DRAFT FINAL REPORT

REVIEW OF "ESTABLISHING AND VALUING THE EFFECTS OF IMPROVED VISIBILITY IN EASTERN UNITED STATES"

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TABLE OF CONTENTS

1.0 INTRODUCTION AND SUMMARY OF CONCLUSIONS AND RECOMMENDATIONS

1.1 PURPOSE OF REVIEW

This is a review of the study, "Establishing and Valuing the Effects of Improved Visibility in Eastern United States," prepared by Tolley et al. (1986) for the U.S. Environmental Protection Agency. The purpose of the review is to help EPA evaluate the validity of the study relative to the state-of-the-art in research of this type, and to evaluate how best to use the results for addressing specific EPA policy questions.

The focus of the review is on the contingent valuation (CV) portion of the study, because it is these results that are potentially most important for assessing regional and national pollution control standards and strategies. Other analyses were also conducted that are interesting and potentially important, such as the effects of visibility on traffic accidents and on rental property values, but these results are not as directly applicable for benefit cost type analysis. They do, however, show how data on actual behavior reveal the impact of visibility, and suggest potentially useful avenues for further research.

The remainder of this section summarizes the conclusions and recommendations of this review. The second section of the review gives some of the key points raised by previous reviewers, several of which are addressed in subsequent sections. The third section evaluates the design of the CV experiment. The fourth section discusses some economic issues behind the selection of a functional form for the bid function. The fifth section presents the results of the re-analysis of the Tolley et al. data that was conducted to empirically address some of the questions that have been raised. Section 6 considers how the Tolley et al. results compare to results of other visibility value studies for urban and residential areas.

1.2 CONCLUSIONS OF THE REVIEW

Many specific questions and limitations are discussed in this review that suggest some significant flaws in this study, but these are considerably tempered by the finding that the mean (statistical average) results look quite consistent with other studies when the change and level of visual range is considered.

The authors claim to provide very comprehensive information about the value of visibility in their estimated bid function that has not been provided in previous studies. While the results of this study do add quite a bit to the body of knowledge concerning visibility values, the claims regarding the estimated function are overblown. In the first place, the function is actually a bid function, not a value function as the authors call it. This distinction is important when it comes to applying the function to different visibility scenarios. The relationship to underlying economic theory is not fully addressed. Moreover, the estimated function is valid only for base visual range levels of 10 miles. The re-analysis that was conducted indicates that there is more error behind the Tolley et al. estimated function than appears on the surface, especially outside the range of visibility changes considered.

Our biggest concern with the CV design is that the photographs used to illustrate the different levels of visibility did not match the changes in visual range considered in the value questions. This is a poor design relative to standard practice in CV studies and was compounded by telling the respondents in every city that typical visual range in their area is about 10 miles when the average levels actually ranged from 9 to 18 miles.

The CV portion of the study as a whole was poorly documented and presented, making evaluation of some important points difficult or impossible. The inadequate presentation of the study design and results casts potentially unnecessary doubt on the validity of the study.

1.3 RECOMMENDATIONS

The Tolley et al. results should be treated as one (or six) more CV study in addition to others, not as a replacement of all previous work. There appears to be a general consistency with the results of previous studies, but due to the limitations pointed out in this review, the Tolley et al. results should not be used as the sole basis for an eastern visibility value assessment.

To obtain estimates of visibility values associated with alternative pollution control policies, we recommend using the simple functions of mean values from all the CV studies that are given in Section 6, rather than the complex negative exponential bid function estimated by Tolley et al. The reasons for this recommendation include the following:

- o The results of all the studies cover a wider range of visibility levels and provide some information about the effects of the base level as well as the size of the change.

- o The simple functions do not give a false sense of precision due to computational complexity.

- o Using the simple functions acknowledges that the estimated effects of socioeconomic variables are extremely uncertain and variable. Even with the Tolley et al. results there is currently little basis for predicting differences in values between people or locations.

2.0 COMMENTS FROM OTHER REVIEWERS

Reviews of the Tolley et al. draft report or related working papers have been made by several individuals including Ray Palmquist, Jon Harford, and Richard Carson. Also, the use of the Tolley et al. results in a report for EPA by Systems Applications, Inc. (SAI, 1984) was reviewed by Paul Ruud for the Utility Air Regulatory Group (UARG). A response to Ruud's comments was made by V. Kerry Smith. This section summarizes some of the key issues raised in these reviews that have, to some extent, guided the questions addressed in this review and limited re-analysis of the Tolley et al. data.

The Ruud review was particularly critical of the Tolley et al. study and of the use that was made of the results in the SAI report. Ruud suggests that the error in the estimates (both from Tolley et al. and from CV visibility studies in general) is so great that they should not be used for policy analysis. Smith's response agrees that the error may be considerable, but suggests that it is a matter of judgement as to whether the error is so bad that better decisions could be made by ignoring the data altogether. Smith suggests and makes a preliminary effort at the kind of cross study analysis that is presented in Section 6. His initial results were relatively inconclusive, but we found that when functional forms for a bid function are used that are derived from value functions for visibility that more than half of the variation in average values across the studies can be explained. We conclude that this shows a great deal of consistency across the studies.

Ruud also raises some important questions about the process by which bids were judged to be valid or invalid in the Tolley et al. study. We agree that this is a very important issue, and one that was not adequately documented by Tolley et al., but we were unable to test the effects of any of the suggested alternatives because the available data had apparently already been cleaned of "invalid" responses. Ruud seems to be concerned that the procedures used by Tolley et al. would lead to an increase in the mean bids, but as Smith points out,this is not necessarily the case since both high and zero bids were involved.

Palmquist raised a question about the appropriateness of pooling the data across all six cities in the bid function and suggested that this could be tested for statistical validity. This is something we have done and is reported in Section 5.

Carson emphasized the potential importance of the 1984 surveys as a test of the consistency of the survey approach and the 1982 estimates. This has been done and is reported in Section 5.

Several of the reviewers raised similar questions to ours concerning the use of photos that did not show the same change in visual range as the respondents were asked to consider.

The reviewers made many other good points regarding the study, both positive and negative. These are not all reiterated here, but those that we perceive as most critical for the purposes of this review have been mentioned.

3.0 CONTINGENT VALUATION METHOD: DESIGN AND EXECUTION

This section evaluates the application of the contingent valuation method (CVM) used by Tolley et al. in terms of the current CVM state-of-the-art for valuing changes in visibility. The discussion is divided into three topics: the CVM experiment design, seasonal and distribution questions, and general survey research methods.

The most important problem in the CVM design was the use of photographs showing visual range levels that did not exactly match the changes in visual range the respondents were asked to value. These questions are difficult to answer and should not be compounded by forcing the respondent to judge for himself how 10 miles or 20 miles might look after showing him 13 miles and 30 miles. Several problems with the 1982 photos were addressed in the 1984 follow-up, but the matching problem was not.

3.1 THE CVM EXPERIMENT

Designing a CVM experiment to obtain the best possible information on measures of value for changes in a public good requires careful definition and presentation of scenarios of potential change in visibility, development of a hypothetical market, and elicitation of specific value estimates. The Tolley et al. study improved upon standard practice in some of these areas and fell short of standard practice in others.

3.1.1 Presentation of Visibility Scenarios

Overall, the presentation of visibility scenarios fell well short of standard practice. Our concerns here are probably more important than for any other part of the Tolley et al. CVM application.

In 1982, three sets of photos, each showing 4, 13, and 30 miles visual range, were used to help the respondents answer the CV questions in each of the six cities where surveys were conducted. The three scenes in the photos were in Chicago, although they do not appear to have been identified as such to the respondents. Judging from the sample questionnaire for Atlanta included in the report, respondents in each city were told that typical visual range is 10 miles in their area. They were then asked CV questions concerning a potential reduction to 5 miles, an increase to 20 miles, and an increase to 30 miles.

The most important shortcoming of this presentation is that the photos did not illustrate all the levels of visual range that respondents were asked to value. The difference between 4 and 5 miles is probably not too important, but the difference between 10 and 13 miles may be significant and the absence of a photo showing 20 miles visual range is definitely a problem. With this presentation, respondents are left to guess for themselves what 20 miles visual range might look like based on the 13 and 30 mile photos. Since 10 miles is the base from which respondents are asked to consider changes, the absence of a 10 mile photo is also a problem.

Another important problem is that respondents were told that 10 miles visual range is typical in each city and were asked to value changes in typical visual range from this presumed 10 mile base. The authors, however, used the following estimates of typical visual range in the analysis of the responses from each city, indicating that typical visual range was not close to 10 miles in all of these cities.

CITY	TYPICAL VISUAL RANGE USED IN ANALYSIS (LOCENDOW)
Cincinnati	9 miles
Mobile	10 miles
Atlanta	12 miles
Miami	13 miles
Washington, D.C.	15 miles
Boston	18 miles

This is especially problematic for Washington, D.C. and Boston where typical visual range is as close or closer to the 20 mile level than the 10 mile level. Small discrepancies (such as 9 or 12 miles) are probably not important when considering 5, 10, or 20 mile increments, but they do raise questions about the suitability of using the responses to value smaller changes in visual range.

Most respondents will have no idea what visual range level is typical in their area, so it might be feasible to show them a picture of 10 miles visual range and tell them it is typical in their area. However, people do have a sense of what it looks like where they live, and the combination of the poor match of the photos to the hypothesized changes and the poor match of the presumed typical level to the actual typical level in each city raises serious questions about the change in visual range that the respondents actually valued.

The respondents were correctly instructed to pay close attention to the changes in color contrast and texture associated with the different levels of visual range. Perceptions work has shown that these guide judgments of visual air quality.

The quality and consistency of the photos was not what it should have been, but the problems were not too great for the Chicago city scenes. Standard practice is to hold everything in the scene (including clouds and sun angle) as constant as possible and vary only the air quality. The outer drive photos for Chicago were not adequately uniform.

In response to concerns raised about the photos used in the 1982 portion of the study, surveys were conducted in 1984 in three cities using city-specific photographs. Judging again from the example of the Atlanta questionnaire included in the report, it appears that respondents in 1984 were told the actual typical visual range in their city and were asked to value changes (-5, 10, and 20) from that level. For Atlanta this was 12 miles, for Chicago this was apparently 10 miles, and for Denver this was apparently 50 miles. The authors are not very clear about this in the text, but these are the values of the LOCENDOW variable and the Atlanta questionnaire asks about changes from 12 to 7, 12 to 22, and 12 to 32. The photos for Atlanta showed 5, 9, and 20 miles visual range, and it appears from the questionnaire that the respondents were told these levels. The authors do not report the visual range levels for the photos in the other cities.

The authors argue that the results from the 1984 surveys are comparable to those from 1982, and conclude that using the Chicago photos was not a problem. See Section 5 for more on these results. From a CVM design point of view is it difficult to say what the comparison of the 1982 and 1984 results can show given that several things were changed: (1) the content of the scene, (2) the levels of visual range illustrated, and (3) the asserted typical level of visual range in each city. It appears that the poor match between the illustrated levels and the hypothesized changes remained in the 1984 surveys.

There were some additional problems with the 1984 photos. One was that aerial views were used. These are not views that people typically see and it is uncertain what visual range means from an elevated angle because the atmosphere is not homogeneous. The use of air brushing to produce the different levels of visual range allowed uniformity between the photos for everything but air quality, but it does not necessarily simulate exactly the change in contrast that occurs with air pollution. There are computer simulation techniques available that can simulate the visual effects of pollution.

