore, Eq. (1) predicts that individuals with the same personal characteristics state the same WTP independent of the level of air pollution where they live.

In our case we consider a three-level model, where respondents are clustered within households and households are clustered within geographical regions. This data structure is illustrated in Fig. 1. The structure implies that respondents who live in the same household state more similar WTP than respondents who live in other households. Furthermore, WTP is more similar among respondents who live in households in the same geographical region than WTP between respondents who live in households located in other regions. We include a three-level data structure in Eq. (1) to consider the hierarchical structure, and the model then becomes

$$WTP_{ijk} = \alpha + \beta' x_{ijk} + \nu_k + \mu_{jk} + \varepsilon_{ijk} \tag{2}$$

where WTP_{ijk} denotes the WTP of the ith individual in the jth household located in the kth region; ν_k is the departure in WTP of region k from the WTP predicted by $\alpha + \beta' x_{ijk}$ (i.e., the fixed part); in a similar manner μ_{jk} and ε_{ijk} measure the departure in WTP of household j located in region k and individual i living in household j located in region k from the respective prediction by the fixed part. Furthermore, we assume that $E[\varepsilon_{ijk}] = E[\mu_{jk}] = E[\nu_k] = 0$.

An important discussion in the panel data literature, which of course also applies to multilevel models, is whether to treat the error terms at level 2 and in our case at level 3 as well (i.e., ν and μ) as random or fixed.[3] The fixed effect approach is performed by using the least-squares dummy variable (LSDV)

[3] See, for example, Hisao (1986) or Rice and Jones (1997) for a general discussion on fixed and random effects.

technique, whereas the random effect approach treats the region and the household as separate random variables with zero mean and constant variance. Here use is made of an iterative generalized least-squares method in the estimations.[4] A fixed effect approach is appropriate if inference relates to the sample investigated or there may be correlation between the error terms and the explanatory variables. On the other hand, if we are interested in inferring to a larger population than the sample surveyed, a random effect approach is preferable. However, application of a random effect model when there is a correlation between the error terms and the explanatory variables results in inconsistent estimates in the random effect model.

When analyzing data on a CV survey on air pollution, it is likely that we include many clusters to account for local differences in the level of air pollution. In such a case the LSDV model may be inefficient, as there is a considerable loss of degrees of freedom due to inclusion of dummy variables. Furthermore, a random effect model allows the variation to be partitioned at different levels, which may be of interest in itself. Thus, the final decision between a fixed or a random effects approach may be guided by the objective of the analysis. If not, a Hausman test may be applied where the fixed model is tested against the random model. In this paper and similar applications, the random effect approach is preferable, as we want to generalize our results and it is likely that not all regions and households within a region are included in the survey. On the other hand, if all regions and households are included to consider local differences in air pollution, a substantial number of dummy variables would be needed and the fixed effect approach would be inefficient. Henceforth we consider the error terms as random and so assume that $Var[\varepsilon_{ijk}] = \sigma^2_\varepsilon$, $Var[\mu_{jk}] = \sigma^2_\mu$ and $Var[\nu_k] = \sigma^2_\nu$. Furthermore, we constrain all covariance terms to zero.

In a multilevel model, the variance component is estimated at each level, and consequently the variance may be partitioned. Hence, we can measure the intralevel correlation at each level, a measure that indicates the strength of the clustering effect. For instance the intrahousehold correlation (i.e., the clustering effect at level 2) is measured as follows.

$$\rho = \frac{\sigma^2_\mu}{\sigma^2_\varepsilon + \sigma^2_\mu + \sigma^2_\nu} \tag{3}$$

This correlation measures the proportion of the total variance, which is between-households; an intraregion correlation for the variance between-regions may be calculated in the same manner.

The difference in WTP among regions and among households may be characterized not only by a constant shift from the regression function as illustrated by ν and μ, respectively. More advanced models may also be applied,

[4] There are several estimation techniques to apply. For a detailed discussion see Goldstein (1995) or Rice and Jones (1997).

which includes a more complex variance structure. For example, we can model the variation at household level as a function of an explanatory variable, and more levels may be analyzed (e.g., Goldstein 1995; Rice and Jones 1997).

