Joint models for noise annoyance and WTP for road noise reduction

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Abstract

Previous CV studies of the WTP for road noise reduction have used stated annoyance as an independent variable. We argue that this may be inappropriate due to potential endogeneity bias. Instead, an alternative model is proposed that treats both WTP and annoyance as endogenous variables in a simultaneous equation model as a combination of a linear regression with an ordered probit with correlated error terms and possibly common parameters. Thus, information on stated annoyance is utilised to estimate WTP without bias. Application of the model to a dataset from Copenhagen indicates a potential for improving the precision of the estimate of WTP for noise reduction with CV data.

1. Introduction[1]

In this paper we consider the statistical specification of models for the willingness to pay (WTP) for noise reduction obtained from valuation surveys. Traditionally, property value methods have been applied to measure the social cost of the annoyance from road noise, but an increasing number of studies now use contingent valuation (CV) to evaluate the WTP.[2] Different valuation scenarios have been used in these studies, but a number of recent CV studies have adopted methods developed by noise researchers, who for several years have analysed the impact of noise on the experienced (self-reported) annoyance. This line of research has developed into standardised methods for asking questions in "socio-acoustic" surveys about level of annoyance using a five-point annoyance scale (ISO, 2003) and there now exists a large body of scientific evidence on the exposure-response relationship between noise and level of annoyance (measured as the probability of being annoyed at a particular annoyance level), e.g. Miedema and Oudshoorn (2001) and Klæboe (2003).

Examples of contingent valuation studies, which combine the socio-acoustic survey tradition with CV questions on the WTP for removing the noise annoyance include Navrud (2000), Lambert et al.

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[1] The research was supported by the Danish Strategic Environmental Research Programme. The authors are grateful for valuable comments from Jacob Nielsen Arendt (but of course any errors and omissions are our own).

[2] For a discussion of the pros and cons of the hedonic and contingent valuation methods with respect to noise see e.g. Navrud (2002) or Bjørner et al. (2003).

(2001) and Bjørner et al. (2003), and the approach is advocated by Navrud (2002) in his recent survey of the state-of-the-art of economic valuation of noise. The underlying idea is that estimates of the WTP conditional of annoyance levels can be combined with noise exposure-annoyance relationship to calculate the expected WTP for the relevant reductions in noise exposure. This involves, as a first step, estimation of annoyance as a function of noise and then, in a second step, estimation of WTP as a function of the stated annoyance level.

However, this sequential method opens the possibility of endogeneity bias, since unobservables in the model for annoyance and the model for WTP may be correlated. Thus, an individual who for some unobserved reason states a higher annoyance level is also more likely to state a higher WTP. This introduces a correlation between the error term and the independent variables in the WTP equation, which renders the estimation of WTP inconsistent.

One solution to the endogeneity problem is to estimate a (one step) reduced form model, where WTP is estimated directly as a function of noise, i.e. without estimating the relationship between noise and annoyance. We estimate a reduced form model specified as a hurdle model (Wooldridge, 2002), which takes account of the censoring of the WTP in a more general way than the standard tobit model.

The hurdle model provides unbiased estimates of the WTP, but it does not utilise the information revealed by the respondents when stating their annoyance levels. The information on annoyance is an important indicator of preferences for noise reduction and it therefore seems worthwhile to explore whether the information on annoyance may be used to obtain better estimates of the WTP for noise reduction. We consider two variations of a model where annoyance is considered as an endogenous variable and estimated jointly with WTP. Given the ordinal nature of the annoyance variable an ordered probit is used to model annoyance, while a linear model is used to estimate log WTP (conditional on a positive WTP being observed). In the first version of the model the ordered probit and the WTP models are linked only though correlation in the error terms. In the second version of the model an index is defined, which affects both stated annoyance and WTP. This index can be interpreted as a latent noise disturbance index, which influences both stated annoyance and WTP. The ordered probit and the linear WTP parts of the model are linked through the common parameters in the index and (as before) through the error terms, which are allowed to be correlated. This gives rise to a likelihood function, which resembles the product of the likelihood functions of OLS and ordered probit, except for the correction for correlation and common parameters. We apply these models to data from a combined socio-acoustic and contingent valuation survey from Copenhagen.

In the next section we further motivate the models presented in the paper. The applied data are briefly described in section 3. In section 4 we present and estimate the hurdle model, while the combined discrete/continuous models are presented in section 5. The conclusion is offered in section 6.