After the respondents were asked the values for changes in visibility in their area, they were asked to value a 10-mile improvement (from the current level in each location) throughout the East and throughout the country. In the 1982 surveys, respondents were shown photos of a scene at Shenandoah National Park at three visual range levels and of a scene at Grand Canyon National Park at three visual range levels to help them answer these two additional questions. In the 1984 surveys, a scene of Niagara Falls and a scene at the Grand Canyon was used. Respondents do not appear to have been told the level of visual range in these photos or the locations of the scenes or what typical visual ranges levels are in the rest of the East and West (although some information on the latter was given in 1984). The authors assert that the responses to these questions provide some information about the option and existence values respondents hold for a 10 mile improvement in visual range in places where they do not live.

There are several problems with these regional value questions that lead us to conclude that the responses suggest non-zero values for the protection of visibility in areas other than the respondents' own residence location, but that the values are not applicable for specific mile changes in visual range and there is no way to know what combination of use, option, existence or altruism values motivate the responses. Most important, the levels of visual range shown in the photos do not appear to have any relationship to the hypothetical 10-mile improvement. This makes it impossible to know what change in visual range the respondents really considered. Another problem is with the use of photos from special scenic areas. Although it is impossible to select a perfectly "typical" scene to represent an entire region, special scenic shots are likely to provoke different (probably higher) responses.

3.1.2 Definition of Hypothetical Market

In the 1982 portion of the study, respondents were told that there are man-made pollutants that affect visibility but not health, and that these can be reduced at a cost of making things we buy more expensive. The respondents were shown the three sets of photos taken in the Chicago area illustrating three levels of visual range. For the potential decline in visibility question respondents were asked to consider what it would be like if typical visual range declined to 5 miles. They were told that a program could be set up to prevent such a decline and were asked the most they would be willing pay each month for such a program. For the 10 and 20 mile improvement questions, respondents were again asked the most they would be willing to pay for a program that could be set up to obtain such an improvement.

Some previous CVM studies (Brookshire et al. 1978, and Loehman et al. 1979) have done more to distinguish between concerns about health effects and visibility aesthetics. One reason was that these studies were trying to estimate total values for air pollution reductions (including health and visibility concerns), but another reason is that this distinction may not be clear in the average person's mind. There is probably a tendency to use visual degradation as a perceptual cue to potential health effects. There may be some truth to this association in that there are some pollutants, such as fine particulates, that have health as well as visual effects. The Tolley et al. questionnaire probably handled this problem a little too lightly. If concerns about health effects, or expectations that health effects would be reduced if visibility were improved, did affect responses then an upward bias would be expected.

The authors of the study purposefully kept the details of the possible programs and the specific avenue by which the respondent would have to pay quite vague, with the intent of minimizing any biasing influences that specific details might cause. This presentation of the hypothetical market has the strength of being very simple and straightforward and may have been effective in keeping the respondents focused on visibility. On the other hand, it is important that a hypothetical market be realistic enough that respondents can imagine how a payment they might make could be related to the availability of the good in question. In the 1984 follow-up study in three cities the authors also tested a hypothetical market mechanism involving asking subjects what they would be willing to pay in terms of higher utility bills if the required pollution controls resulted in higher costs to the producers of electricity. They report responses about $2 per month less than with the unspecified payment vehicle and they conclude that the utility vehicle caused downward bias because people already feel that their utility bills are too high. This may be true, but it is also possible that the more concrete vehicle made the potential payment seem more realistic, causing respondents to give answers closer to their true values. Our conclusion is that this is still an open question. Tolley et al. made reasonable choices concerning the presentation of the hypothetical market, but there is still the possibility that the vagueness of the payment vehicle could have led to some bias (possibly upward).

A possible limitation of the presentation of the hypothetical market is that there was not an option to accept worse visibility for lower prices. The presumption in the way the questions were presented is that respondents prefer higher visual range. This was standard practice in CVM studies at the time this one was designed, but more recent CVM studies have been making more of an effort to allow an option of lower visibility and lower prices. This may reduce protest responses.

3.1.3 Eliciting Value Estimates

The CVM literature is quite extensive in considering how to ask the value question, although there is no agreement as to a single best way. Tolley et al. gave careful treatment to this issue in the 1981 pretest. Six different question formats were tested in the pretest. The one with the lowest number of protest responses was selected for the full survey. This format included a payment card showing typical household payments for several public and private goods, and an iterative bidding style question. It is worth noting that as well as obtaining the smallest percentage of protest responses, this format elicited the highest average bids of all the formats used in the pretest. This raises some question about whether the respondents are being led in some way by the payment card examples, but may simply be the result of a better received question. The report does not include any examples of the payment card used, so further evaluation of this issue is not possible.

With an iterative bidding style question it is necessary to start with a specific dollar amount. The authors report that no starting point bias was found in the pretest, but they do not report adequate information about the evidence for this conclusion to allow an independent assessment. This is unfortunate since starting point bias has been found in many CVM studies, making a simple assertion that starting point bias was not a problem difficult to accept. Based on this conclusion from the pretest, a single starting point of $13 per month was used in the final surveys (in 1982 and 1984). Using a single value makes it impossible to test for effects of starting point and was probably not a prudent choice, the pretest results notwithstanding.

The zero bid follow-up question was fairly standard, but with a nice addition of explaining that the respondent would have a chance to say who he thought should have to pay and asking him to reconsider his response. Unfortunately, the authors do not report the effectiveness of this follow-up approach.

3.2 SEASONAL AND DISTRIBUTION QUESTIONS ASKED IN 1984

Some additional questions were asked in 1984 concerning values for changes in visibility in summer or winter or on only 10 days per year. The sample sizes were quite small so conclusions are tentative and alone should not be used for policy analysis. One finding for all of these questions was that values did not decrease in proportion to the decrease in time that visibility would be improved. For example, the values for visibility improvements during the half of the year that includes summer exceeded one-half the value given for the whole year. The values for 10 days only implied much higher annual values if multiplied by 36.5. The authors argue that this is consistent with the declining marginal utility observed in the annual estimates for increasing increments in visual range change. This may be the case, but it also raises questions about the transferability of results obtained for one scenario to another. In fact, the authors report that initially the values for 10 days exceeded the annual values. After changes in the questions were made that included a more thorough illustration of the hypothesized change in visibility, the values for 10 days fell to about one-half what they were originally. This illustrates the dramatic influence that the details of the survey design can have. Photos and graphics designed to explicitly present each of the seasonal or distribution questions should have been used.

The authors conclude from the summer/winter questions that visibility improvements in the winter are slightly more highly valued. This conclusion does not seem appropriate. Looking at the individual city results, Chicago and Atlanta show significantly higher values for summer improvements. Only Denver shows higher values in the winter. This can simply be explained by the fact that visibility due to man-made pollution is much worse in the winter in Denver than in the summer (due to the more frequent occurrence of temperature inversions). Such a dramatic seasonal difference does not occur in the Eastern cities, although summer might tend to be somewhat worse than winter. It makes sense that summer improvements would be more highly valued in the East when people spend more time outdoors. These important regional differences were blurred in the analysis that put all three cities together and found a slight preference for improvements in the winter. These results also suggest that respondents may be thinking as much about typical conditions as they know them than about the photos shown to them.

Another interesting question was asked about improving poor visibility days to typical days and improving typical days to good days. The responses revealed a preference for reducing poor days rather than increasing good days. This could have some policy relevance if confirmed with additional study.

3.3 SURVEY RESEARCH METHODS

The details of the survey research methods used by Tolley et al. are not very well reported. This is a concern because any survey research effort is potentially subject to important influences or biases as a result of the way in which the survey was conducted. This is especially important for CVM surveys and is therefore standard professional practice to report on interviewer training, field practices, sampling procedures, refusal rates, and other details. The lack of information reported by Tolley et al. concerning these details makes it impossible to evaluate the appropriateness of the survey implementation approach taken. This should not be allowed to set a precedent for future CVM work.

A strength of the survey procedure used by Tolley et al. is the extensive pretest that was conducted in Chicago in 1981. Alternative formats for the CV questions were tested as were other details of the survey design. The reporting of the pretest findings upon which the final questionnaire was based was not as thorough as it should have been. The specific conclusions and ultimate design of the CV questions used in the 1982 six cities portion of the study are discussed in the following section on economic considerations.

An important factor that does not appear to have been considered is the potential for interviewer bias. It is standard practice for CVM studies using personal interviews to keep a record of the interviewer in each case and test whether there may have been some influence by the individual interviewer on the willingness-to-pay responses. This information does not appear in either the report or the computer dataset available to us.

4.0 FUNCTIONAL FORM ISSUES IN THE ANALYSIS AND APPLICATION OF THE CONTINGENT VALUATION RESULTS

Tolley et al. estimate and apply a visibility value function using results from the CV survey. Estimating such a function is a useful objective. Tolley et al. conduct an acceptable analysis using reasonable assumptions based on their data. However, some limitations of their approach are worth noting and some suggestions for alternative estimations can be made. These are discussed in this section and are summarized as follows:

- The functional form selected by Tolley et al. does not appear to have a direct relationship to any underlying utility theory beyond the signs of the first and second derivatives, equalling a priori assumptions. However, these properties are forced to occur and are not tested.

- The functional form selected appears to be consistent with the data, but the results are not particularly robust across location and year (contrary to the assertion of the authors). This may be in part due to the lack of consistency between the form and underlying utility theory and the requirement that changes in visibility may only affect bids interactively with socioeconomic variables, which are often not strong correlates with environmental preferences and values.

Some suggestions based on the analysis reported in this section have been carried out and are reported in Sections 5 and 6. These include the use of more flexible functional forms, the use of functional forms that more closely reflect underlying utility theory, and consideration of the results of all urban visibility CV studies especially as they relate to the effects of different base levels of visual range.

4.1 UTILITY AND CONSUMER SURPLUS MEASURES

A simple utility model can give some insight about how we would expect a bid function to look. Consider the following utility function.

$$U_{ij} = U(S_j, Y_i, X_i) + E_i \qquad 4.1$$

where:

- U_{ij} = utility of individual i with available scenic resources at site j
- S_j = scenic resource level at site j
- Y_i = income for individual or household i
- X_i = socioeconomic vector for individual i
- E_i = error term in decision of individual or in observer' measurement of U_{ij} (see Hanemann, 1984, for discussion)

Let us assume that for estimation purposes visual range can be used as a measure of scenic resources. Some limitations of this assumption are discussed in the next section. Consider three levels of S_j such that $SO_j < S1_j < S2_j$ with $S1_j$ being the current level of visibility. The compensating surplus (CS_i) measure for an improvement in visual range from $S1_j$ to $S2_j$ is defined as in equation 4.2. This is the decrease in income that would keep utility the same as it was before the improvement in visual range occurred. This is the measure obtained when a subject is asked the maximum he or she would pay to have an improvement in visual range.

$$U(Y_i, S1_j, X_i) + E1 = U(Y_i - CS_i, S2_j, X_i) + E2 \qquad 4.2$$

The equivalent surplus (ES_i) measure for a decrease in visual range is defined in equation 4.3. This is the decrease in income that would cause the same decrease in utility as the decrease in visual range. This is the measure obtained when a subject is asked the maximum he or she would pay to prevent a decrease in visual range.

$$U(Y_j - ES_i, S1_j, X_i) + E1 = U(Y_j, SO_j, X_i) + E2 \qquad 4.3$$

For convenience, the subscripts i and j will be deleted in subsequent discussion. Table 4-1 shows some specific utility functional forms and the implied CS and ES functions. These show the effect of additive and multiplicative utility terms and forms on the functional form of the CS and ES equations.