Finally, let us consider a binary model in the multilevel framework. A binary model is applicable in at least two cases when analyzing CV data: (1) to estimate the influences on whether to state a positive WTP in an open-ended CV survey; and (2) to analyze data from a closed-ended CV study. Let us concentrate on the former case, and then the binary model estimates the probability of stating a positive WTP to a program as a function of certain explanatory variables. We could then model the binary choice for a three-level model as follows.

$$y^*_{ijk} = \alpha + \beta' x_{ijk} + \nu_k + \mu_{jk} + \varepsilon_{ijk} \tag{4}$$

$$y_{ijk} = 1 \quad \text{if} \quad y^*_{ijk} > 0$$

$$y_{ijk} = 0 \quad \text{if} \quad y^*_{ijk} \leq 0$$

where $E[\varepsilon_{ijk}] = E[\mu_{jk}] = E[\nu_k] = 0$, $Var[\varepsilon_{ijk}] = \sigma^2_\varepsilon$, $Var[\mu_{jk}] = \sigma^2_\mu$, and $Var[\nu_k] = \sigma^2_\nu$. Again we constrain all covariance terms to zero. Furthermore, we assume that the observed binary responses are binomially distributed, $y_{ijk} \sim Bin(\pi_{ijk},1)$. If the cumulative distribution of ε_{ijk} is logistically distributed we have a logit model, and the probability of contributing is then

$$\pi_{ijk} = \frac{\exp(\alpha + \beta' x_{ijk} + \nu_k + \mu_{jk})}{1 + \exp(\alpha + \beta' x_{ijk} + \nu_k + \mu_{jk})} \tag{5}$$

The logit regression model may then be written as

$$y_{ijk} = \pi_{ijk} + \varepsilon_{ijk} z_{ijk} \tag{6}$$

where $z_{ijk} = [\pi_{ijk}(1 - \pi_{ijk})]^{0.5}$. Constraining the level 1 variance to one (i.e., that $\sigma^2_\varepsilon = 1$) and using the explanatory variable z_{ijk}, we obtain the binomial variance for y_{ijk} as assumed above.

3 Survey

3.1 Descriptive statistics

The data used in this paper came from a large survey on market and nonmarket activities in Swedish households conducted in 1996.[5] All individuals aged 18 years and older were included in each interviewed household. There were 3240 respondents in 1922 households who were interviewed by telephone (the questionnaire had been sent out in advance to the respondent).[6] The survey

[5] The survey population was Swedish-speaking persons aged 18–74 living in Sweden.
[6] The nonresponse rate in the survey was 24%.

Table 1. Descriptive statistics

Name	Description	Mean	SD
Income	Individual net income	113022	56327
Children	Number of children	0.66	0.47
Age	Age (years)	46.9	15.8
Male	One if male	0.52	0.50
Married	One if married	0.78	0.41
Education	Education in years	11.9	3.4
House owner	One if respondent owns house	0.16	0.37
Serious disease	One if respondent has some pollution-related disease (e.g., asthma or bronchitis)	0.08	0.27
Pollution knowledge	One if respondent has good knowledge about what substances are present in exhaust fumes from petrol-driven private vehicles	0.44	0.50
Environmental organization	One if member of an environmental organization	0.09	0.29
Car	One if respondent owns a car	0.52	0.50

included a CV question in addition to specific questions about the environment, such as knowledge about emissions from car traffic and about nature. The CV scenario presents a program that can reduce the concentration of harmful substances in the region where the respondent lives and works by 50%. The aim to exclude global environmental effects such as greenhouse effects from the scenario and the wordings of the scenario are found in Appendix 1. A detailed description of the survey was presented in Flood and Olovsson (1999) and Carlsson and Johansson-Stenman (1999).