2. Motivation

Let us consider a sequential two-step procedure, which (implicitly or explicitly) has been used in the previous contingent valuation studies on WTP for avoiding noise annoyance referenced in the introduction. For simplicity annoyance is described as a continuous variable A depending on noise (N) and other independent variables Z_1, while WTP is a function of annoyance and other independent variables Z_2.

$$A = \gamma_1 Z_1 + \gamma_2 N + e_1 \tag{1.}$$

$$WTP = \gamma_3 Z_2 + \gamma_4 A + e_2 \tag{2.}$$

Now for OLS of equation 2 to be consistent, we must have E(Ae_2)=0, but E(Ae_2)=E(e_1e_2) which is generally not zero, when the errors are correlated. One likely source of correlation is the use of computed rather than measured values for the noise variable[3]. Discrepancies between the computed and the actual noise would affect both annoyance and WTP and introduce correlation in the error terms. Differences in individual preferences could also cause correlation: An individual who for some unobserved reason is more disturbed by noise may both state a higher degree of annoyance and a higher WTP.

Hence OLS of equation 2 is inconsistent. For the same reason it is also not appropriate to compute average WTP for each annoyance level, as this just amounts to a regression of WTP on annoyance dummies only with no other variables.

Equations 1 and 2 resemble structural equations. But there is nothing structural about the relationship between annoyance and WTP as there is, e.g., in the formulation of structural equations for supply and demand. In this case the structural equations describe the behaviour of different agents. In our case, it is not meaningful to suppose that annoyance can be varied independently to yield the relationship with WTP in equation 2. Wooldridge (2002) argues that it is misleading to estimate structural equations for individual responses, since the endogenous variables are choices of the same economic unit. Such equations should be estimated in reduced form.

As an alternative to the two-step model a reduced form can be estimated, which will yield unbiased estimates of WTP as a function of noise. Such a model (taking into account that the WTP variable is censored) is described in section 4. However, a disadvantage of the reduced form is that it does not exploit the information offered by the respondents, when stating their annoyance level. As an example, there are respondents who do not provide information on their WTP (either because they do not answer the relatively complex question or because they provide an implausible protest bid). These respondents are not included in the reduced form model even though they have preferences for noise reduction indirectly expressed in their stated annoyance levels. In the combined models presented in section 5, the information on annoyance of the non-respondents to the WTP question is utilized to obtain better prediction.

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[3] Measured values of noise are rarely used in traffic planning and valuation studies. Instead noise is computed as function of traffic volumes, speed, distance etc.

3. Data

The data applied were obtained from a recent study (Bjørner et al., 2003), where data were collected using a combined socio-acoustic and contingent valuation survey, administered by mail to a sample of 2,200 respondents from the Municipality of Copenhagen. Respondents living in areas with relatively high traffic levels were over-sampled in order to obtain a reasonable number of respondents exposed to medium and high noise levels. The survey questions on noise annoyance followed the guidelines specified in ISO (2003), where respondents indicate a level of annoyance on a five-level scale (not at all annoyed, slightly annoyed, moderately annoyed, very annoyed or extremely annoyed). The questions on noise annoyance were combined with questions on the WTP for avoiding the noise annoyance. Follow-up questions were used to distinguish between genuine and protest zero bids. Further description of the data and motivation for the question format can be found in Bjørner et al. (2003). [4]

In total 1,149 of the questionnaires were returned, but due to item non-response (especially for household income) the results reported in this article are based on answers from 1,072 respondents. The noise level did not have significant impact on response level at a 5% level. Of the utilised questionnaires 574 (53%) stated a positive WTP for removal of the noise annoyance, while genuine zero bids were obtained in 254 (24%) cases, and "protest" bids (including item non-response to the WTP question) were obtained in 244 (23%) cases. A high share of zero bids (legitimate and protest) has also been found in previous CV studies on noise reduction, see e.g. Navrud (1997), Lambert et al. (2001), Soguel (1996) and Vainio (1995 and 2001).

Data on the exposure of noise for each dwelling were obtained from the Environmental Protection Agency, Copenhagen. They calculated the noise exposure using the Nordic Prediction Method for traffic noise, where noise is described as a function of traffic levels, speed and share of heavy traffic. The calculated noise at street level was subsequently combined with GIS to calculate the distance between the noise source and each dwelling. Noise exposure in dB is measured as $L_{Aeq,24}$, which is the average daily noise level using an A-weighting of the sound frequencies, which makes the sound measure consistent to the subjective perception of noise by the human ear.

In the model we use log(WTP) as the dependent variable (given WTP > 0) as the transformed distribution is about normal. The choice of explanatory variables in the model, based on previous studies and preliminary estimations, includes noise, noise squared, log of household income, sex, and dummy variables for level of education. Finally, we included age and age squared inspired by sur-

[4] An English translation of the questionnaire can be found in Bjørner et al. (2003). It should be noted that the WTP responses were obtained using an open-ended question format, which yields a continuous variable for WTP. The choice of question format for WTP has obtained massive attention in the valuation literature. A number of scholars advocate a dichotomous choice WTP format because it is incentive compatible in theory, but the dichotomous format has also been suspected of providing upward biased estimates due to "yeah-saying". The models described in the following sections of course only apply to the open-ended WTP format, but in principle the ideas can also be applied to a model relying on dichotomous choice WTP data.

vey results of Miedema (2001), who finds that age has a significant impact on noise annoyance with annoyance being lower for young and old respondents. Table 1 presents descriptive statistics for the variables.