The first derivatives of all the utility functions with respect to visual range are expected to be positive (more visual range means higher utility). The sign of the second derivative may vary in some cases depending on the sizes and signs of the parameters. If visual range is similar to other consumption goods, it would be expected that the second derivative would be negative (when a person is at a higher level of visual range then the value of an additional unit is less). There is no reason why this has to be the case, however, since visual range is not something that a consumer necessarily becomes satiated with at higher levels. Tolley et al. presumed that visibility is a typical consumer good and therefore selected a functional form that forces the same derivative with respect to changes in visual range to be negative when the first derivative is positive. Moreover, visual range is an input to the production of S, and the function may have an increasing or decreasing second derivative over different values of VR in different locations.

Forms 3 and 4 in Table 4-1 help to illustrate that the function used in Tolley et al. is unlikely to be well related to underlying utility theory. Form 3 indicates that it is not possible to get a CS function in the $g[1-e^{\text{power}}]$ form with Y in the power term and not in the g term. Only a transformation on the CS function, as shown with form 4 in Table 4-1 results in a form similar to that used by Tolley et al.

Table 4-1

Some Utility Functions and Their Related CS and ES Functions

1. $$U = bY + aS + cYS + \sum_k d_k X_k + \sum_k f_k S X_k + E$$

$$CS = \frac{(S_2 - S_1)(a + cY + \sum_k f_k X_k) + \Delta E}{b + cS_1}$$

$$ES = \frac{(S_1 - S_0)(a + cY + \sum_k f_k X_k) + \Delta E}{b + cS_1}$$

NOTES: Assume a, b > 0, $X_k > 0$

$$\frac{\partial U}{\partial S} > 0 \text{ if } a+cY+\Sigma f_k X_k > 0; \quad \frac{\partial^2 U}{\partial S^2} = 0$$

used in Rowe et al. (1980)

2. $$U = aY + bS^p \prod_k X_k^{q_k} + cX^g + E$$

$$CS = b/a\,(S_2^p - S_1^p) \prod_k X_k^{q_k} + \Delta E/a$$

$$ES = b/a\,(S_1^p - S_0^p) \prod_k X_k^{q_k} + \Delta E/a$$

NOTES: Assume a, b > 0

$$\frac{\partial U}{\partial S} > 0 \;\forall\; S; \quad \frac{\partial^2 U}{\partial S^2} \lesseqgtr 0 \text{ if } p \lesseqgtr 1 \;\forall\; S$$

Table 4-1 - Continued

3. $U = aYe^{bS\sum_k a_k X_k} * e^E$

$CS = Y[1-e^{b(S_1-S_2)\sum_k a_k X_k} * e^{\Delta E}]$

$ES = Y[1-e^{b(S_0-S_1)\sum_k a_k X_k} * e^{\Delta E}$

NOTES: Adding Y as a variable in the exponent greatly complicates the CS and ES expressions. Tolley et al. form (without Y in exponent) = $g * cS/Y$

Assume $b \sum_k q_k X_k > 0$

$\frac{\partial U}{\partial S} > 0 \; \forall \; S; \; \frac{\partial^2 U}{\partial S^2} > 0 \; \forall \; S$

4. $U = e^{aS} + cYS + S\sum_k d_k X_k + E$

$CS = (a + cY + \sum_k d_k X_k)(S_2-S_1) + \Delta E$

$ES = (a + cY + \sum_k d_k X_k)(S_1-S_0) + \Delta E$

NOTES: Assume $b \sum_k q_k X_k > 0$

$\frac{\partial U}{\partial S} > 0 \; \forall \; S; \; \frac{\partial^2 U}{\partial S^2} > 0 \; \forall \; S$

Tolley et al. bid function (without Y in exponent) =

$q(1-e^{CS}) = q[1-e^{[(a+cY+\sum_k d_k X_k)(S_2-S_1) + \Delta E]}]$

4.2 VALUE VERSUS BID FUNCTIONS

Tolley et al. refer to their estimated function as a value function, but it would be more accurate to call it a bid function, because visual range enters only as a change. A value function would give a dollar measure of the total value associated with each level of visual range. The value function is not estimated by the CV questions because these are typically for changes in visibility from one level to another. By referring to their bid function as a value function, Tolley et al. confuse this distinction and make it appear as though they have made a contribution that no other CV studies have made. In fact, most CV studies have made some attempt to estimate a bid function.

Tolley et al. actually estimated a bid function for changes in visual range from a base level of 10 miles. It is not appropriate to use the function to estimate values for changes from other base levels, because there is no information in the Tolley et al. data that says what values would be for changes from other base levels.

In selecting the functional form for the bid function it is appropriate to consider the expected properties of the underlying value function and then derive the bid function by taking the difference in the value functions for two different levels of visual range.

5.0 ADDITIONAL EMPIRICAL ANALYSES OF THE TOLLEY ET AL. DATA

The Tolley et al. data for 1982 and 1984 were obtained and several issues were addressed concerning the estimated value function. This re-analysis of the data involved obtaining more detailed descriptive statistics than included in the report, estimating different functional forms to test the consistency of the predicted value estimates, testing for the appropriateness of pooling the data across the different cities, conducting a more rigorous comparison of the 1982 and 1984 results, and considering functional forms more consistent with underlying value (as opposed to bid) functions.

The results reported in this section suggest there is less precision in the data for predictive purposes than is implied by the estimation and presentation of the negative exponential model by Tolley et al. Less restrictive functional forms support the basic functional curvature properties of the negative exponential form, but show the limitations of the data for predicting outside the range of visibility changes considered in the survey.

The separate analyses for the six cities reveal some apparent problems with the results from Miami and suggest the pooling of data across the cities into one bid function may not have been appropriate. Predicted bids are, however, reasonably consistent for the other cities. Most important, very little of the differences in the bids across cities is explained by the single equation model, limiting the confidence with which one could apply the bid function for a large area such as the eastern U.S.

5.1 DESCRIPTION OF THE SIX CITIES DATASET

This subsection is to provide a more complete description of the six cities dataset than is presented in the report. Unfortunately, the dataset made available to us were apparently already purged of data that were judged unacceptable for the analysis. This made it impossible to evaluate the decisions made about what data to omit.

The criteria for deciding what data to consider valid in a CV study are controversial and should be reported in detail in any CV study. It is standard practice to eliminate "protest" zeros that are identified by a follow-up question. Tolley et al. apparently used this procedure but failed to report the number of responses that were eliminated for this reason. On page 129 they report that responses from 792 households were obtained and that 538 were used in the analysis. They report that the major reason for omitting data was a refusal to give income information, that "some" cases were eliminated due to protest zeros and in a "few" cases unreasonably high bids were also eliminated. In the 1981 pretest it was reported that bids exceeding 10% of income were recoded to 10% of income. This was apparently not done to any significant extent in the 1982 data because there are only four cases where bids equal 10% of income. The scanty reporting of what was done to clean the data is unacceptable in a study of this type.

There are two discrepancies between our dataset and that reported in Tolley et al. (Section 2.4). First, we have 2616 valid cases, whereas they report 2615. The computer printout of their estimated value function (Table 2-19) does indicate that 2616 observations were used, however. It appears, therefore, that we have the same dataset. Moreover, the estimates of the value function presented below in Table 5.2.1 are very close to that presented by Tolley et al.

The second discrepancy is in the overall average bid. Tolley et al. report 108.74., while the data used here have an average bid of 130.65. A probable explanation is that this figure is a typo in Tolley et al. On the other hand, the discussion in Section 2.3 of Tolley et al. indicates that some "data trimming" were performed in the 1981 pretest survey. If similar transformations were performed on the 1982 data, they are not coded in the data made available to us, but because the value function estimates are so close, we believe the dataset we have is the final dataset used by Tolley et al.

Summary statistics for the entire sample are presented in Table 5.1.1. BID represents all bids, while BID1 to BID5 represent the breakdown of the data by type of change in visual range; -5, 10 (local), 20 (local), 10 (regional), and 10 (entire U.S.), respectively. The other variables are the same as those

Table 5.1.1
Summary Statistics--Six Cities Dataset
(All Data)

Variable	Mean	Standard Dev.	Minimum	Maximum
Bid	130.65	294.06	-1320	4200
Bid1	-150.12	180.92	-1320	0
Bid2	149.75	182.48	0	1320
Bid3	191.15	241.98	0	1800
Bid4	210.98	291.34	0	3600
Bid5	246.35	347.58	0	4200
Locendow	13.02	3.28	9	18
Income	23.21	17.30	0	125
Hsldsiz	3.17	1.93	1	21
Hohed	13.07	4.41	1	76
Hohage	45.38	16.40	19	92
Exview	.49	.50	0	1
Badeyes	.22	.42	0	1
Actcindx	11.93	7.59	0	36
Prop	.14	.34	0	1
Femhoh	.39	.49	0	1
Own	.66	.47	0	1
Rural	.11	.32	0	1
Nonwhite	.32	.47	0	1
Dvr	9.05	7.97	-5	20

described in Tolley et al. (Table 2-18). As noted, the major difference is in the overall average for the bids (BID).

More descriptions of the data are presented by city in Tables 5.1.2 - 5.1.7. Several interesting comparisons are possible. Average income ranges from a low (in Atlanta) of about $20,000 to a high (in Washington) of over $27,000. Some cases were coded with zero income. In the Atlanta sample, only 44% of the households owned their current place of residence, while in Cincinnati, over 80% owned their place of residence. About 60% of the Washington and Miami samples and about 50% of the Atlanta sample were non-white. Although these figures are probably representative of these immediate urban areas, they seem a little high for the regions under consideration. In Boston, over half the sample were households with female heads.

The most interesting figures are the percentages of remaining zero bids. These figures are quite large for Miami (about 50%) and Cincinnati (about 30%). These are presumably "true" zero bids because it appears that protest zeros were already purged from the dataset. The corresponding average bids for these two cities are substantially lower than for the other cities. In reading these tables, the 25%, 50%, and 75% columns reflect that 25% or 50% or 75% of the data fall below the value reported in that column. In Atlanta, for example, 50% of the bids for the local 10-mile improvement (BID2) fall below $120/year. Therefore, the median for BID2 is $120/year. The percentile figures give some feeling for the distribution of the bid data. The means are generally higher than the medians for these data, reflecting the large number of zero bids and the presence of some relatively high values. Dependent variables with this type of distribution can imply some problems for hypothesis testing when a model is estimated under the least squares criterion. However, this does not necessarily mean that the least squares criterion will produce inappropriate models for prediction.

