Valuing WTP for Diesel Odor Reductions: An Application of Contingent Ranking Technique*

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I. Introduction

In valuing environmental change, it is desirable to use market data, which reflect citizens' willingness-to-pay (WTP) for a better quality environment. Unfortunately, market data often are unavailable for this purpose. When this happens, WTP often is elicited from survey data. Of course, there are risks that consumers may not respond to a survey in the same manner that they respond in a real market. These risks can be reduced by framing the hypothetical context of the market as realistically as possible. In most prior applications, contingent valuation efforts have employed some variant of a direct WTP question. However, requesting survey respondents to supply a dollar value for what is probably an unfamiliar commodity inherently is problematic. In contrast, the contingent ranking procedure asks participants to compare and rank alternatives, each describing a different tradeoff between the provision of an environmental good and its price.

The contingent ranking approach is employed in this paper to estimate the value of reduced exposure to diesel vehicle odors from a 1984 survey of 140 respondents in the Philadelphia area. Diesel vehicle odors are related physically to the broader mobile source particulate emissions problem. In diesel fuel combustion processes, odor-causing unburned hydrocarbons are attached to particulate byproducts. Since particle removal technologies contribute in varying degrees to odor reduction, policies to reduce mobile source particulate emissions will provide the additional benefit of reducing the diesel odor nuisance type of externality. Given the pervasive nature of the diesel odor problem, even values to avoid a single odor contact of a few cents can amount in the aggregate to many millions of dollars. Thus, the benefit of odor reduction could be comparable to the magnitude of other health and welfare benefits associated with control of mobile source particulate emissions.[1]

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1. Prior to promulgating more stringent standards on emissions from heavy-duty trucks in March 1985, EPA performed a benefit-cost analysis of mobile source particulate emissions that included health and welfare, but not odor, effects.

II. Contingent Ranking Model

The contingent ranking approach presents individuals with a set of alternatives. In environmental applications, these alternatives describe different environmental quality conditions and the costs of obtaining them. Respondents rank these alternatives from most to least preferred. The estimated parameters of a discrete, utility maximizing, probability model provide a basis to compute the tradeoff between dollars and environmental quality. In this application, the contingent ranking model estimates an income compensated measure of WTP for reduced exposure to diesel odor.

The contingent ranking model, which makes use of the information contained in the full ranking of alternatives, is a refinement of logit and probit models. Logit and probit models utilize only some of the choice information that can be elicited from respondents. These discrete choice models have been widely used in transportation studies and consumer market research since the 1970s.[2] More recently, Beggs, Cardell, and Hausman [3] developed the contingent ranking model to utilize data from surveys that not only identify first choices, but also provide information on the relative rankings of second and subsequent choices.

The contingent ranking approach has been applied in environmental studies to estimate the value of visibility, water quality, and other environmental goods. The approach has certain advantages in that survey respondents only make comparisons among alternatives rather than trying to value them directly. The complexity of experimental design, however, has proved to be a problem in some past studies, so that parameter estimates may be sensitive to the number and range of choices that respondents are asked to consider.

The process of evaluating, comparing, and ranking alternatives based on price and other quality or performance attributes is well within the experience of most consumers. Appraising the value of a good directly, however, as required in other direct contingent valuation approaches, lies outside the everyday experience of most consumers. Hanemann comparing the discrete choice format and the direct WTP question, states:

> Most of the time, people do not consciously know their preferences; they usually cannot introspect their utility functions. Instead they discover their preferences when they actually make a choice [8, 6].
>
> Perhaps it is unwise, whether using an iterative or some noniterative procedure, to hope to pin people down to exact values of their willingness to pay for hypothetical changes in the supply of environmental goods. I want to suggest that their responses will be more reliable if they are required only to place bounds on their willingness to pay . . . This leads me to argue that certain surveys involving only discrete responses are inherently more reliable than the conventional surveys which require a continuous response [8, 9].

Mitchell and Carson [13] also advocate discrete choice methods, recommending that environmental valuation surveys use a referendum format rather than a direct WTP question. As pointed out both in Hanemann [8] and Mitchell and Carson [13], discrete choice methods also avoid starting point or interviewer biases that are associated with the direct question format when iterative bidding or other interviewer interaction is part of the protocol.

While the advantages of the contingent ranking approach are compelling, the complexity of the experimental design is a practical limitation. Respondents may be overwhelmed by the task of ranking a large number of alternatives with more than a few attributes. Also, the alternatives must be carefully designed to provide a range of prices that force a tradeoff among attributes. If prices

2. See, for example, Domencich and McFadden [5] for transportation demand study, Green and Srinavasen [6] for consumer research analysis, and Madansky [11] for comparison of conjoint and probability choice models.

are too low, respondents order alternatives by focusing mainly on the environmental attribute, while if prices are too high, respondents order alternatives according to the price attribute; precise trade-off estimates can not be determined in either situation.