Variable	Mean	Std Dev	Minimum	Maximum	N
annoyance level[1]	2.42	1.16	1	5	1072
WTP[2]	1.03	2.76	0	50.00	828
dB ($l_{Aeq,24}$)[3]	63.96	7.74	29.20	76.20	1072
sex[4]	0.56	0.50	0	1	1072
age	41.44	16.42	17.00	102.00	1072
log(income)[5]	10.12	0.76	7.82	11.51	1072
high_edu	0.25	0.43	0	1	1072
medium_edu	0.26	0.44	0	1	1072

Notes:
1: 1 is the lowest level of annoyance (not at all annoyed), while 5 is highest (extremely annoyed). The distribution across annoyance levels is 22.3%, 39.2%, 20.2%, 11.3% and 7.0%;
2: Annual WTP in 1000 DKK;
3: Noise is rescaled by subtracting 29 when estimating the model;
4: Female=1;
5: Log of monthly household income.

Table 1. Descriptive Statistics

4. Modelling WTP alone

The distribution of legitimate WTP bids includes a large share stating zero and a distribution of positive WTP skewed to the right. We therefore employ a general version of the hurdle model (Blundell and Meghir, 1987; Wooldridge, 2002), which consists of probit for the choice between zero or positive WTP and a regression for log WTP. We generalise this formulation by allowing for correlated errors and common parameters.

Assume a latent index $y^*=\gamma x+\varepsilon_1$. When $y^*<0$ we observe a zero WTP response WTP=0; when $y^*>0$ we observe a positive WTP, which we model by log(WTP)=$\beta x+\varepsilon_2$. This amounts to the product of a probit model and a linear regression. The errors are taken as jointly normal with variances σ_1^2 and σ_2^2 and correlation ρ_{12}. The probability of observing zero WTP is P(WTP=0)=1-$\Phi(\gamma x/\sigma_1)$, while the probability of observing some positive y becomes

$$\begin{aligned} P(\log(WTP)=t) &= P(\beta x+\varepsilon_2=t,\varepsilon_1>-\gamma x) \\ &= \frac{1}{\sigma_2}\varphi\left(\frac{t-\beta x}{\sigma_2}\right)\Phi\left(\frac{\gamma x}{\sigma_1\sqrt{1-\rho_{12}^2}}+\rho_{12}\frac{t-\beta x}{\sigma_2\sqrt{1-\rho_{12}^2}}\right) \end{aligned} \tag{3.}$$

We may be able to use the estimates of the parameters for noise from the probit model to improve precision in the estimates of the parameters for noise in the regression. The variance in the probit is not identified separately from the other parameters and therefore the probit variance is usually normalised to one. As we want to be able to impose common parameters we do not use this normalisation. Instead we let at least one parameter be common for the two equations in order to set the scale for the probit model, that is $\gamma_i=\beta_i$ for at least one i. This restriction is sufficient to identify the probit model. When $\rho_{12}=0$ we just achieve two independent models. With only one cross-equation parameter restriction this is equivalent to separate probit and linear regression models. With more cross-equation restrictions it is really only the ratio of the parameters that is restricted to be equal across equations, since the scale of the parameters in the probit equation is not identified.

Variables for the probit and linear regression parts of the model were identified as those significant at 5% in preliminary separate probit and OLS models for 1{WTP>0} and log(WTP). We have noise, noise squared and log(income) in both equations, age, age squared and a constant in the probit and dummies for high and medium education in the linear regression.

Here and later a constant 29 dB is subtracted from the noise variable in order to avoid large numbers in the likelihood function. This involves no restriction on the models and does not affect results. However, since all models presented contain noise and noise squared, the scaling affects not only the constants in the model, but also the size of the parameter to the first-order noise term. In fact, any value for the first-order term can be obtained depending on the choice of scaling. Therefore, the significance of the first-order term is not really relevant, which should be kept in mind when interpreting results.

Model estimation started with a model where all variables enter both equations with different parameters except for the parameter for noise squared, which links the two equations.[5] Insignificant variables were removed which led to the same variables entering each equation as in the preliminary models that led to the selection of variables. We then estimate three models; results are shown in table 2. H1 is the starting model; in H2 we restrict the correlation to be zero with little loss of likelihood, the restriction is accepted with p=0.39 from the likelihood ratio test; in H3 we constrain the parameter for noise to be equal across equations, this time with somewhat larger loss of likelihood: p=0.08 against H2 from the likelihood ratio test. Normality of the residuals of log(WTP) is easily accepted using a range of tests.[6]

The model is estimated for data with positive WTP and legitimate zero bids, while protest bids are not included.[7] A common noise index is accepted in H3 and the standard deviations of the estimated parameters are generally reduced, particularly those for noise. Thus, if only WTP information was to be analysed, H3 would be the preferred model. However, the main observation for the purpose of this paper is that the error terms of the binary probit and the regression can be taken as independent.