Altogether, 96% of the respondents answered the valuation question (3107). However, due to the nonitem responses mainly on socioeconomic characteristics, the sample size analyzed was reduced to 2120 respondents. In the sample, 34% stated that they were not prepared to pay anything for the program. The mean WTP for the whole sample was 156 Swedish Kronas (SEK), and among those with a positive WTP it was 236 SEK. The corresponding medians were 100 and 150 SEK, respectively.

Apart from the standard socioeconomic variables, information was collected about whether the respondent suffered from diseases (e.g., asthma, bronchitis, recurring headaches) that could be related to air pollution. A question was posed about whether they were members of any environmental organization. This variable is used as a proxy for environmental concern. Finally, we wished to test whether knowledge about what causes air pollution affects the WTP, which was done by analyzing responses to what substances they thought were present in exhaust fumes from petrol-driven private vehicles. Summary statistics for the explanatory variables used in the estimations are presented in Table 1.

3.2 Econometric model and results

The data are hierarchically structured as it is likely that individuals in the same household have homogeneous preferences for a reduction in the level of air pollution, and member of households in the same region have homogeneous preferences for a reduction. Thus we applied a three-level model when analyzing the responses. We constructed four regions to consider differences in the level of air pollution based on population densities: large cities, medium-sized cities, small cities, and countryside. Because it is almost impossible to obtain an accurate measure of the level of air pollution for each household, it is impossible to cluster households accurately with regard to the level of air pollution. Hence, variations in valuation among households may be explained not only by heterogeneous preferences for the valuation of a reduction between households but also by local differences in the level of air pollution across households within the same region.

There were two decisions to be analyzed: (1) whether to contribute to the program (i.e., a participation decision); and (2) the maximum WTP a respondent states, provided the respondent contributes (i.e., a valuation decision). We assumed that these two decisions were made independently of each other. Consequently, we used a two-stage sample selection model without any correlation between the two decisions.[7] The participation decision is modeled by a logit model with three levels. The valuation decision is modeled by a three-level OLS model including only the respondents with a positive WTP, and the dependent variable is the natural logarithm of WTP. We chose the natural logarithm to account for skewness of the WTP distribution and to restrict the WTP to positive values. We performed all estimations using MLwiN (Goldstein et al. 1998).

Table 2 presents the coefficients of the estimated models.[8] The results from estimations of the participation model are presented in the second column and those of the valuation model in the third column. In the survey, 653 of the 2120 stated zero WTP. Being male reduced the probability of participating significantly. However, participating male subjects were willing to pay significantly more for reduction. Age has a significantly negative effect on the probability of participation and on the WTP, given participation. On the other hand, years of schooling and income increased participation and valuation significantly. The latter effect may be expected, as the ability to pay increased with income. The number of children also increased the WTP significantly, which may indicate a concern for the effect of air pollution on the respondents' children.

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[7] For an application of multilevel models with sample selection models with correlation between the two decisions, see Langford et al. (1998b).

[8] The estimation of the binary contribution model uses a second-order predictive quasi-likelihood procedure, and the continuous valuation model is estimated by restricted iterative generalized least squares. For details on estimation procedures see Goldstein (1995) or Rice and Jones (1997).

Table 2. Estimates of the participation equation and valuation equation

Parameter	Participation	Valuation
Fixed part		
Constant	1.844* (0.486)	3.792* (0.205)
Male	−0.248* (0.116)	0.180* (0.048)
Age	−0.045* (0.004)	−0.009* (0.002)
Education	0.330* (0.148)	0.354* (0.056)
Log income	0.107* (0.043)	0.105* (0.019)
Serious disease	−0.186 (0.192)	0.091 (0.085)
Environmental organization	0.460* (0.213)	0.181* (0.077)
Pollution knowledge	−0.070 (0.112)	0.094* (0.047)
Married	0.182 (0.152)	0.094 (0.065)
Children	−0.088 (0.068)	0.064* (0.026)
Car	0.056 (0.116)	0.120* (0.048)
House owner	0.096 (0.131)	0.110* (0.053)
Random part		
Level 3 σ_v^2	0 (0.00)	0.004 (0.005)
Level 2 σ_μ^2	0.706* (0.157)	0.089* (0.036)
Level 1 σ_ε^2	1.000 (0.00)	0.666* (0.041)
Total	2120	1467