Beggs, Cardell, and Hausman [3] first applied an ordered logit discrete probability choice model to ranked (panel) data to determine the potential demand for electric powered urban vehicles by focusing on the their performance attributes. Rae, Reddy, et al. [14; 15] initiated use of the contingent ranking methodology in environmental applications by estimating WTP for visibility improvements in Mesa Verde and Great Smoky Mountain National Parks and in Cincinnati. Subsequently, Desvousges, Smith, and McGivney [4] collected ranked survey data for water quality —safe to drink, safe for swimming, or fishable. These studies clearly demonstrated that the ranking technique could measure WTP successfully. However, the results were not always plausible [15], statistical significance was at times weak [14; 15], and the signs on income or price terms were sometimes incorrect [4].

A key question is whether the problems encountered by these environmental studies are due primarily to information overload—too many alternatives with too many complex attributes—or whether the ranking process is prone to yield unstable results regardless of the experimental design. Two visibility studies [14; 15] were tested for stability of the results across specifications using different choice sets. The authors found that the null hypothesis of no significant difference in results of specifications using the first choice (standard multinomial logit), first two choices, etc. could be rejected. Whether this instability is due to the highly complex survey design that ranked eight alternatives with three and four attributes or a more fundamental problem in respondents' abilities to rank alternatives consistently remains to be determined.

There are also theoretical concerns in applying the contingent ranking methodology. The logit-based discrete choice model requires all alternatives be independent of each other, since the addition of one alternative affects the choice probabilities of all other alternatives. This restriction precludes using the logit model where the environmental good to be measured is a close substitute for another environmental good in the choice set. Other assumptions also affect the applicability of the contingent ranking model or its estimation. One is that the indirect utility function is assumed to be well behaved and homogeneous of degree zero in prices and income. Since the underlying model is probabilistic, WTP is a random variable, so that statistical assumptions also affect estimation of WTP.

In contrast to paired alternative procedures, ranked data more fully describe a respondent's preferences. This suggests that a generalization of the logit specification can take advantage of the additional information revealed between most and least preferred alternatives. The generalized probability choice model assumes that an individual's choice is influenced by both the alternatives and by personal tastes, for which the usual mix of socioeconomic and demographic factors serve as proxies. The model also assumes that individuals select alternatives to maximize utility. Using cross-sectional survey data, the model finds the attribute parameters that maximize the likelihood that a randomly selected individual ranks the alternatives in the order they actually were chosen.

Starting with the multinomial logit form of the probability choice model, it can be shown that for any individual the probability of alternative j being preferred to alternative k is:[3]

$$\text{Prob}\left[U_j > U_k, j \neq k\right] = \exp(V_j)/\left[\exp(V_j) + \exp(V_k)\right] \tag{1}$$

3. Since derivations of probability choice models have been published elsewhere—see McFadden [12] for binary case and Beggs, Cardell, and Hausman [3] for complete ordered case—only an overview is presented here.

where V is the deterministic part of an individual's utility, U. Equation (1) is derived assuming that the random component of utility, ε_j, is independently and identically distributed with an extreme-value (Wiebull) distribution: $\text{prob}[\varepsilon_j \leq t] = \exp(-e^{-t})$. To conform to utility maximizing behavior, the V's are interpreted as indirect utility functions,

$$V = v(p, m, e, s) \tag{2}$$

where p represents the implicit prices or costs associated with the environmental alternatives as well as the prices for other goods; m is income; e, the environmental alternatives; and s, socioeconomic and demographic factors.

The binary specification can be extended to the case where a given alternative, whose utility is U_1, is preferred to all other alternatives, j. Then:

$$\text{Prob}[U_1 > U_j, j \neq 1] = \exp(V_1)/[\textstyle\sum \exp(V_j)]. \tag{3}$$

Given the assumed independence of alternatives, the products of equation (3) yield the probability of a complete ordering of choices, $r_1, \ldots, r_H$:

$$\text{Prob}[U_{r_1} > U_{r_2} > \ldots U_{r_H}] = \prod_{h=1}^{H} \{\exp(V_h)/[\sum_{j=h}^{H} \exp(V_j)]\} \tag{4}$$

where H is the number of alternatives.

The assumption of independent and identically distributed errors underlying the logit specification imposes the "independence of irrelevant alternatives" restriction on the contingent ranking technique. This restriction follows from the equality between the ratio of probabilities for the ith relative to the jth alternative and $\exp(V_i)/\exp(V_j)$. The latter ratio is independent of other non-included alternatives or the number of choices. This poses a problem for valuation of narrowly defined environmental amenities that have close substitutes which are not included in the choice set provided to respondents. In fact, there is evidence that contingent bids are affected by what respondents are told about the breadth of the set of environmental goods on which they can bid.[4] Thus, while the problem of dependence on choice alternatives potentially is present in ranked data, creating a valid general equilibrium choice setting may be problematic for all contingent methods. To minimize such respondent myopia, the survey protocol in this study provided for a multi-good setting. This is discussed further in the following section.