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[5] Estimation of this and later models was carried out using the Logl object in EViews.

6 In previous models without log transformation of WTP, normality of the residuals could not be accepted.

[7] Both equations have been tested for selection bias with respect to protest bids using the inverse Mills ratio from a binary probit on protest bids (Heckman, 1979). The corresponding parameter was insignificant in both cases.

This allows us to also treat the two equations independently. We shall utilise this in the following section.

		H1 Coef.	H1 Std. Err.	H2 Coef.	H2 Std. Err.	H3 Coef.	H3 Std. Err.
$\gamma=\beta$	Noise					-0.047	0.019*
	Noise^2/100	0.19	0.050	0.18	0.048**	0.11	0.035**
γ	Constant	-3.0	1.9	-2.8	1.9	-1.1	0.64
	Noise	-0.065	0.030*	-0.059	0.026*		
	Age	0.049	0.030	0.049	0.031	0.025	0.014
	Age^2/100	-0.079	0.037*	-0.078	0.040*	-0.040	0.017*
	Log(income)	0.31	0.16	0.28	0.16	0.14	0.061*
β	Constant	2.6	1.0**	3.2	0.82**	2.4	0.74**
	Noise	-0.093	0.030**	-0.090	0.029**		
	Log(income)	0.42	0.077**	0.38	0.069**	0.38	0.070**
	high_edu	0.47	0.12**	0.46	0.12**	0.47	0.12**
	medium_edu	0.51	0.12**	0.51	0.12**	0.50	0.12**
σ_1		1.4	0.56*	1.4	0.60**	0.68	0.20**
σ_2		1.2	0.062**	1.2	0.037**	1.2	0.036**
2*logit(ρ_{12})-1		0.58	0.66				
Log likelihood		-1359.2		-1359.6		-1361.1	
Number of Coefs.		14		13		12	
Number of obs.		1072		1072		1072	

Table 2. Parameter estimates for the hurdle model (Significance at 5% and 1% indicated by one and two asterisks).

In the case when the error terms are not correlated, the expected WTP for noise reduction can be computed from expression (1) as follows.

$$E(WTP) = E(WTP \mid WTP > 0) \times P(WTP > 0) = e^{\beta x + \sigma_2^2/2} \Phi\left(\frac{\gamma x}{\sigma_1}\right) \tag{4.}$$

Differentiating with respect to the noise variable yields marginal WTPs per dB at different noise levels, where *N* is the noise level.

$$\frac{\partial E(WTP)}{\partial N} = \frac{\partial \beta x}{\partial N} e^{\beta x + \sigma_2^2/2} \Phi\left(\frac{\gamma x}{\sigma_1}\right) + \frac{\partial \gamma x}{\partial N} e^{\beta x + \sigma_2^2/2} \varphi\left(\frac{\gamma x}{\sigma_1}\right) \frac{1}{\sigma_1} \tag{5.}$$

Marginal WTPs have been computed using the parameter estimates from H2. Table 3 shows the two parts of expression (5), differentiating with respect to regression and probit parameters respectively, and the sum. The estimated marginal WTP increases with the noise level. At 52 dB the expected marginal WTP is zero. This corresponds well with results from the property value literature, which generally finds that property prices are not affected by changes in noise levels below 50 or 55 dB, see e.g. Navrud (2002).

It should be noted that the main part of marginal WTP is due to increasing WTP conditional on WTP>0. Increasing probability of stating a positive WTP contributes less. This does not mean, however, that it is not important to take account of zero bids. All terms involving γ would be missing if zero bids were not taken into account.

Armed with these two observations: that the error terms of the probit and the linear regression can be taken as independent, and that the linear regression accounts for most of the marginal WTP, we go on in the next section to see how it is possible to improve the precision of the regression by incorporating information on stated annoyance.

N	Regression	Probit	∂dE(WTP)/∂N
40	-25.9	-7.6	-33.5
45	-20.5	-0.8	-21.3
50	-8.8	4.0	-4.8
55	0.9	8.2	9.0
60	12.3	12.5	24.8
65	30.0	17.2	47.3
70	61.8	21.6	83.5
75	122.3	24.2	146.5

Table 3. Estimated marginal WTP (DKK per dB) from the H2 at various noise levels, DKK

5. Joint models for conditional WTP and annoyance

We have available the stated annoyance level, which is an ordinal variable with five categories. As discussed in section 2, it is quite likely that the error terms in models for annoyance and WTP are correlated. Accounting for this correlation might improve the estimate of WTP. Moreover, it is conceivable that there exists a common latent noise disturbance index behind both the ordered annoyance response and the WTP. If such an index could be identified, then incorporating the annoyance variable to estimate WTP could potentially improve precision of the estimates. This could be achieved by introducing cross-equation parameter constraints between a model for annoyance and a model for WTP. Finally, including annoyance in the model allows the use of information from all respondents including those giving protest bids. In a large proportion of cases respondents have stated their annoyance level without stating a positive WTP.