5.2 BID FUNCTION ANALYSIS -- AGGREGATE DATA

A comparison is made between the negative exponential form used by Tolley et al. and two other forms. The additional models estimated here are easier to

Table 5.1.2
Summary Statistics--Six Cities Dataset
(Atlanta, N=453, Locendow=12)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	19.93	17.28	.598	85
Hsldsiz	3.47	2.55	1	21
Hohed	11.37	3.59	2	19
Hohage	42.44	14.55	20	79
Exview	.54	.50	0	1
Badeyes	.13	.34	0	1
Actcindx	10.69	7.18	0	27
Prop	.03	.17	0	1
Femhoh	.36	.48	0	1
Own	.44	.50	0	1
Rural	.12	.33	0	1
Nonwhite	.50	.50	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	184.24	359.51	-1200	0	120	276	1632	17
Bid1	-195.92	221.87	-1200	-240	-156	-60	0	17
Bid2	188.39	214.59	0	48	120	276	1116	19
Bid3	281.42	315.31	0	60	156	444	1632	18
Bid4	286.21	325.12	0	60	156	396	1632	17
Bid5	352.81	397.59	0	60	204	516	1632	15

Table 5.1.3
Summary Statistics--Six Cities Dataset
(Boston, N=574, Locendow=18)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	25.03	17.83	0	125
Hsldsiz	3.18	1.75	1	10
Hohed	13.76	3.01	7	20
Hohage	47.66	16.76	21	90
Exview	.49	.50	0	1
Badeyes	.17	.38	0	1
Actcindx	14.51	8.05	0	36
Prop	.18	.39	0	1
Femhoh	.53	.50	0	1
Own	.73	.44	0	1
Rural	.18	.39	0	1
Nonwhite	.03	.16	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	117.26	256.68	-1200	0	60	240	2400	17
Bid1	-144.59	163.50	-1200	-216	-114	-25.5	0	15
Bid2	138.94	158.48	0	18	120	216	1200	20
Bid3	170.56	216.18	0	18	156	276	1800	19
Bid4	188.79	238.19	0	19.5	156	276	1920	17
Bid5	224.22	296.20	0	36	156	300	2400	15

Table 5.1.4
Summary Statistics--Six Cities Dataset
(Cincinnati, N=469, Locendow=9)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	23.75	17.48	2.5	125
Hsldsiz	3.24	1.86	1	15
Hohed	13.49	3.12	1	20
Hohage	45.27	16.79	19	79
Exview	.65	.48	0	1
Badeyes	.26	.44	0	1
Actcindx	12.93	7.17	2	31
Prop	.05	.23	0	1
Femhoh	.31	.46	0	1
Own	.81	.40	0	1
Rural	.22	.42	0	1
Nonwhite	.16	.36	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	43.48	107.35	-396	0	12	60	672	28
Bid1	-57.48	77.24	-396	-72	-24	0	0	27
Bid2	56.94	82.28	0	0	24	72	396	30
Bid3	63.64	89.89	0	0	36	72	396	30
Bid4	73.53	106.75	0	0	36	91.5	672	27
Bid5	79.72	113.22	0	0	36	102	672	26

Table 5.1.5
Summary Statistics--Six Cities Dataset
(Mobile, N=451, Locendow=10)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	20.17	17.47	0	125
Hsldsiz	2.84	1.54	1	8
Hohed	13.15	7.35	1	76
Hohage	43.27	16.27	22	80
Exview	.37	.49	0	1
Badeyes	.21	.41	0	1
Actcindx	7.19	5.68	1	25
Prop	.18	.38	0	1
Femhoh	.48	.50	0	1
Own	.68	.47	0	1
Rural	.07	.25	0	1
Nonwhite	.27	.45	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	133.40	218.84	-516	0	120	276	876	11
Bid1	-156.40	140.92	-516	-216	-156	-39	0	12
Bid2	168.00	140.92	0	60	156	276	516	10
Bid3	196.68	163.32	0	60	180	276	636	12
Bid4	214.62	175.96	0	72	180	300	756	11
Bid5	238.48	191.95	0	96	216	312	876	10

Table 5.1.6
Summary Statistics--Six Cities Dataset
(Miami, N=235, Locendow=13)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	21.99	14.08	3.9	55
Hsldsiz	2.87	2.07	1	12
Hohed	12.13	3.90	3	20
Hohage	47.57	18.56	20	92
Exview	.34	.48	0	1
Badeyes	.34	.48	0	1
Actcindx	10.91	8.03	0	35
Prop	.13	.33	0	1
Femhoh	.17	.38	0	1
Own	.57	.50	0	1
Rural	.02	.15	0	1
Nonwhite	.60	.50	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	65.59	167.34	-636	0	0	156	660	47
Bid1	-98.69	135.21	-636	-156	-36	0	0	43
Bid2	88.47	128.88	0	0	0	156	636	51
Bid3	104.04	142.52	0	0	24	156	636	49
Bid4	115.53	159.63	0	0	36	180	660	47
Bid5	118.34	163.59	0	0	36	180	660	47

Table 5.1.7
Summary Statistics--Six Cities Dataset
(Washington, N=434, Locendow=15)

Independent Variables

Variable	Mean	Standard Dev.	Minimum	Maximum
Income	27.45	16.94	2.5	75
Hsldsiz	3.34	1.71	1	11
Hohed	13.94	3.45	2	20
Hohage	46.29	16.07	23	82
Exview	.48	.50	0	1
Badeyes	.31	.47	0	1
Actcindx	14.17	6.78	1	27
Prop	.24	.43	0	1
Femhoh	.38	.49	0	1
Own	.69	.47	0	1
Rural	.01	.11	0	1
Nonwhite	.60	.49	0	1

Bids

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid	218.98	448.53	-1320	0	156	360	4200	10
Bid1	-231.70	235.96	-1320	-300	-162	-81	0	7
Bid2	238.36	250.21	0	72	168	300	1320	12
Bid3	302.97	315.34	0	120	216	420	1740	12
Bid4	358.13	468.09	0	120	240	456	3600	10
Bid5	421.93	552.11	0	120	276	540	4200	10

interpret, easier to estimate, and less restrictive than the negative exponential form. The purpose of this section is not to present an exhaustive functional form search, but to consider the sensitivity of the Tolley et al. estimates and predicted values to model selection. This analysis is important for policy makers who are attempting to use the Tolley et al. results. More material on functional forms related to the underlying value function is presented in Section 5.5.

Tolley et al. assert that the theory behind the value function suggests:

(a) the bid should equal zero when DVR (change in visual range) equals zero,

(b) the bids should be increasing with DVR, and

(c) the bids should increase at a decreasing rate with respect to DVR.

These conditions (or hypotheses) are forced in the negative exponential function. Rather than impose these conditions by choice of functional form, an alternative is to test for their satisfaction empirically. To facilitate this, the first additional model considered is:

$$\text{BID} = a + \Sigma\, b_i X_i * \text{DVR} + c_1\, \text{DVR} + c_2\, \text{DVR}^2 \tag{5.2.1}$$

This model is simple and does not force the assumptions to hold.

In addition to the form represented in equation (5.2.1), a model with just DVR, INCOME, and city dummy variables was estimated. This model is given by:

$$\begin{aligned}\text{BID} = a &+ b_1\, \text{DVR} + b_2\, \text{DVR}^2 + b_3\, \text{INCOME} + b_4\, \text{INCOME}^2 \\ &+ b_5\, \text{INCOME} * \text{DVR} + \sum_i c_i\, \text{CITY}_i\end{aligned} \tag{5.2.2}$$

This form enables us to gauge the importance of the other independent variables in predicting bids for changes in visual range. It may also be more comparable with other CV studies. The influence of LOCENDOW is captured by the city dummy variables. Age, sex, race, and education are, at least partially, captured by the differences in income.

The estimates using the dataset provided to us of the negative exponential form, equation 5.2.1, and equation 5.2.2 are presented in Tables 5.2.1, 5.2.2, and 5.2.3, respectively. The negative exponential is very similar to the one reported by Tolley et al. The slight differences are probably due to different estimation routines. The model seemed sensitive to the type of estimation method employed. The method used herein is a numerical derivative method which produces more accurate results than other derivative methods. The major difference between the model reported here and that of Tolley et al. is the R-square figure (.36 versus .47). Again, this is probably due to differences in computer routines. This discrepancy does point out, however, the problem with using the R-square, even as a descriptive statistic. The intercept term in Table 5.2.2 is significantly less than zero, indicating that property (a) is rejected. However, the magnitude of the coefficient is relatively small (-$18); the function goes close to zero. The estimate of c_2 is negative and significant, supporting property (c) for positive changes in DVR. By entering the bids for preventing a decline in visual range as negative values for a negative change, the function is forced to have a steeper slope in the negative range. It is inappropriate to draw any conclusion about this, however, because there is only one data point in the negative range. The actual slope (if it were completely unrestricted) of the function in the negative range is uncertain.

Some differences in the results in Table 5.2.2 and the negative exponential in Table 5.2.1 are worth noting. First, the influence of LOCENDOW is negative and significant in the new specification. This would support the diminishing returns to visibility hypothesis put forth by Tolley et al. (page 138). Some of the socioeconomic coefficients have different statistical significance.

The estimates for equation 5.2.2 (presented in Table 5.2.3) provide some information about the sensitivity of the value function to alternative sets of independent variables. In this equation, the bids are a function of DVR and INCOME; all other variables are dropped from the specification. The DVR terms and four of the city dummy variables (CD2 to CD5) are significant. The income terms are marginally significant.

Table 5.2.1

NONLINEAR OLS SUMMARY OF RESIDUAL ERRORS

EQUATION	DF MODEL	DF ERROR	SSE	MSE	ROOT MSE	R-SQUARE
BID	20	2596	143737500	55368.84	235.31	0.3644

NONLINEAR OLS PARAMETER ESTIMATES

Variable	PARAMETER	ESTIMATE	APPROX. STD ERROR	'T' RATIO	APPROX. PROB>|T|
Intercept	A0	525.04	58.78321	8.93	0.0001
East	A1	314.91	56.49715	5.57	0.0001
West	A2	148.63	52.56575	2.83	0.0047
Locendow	B1	2.43E-05	.00027893	0.09	0.9306
Income	B2	.00051942	.00010671	4.87	0.0001
Hsldsiz	B3	.00173605	.00053379	3.25	0.0012
Hohed	B4	.00064995	.00022315	2.91	0.0036
Hohage	B5	2.00E-05	5.60E-05	0.36	0.7213
Exview	B6	-.0061933	.00199314	-3.11	0.0019
Badeyes	B7	0.0012172	.00198147	0.61	0.5391
Actcindx	B8	.00063906	.00017489	3.65	0.0003
Prop	B9	0.01130	.00335658	3.37	0.0008
Femhoh	B10	.00587712	.00189009	3.11	0.0019
Own	B11	-0.01151	.00271963	-4.23	0.0001
Rural	B12	-.0042113	.00260589	-1.62	0.1062
Nonwhite	B13	-.0031273	.00208366	-1.50	0.1335
A	B14	0.02060	.00423829	4.86	0.0001
C	B15	-0.01323	0.0031163	-4.24	0.0001
M	B16	-.0085526	.00312331	-2.74	0.0062
W	B17	0.02236	.00485163	4.61	0.0001

NUMBER OF OBSERVATIONS		STATISTICS FOR SYSTEM	
USED	2616	OBJECTIVE	54945.53
MISSING	0	OBJECTIVE*N	143737500

Estimates of Negative Exponential--All Data 1982

Table 5.2.2

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	21	85267454.34	4060354.97	74.771	0.0001
ERROR	2594	140864624	54304.01850		
C TOTAL	2615	226132078			