The choice model is completed by specifying the indirect utility function. Estimation then follows by forming a likelihood function, which defines the joint probability of the sampled respondent rankings as a function of the parameters of the indirect utility function. It is assumed that the indirect utility function, V, is linear in its arguments:

$$V = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n. \tag{5}$$

A maximum likelihood estimation procedure finds the β's that maximize the likelihood that a randomly selected individual ranks the alternatives in the order they actually were chosen.

4. Randall, Hoehn, and Tolley [16] found that preserving visibility at Grand Canyon was worth about $90 per household annually, when valued as a single good. In contrast, visibility improvement was worth only $15, when it was presented as the third component of a three good visibility package. Similarly, Rae et. al. [14] found preserving air quality in Smoky Mountain National Park was valued at about $60 annually when presented as a single good, but only $20 when presented in a competing context with ten other public causes.

Household characteristics can be included in an interactive manner in equation (5) to account for different households' preference patterns. The preference function, V, is identical for all households, since the β's are identical. Indirect utility differs only because the x's differ among households. A Newton-Raphson algorithm with variable step size was used to search for the maximum likelihood parameter estimates. From these estimates, it is possible to determine the implicit tradeoffs between the environmental states and changes in income.

Intuitively, if the estimate for one of the β's is negative, an increase in the availability of the corresponding attribute will decrease utility. This in turn will decrease the probability of a higher respondent ranking for alternatives with high levels of that attribute. The tradeoff between attributes and dollars is derived in a straightforward manner. Assume the indirect utility function has the following simple specification:

$$V = \alpha e + \mu c \tag{6}$$

where c is the cost variable associated with different environmental quality states, e, in this case the number of weekly exposures to diesel odor. Holding utility constant, and assuming a one unit decrease in e, the change in cost relative to the change in environmental quality, $\Delta c/\Delta e$, is simply the ratio $-\alpha/\mu$. Since α and μ are expected to be negative, a priori, the ratio is positive. Consequently, a decrease in the number of odor contacts results in a positive WTP.

More complex specifications for V yield somewhat more complex formulas for the benefit estimate. Consider, for example, a specification that includes income and multiple interactions of socioeconomic and demographic variables with both the environmental and cost variables:

$$V = \alpha e + \mu c + \theta[c/I] + \sum \tau_i e S_i + \sum \tau_j c S_j \tag{7}$$

where I is household income, and S_i and S_j are socioeconomic and demographic variables that interact with e and c, respectively. Socioeconomic and demographic variables are entered interactively, since they are respondent specific and do not vary with the ranked alternatives. In this example, the WTP tradeoff, $\Delta c/\Delta e$, is:

$$\Delta c/\Delta e = -(\alpha + \sum \tau_i S_i)/(\mu + \theta/I + \sum \tau_j S_j). \tag{8}$$

Since these benefit estimates are derived from first differences of the indirect utility function, Δc is a compensating surplus benefit measure, as long as Δc is measured as a change in income.[5] The survey narrative depicts the payment vehicle in terms of reduced purchasing power, which results from higher transportation costs that are passed along to consumers. Thus, by design, Δc, is an income adjustment rather than a fee for reducing odor contacts.

Interpretation of V as an indirect utility function is convenient in terms of the theoretical plausibility of the probability choice model and the measurement of WTP.[6] However, the empirical specification of V deviates from the general specification in equation (2). As explained above,

5. See Hause [9]. The compensating surplus measure of benefit is the change in income required to offset the utility change associated with the change in e. Complexities introduced by the probabilistic context of the model are ignored. See Hanemann [7] for a discussion of welfare estimation with discrete data.

6. McFadden [12] and Domencich and McFadden [5] developed utility interpretations of logit models. More recently Beggs, Cardell, and Hausman [3] and Desvousges, Smith, and McGivney [4] extended the utility analysis for ranked models.

an income change variable represents the change in transportation costs in lieu of an environmental price variable. In addition, prices of other product or service groupings are not included in the empirical specification. The omission of price variables is reasonable given the data are cross-sectional, especially when regional variation, and thus price variation, is negligible. In these circumstances, price variation probably will not be an important explanatory variable for respondent preferences. On this basis, the simplified indirect utility function, represented by equation (7), is considered a reasonable approximation.

III. Ranked Survey Data

A small sample of 140 respondents completed the diesel odor survey in 1984 from which we estimated WTP for reduced exposure to vehicle diesel odors. A random digit dialing technique provided a stratified (by age, sex, and education) random sample of the metropolitan population of Philadelphia. Some selection bias may have occurred, given that not everyone called chose to participate.

To reduce the hypothetical element intrinsic to any survey, the survey protocol required each respondent to smell two odors: *ODOR A*, characterized by a mild diesel smell, and *ODOR B*, which was more intense. An "odor" machine generated the calibrated odors from chemical constituents, and distributed them via a mask for a timed exposure.[7] Respondents then proceeded to the ranking procedure.