These considerations lead us to formulate a joint model with two dependent variables: Annoyance and log(WTP). The binary choice of whether to state a positive WTP is not included in this formulation.[8] Annoyance is described by an ordered probit model with latent variable A^* depending on independent variables x and a random component.

[8] It is possible to specify the likelihood function for a model also including the binary choice of whether to state a positive WTP. This involves, however, the evaluation of double integrals necessitating the use of numerical integration methods. Given the observations from the hurdle model above that only a smaller part of the marginal WTP is due to

$$A^* = \alpha x + \varepsilon_3 \quad (6.)$$

The stated annoyance is determined by A^* and a number of threshold parameters:

$$A = i \Leftrightarrow \tau_{i-1} < A^* < \tau_i\,,\ -\infty = \tau_0 < \tau_1 < ... < \tau_5 = \infty \quad (7.)$$

Note that α must restrict the parameter for a constant within x to be zero, since the thresholds τ are free to vary. We maintain the model from above for log(WTP) conditional of a positive WTP being observed.

$$\log(WTP) = \beta x + \varepsilon_2 \quad (8.)$$

One parameter must be equal across (5) and (6) in order to normalise the ordered probit, since the variance of ε_3 is free to vary. The errors are specified as joint normal with zero means, variances σ_2^2 and σ_3^2, and covariance $\rho_{23}\sigma_2\sigma_3$. This yields the likelihood function in (9), which can be estimated by maximum likelihood. Terza (1987) considers a similar model, however without regressors for the qualitative variable, and establishes the properties a two-stage estimator. He finds considerable gains in bias and efficiency compared to using dummies for the ordinal response.

$$P\left(A = i,\ \log(\mathrm{WTP}) = t\right) = \frac{1}{\sigma_2}\varphi\left(\frac{\mathrm{t} - \beta\mathrm{x}}{\sigma_2}\right)\left(\begin{array}{l}\Phi\left(\dfrac{\tau_i - \alpha x}{\sigma_3\sqrt{1-\rho_{23}{}^2}} - \rho_{23}\dfrac{t - \beta x}{\sigma_2\sqrt{1-\rho_{23}{}^2}}\right)\\ -\Phi\left(\dfrac{\tau_{i-1} - \alpha x}{\sigma_3\sqrt{1-\rho_{23}{}^2}} - \rho_{23}\dfrac{t - \beta x}{\sigma_2\sqrt{1-\rho_{23}{}^2}}\right)\end{array}\right) \quad (9.)$$

When ρ_{23}=0 the likelihood collapses to the product of an ordered probit and a linear regression with possible common parameter restrictions. When there is only one common parameter as there must be to achieve identification this is equivalent to estimating the models separately.

We include the cases where a positive WTP is not recorded, either because a zero bid or a protest bid has been given, and only A is observed. The likelihood then collapses to an ordered probit, i.e.

$$P\left(A = i \middle| X\right) = \Phi\left(\frac{\tau_i - \alpha x}{\sigma_3}\right) - \Phi\left(\frac{\tau_{i-1} - \alpha x}{\sigma_3}\right). \quad (10.)$$

Like with the hurdle model in section 4 we identified variables for the joint model as those significant at 5% in separate preliminary models. For the ordered probit part of the model we have noise and noise squared, age and age squared and sex. For the regression we again have noise and noise squared, log(income) and dummies for high and medium education. Initially, all variables were en-

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changing probability of stating a zero WTP and that the error terms in the hurdle model are independent, it seems that the effort involved in estimating the more complicated model with the binary choice included is not worthwhile.

tered in both equations. Discarding insignificant variables lead to the same selection of variables as in the preliminary models.

We estimate three models; results are shown in table 4. In the first we simply estimate an ordered probit for annoyance and a linear log(WTP) regression separately. These results are shown for comparison with the results from the models using the above specification. Moreover, the regression estimates are identical to those obtained from the hurdle model in H2 with independent errors and just one common parameter. Normality of the generalised residuals from the ordered probit is easily accepted using a range of tests.

In M1 the two models are joined by the coefficient on noise squared which is the one with highest t-statistics in the separate models. Although the choice of parameter for this normalisation does not matter for results, choosing a variable that is determined relatively precisely in the regression helps the estimation procedure. The correlation term that is introduced increases the likelihood quite dramatically by almost 11. Thus, the correlation of the error terms is extremely significant. In M2 we constrain also the parameter for noise to be equal across equations. Since the scale of the parameters in the probit is not identified this amounts to a test that the ratio between the parameters for noise and noise squared are equal. The LR test for this restriction has p=0.01, which suggests that M1 should be preferred.