ROOT MSE	233.0322	R-SQUARE	0.3771
DEP MEAN	130.6452	ADJ R-SQ	0.3720
C.V.	178.3703		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-18.26065641	8.95666290	-2.039	0.0416
DVR	1	33.15275271	3.32103796	9.983	0.0001
DVR2	1	-0.63428982	0.08377474	-7.571	0.0001
East	1	6.11348783	1.43900565	4.248	0.0001
West	1	3.53746768	1.43693827	2.462	0.0139
Locendow	1	-0.61802169	0.16691829	-3.703	0.0002
Income	1	0.20706376	0.02688297	7.702	0.0001
Hsldsiz	1	0.28448925	0.21119182	1.347	0.1781
Hohed	1	-0.11009636	0.09841000	-1.119	0.2633
Hohage	1	-0.11062982	0.02904361	-3.809	0.0001
Exview	1	-3.51365752	0.80630281	-4.358	0.0001
Badeyes	1	0.40112561	0.94801900	0.423	0.6722
Actcindx	1	0.31750369	0.06437088	4.932	0.0001
Prop	1	5.01847748	1.16367610	4.313	0.0001
Femhoh	1	2.27331955	0.81415990	2.792	0.0053
Own	1	-5.70971539	0.95158767	-6.000	0.0001
Rural	1	-1.79811064	1.26258692	-1.424	0.1545
Nonwhite	1	-4.34831281	0.99594101	-4.366	0.0001
A	1	6.46785524	1.24181479	5.208	0.0001
C	1	-10.59112476	1.46949617	-7.207	0.0001
M	1	-4.94553715	1.51540697	-3.264	0.0011
W	1	10.19626016	1.24548112	8.187	0.0001

Estimates of Equation 5.2.1--All Data 1982

BID

Table 5.2.3

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	10	65624515.97	6562451.60	106.507	0.0001
ERROR	2605	160507562	61615.18709		
C TOTAL	2615	226132078			

ROOT MSE	248.2241	R-SQUARE	0.2902
DEP MEAN	130.6452	ADJ R-SQ	0.2875
C.V.	189.9986		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	79.82922241	19.11363907	4.177	0.0001
DVR	1	23.50396863	1.37279882	17.121	0.0001
DVR2	1	-0.98521460	0.06682725	-14.743	0.0001
INCOME	1	1.14455845	0.73452478	1.558	0.1193
INCOME2	1	-0.01278591	0.007407853	-1.726	0.0845
DVRINC	1	0.21203419	0.03518640	6.026	0.0001
CD1	1	-17.41154295	16.89833847	-1.030	0.3029
CD2	1	-97.39453133	15.81447716	-6.158	0.0001
CD3	1	-167.03903	16.58413779	-10.072	0.0001
CD4	1	-68.35916399	16.91352059	-4.042	0.0001
CD5	1	-141.44386	20.16546265	-7.014	0.0001

5-15

Estimates of Equation 5.2.2--All Data 1982

Because the three forms presented here are not nested, there is not a statistical method for choosing between them. As an alternative, predictions of bids are presented by type of functional form in Tables 5.2.4 - 5.2.6. In each case, predictions are made by city for several values of DVR and for two levels of income.

The predictions from the negative exponential and the form of equation 5.2.1 were generated by setting HOLDSIZ = 3, HOHED = 12, HOHAGE = 40, EXVIEW = 0, BADEYES = 0, ACTCINDX = 12, PROP = 0, FEMHOH = 0, OWN = 1, RURAL = 0, NONWHITE = 0, EAST = 0, and WEST = 0. Then, the appropriate value for LOCENDOW was entered for each city along with the correct city dummy variable value. Even though there are only 4 city dummy variables, bids are predicted for each city because LOCENDOW changes for each city. These tables reveal the sensitivity of the value function to the specific forms and to changes in income. Note that since the model of equation 5.2.2 contains a dummy for each city, the bids are predicted for each city directly.

Consider the predictions for Atlanta when DVR = -5. The negative exponential yields -105 and -130 for income equal to $25,000 and $40,000, respectively. The model of equation 5.2.1 yields -187 and -203, while the simple quadratic model yields -85 and -97, respectively. There is a considerable range evidenced here in terms of value estimates, and the two quadratic forms appear to be less sensitive to the income change than the negative exponential.

In general, the results using more flexible functional forms suggest that the data are consistent with the properties for which the negative exponential form was selected. The results show, however, the variability in predicted values that can occur with different functional forms. This is especially true for small changes in visual range as illustrated by the predicted values for a one mile change. Because the more flexible forms are not forced through the origin, the predicted value estimates for changes close to the origin are very unstable. This points to the potential error that may be involved when predictions are made for changes outside the range of those considered in the survey and to the uncertainty that is essentially covered up by fitting a smooth function with expected properties (that are forced) with what amounts to only three data points (which are not near the origin).

Table 5.2.4
Predicted Bids By Change In Visual Range
For The Negative Exponential Function
(Single Equation Model)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-105.09	18.81	87.57	160.53	271.98
Boston	-42.70	8.15	39.49	76.01	141.01
Cincinnati	-5.86	1.16	5.79	11.52	22.79
Mobile	-42.15	8.05	39.02	75.13	139.51
Miami	-18.61	3.64	17.97	35.33	68.28
Washington	-109.62	19.54	90.69	165.71	279.13

Income=$40000

Atlanta	-130.15	22.75	104.30	187.88	308.53
Boston	-65.28	12.16	58.06	109.70	196.48
Cincinnati	-26.97	5.23	25.65	50.05	95.33
Mobile	-64.70	12.06	57.61	108.89	195.20
Miami	-40.23	7.70	37.37	72.07	134.26
Washington	-134.87	23.47	107.30	192.68	314.65

Table 5.2.5
Predicted Bids By Change In Visual Range
For Equation 5.2.1
(Single Equation Model)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-187.06	11.69	118.83	224.22	339.85
Boston	-136.17	1.52	67.94	122.44	136.29
Cincinnati	-111.03	-3.51	42.80	72.16	35.73
Mobile	-160.89	6.46	92.66	171.88	235.17
Miami	-126.90	-0.34	58.67	103.88	99.18
Washington	-196.42	13.57	128.19	242.94	377.29

Income=$40000

Atlanta	-202.59	14.80	134.36	255.27	401.95
Boston	-151.70	4.62	83.47	153.49	198.39
Cincinnati	-126.56	-0.41	58.33	103.21	97.83
Mobile	-176.42	9.57	108.19	202.93	297.27
Miami	-142.42	2.77	74.19	134.93	161.28
Washington	-211.95	16.67	143.72	273.99	439.39

Table 5.2.6
Predicted Bids By Change In Visual Range
For Equation 5.2.2
(Single Equation Model)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-85.59	110.85	202.41	272.53	265.03
Boston	-165.57	30.87	122.43	192.55	185.05
Cincinnati	-235.22	-38.78	52.78	122.90	115.40
Mobile	-136.54	59.90	151.46	221.58	214.08
Miami	-209.62	-13.18	78.38	148.50	141.00
Washington	-68.18	128.26	219.82	289.94	282.44

Income=$40000

Atlanta	-96.81	118.72	223.00	309.02	333.32
Boston	-176.79	38.74	143.02	229.04	253.34
Cincinnati	-246.44	-30.92	73.37	159.39	183.69
Mobile	-147.76	67.77	172.05	258.07	282.37
Miami	-220.84	-5.31	98.97	184.99	209.29
Washingtin	-79.40	136.13	240.41	326.43	350.73

The predicted bids, even for the negative exponential form, show as much or more variability across the cities as is in the simple mean bids for each city. This is surprising when the predicted bids are for an essentially identical household in each city. This means that there is a great deal of unexplained difference in bids across cities that is being picked up by the city dummy variables (or by LOCENDOW, which may also be serving as a city dummy). This raises questions about applying the bid function estimated by Tolley et al. to cities or areas that were not included in this survey.

The negative exponential form was also estimated with a constant term added to the exponent to see if the socioeconomic coefficients were being dominated by DVR. This form was otherwise equivalent to the form estimated by Tolley et al. and replicated in Table 5.2.1. The new form was:

$$BID = a[1 - \exp(-g(DVR))]$$

$$\text{where } g = c + b_1X_1 + \ldots b_nX_n$$

Thus, the coefficient c shows the effect of DVR alone. The results of this estimation are shown in Table 5.2.7. The coefficient for DVR is statistically significant, but most of the socioeconomic coefficients are no longer or are only marginally significant. This is additional evidence of the instability of the predicted influence of the socioeconomic variables.

5.3 BID FUNCTION ANALYSIS — SUBSAMPLES

The robustness of the value function in predicting willingness to pay for changes in visibility can be analyzed further by estimating equations with different subsamples. In particular, estimates and predictions are presented (a) for each city and (b) using only the data from the first three bids. Because the negative exponential is expensive to estimate, the analysis in this section is confined to the form represented by equations 5.2.1 and 5.2.2.

Table 5.2.7

NONLINEAR OLS SUMMARY OF RESIDUAL ERRORS

EQUATION	DF MODEL	DF ERROR	SSE	MSE	ROOT MSE	R-SQUARE
BID	21	2595	140992451	54332.35	233.09	0.3765

NONLINEAR OLS PARAMETER ESTIMATES

Variable	PARAMETER	ESTIMATE	APPROX. STD ERROR	'T' RATIO	APPROX. PROB>|T|
Intercept	A0	1390.93	619.84	2.23	0.0260
East	A1	1068.90	540.26	1.98	0.0480
West	A2	425.05	243.34	1.75	0.0808
Locendow	B1	-3.93E-04	.00022625	-1.74	0.0828
Income	B2	.00014219	7.67E-05	1.85	0.0639
Hsldsiz	B3	.00023621	.00018055	1.31	0.1909
Hohed	B4	-5.38E-05	6.43E-05	-0.84	0.4030
Hohage	B5	-5.93E-05	3.36E-05	-1.77	0.0774
Exview	B6	-.0022014	.00126929	-1.73	0.0830
Badeyes	B7	.00013934	.00057733	0.24	0.8093
Actcindx	B8	.00019798	.00010971	1.80	0.0713
Prop	B9	.00325843	.00187915	1.73	0.0830
Femhoh	B10	.00140385	.00087854	1.60	0.1102
Own	B11	-.0038903	.00211680	-1.84	0.0662
Rural	B12	-.0012351	0.0009936	-1.24	0.2140
Nonwhite	B13	-.0026959	.00153355	-1.76	0.0789
A	B14	.00425867	.00236689	1.80	0.0721
C	B15	-.0065725	.00337435	-1.95	0.0515
M	B16	-.0032296	.00183136	-1.76	0.0779
W	B17	.00689163	.00375632	1.83	0.0667
DVR	C1	0.01465	.00750303	1.95	0.0510

NUMBER OF OBSERVATIONS		STATISTICS FOR SYSTEM	
USED	2616	OBJECTIVE	53896.20
MISSING	9	OBJECTIVE*N	140992451

Estimates of Negative Exponential -- with Constant in Exponent

5.3.1 City Analysis

The first subsample test requires that separate equations be estimated for each city. These equations (referred to as Six Equation Model in the Tables) constitute an unrestricted model that can be used to test the restricted model (referred to as Single Equation Model in the Tables). The restricted model includes city dummy variables. In the form given in equation 5.2.1, the unrestricted model yields 96 coefficients to be estimated, while the restricted version has 20. For the simple quadratic form given in equation 5.2.2, the unrestricted model has 30 coefficients and the restricted model only 10. An F-test can be used to compare the reduction in the residual sum of squares gained by relaxing the restrictions. The F-statistic for the first form is 5.11. The critical value with 96 degrees of freedom in the numerator and infinity in the denominator is approximately 1.40. The F-statistic from the simple quadratic form is 11.20, while the critical value with 20 degrees of freedom in the numerator and infinity in the denominator is 1.88. The alpha level is .01 in both cases. Both F-statistics indicate that the restrictions implied by the single equation models are rejected. These restrictions are that the "slopes" of the independent variables and the variances of the error terms are constant across equations.