After describing the survey's purpose and procedures, monitors distributed a card set with four alternatives to each participant. Each alternative showed the number of weekly exposures to the two odors and the associated increased annual transportation cost required to reduce particulate emissions. The set shown in Figure 1 is typical. The survey protocol required the use of twelve different card decks. The alternatives in these decks differed in the number of weekly odor contacts and added annual transportation costs. Odor exposures were defined over three ranges: a low range, with one to four *ODOR A* and zero to four *ODOR B* exposures; a midrange, with two to eight *ODOR A* and one to four *ODOR B* exposures; and a high range, with two to ten *ODOR A* and one to ten *ODOR B* exposures. Annual costs were grouped into four sets: the first ranged up to \$12, the second up to \$35, the third up to \$50, and the fourth up to \$105. No clearly dominant choice was available in any one deck. The use of twelve card sets permitted a broad range of potential WTP responses without overly burdening any one respondent.

The survey instrument emphasized the connection between odor exposure reduction and increased transportation costs, since the credibility of the contingent market depends on establishing a realistic linkage between emissions control costs and WTP. In the case of diesel automobiles, a connection between citizens' demand for less odor exposure and a car owner's purchase of control equipment is difficult to establish. A direct payment link exists, however, for commercial diesel trucks. One would expect commercial operators of diesel trucks to pass along to consumers the increased costs caused by added emission controls of transporting a wide variety of goods. The

7. The odor generating machine uses a mixture of ingredients (called the Turk kit), that consists principally of unburned diesel fuel. This mixture is diluted heavily with air and delivered to a mask for a timed release. This simulated odor is safe (it does not contain potentially harmful combustion byproducts that are present in actual diesel exhaust), yet quite realistically characterizes diesel odors. The intensity of *ODOR A* is approximately 2 on an 8 point odor butanol scale, similar to that of a nearby diesel car; while *ODOR B* is approximately a butanol 5, similar to that of a nearby diesel truck.

PHILADELPHIA 3

ODOR A: 8 CONTACTS PER WEEK

ODOR B: 4 CONTACTS PER WEEK

ANNUAL HOUSEHOLD INCREASED COST: NONE

PHILADELPHIA 16

ODOR A: 4 CONTACTS PER WEEK

ODOR B: 2 CONTACTS PER WEEK

ANNUAL HOUSEHOLD INCREASED COSTS: $30

PHILADELPHIA 27

ODOR A: 3 CONTACTS PER WEEK

ODOR B: 3 CONTACTS PER WEEK

ANNUAL HOUSEHOLD INCREASED COSTS: $24

PHILADELPHIA 33

ODOR A: 2 CONTACTS PER WEEK

ODOR B: 1 CONTACTS PER WEEK

ANNUAL HOUSEHOLD INCREASED COSTS: $45

Figure 1. Attribute Cards Used in Ranking

tradeoffs specified in the odor survey are based on this description of increased transportation costs to all consumers.

To emphasize the opportunity cost of these tradeoffs, the survey asked respondents to specify the categories in their budgets that would be decreased to pay for their highest ranked alternative. In addition, prior to ranking the four alternatives, the survey questioned respondents about their willingness to support public types of goods and public causes, such as public television, United Way, educational institutions, the arts, and environmental causes. This process was designed to create a multi-good environment and to remind participants of the substitutions implied by their choices.

IV. Results

Initially, the choice specification assumes the rankings are not affected by socioeconomic and demographic factors. Table I shows two simple specifications, one with an income interaction term included, one without. The estimates for these models are quite plausible. As anticipated, respondents value increases in the frequency of odor contacts negatively (in terms of reduced utility). Similarly, respondents place a negative value on an increase in control costs. These variables are statistically significant at the 95 percent confidence level, with the exception of annual household cost in the second model, which could be characterized as borderline significant.[8] The

8. Since the standard errors of the estimated coefficients are estimated assuming asymptotic distributions, and since the standard errors for the WTP tradeoff values are indirectly estimated using a truncated Taylor series expansion, significance is somewhat uncertain. However, in most instances the magnitudes of the t-values are large enough to cover these doubts.