		Independent		M1		M2	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
$\alpha=\beta$	Noise					-0.020	0.0096*
	Noise^2/100			0.19	0.047**	0.073	0.022**
α	Noise	-0.039	0.022	-0.045	0.019*		
	Noise^2/100	0.16	0.036**				
	Age	0.058	0.011**	0.065	0.024**	0.023	0.0072**
	Age^2/100	-0.064	0.00012**	-0.072	0.026**	-0.026	0.0077**
	Female	0.13	0.066*	0.17	0.091	0.061	0.031*
β	C	3.2	0.87**	2.9	0.81**	1.7	0.72*
	Noise	-0.090	0.032**	-0.095	0.029**		
	Noise^2/100	0.18	0.051**				
	Log(income)	0.38	0.069**	0.40	0.069**	0.41	0.069**
	High_edu	0.46	0.12**	0.47	0.12**	0.48	0.12**
	Medium_edu	0.51	0.12**	0.47	0.12**	0.45	0.12**
τ_1		1.1	0.43*	1.2	0.68	0.38	0.18*
τ_2		2.3	0.44**	2.6	1.0**	0.87	0.26**
τ_3		3.0	0.44**	3.4	1.3**	1.2	0.32**
τ_4		3.6	0.44**	4.1	1.5**	1.4	0.37**
σ_3		1	-	1.14	0.34**	0.41	0.099**
σ_2		1.17	0.037**	1.17	0.037**	1.18	0.037**
ρ_{23}				0.22	0.044**	0.22	0.044**
Log likelihood		-2344.5		-2333.6		-2336.8	
Number of Coefs.		16		17		16	
Number of obs.		1072		1072		1072	

Table 4. Parameter estimates for the joint models (Significance at 5% and 1% indicated by one and two asterisks).

In relation to the two independent models we have gained much from allowing for correlation of the error terms. It is clearly impossible to accept a model without this correlation due to the strong increase in likelihood yielded. But it is also hard to accept the restriction imposed on parameters by assuming a common noise index. We also note that the standard deviations of the noise parameters in the WTP equation decrease from the stand-alone OLS to M1 and even further from M1 to M2. The latter decrease seems, however, to be due to a decrease in the estimated variance of the probit equation, σ_3.

Table 5 shows the expected log(WTP) for all three models at sample averages and different noise levels with standard deviations calculated using the estimated parameter covariance matrix. The expected marginal WTPs are quite close in the M1 and OLS models (same as H2) and become positive between 50 and 55 dB as was also found with the hurdle model. There is a noticeable increase in precision going from OLS to M1 with standard deviations of log(WTP) being reduced by 5-10%. The estimated marginal log(WTP)s are not significantly different.

Imposing the equality restriction on the noise parameters in M2 yields significantly different results with expected WTP becoming positive between 40 and 45 dB, similar values to M1 around 60-65 dB and smaller values above.

We have thus achieved an improvement in precision by allowing for correlated errors in equations for annoyance and WTP but we have rejected the assumption of a common noise index behind both equations.

d B	OLS	M1	M2
40	-0.051 (0.021)	-0.054 (0.019)	-0.004 (0.006)
45	-0.034 (0.016)	-0.035 (0.015)	0.004 (0.004)
50	-0.016 (0.012)	-0.016 (0.011)	0.011 (0.004)
55	0.002 (0.008)	0.003 (0.007)	0.018 (0.005)
60	0.019 (0.007)	0.021 (0.006)	0.025 (0.006)
65	0.037 (0.009)	0.040 (0.008)	0.033 (0.008)
70	0.055 (0.013)	0.059 (0.012)	0.040 (0.010)
75	0.072 (0.017)	0.078 (0.016)	0.047 (0.012)

Table 5. Expected values of ∂log(WTP)/∂N (DKK per dB), standard errors in parentheses

Having estimated a joint model for annoyance and WTP it is possible to calculate the expected log(WTP) conditional on annoyance as the conditional expectation from the regression plus a parameter times the generalised ordered probit residual (Gourieroux et al., 1987).

$$
\begin{aligned}
E\left(\log(WTP)\middle|x, A=i\right) &= \beta x + E\left(\varepsilon_2 \middle| \tau_{i-1} < \varepsilon_3 + \alpha x < \tau_i\right) \\
&= \beta x + \rho_{23}\sigma_2 \frac{\varphi\left(\dfrac{\tau_{i-1}-\alpha x}{\sigma_3}\right) - \varphi\left(\dfrac{\tau_i-\alpha x}{\sigma_3}\right)}{\Phi\left(\dfrac{\tau_i-\alpha x}{\sigma_3}\right) - \Phi\left(\dfrac{\tau_{i-1}-\alpha x}{\sigma_3}\right)}.
\end{aligned}
\tag{11.}
$$

This is instructive as an illustration of the way in which the model works. The predicted shares of each annoyance level are shown in figure 1 using the results from M1. The share not at all annoyed (A=1) decreases from 0.54 at 40 dB to 0.04 at 75 dB, while the share of extremely annoyed (A=5) increases from 0 at 40 dB to 0.23 at 75 dB.