The Six Equation Models are presented in the appendix for the two functional forms. In none of the estimations using equation 5.2.1 and in only one (Cincinnati) using equation 5.2.2 are the intercept terms significantly different than zero. This finding is empirical support for the analytical assumptions used by Tolley et al., since the value function is expected to go through the origin.

For estimations using equation 5.2.1, the coefficient for DVR is not statistically significant for Cincinnati and Miami (recall that Cincinnati and Miami had the highest percentages of zero bids), but the DVR^2 term is always negative and significant. The influence of DVR and DVR^2 is significant with expected sign in every estimation using equation 5.2.2.

Predictions by city are presented for the first form in Tables 5.3.1. These can be compared to the predictions from the single equation model presented in Table

Table 5.3.1
Predicted Bids By Change In Visual Range
For Equation 5.2.1
(Six Equation Model)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-170.67	29.21	129.67	194.24	224.48
Boston	-127.06	21.09	91.06	125.22	106.44
Cincinnati	-51.43	8.49	36.43	55.66	51.32
Mobile	-157.60	26.72	117.60	185.40	210.80
Miami	-218.40	13.08	-36.60	-393.00	-1806.00
Washington	-230.35	39.35	174.35	254.20	284.40

Income=$40000

Atlanta	-183.72	31.82	142.72	220.34	276.68
Boston	-137.56	23.19	101.56	146.22	148.44
Cincinnati	-63.43	10.89	48.43	79.66	99.32
Mobile	-161.35	27.47	121.35	192.90	225.80
Miami	-223.05	14.01	-31.95	-383.70	-1787.40
Washington	-261.85	45.65	205.85	317.20	410.40

5.2.5. The two models generate similar predictions, except in the case of Miami. When DVR = 20, the models diverge in their predictions, slightly owing to the fact that the value function reaches its peak earlier when a separate equation is estimated for each city. For example, the Miami equation peaks before DVR = 5!

The predictions for the simple quadratic form are presented in Table 5.3.2. These can be compared to the predictions presented in Table 5.2.6. The differences between these predictions are less striking than for the previous form.

There are two general conclusions that can be made after comparing the six equation model to the single equation model. First, the results of the F-test indicate that some aggregation bias will result in the single equation model. This bias does not seem to be severe for Atlanta, Boston, Cincinnati, Mobile, and Washington. The equations and predictions for Miami indicate that some problem in the Miami data may be buried in the aggregate approach.

The second general conclusion that can be drawn at this point concerns the range of the predicted bids generated so far. Consider the case of DVR = 10 for each city. In Atlanta our predictions (income = $25,000) range from $160 to $272. A range of between $76 to $140 is found for Boston, while for Cincinnati the range is $11 to $122. The results for Mobile yield $75 to $221. The Miami figures are -$393 to $148, while Washington's are $165 to $254. The ranges for Cincinnati and Miami are probably unacceptable, and may reflect survey and/or data problems for Cincinnati and Miami.

5.3.2 Type of Bid Analysis

The second subsample issue concerns using all the bid types together to estimate a value function. Since the regional bids and national bids change the nature of the good, we can hypothesize that they should not be used with the local improvement bids. Moreover, the regional and national bids represent an attempt to measure option and existence values and as noted elsewhere, the design of these questions is flawed.

Table 5.3.2
Predicted Bids By Changes In Visual Range
For Equation 5.2.2
(Six Equation Model)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-177.98	13.84	115.72	213.82	312.52
Boston	-142.24	4.80	77.62	140.29	171.14
Cincinnati	-63.87	-2.02	28.13	53.36	62.26
Mobile	-160.81	12.23	97.59	170.54	203.94
Miami	-101.42	1.54	52.58	96.58	118.58
Washington	-221.68	13.83	131.23	233.43	289.33

Income=$40000

Atlanta	-191.33	9.49	117.37	222.97	336.67
Boston	-170.66	-6.26	78.14	155.29	215.09
Cincinnati	-87.05	-10.08	30.16	67.98	102.08
Mobile	-176.41	6.53	98.49	179.69	229.59
Miami	-138.02	-10.76	56.48	120.73	183.23
Washington	-268.63	1.97	142.78	274.23	388.63

To briefly address this issue, equation 5.2.1 was estimated using only the data from the first three bids. The estimates are presented in Table 5.3.3, with corresponding predictions presented in Table 5.3.4. The number of observations is reduced to 1564 (60% of the original size). The R-square improves a bit and the coefficients change slightly, when compared to the estimates presented in Table 5.2.2. The predictions can be compared to those presented in Table 5.2.5. The predictions from both models are very similar, indicating that including the regional bids in the estimated function may not have a significant effect on predicted values.

5.4 THE 1984 DATASET

The 1984 CV study used photos specific to each of three cities and used a utility bill payment mechanism with some respondents. The write-up of this portion by Tolley et al. (Section 2.5) is somewhat more complete than the section describing the 1982 CV study, however, the comparison of the 1984 results to the 1982 results was too vague to substantiate the conclusion that the results are consistent.

5.4.1 Distributions of the Bid Data

The distributions of the bids for the 1984 data are presented by city in Table 5.4.1 for the "non-utility" (no specific payment mechanism) data and in Table 5.4.2 for the utility data. The utility payment vehicle does drive the average bids down, but as shown below, the influence of this effect is not significant in a value function estimated for Atlanta. There does not seem to be a general pattern for the percentage of zero bids. However, these figures are somewhat higher than those for 1982 in Atlanta, Boston, Mobile, and Washington. The average bids in Atlanta are lower for the 1984 dataset. Several changes were made in addition to using photos for Atlanta, including use of photos showing different levels of visual range (5, 9, and 20 as opposed to 4, 13, and 30 shown in 1982) and starting at a typical visual range of 12 miles rather than 10. It is uncertain how all these changes would be expected to influence the bids, but the size of the difference in the mean bids is unexpected and not reassuring.

Table 5.3.3

BID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	19	48846321.97	2570859.03	76.242	0.0001
ERROR	1544	52063134.69	33719.64682		
C TOTAL	1563	100909457			

ROOT MSE	183.6291	R-SQUARE	0.4841
DEP MEAN	64.71292	ADJ R-SQ	0.4777
C.V.	283.7596		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-18.30536702	7.05787104	-2.594	0.0096
OVR	1	31.77860554	3.00805069	10.565	0.0001
OVR2	1	-0.63432599	0.06601458	-9.609	0.0001
Locendow	1	-0.50355392	0.15467096	-3.256	0.0012
Income	1	0.13961111	0.02490082	5.607	0.0001
Hsldsiz	1	0.13999117	0.19559966	0.716	0.4743
Hohed	1	-0.08819356	0.09118117	-0.967	0.3336
Hohage	1	-0.09787553	0.02690234	-3.638	0.0003
Exview	1	-2.35006055	0.74711477	-3.146	0.0017
Badeyes	1	0.44563001	0.87818327	0.507	0.6119
Actcindx	1	0.25491727	0.05961659	4.276	0.0001
Prop	1	3.52546601	1.07785908	3.271	0.0011
Femhoh	1	1.70319880	0.75432681	2.253	0.0241
Own	1	-3.38647121	0.88177269	-3.841	0.0001
Rural	1	-1.50421057	1.17171342	-1.284	0.1994
Nonwhite	1	-3.13610040	0.92254759	-3.399	0.0007
A	1	4.91454197	1.15034097	4.272	0.0001
C	1	-8.75999583	1.36125022	-6.435	0.0001
M	1	-3.82305428	1.40344691	-2.725	0.0065
W	1	7.25293539	1.15354701	6.287	0.0001

Estimates of Equation 5.2.1

Table 5.3.4
Predicted Bids By Change In Visual Range
For Equation 5.2.1
(Data For Local Bids Only)

Income=$25000

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Atlanta	-180.15	10.65	112.65	211.80	315.60
Boston	-140.65	2.75	73.15	132.80	157.60
Cincinnati	-119.35	-1.51	51.85	90.20	72.40
Mobile	-160.65	6.75	93.15	172.80	237.60
Miami	-134.15	1.45	66.65	119.80	131.60
Washington	-184.40	11.50	116.90	220.30	332.60

Table 5.4.1
Summary Statistics--1984 Nonutility Bids by City

Atlanta

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-86.82	117.54	-516	-156	-24	0	0	32
Bid2	96.28	114.34	0	0	54	156	396	26
Bid3	143.82	176.65	0	6	72	216	636	24
Bid4	153.53	172.20	0	12	90	228	636	21
Bid5	181.73	206.62	0	12	156	255	876	21

Denver

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-120.77	90.44	-300	-180	-120	-60	0	19
Bid2	127.50	110.39	0	24	102	240	360	22
Bid3	162.38	133.52	0	24	168	276	420	22
Bid4	183.75	146.73	0	60	180	300	480	19
Bid5	205.88	172.32	0	60	210	345	600	19

Chicago

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-116.57	117.46	-480	-210	-96	0	0	38
Bid2	126.28	118.47	0	0	156	220	360	38
Bid3	152.00	151.33	0	0	156	240	480	38
Bid4	137.71	126.12	0	0	156	240	360	38
Bid5	165.60	205.85	0	0	156	237	840	40

Table 5.4.2
Summary Statistics--1984 Utility Bids by City

Atlanta

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-63.84	72.72	-276	-102	-36	0	0	28
Bid2	68.64	75.54	0	6	36	114	276	24
Bid3	94.56	102.43	0	6	60	168	396	24
Bid4	105.12	105.32	0	6	72	180	396	24
Bid5	128.16	135.93	0	6	72	198	516	24

Denver

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-82.45	88.71	-300	-156	-60	0	0	32
Bid2	102.19	96.94	0	0	96	156	300	29
Bid3	145.48	151.24	0	0	120	180	516	26
Bid4	156.00	141.51	0	24	156	240	540	23
Bid5	170.71	156.82	0	24	156	240	540	23

Chicago

Type	Mean	St. Dev.	Min	25%	50%	75%	Max	%0
Bid1	-112.75	139.08	-480	-180	-60	0	0	33
Bid2	115.25	135.43	0	0	60	174	480	29
Bid3	136.44	161.59	0	0	60	240	540	30
Bid4	131.74	169.50	0	0	60	180	540	30
Bid5	143.22	181.65	0	0	60	180	600	30

5.4.2 Value Functions for Atlanta

Data are available for Atlanta in both the 1984 and 1982 datasets. A comparison between just the Atlanta equations can potentially address the issue of the effects of the different picture sets. Several equations are presented for the 1984 Atlanta value function. In Table 5.4.3, the form represented by equation 5.2.1 is presented. These results can be compared to those presented in Appendix Table A.1, with the exception of a coefficient for RURAL. The results for the form represented by equation 5.2.2 are presented in Table 5.4.4, which are comparable to those presented in Appendix Table A.7. The negative exponential for the 1984 data is given in Table 5.4.5. Since the negative exponential form was not employed in Section 5.3, the 1982 Atlanta data were used to estimate this form. The 1982 results are presented in Table 5.4.6. The predicted bids for the three forms are presented in Table 5.4.8 for both of the datasets. To generate the predictions, the following values were used for the independent variables: EAST = WEST = EXVIEW = BADEYES = PROP = FEMHOH = RURAL = NONWHITE = 0, INCOME = $25,000, HSLDSIZ = 3, HOHED = 12, HOHAGE = 40, ACTCINDX = 12, and OWN = 1. Initially, only the "non-utility" data were used to estimate the equations for 1984. The units for measuring income in 1984 are dollars, not thousands of dollars like in 1982. Therefore, when comparing the coefficients for the income terms, the 1984 measures appear smaller.