Table I. Contingent Ranking: Basic Specifications

Variable	Basic Specification		Income Interaction	
	Parameter	WTP($)	Parameter	WTP($)
ODOR A	−0.0798	5.86	−0.0840	7.96
(exposures/wk)	(−2.81)	(2.42)	(−2.92)	(2.17)
ODOR B	−0.2112	15.53	−0.2213	20.97
(exposures/wk)	(−6.00)	(3.28)	(−6.17)	(3.46)
Control Cost	−0.0136		−0.0057	
($/yr)	(−3.96)		(−1.35)	
Cost/Income			−0.1099	
($/$10^3)			(−3.82)	
Initial Log-Likelihood	−444.9		−444.9	
Maximum Log-Likelihood	−415.5		−410.8	
Likelihood Ratio Test	58.9		68.2	
R^2	.066		.077	

a. Sample size is 140 in both specifications.

b. Asymptotic t-values are shown in parentheses. The variances of the tradeoff values were indirectly estimated by using a truncated Taylor series expansion. See Johnston [10] pp. 401–402 for details of this procedure.

c. The initial log-likelihood reflects the probability of choosing (for an individual chosen randomly) the correct preference ordering without the variables in the indirect utility function.

d. The likelihood ratio, which is equal to 2 times the difference between the initial and maximum log-likelihood, has a chi-squared distribution. At the .95 confidence level, the critical value is 7.81 with 3 d.f., and 9.49 with 4 d.f.

e. R^2 is computed as 1 − (max. log-likelihood/init. log-likelihood), and is an alternate goodness of fit indicator for probability choice models. See McFadden [12].

WTP tradeoffs in these two specifications are $5.86 and $7.96 per household per year for a reduction of one *ODOR A* exposure per week, and $15.53 and $20.97 for a reduction of one *ODOR B* exposure. These estimates likewise are statistically significant. On a single odor event basis, the WTP ranges between $0.11 and $0.40. A likelihood ratio test confirms that the estimates of the overall models are statistically significant.

The addition of the income interaction term, entered as c/I, moderately improves the results. The parameter estimate of c/I is negative, as expected, and is statistically significant. At the sample mean income of $22,643, the income elasticity of WTP for either *ODOR A* or *B* is approximately .45. The relative insensitivity of WTP to income is somewhat surprising, since environmental amenities often are characterized as luxury goods. This result suggests that odor reduction is relatively more important to lower income households than is usually the case for improvements in environmental quality.

Additional specifications include attitudinal, demographic, and odor sensitivity variables. These are: (i) respondent evaluation of survey odor intensity (valued on a one to seven scale with a one being most unpleasant); (ii) a yes or no vote on a referendum question;[9] (iii) presence (or absence) of a medical condition related to air quality; (iv) children in family (yes or no); (v) attitude about expenditures on environmental quality (valued on a five point scale with one being too low and five too high); (vi) respondent self-evaluated sensitivity to general odors (valued

9. The referendum question was posed to respondents after they had completed the ranking procedure. Respondents were asked how they would vote on mandatory controls on diesel trucks and buses that would cost households between $11 and $22 a year.

Table II. Contingent Ranking: Odor Interaction Specifications

Variable	Specification A	B	C	D
ODOR A (exposures/wk)	−.4952 (−13.9)	−.2382 (−6.89)	−.3542 (−9.90)	−.3935 (−11.4)
ODOR B (exposures/wk)	−.6032 (−15.5)	−.5241 (−13.7)	−.7088 (−17.9)	−.4934 (−12.8)
Control Cost ($/yr)	−.0147 (−3.19)	−.0134 (−2.96)	−.0157 (−3.33)	−.0119 (−2.66)
Cost/Income ($/$$10^3$)	−.1156 (−3.61)	−.0993 (−3.14)	−.0982 (−2.97)	−.1124 (−3.57)
*A*Intensity* (unpleasant=1)	.0190 (1.38)			
*B*Intensity* (pleasant=7)	.0481 (4.03)			
*A*Diesel Vote* (yes=1, no=2)	.1503 (4.90)		.1785 (5.83)	
*B*Diesel Vote*	.1747 (5.48)		.1739 (5.48)	
*A*Medical Condition* (yes=1, no=0)	−.0240 (−.50)		−.0329 (−.07)	
*B*Medical Condition*	−.1231 (−2.41)		−.0861 (−1.69)	
*A*Child* (yes=1, no=0)	.0166 (.36)	.0320 (.72)		.0400 (.88)
*B*Child*	.0954 (2.02)	.0526 (1.15)		.0899 (1.88)
*A*Env. Expd.* (too low=1)	.0654 (3.81)	.0742 (4.84)	.0633 (4.01)	.1056 (5.14)
*B*Env. Expd.* (too high=5)	.1252 (6.51)	.1241 (8.70)	.1217 (8.28)	.1796 (9.74)
*A*Odor Sensitivity* (sens.=1)	.0338 (2.84)			.0484 (4.56)
*B*Odor Sensitivity* (not sens.=5)	−.0724 (−5.47)			−.0455 (−4.25)
*A*Smoke* (yes=1, no=0)		−.0499 (−.99)	−.0642 (−1.25)	
*B*Smoke*		.1348 (2.69)	.1486 (2.87)	
*A*Ethnic* (white=1)		.0501 (1.15)		
*B*Ethnic* (nonwhite=0)		−.0920 (−1.98)		
*A*Env. Contr.* (if Contr>0, 1)				.0041 (.07)
*B*Env. Contr.* (if Contr=0, 0)				−.1238 (−1.87)