Results are coefficients and standard errors (in parentheses)
*Significant at the 5% level

Furthermore, assets in terms of car and house ownership increased the WTP significantly, which may also be seen as an indication that the ability to pay affects the valuation. As expected, the probability of participating and the WTP increased if the respondent was a member of an environmental organization. Furthermore, valuation increased significantly when the respondent had some knowledge about pollution. However, it is surprising that respondents who suffered from a serious disease related to air pollution neither had a significantly higher probability of contributing nor a significantly higher level of WTP than respondents who did not suffer from such a disease. Comparing these results with a standard logit and OLS (not reported here), we found that the standards errors were lower but that there were no systematic differences in terms of significance.

The distribution of variance between the levels is of special interest. The coefficients of the variance terms at level 3 were not significant in any of the estimated models. This means that for a 50% reduction in the level of air pollution the probability of participating and WTP being conditional on participation did not differ among regions. At level 2 there was a great variation across households, as the coefficients of the variance terms at level 2 were significant in both models. Moreover, the intrahousehold correlation was 0.12 in the participation model and 0.42 in the valuation model, indicating that the predictions from the fixed parts of both models differed significantly from the probability of participation and WTP of individuals in household j.

4 Discussion

This paper has discussed the application of multilevel models to CV surveys asking for individuals' WTP for a reduction in the level of air pollution; individuals' valuations have accordingly been clustered into groups. Furthermore, we applied the multilevel model approach to a CV survey on a 50% reduction in the local level of air pollution in Sweden. Our results indicate that there are no differences among regions in Sweden. However, as each region covers a large area, the variations among households may at least be partly explained by differences in the level of air pollution within a region. For example, a study in Stockholm reported substantial differences in the level of air pollution between different parts of Stockholm (Johansson et al. 1999), which may support the hypothesis that some of the variations among households may be explained by variations in the local level of air pollution. However, most variations in both models are among individuals within households.

From a policy perspective it is interesting to note that a 50% reduction in the level of air pollution is valued the same, independent of region. This implies that fixed shadow values of emission reductions could be used for policy purposes in the case of changes in the level of local air pollution. The question is how much of the variation at the household level accounts for variations in the level of air pollution within a region. Further research is needed to test for regional differences based on local data on the level of air pollution such that household and regional effects may be partitioned with certainty. The result from such a study is important to justify whether fixed shadow values of emissions in environmental policies can be used.

We suggest that the researcher routinely considers a multilevel model approach when analyzing CV data collected in areas with different levels of air pollution. The approach is probably more applicable to surveys in countries that have higher levels of air pollution or when the levels of air pollution differ more substantially among regions. Furthermore, the multilevel approach may be directly applicable to other areas in environmental economics, such as to CV surveys on improvements in water quality.

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Appendix 1: Scenario

Assume that a number of measures can be taken to reduce the level of air pollution in the area where you live and work. However, money must be raised to cover the costs arising from these measures. Imagine that these measures will be financed through a charge paid by the residents in your area, the level of which would be dependent on income. What is the maximum amount you would be willing to pay PER MONTH in KRONOR [1 GPB = 13.50 SEK at June 1999 exchange rates] for implementation of measures that will reduce the level of harmful substances by 50% (i.e., by half) in the area where you live and work? Please consider how this charge would affect your household budget each month.

For example, stricter regulations might be implemented for permitted levels of discharge from cars, traffic diversions, and reduced emissions from industry. The level of air pollution remains unchanged in all other areas in Sweden. Your answer must be given using your present situation as a starting point (e.g., not a situation in which you had greater means). The reduction in air pollution is maintained only so long as payment is made. The charge is not tax-deductible and affects all households, but it does not affect industry.