The 1984 equations with just the non-utility data are very poor representations. In the negative exponential, none of the coefficients are significant. The predictions presented in Table 5.4.8 are negative for positive changes in DVR. Clearly, there are some problems fitting these data. A better equation was obtained by combining the utility bill payment data with the non-utility data and adding in a dummy variable for the payment vehicle (called utility). This representation is presented in Table 5.4.7 for the negative exponential form. The predictions are presented at the bottom of Table 5.4.8. Even the function presented in Table 5.4.7 has some strange results. For example, the income term is seen to influence the bid negatively.

The influence of the payment vehicle is insignificant. This finding held true for other forms and combinations of data tried but not reported here.

Table 5.4.3

Atlanta--1984

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	15	3052572.47	203504.83	11.142	0.0001
ERROR	153	2794502.25	18264.72051		
C TOTAL	168	5847074.72			

ROOT MSE	135.147	R-SQUARE	0.5221
DEP MEAN	97.43432	ADJ R-SQ	0.4752
C.V.	138.7038		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-9.63135027	20.34393107	-0.473	0.6366
DVR	1	23.46531349	7.52867772	3.117	0.0022
DVR2	1	-0.32313770	0.19137077	-1.689	0.0933
East	1	5.72470588	3.27779702	1.747	0.0827
West	1	8.54470588	3.27779702	2.607	0.0100
Income	1	0.000078670	0.000072624	1.083	0.2804
Hsldsiz	1	-4.98273838	0.85463633	-5.830	0.0001
Hohed	1	0.12256839	0.35179533	0.349	0.7274
Hohage	1	-0.25276194	0.07602054	-3.325	0.0011
Exview	1	8.38799890	2.29663273	3.668	0.0003
Badeyes	1	0.89679831	2.72465952	0.329	0.7425
Actcindx	1	0.13487469	0.16319383	1.133	0.2590
Prop	1	1.86639882	3.25015450	0.574	0.5666
Femhoh	1	1.34879378	2.32079293	0.581	0.5620
Own	1	-0.19095559	2.78449439	-0.069	0.9454
Nonwhite	1	16.47485177	2.55875985	6.439	0.0001

Estimates of Equation 5.2.1

810

Table 5.4.4

Atlanta--1984

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	1588262.93	317652.59	12.158	0.0001
ERROR	163	4258811.79	26127.57969		
C TOTAL	168	5847074.72			

ROOT MSE	161.6406	R-SQUARE	0.2716
DEP MEAN	97.43432	ADJ R-SQ	0.2493
C.V.	165.897		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-14.69534153	34.10242259	-0.431	0.6673
DVR	1	18.32675411	3.25538282	5.630	0.0001
DVR2	1	-0.61731829	0.17182175	-3.593	0.0004
INCOME	1	0.002974435	0.001632530	1.822	0.0703
INCOME2	1	-3.28337E-08	1.45252E-08	-2.260	0.0251
DVRINC	1	.00000496064	0.000060712	0.082	0.9348

Estimates of Equation 5.2.2

Table 5.4.5

Atlanta--1984

NONLINEAR OLS SUMMARY OF RESIDUAL ERRORS

EQUATION	DF MODEL	DF ERROR	SSE	MSE	ROOT MSE	R-SQUARE
BID	14	155	2915015	18806.55	137.14	0.5015

NONLINEAR OLS PARAMETER ESTIMATES

Variable	PARAMETER	ESTIMATE	APPROX. STD ERROR	'T' RATIO	APPROX. PROB>|T|
Intercept	A0	633.90	432.09	1.47	0.1444
East	A1	434.10	378.81	1.15	0.2536
West	A2	610.29	499.66	1.22	0.2229
Income	B1	-1.63E-08	1.02E-07	-0.16	0.8727
Hsldsiz	B2	-.0059763	.00534084	-1.12	0.2649
Hohed	B3	.00139632	.00121992	1.14	0.2541
Hohage	B4	-1.92E-04	0.0001917	-1.00	0.3171
Exview	B5	0.01142	0.01022	1.12	0.2656
Badeyes	B6	.00521659	.00585272	0.89	0.3766
Actclndx	B7	.00049011	.00049669	0.99	0.3253
Prop	B8	.00652941	.00744252	0.88	0.3817
Femhoh	B9	.00250059	.00425935	0.59	0.5580
Own	B10	-9.13E-04	.00415843	-0.22	0.8257
Nonwhite	B11	0.02717	0.02382	1.14	0.2557

NUMBER OF OBSERVATIONS		STATISTICS FOR SYSTEM	
USED	169	OBJECTIVE	17248.61
MISSING	0	OBJECTIVE*N	2915015

Estimates of Negative Exponential

Table 5.4.6

Atlanta--1982

NONLINEAR OLS SUMMARY OF RESIDUAL ERRORS

EQUATION	DF MODEL	DF ERROR	SSE	MSE	ROOT MSE	R-SQUARE
B10	13	430	34662908	79134.72	281.40	0.4063

NONLINEAR OLS PARAMETER ESTIMATES

Variable	PARAMETER	ESTIMATE	APPROX. STD ERROR	'T' RATIO	APPROX. PROB>|T|
Intercept	A0	575.00	103.94	5.56	0.0001
East	A1	316.07	108.65	2.91	0.0038
West	A2	206.05	122.30	1.68	0.0927
Income	B2	.00016131	.00020368	0.79	0.4288
Hsldsiz	B3	.00663384	.00187143	3.54	0.0004
Hohed	B4	0.002642	.00091032	2.90	0.0039
Hohage	B5	-4.095E-04	.00015753	-2.60	0.0097
Exview	B6	-0.01085	.00575695	-1.89	0.0594
Badeyes	B7	0.02925	0.01113	2.63	0.0089
Actcindx	B8	.00048057	.00042907	1.12	0.2633
Prop	B9	-.0088612	0.01186	-0.75	0.4554
Femhoh	B10	0.01170	.00636004	1.84	0.0666
Own	B11	-0.00703	.00564056	-1.25	0.2133
Rural	B12	0.01243	.00842017	1.47	0.1415
Nonwhite	B13	-.0056246	.00532713	-1.06	0.2916

NUMBER OF OBSERVATIONS		STATISTICS FOR SYSTEM	
USED	453	OBJECTIVE	76562.71
MISSING	0	OBJECTIVE*N	34682908

Estimates of Negative Exponential

Table 5.4.7

Atlanta--1984

NONLINEAR OLS SUMMARY OF RESIDUAL ERRORS

EQUATION	DF MODEL	DF ERROR	SSE	MSE	ROOT MSE	R-SQUARE
BID	15	279	4563344	16356.07	127.89	0.4087

NONLINEAR OLS PARAMETER ESTIMATES

Variable	PARAMETER	ESTIMATE	APPROX. STD ERROR	'T' RATIO	APPROX. PROB>|T|
Intercept	A0	274.91	68.14514	4.03	0.0001
East	A1	178.07	75.11355	2.37	0.0184
West	A2	264.41	90.70848	2.91	0.0038
Income	B1	-2.99E-07	1.75E-07	-1.71	0.0892
Hsldsiz	B2	-.0085141	.00407189	-2.09	0.0374
Hohed	B3	.00090426	.00081354	1.11	0.2673
Hohage	B4	.00018672	.00015897	1.18	0.2409
Exview	B5	0.01809	.00901027	2.01	0.0456
Badeyes	B6	.00096451	.00701445	0.14	0.8907
Actcindx	B7	.00156295	.00069543	2.25	0.0254
Prop	B8	0.02086	0.01095	1.91	0.0578
Femhoh	B9	-3.73E-04	.00631213	-0.06	0.9530
Own	B10	.00119744	.00733376	0.16	0.8715
Nonwhite	B11	0.05798	0.02291	2.53	0.0119
Utility	B12	-0.02680	0.04452	-0.60	0.5477

NUMBER OF OBSERVATIONS		STATISTICS FOR SYSTEM	
USED	294	OBJECTIVE	15521.58
MISSING	0	OBJECTIVE*N	4563344

Estimates of Negative Exponential

Table 5.4.8
Predicted Bids By Changes In Visual Range
For Three Functional Forms Using The Atlanta
Single Equation Models

1982

City	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Form 5.2.1	-170.67	29.21	129.67	194.24	224.48
Form 5.2.2	-177.98	13.84	115.72	213.82	312.52
Neg Expon'l	-94.00	17.31	81.50	151.52	263.31

1984--Nonutility Data

Form 5.2.1	-66.95	-6.10	1.54	-3.45	-61.90
Form 5.2.2	-47.99	77.37	136.26	182.11	181.26
Neg Expon'l	37.64	-7.81	-40.01	-82.55	-175.85

1984--All Data

Neg Expon'l	-6.15	1.21	6.02	11.90	23.28

Unfortunately, the findings in this section are not very conducive for analyzing the role of the picture sets. The predictions from the 1984 data are lower (and these are nominal terms), but the single city model does not perform very well. Overall, we have yet to make any reasonable analysis of this issue except to say that we do not agree with the authors' conclusion that the 1984 results support the validity of the 1982 results.

5.5 VALUE FUNCTIONAL FORM ANALYSIS

The purpose in this section is to present the results from estimating two additional functional forms. These results can be used to compare the Tolley et al. data with results of other CVM studies. These forms are related to the utility function discussion presented in Section 4 and are a variation on the second form in Table 4.1. They have been simplified to allow OLS estimation.

Specifically, estimated equations and the corresponding predictions for the bids are presented for the following forms:

$$BID = b_1 \, DVR + b_2[VR_2^{\,2} - VR_1^{\,2}] + \sum_i g_i X_i * DVR \qquad 5.5.1$$

and

$$BID = b_1 \ln (VR_2/VR_1) + \sum_i g_i X_i * \ln (VR_2/VR_1) \qquad 5.5.2$$

VR_1 and VR_2 represent the initial and ending visual range given in the CV question. When $DVR = -5$, $VR_1 = 10$ and $VR_2 = 5$, and so forth. The X_i's are the socioeconomic independent variables.

The underlying visibility value functions from which these bid functions are derived are as follows.

For 5.5.1 the value function is

$$\text{Value} = b_1 \, VR + b_2 \, VR^2 + \sum_i g_i X_i * VR \qquad 5.5.3$$

For 5.5.2 the value function is

$$\text{Value} = \ln (VR) * [b_1 + \sum_i g_i X_i] \qquad 5.5.4$$

With a positive value for b_1 in equation 5.3.3, the value function can have a positive or negative second derivative with respect to VR depending on the sign of b_2 and the level of VR. Equation 5.5.4 is somewhat more restrictive in that a negative second derivative occurs for all VR. This equation implies that the bid will be constant for the same percentage change in VR.

The estimated equations are presented in Tables 5.5.1 and 5.5.2. Corresponding predicted bids for the city of Atlanta are presented in Table 5.5.3.

In the regression output tables, the following new variables are used:

$$DVIS2 = VR_2^{\,2} - VR_1^{\,2}$$

$$LVR = \ln (VR_2/VR_1)$$

Both equations show statistically significant coefficients for the VR terms, and seem to fit the data better than the negative exponential and the quadratic forms reported in subsection 5.2. The predicted values for form 5.5.2 are very similar to those for the negative exponential form. The predicted values for form 5.5.1 are considerably higher for some visibility changes, although the results are within a factor of two or less.