Table II. Continued

Variable	Specification A	Specification B	Specification C	Specification D
Maximum Log-likelihood	−383.0	−391.8	−386.2	−391.4
R^2	.162	.136	.152	.137
WTP *ODOR A*	3.03	5.03	4.15	3.63
($/yr/wkly exp)	(1.70)	(2.55)	(2.42)	(1.80)
WTP *ODOR B*	15.54	16.03	14.57	18.16
	(5.37)	(5.17)	(5.41)	(4.82)

a. See Notes to Table I. Likelihood ratios for specifications A through D range from 107.1 to 123.9, which are significant at the .95 confidence level.

b. "*A*" in interaction terms refers to number of exposures to *ODOR A*; "*B*" to number of exposures to *ODOR B*. See text for definition of other variables. The mean values of the variables are: *Intensity*, 2.01; *Diesel Vote*, 1.13; *Medical Condition*, 0.48; *Child*, 0.46; *Environmental Expenditures*, 1.71; *Odor Sensitivity*, 2.73; *Smoke*, 0.36; *Ethnic*, 0.50; and *Environmental Contributions*, 0.30.

c. WTP for *ODORs A* and *B* are computed from coefficients, using equation (8) as described in text.

on a five point scale with one representing very sensitive); (vii) willingness to contribute to environmental causes (a dichotomous variable with yes equal to one); (viii) ethnic origin of respondent; and (ix) whether or not respondent smokes. Given that there is some overlap in what is measured by the variables and that the importance of each variable is uncertain, a priori, several different specifications are estimated. Table II presents the results from four models with odor interaction terms, and Table III presents the results from four similarly specified models with cost interaction terms.

Overall, including individual specific variables improves the explanatory power of the models. The maximum log-likelihood increases, as does the significance of the odor exposure and household cost variables. In addition, the magnitude of WTP computed from the estimated parameters is fairly robust across the specifications. As expected, the variables which interact with the more intense *ODOR B* in Table II generally are more significant than those which interact with *ODOR A*. The statistical significance of the socioeconomic and demographic variables improves in the models that interact with the cost variable in Table III relative to the specifications in Table II that interact with the two odor intensity variables. This also is expected, given that the variation is shared between two terms when the variables interact with odor and only one term when the variables interact with cost.

The signs of the estimated parameters generally match intuitive expectations, with well over one-half of the parameters significant at a 95 percent confidence level. When interaction terms are present, interpreting the sign and magnitude of estimated coefficients for attitudinal, demographic, or odor sensitivity variables is not straightforward. To ascertain the expected sign of a given variable, it is necessary to work through equation (8), using the estimated parameters to see how a change in a particular S_i or S_j affects $\Delta c/\Delta e$. Noting the negativity of both the numerator and denominator in equation (8), and that $\Delta e = -1$, the following is expected: (i) in the odor exposure interaction specifications, increases in attitudinal, sensitivity, or demographic variables that are expected to increase WTP should have negative coefficients; and (ii) in the cost interaction specifications, increases in these variables that are expected to increase WTP should have positive coefficients. For example, Specification A in Table II shows a positive estimate for the *ODOR A*Intensity* scale variable. This confirms expectations, since as the numerical scale

Table III. Contingent Ranking: Cost Interaction Specifications

Variable	Specification A	B	C	D
ODOR A (exposures/wk)	−.1328 (−3.89)	−.0778 (−2.64)	−.0777 (−2.62)	−.0775 (−2.62)
ODOR B (exposures/wk)	−.3801 (−9.74)	−.2621 (−7.03)	−.2642 (−7.01)	−.2647 (−7.07)
Control Cost ($/yr)	.1089 (21.5)	.0509 (10.6)	.0553 (11.0)	.0719 (14.7)
Cost/Income ($/$$10^3$)	−.1079 (−3.22)	−.1041 (−3.18)	−.0995 (−2.98)	−.1017 (−3.12)
*A*Intensity* (unpleasant=1)	.0155 (1.94)			
*B*Intensity* (pleasant=7)	.0495 (4.06)			
*C*Diesel Vote* (yes=1, no=2)	−.0430 (−9.44)		−.0280 (−6.13)	
*C*Medical Condition* (yes=1, no=0)	.0174 (2.60)		.0193 (2.85)	
*C*Child* (yes=1, no=0)	−.0202 (−3.24)	−.0175 (−2.84)		−.0158 (−2.47)
*C*Env. Expd.* (too low=1, too high=5)	−.0254 (−8.68)	−.0256 (−12.3)	−.0237 (−11.1)	−.0253 (−9.04)
*C*Odor Sensitivity* (sens.=1, not sens.=5)	−.0107 (−6.75)			−.0117 (−8.36)
*C*Smoke* (yes=1, no=0)		−.0197 (−3.23)	−.0141 (−2.24)	
*C*Ethnic* (wh=1, nw=0)		−.0031 (−0.52)		
*C*Env. Contr.* (if Contr>0, 1; if Contr=0, 0)				−.0041 (−0.52)
Maximum Log-likelihood	−384.8	−393.4	−391.0	−391.4
R^2	.135	.116	.121	.120
WTP *ODOR A* ($/yr/wkly exp)	4.41 (1.71)	5.49 (2.30)	4.55 (2.30)	4.76 (2.26)
WTP *ODOR B*	15.55 (3.71)	18.50 (4.79)	15.47 (4.65)	16.25 (4.26)

a. See notes in Tables I and II. "*C*" in interaction terms refers to Cost variable.