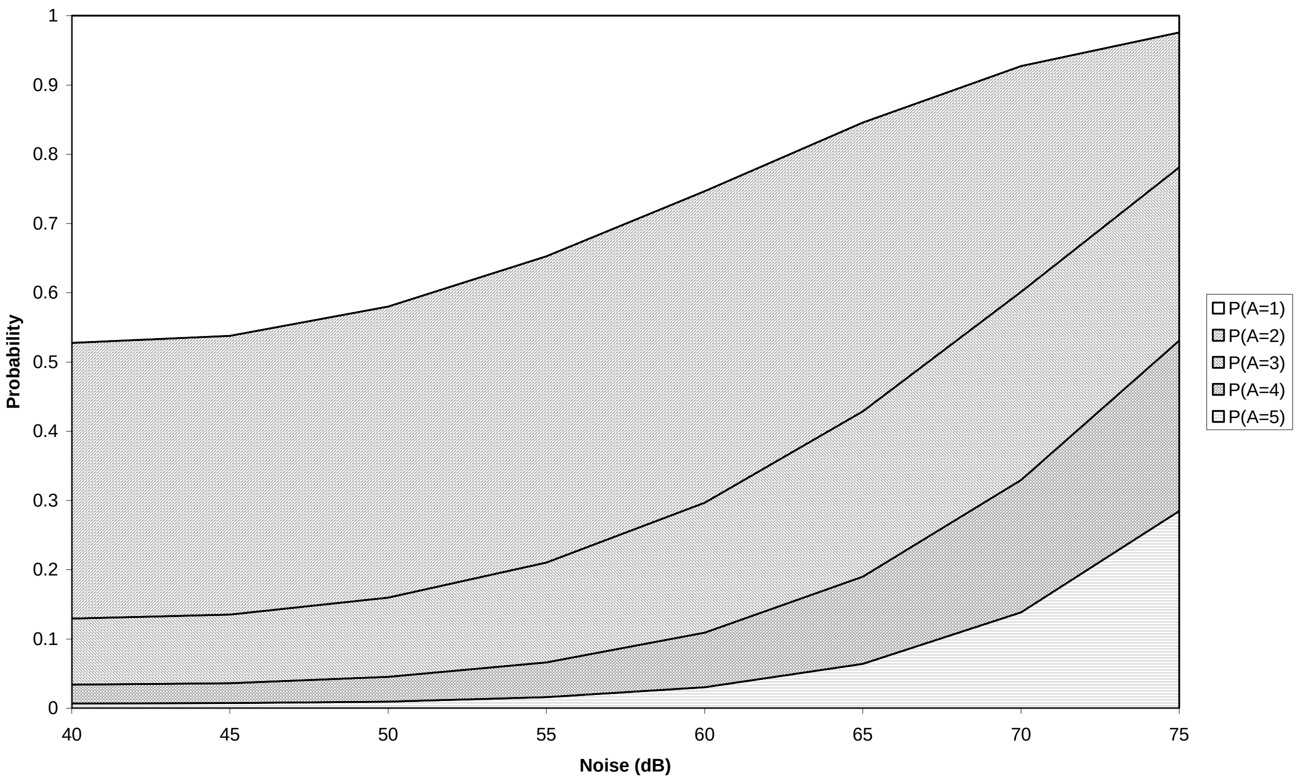

Figure 1. Estimated distribution of annoyance levels for different levels of noise

The results of applying equation (11) for the expected log(WTP) to the results from M1 are shown in figure 2. The expected unconditional log(WTP) ranges from 6.0 to 6.8 when noise ranges from 55 to 75 dB. However, when the respondent has stated that he is not at all annoyed the expected WTP ranges only from 5.8 to 6.2. When the respondent has stated that he is extremely annoyed, the expected WTP ranges from 6.7 to 7.2. The differences come from the information on the error term in the log(WTP) equation, which is gained from the annoyance variable. Thus, there is a strong relation between stated annoyance and expected WTP.