of intensity increases (that is, odor becomes less unpleasant), the magnitude of the numerator in equation (8) decreases, and WTP is less. These rules explain why the signs on most of the odor exposure interaction terms in Table II are opposite from the corresponding cost interaction terms in Table III.

The attitudinal variables, diesel vote, adequacy of government expenditures for improving the environment, and willingness to contribute to environmental causes, are consistently significant determinants of utility. Only the *ODOR A*Environmental Contribution* variable in Specification D in Table II and the *Cost*Environmental Contribution* variable in Specification D in Table III have unexpected signs. Otherwise, respondents who voted against odor controls on buses and trucks exhibited less willingness to pay to avoid odor contacts than those who voted in favor of controls. Similarly, people who believe that too much is spent on environmental quality were willing to pay less for reduced odor exposure than those who believe too little is spent on environmental quality.

The sensitivity and health related variables generally have the expected signs and often are significant, though there are anomalies. The intensity scale variable, which measures the respondent's perception of the unpleasantness of the simulated diesel odors, is included in Specification A in both Tables II and III interacting with the odor exposure variables. The estimated parameters are positive, as expected, and significant in three out of four cases, indicating that WTP to avoid the odor decreases if respondents perceive the simulated diesel odors to be less unpleasant. Also as anticipated, people with medical conditions express greater disutility from increased odor contacts. The medical conditions variable, included in Specifications A and C, is significant when interacted with *ODOR B* and *Cost*, but is not significant when interacted with the weaker *ODOR A*.

Interactions with the respondents' self-evaluated odor sensitivity variable are more problematic. The odor sensitivity variables are all significant in Specifications A and D in Table II. However, the signs on the *ODOR B* interaction terms are counterintuitive, indicating that those who perceive themselves to have a higher sensitivity to odors are willing to pay less for odor reduction than those who perceive themselves to be less sensitive. In contrast, however, the odor sensitivity variable enters significantly with the expected sign in the cost interaction models in Table III. In sum, the reliability of the self-perceived measure of odor sensitivity is questionable. The smoking variable, which is expected to influence a person's sense of smell, is generally a better sensitivity control. Its parameter signs are correct and significant in Specifications B and C for interactions with *ODOR B*, but are incorrect, though insignificant, for *ODOR A* interaction terms. This is consistent with the result that interaction terms with the weaker smelling odor generally are less significant. When included in the cost interaction specifications in Table III, the smoking variable terms have the anticipated negative signs and are highly significant.

Unlike the sensitivity and health variables, the directional influence of demographic variables is uncertain, a priori. The presence of children in the household turns out to be significant in two of six instances in the odor interaction specifications in Table II, and in all three of the cost interaction cases in Table III. The parameter signs uniformly indicate that respondents with children in the household are less willing to pay for control of diesel odor than those without children. While households with more members could be expected to be willing to pay more for reduced odor contacts, the results suggest that the presence of children variable is dominated by an income effect. Families with children have higher consumption needs, and thus are less willing to pay for control of diesel odor. The ethnic variable is significant when interacted with *ODOR B*, indicating that on the average white individuals are willing to pay more to reduce *ODOR B* than nonwhites. The ethnic variable is not significant when interacted with *ODOR A*, or when interacted with control cost. Specifications that included other demographic variables, such as respondent's sex, age, and educational level, did not yield significant parameter estimates, and are not presented.

The WTP tradeoff, computed from the eight specifications in Tables II and III, indicates that respondents are willing to pay between \$3.03 and \$5.49 per year to avoid one weekly contact with *ODOR A* and between \$14.57 and \$18.50 to avoid one weekly contact with *ODOR B*. These estimated intervals are slightly lower than the results obtained in the models that did not include socioeconomic and demographic variables. In general though, the WTP estimates change very little from one specification to another. Thus, aside from the odor and cost tradeoff variables, the variables included in the indirect utility function only have a marginal influence on the estimated WTP.

V. Specification Tests

As discussed in section II, a key issue in the use of the contingent ranking method is whether respondent rankings are stable. The parameters estimated from the specifications reported above utilized data from four ranked choices. These estimates would not be expected to be significantly different from parameters estimated from specifications that utilize fewer choices. Two null hypotheses are tested below. One: the unconstrained set of specifications based on ranking each alternative separately does not differ from the constrained model specification that uses rankings of all four choices. Two: the model estimated from only the first alternative, equivalent to the standard multinomial logit specification, does not differ from the model estimated using all four ranked choices.

These two hypotheses are tested by comparing the sum of the final log-likelihoods from unconstrained multinomial logit specifications using first, second, and third choices against the final log-likelihood from the constrained model that estimates one set of parameters over all four ranked choices. One would expect that the unconstrained models perform better; that is, the sum of the log-likelihoods will be less negative. Whether this difference is significant is tested by chi-square with degrees of freedom equal to the difference in estimated parameters. Table IV summarizes the log-likelihood results of model specifications to test these two hypotheses.

The difference in estimated log-likelihood between the constrained ordered logit model and the unconstrained models is 6.1 with 6 degrees of freedom. A chi-squared value of 12.6 is necessary to reject the hypothesis that there is no difference between the constrained and unconstrained models at the 95 percent confidence level. Similarly, the difference in log-likelihood between the constrained ordered logit model and the unconstrained first choice model is 2.7 with 3 degrees of freedom. Again, at a 95 percent confidence level a chi-squared value of 7.8 would be necessary to reject the hypothesis that there is no difference between a model that uses only first choices and a model that uses all four ranked choices.

The parameter estimates from a model that includes all four diesel odor alternatives are found to be quite robust across specifications, and a chi-squared test of differences in model specifications fails to reject the null hypothesis of no significant differences. This is reassuring, since earlier studies of visibility benefits found significant variability in estimates across specifications with different choice sets and rejected the hypothesis that there was no difference between model specifications with different choice sets [15]. The results reported here suggest that the problems

Table IV. Specification Tests

Specification	DF	Max. Log-likelihood
Unconstrained Models:		
Prob [1:1, 2, 3, 4]	3	−186.7
Prob [2:2, 3, 4]	3	−145.6
Prob [3:3, 4]	3	−77.1
Sum	9	−409.4
Unconstrained First Choice Model:		
Prob [1:1, 2, 3, 4]	3	−186.7
Prob [2 > 3 > 4]	3	−226.1
Sum	6	−412.8
Constrained Ordered Logit Model:		
Prob [1 > 2 > 3 > 4]	3	−415.5

a. Prob [1:1, 2, 3, 4] is the probability of choosing one alternative first out of a set of four alternatives; Prob [2:2, 3, 4] is the probability of choosing one alternative out of the remaining three [2, 3, 4]; and Prob [3:3, 4] is the probability of choosing one alternative out of the remaining two [3, 4].

b. Prob [1 > 2 > 3 > 4] is the probability of ranking four alternatives [1, 2, 3, 4] in a given order: first, second, third, fourth.

in these visibility studies might well be due to an overly complex survey design rather than to any systematic problem with respondents' abilities to provide consistent and reliable rankings of alternatives in a survey context.

VI. Concluding Observations

Estimation of a probabilistic choice model using ranked data provided encouraging results in this environmental application. The environmental odor exposure and cost variables proved to be significant determinants of indirect utility as did many of the socioeconomic and demographic variables. The estimated WTP tradeoffs are quite stable across different specifications of the indirect utility function, V. The limited evidence from this application generally confirms that discrete survey formats are helpful in estimating environmental values, which consumers often find difficult to quantify in response to direct questions. While these results demonstrate the usefulness of the contingent ranking technique, it is important to recognize the estimated WTP values are based on a relatively small sample in only one city. In addition, the results are dependent on an imposed specification for the indirect utility function; other specifications could yield somewhat different estimates. With these caveats in mind, it is still interesting to speculate on how much vehicle diesel odor reduction is worth.

A tentative indication of the aggregate WTP to avoid urban diesel odor exposures can be computed using some further data gathered in the Philadelphia survey. As part of the survey, respondents were asked to record on a log the number of odor contacts they experienced in the week following the survey. Eighty-two respondents complied with this request and recorded the location, vehicle source, and odor intensity for each contact. On average, respondents recorded 2.2 contacts per week with odors similar to *ODOR A*, of which about half were attributed to cars and half to buses or trucks. There were 4.1 contacts per week recorded for odors similar to *ODOR B*, with trucks accounting for slightly more than three-quarters of the total.

With these exposure estimates, the average household in the Philadelphia metropolitan area would be willing to pay approximately $75 annually to avoid completely all diesel odor exposures. Is the control of diesel odor worthwhile? The results presented in this study suggest an affirmative answer. EPA in its Regulatory Impact Analysis of mobile source particles estimated that control of diesel particles from heavy-duty trucks would cost something like $300 million per year, or about $3.60 per urban household. While such a program would only partially ameliorate the diesel odor externality (the regulation only specifically requires reduction of particle emissions—odor reducing catalytic technologies are not mandated), the difference between the benefit and cost of control is large. Thus, if the WTP and the number of odor exposures were comparable in other cities to the estimated values in Philadelphia, vehicle control of diesel particle emissions and associated odor would be worthwhile.

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