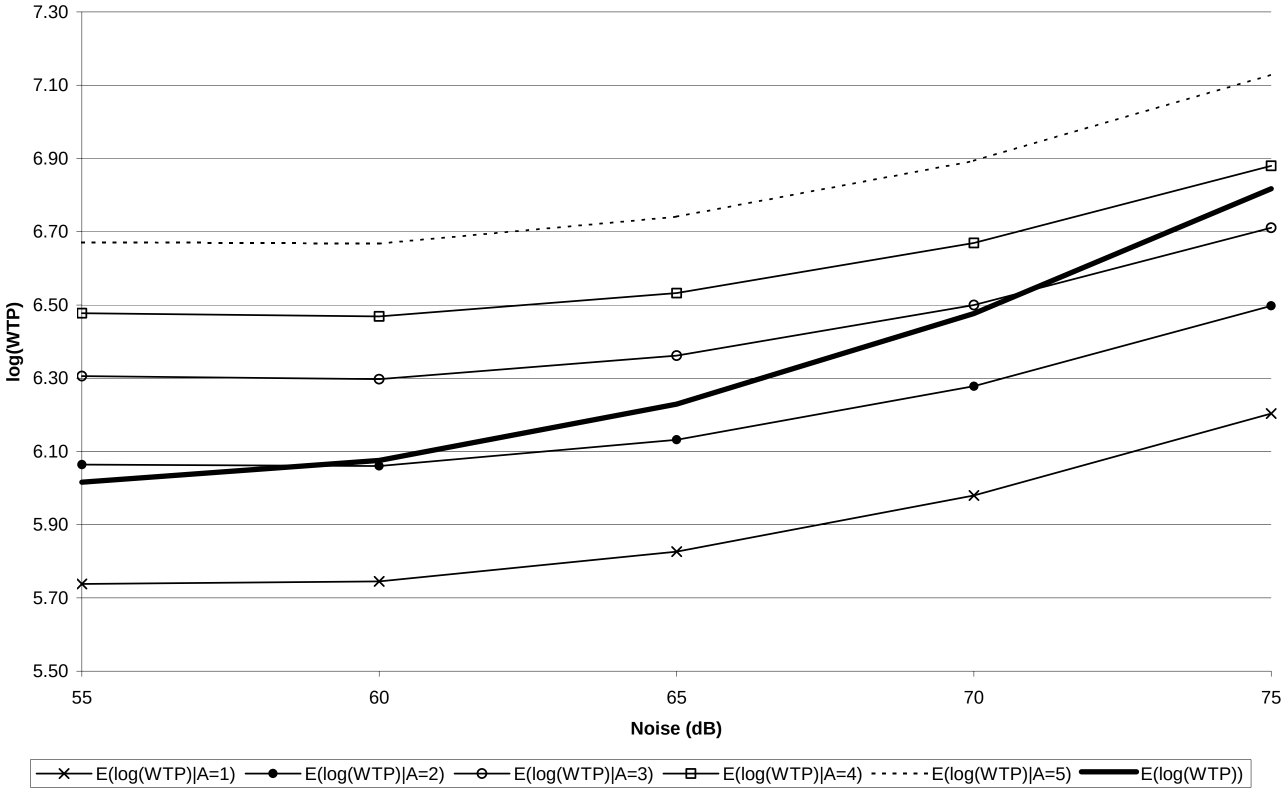

Figure 2. Expected log(WTP) conditional on different levels of annoyance

The slopes of the conditional log(WTP) curves are each about half of the slope of the unconditional log(WTP) curve. This reflects the distribution shown in figure 1, where an increasing noise level increases the probability of being more annoyed. The unconditional expected log(WTP) is a weighted average of the conditional expected log(WTP)s with the probabilities of the different annoyance levels as weights.

6. Concluding remarks

Given the large costs associated with collection of contingent valuation surveys it is certainly worthwhile to seek to improve precision by utilising as much of the available information as possible. Including information on stated annoyance to estimate WTP for road noise reduction aims to achieve this.

We have argued that the sequential two-step combination of annoyance and WTP information that has previously been applied is likely to involve an endogeneity bias and therefore not appropriate. Instead we develop an alternative model that treats both annoyance and WTP as endogenous, which we test on data from a CV study of the WTP for noise reduction that also contain stated annoyance as an ordered variable.

We first estimated a generalised hurdle model capable of describing the WTP data well. The results from this model show that the error terms of a probit for the decision of whether to give a zero bid or not and a regression for log(WTP) can be assumed to be independent and that the regression accounts for a large share of marginal WTP. These observations allow us to concentrate on the regression for log(WTP).

In order to combine this with the information on annoyance we have formulated a model that enhances precision in the estimation of an OLS regression by incorporating information from an ordinal response variable. This can work both through correlated error terms and through cross-equation parameter constraints, the latter giving rise to a latent index interpretation. The approach is quite general and may be applied in other situations where efficiency can be gained from the joint utilisation of a continuous and an ordinal variable.

The inclusion of information on annoyance succeeded in reducing the estimated standard deviation of marginal log(WTP) by 5-10% by accounting for correlated error terms and the correlation between the error terms was extremely significant. Thus, inclusion of annoyance in a model for WTP has merit. We rejected the hypothesis of a common noise index. It would be of interest to test the model on similar datasets, where there might be other possibilities for defining a common index than was the case here.

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