These results still show the variability that can result in predicted values when different functional forms are used, but also show that bid function forms derived from specific value functions are preferable.

Table 5.5.1

Estimates of Equation 5.5.1

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	20	51167429.25	2558371.46	70.172	0.0001
ERROR	1544	56291686.32	36458.34606		
U TOTAL	1564	107459115			

ROOT MSE	190.9407	R-SQUARE	0.4762
DEP MEAN	64.71292	ADJ R-SQ	0.4694
C.V.	295.0581		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
DVR	1	33.02331369	3.49358004	9.453	0.0001
DVIS2	1	-0.62934293	0.06581306	-9.563	0.0001
Locendow	1	0.40158975	0.14772989	2.718	0.0066
Income	1	0.15109982	0.02577093	6.251	0.0001
Hsldsiz	1	0.16994008	0.20297377	0.837	0.4026
Hohed	1	-0.09841234	0.09410857	-1.046	0.2958
Hohage	1	-0.10398189	0.02780213	-3.920	0.0001
Exview	1	-2.48099653	0.77113418	-3.217	0.0013
Badeyes	1	0.52178113	0.90475735	0.577	0.5642
Actcindx	1	0.20384543	0.06043115	3.373	0.0008
Prop	1	4.12820980	1.10695366	3.729	0.0002
Pemhoh	1	1.31242456	0.77667564	2.334	0.0197
Own	1	-3.93677520	0.90752830	-4.393	0.0001
Rural	1	-2.64277226	1.20656239	-2.190	0.0286
Nonwhite	1	-0.77024141	0.88062514	-0.875	0.3819
Atlanta	1	14.21671009	12.93934122	1.099	0.2721
Boston	1	-50.25479114	12.98915125	-3.869	0.0001
Cincinnati	1	-37.32546894	13.67873246	-2.729	0.0064
Mobile	1	2.18437026	13.53045854	0.161	0.8718
Miami	1	-49.40703494	17.01962611	-2.903	0.0037

Table 5.5.2

Estimates of Equation 5.5.2

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	19	51702021.19	2721159.01	75.402	0.0001
ERROR	1545	55757094.39	36088.73423		
U TOTAL	1564	107459115			
ROOT MSE		189.9704	R-SQUARE	0.4811	
DEP MEAN		64.71292	ADJ R-SQ	0.4748	
C.V.		293.5586			

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > |T|
LVR	1	165.49367	40.05784803	4.131	0.0001
Locendow	1	5.07951164	2.01414936	2.522	0.0118
Income	1	2.74725926	0.39900313	6.885	0.0001
Hsldsiz	1	2.88497873	3.14226878	0.918	0.3587
Hohed	1	-1.52564043	1.45654356	-1.047	0.2951
Hohage	1	-1.78001806	0.43032990	-4.136	0.0001
Exview	1	-40.70730095	11.93605251	-3.410	0.0007
Badeyes	1	10.43704667	13.99683561	0.746	0.4560
Actcindx	1	3.39129363	0.92953437	3.648	0.0003
Prop	1	70.82099269	17.13087452	4.134	0.0001
Femhoh	1	32.26210909	12.01011678	2.686	0.0073
Own	1	-64.54455546	14.02744914	-4.601	0.0001
Rural	1	-45.96446703	18.75416688	-2.451	0.0144
Nonwhite	1	-7.08203852	13.45639053	-0.526	0.5988
Atlanta	1	22.51069500	11.89180970	1.893	0.0586
Boston	1	-30.68934852	11.18972685	-2.743	0.0062
Cincinnati	1	-36.20264633	12.00454285	-3.016	0.0026
Mobile	1	6.09316491	12.11505508	0.503	0.6151
Miami	1	-40.50572849	16.25479229	-2.492	0.0128

Table 5.5.3
Predicted Bids For Atlanta By Functional
And Change In Visual Range

Functional Form	Dvr=-5	Dvr=1	Dvr=5	Dvr=10	Dvr=20
Form 5.5.1	-199.65	36.15	168.15	304.80	483.60
Form 5.5.2	-173.60	23.80	101.56	173.60	275.21

6.0 COMPARISON TO RESULTS OF OTHER VISIBILITY VALUE STUDIES

Four studies previous to Tolley et al. have estimated values for changes in visibility in urban residential areas using contingent valuation (CV) surveys (Brookshire et al., 1979; Loehman et al., 1981; Rae et al., 1983; and Rowe et al. 1980). Two of these studies also obtained estimates of values for changes in air quality using property value data (Brookshire et al., 1979; and Loehman et al., 1981). A third property value study has also been conducted that specifically used measures of visibility (Trijonis et al., 1984). The results of these studies provide another perspective on the Tolley et al. results.

In this section the average visibility values estimated in each of these studies are compared, and the Tolley et al. results are found to be quite consistent with previous results. The results of property value studies are not strictly comparable to the CV results, but they provide a sense of the "reasonableness" of the results of the CV visibility studies.

6.1 COMPARISON OF CV STUDIES

All of the CV studies have used personal interviews in which subjects were shown photographs of different levels of visibility and were asked to estimate how much they would be willing to pay each month to have one level rather than another. In some cases subjects were asked to give separate values for concerns related to health effects of air pollution versus the visual aesthetic effects. In other cases subjects were asked to consider only the visual aesthetic effects of air pollution. Most of the studies asked about two or more different changes in visual range. In most cases the subjects were told that the payment would be in the form of different monthly utility bills. In one study (Rae et al.) contingent ranking was used. This involves asking subjects to rank in order of preference a list of possible combinations of payments and air quality levels. Willingness to pay estimates are then derived by the analyst from the ordering given.

For this comparison, we hypothesized the following model of the effect of visual aesthetics (as measured by visual range) on utility.

$$U = aY + (bVR + cVR^2) * f(x) \qquad 6.1$$

where

U = utility

Y = income

VR = visual range

$f(x)$ = some function of the vector of variables x related to the consumption or enjoyment of visual range

Utility is expected to be increasing in income and visual range, but depending on the sign and magnitude of the parameter c the second derivative of utility with respect to visual range may be positive or negative. Equation 6.1 implies the following compensating surplus function.

$$CS = [(b/a)(VR2 - VR1) + (c/a)(VR2^2 - VR1^2)]f(x) \qquad 6.2$$

This suggests that the bids from the surveys can be expected to be a function of the change in visual range considered and of the base level (VR1) and new level (VR2) of visual range hypothesized.

The average annual household value estimates from each of the studies for each hypothesized change in visual range were compiled to estimate equation 6.2. The function f(x) was presumed to be held constant across the different studies (implying that each sample is similar on average). The variables used in this analysis are defined in Table 6-1 and the entire data set used is given in Table 6-2.[1]

Four dummy variables were defined for study characteristics that might influence the value estimates. These are RANK, DIST, PRETEST, and WEST and are defined in Table 6-1.

Table 6-3 shows the OLS estimates of equation 6-2. Both DVR and DIFSQ are significant. The negative coefficient for DIFSQ combined with the positive coefficient for DVR indicates that over the range of visibility considered in

Table 6-1

Variables Used in Analysis of Results From CVM Studies

Variable	Description	Mean
CITY	Cities where the means were estimated--entered separately if more than one city covered in one study. Value codes as follows (date of survey): 1 = Chicago - Tolley et al. (1981) 2 = Atlanta - Tolley et al. (1982) 3 = Boston - Tolley et al. (1982) 4 = Cincinnati - Tolley et al. (1982) 5 = Miami - Tolley et al. (1982) 6 = Mobile - Tolley et al. (1982) 7 = Washington DC - Tolley et al. (1982) 8 = Los Angeles - Brookshire et al. (1978) 9 = San Francisco - Loehman et al. (1980) 10 = Cincinnati - Rae et al. (1982) 11 = Farmington, New Mexico - Rowe et al. (1977)	
BID	Annual willingness to pay per household in 1984 dollars. Mid points of ranges were used for Rae study. Format C2 (payment card with private and public goods) was used for Tolley et al. pretest.	100.47
VR1	Visual range in miles that was the presumed starting point for the hypothesized change	14.98
VR2	Visual range in miles that was the hypothesized new level	19.48
DVR	Change in visual range hypothesized (VR2 - VR1)	4.50
PERMILE	BID/DVR	29.64
DIFSQ	$[(VR2)^2 - (VR1)^2]$	-4.74
PERCENT	DVR/VR	.82
LOGRAT	LOG(VR2/VR1)	.34
RANK	1 = contingent ranking method was used.	.17
DIST	1 = visual range was presented as a distribution of several levels, not a single average value.	.17
PRETEST	1 = study was a pretest for a larger effort.	.19
WEST	1 = study conducted in the Western U.S.	.19

Table 6-2

DATA USED IN ANALYSIS OF RESULTS FROM CV STUDIES

CITY	BID	VR1	VR2	DVR	PERMILE	DIFSQ	PERCENT	LOGRAT	RANK	DIST	PRETEST	WEST
1	-323	9.0	4.0	-5.0	64.600	-65.0	-0.55556	-0.8109	0	0	1	0
1	369	9.0	18.0	9.0	41.000	243.0	1.00000	0.6931	0	0	1	0
1	520	9.0	30.0	21.0	24.762	819.0	2.33333	1.2040	0	0	1	0
2	-212	10.0	5.0	-5.0	42.400	-75.0	-0.50000	-0.6931	0	0	0	0
2	203	10.0	20.0	10.0	20.300	300.0	1.00000	0.6931	0	0	0	0
2	309	10.0	30.0	20.0	15.450	800.0	2.00000	1.0986	0	0	0	0
3	-157	10.0	5.0	-5.0	31.400	-75.0	-0.50000	-0.6931	0	0	0	0
3	150	10.0	20.0	10.0	15.000	300.0	1.00000	0.6931	0	0	0	0
3	185	10.0	30.0	20.0	9.250	800.0	2.00000	1.0986	0	0	0	0
4	-62	10.0	5.0	-5.0	12.400	-75.0	-0.50000	-0.6931	0	0	0	0
4	62	10.0	20.0	10.0	6.200	300.0	1.00000	0.6931	0	0	0	0
4	69	10.0	30.0	20.0	3.450	800.0	2.00000	1.0986	0	0	0	0
5	-107	10.0	5.0	-5.0	21.400	-75.0	-0.50000	-0.6931	0	0	0	0
5	95	10.0	20.0	10.0	9.500	300.0	1.00000	0.6931	0	0	0	0
5	112	10.0	30.0	20.0	5.600	800.0	2.00000	1.0986	0	0	0	0
6	-168	10.0	5.0	-5.0	33.600	-75.0	-0.50000	-0.6931	0	0	0	0
6	181	10.0	20.0	10.0	18.100	300.0	1.00000	0.6931	0	0	0	0
6	213	10.0	30.0	20.0	10.650	800.0	2.00000	1.0986	0	0	0	0
7	-251	10.0	5.0	-5.0	50.200	-75.0	-0.50000	-0.6931	0	0	0	0
7	257	10.0	20.0	10.0	25.700	300.0	1.00000	0.6931	0	0	0	0
7	327	10.0	30.0	20.0	16.350	800.0	2.00000	1.0986	0	0	0	0
8	94	2.0	12.0	10.0	9.400	140.0	5.00000	1.7918	0	0	0	1
8	132	12.0	28.0	16.0	8.250	640.0	1.33333	0.8473	0	0	0	1
9	91	16.3	18.6	2.3	39.565	80.3	0.14110	0.1320	0	1	0	1
9	-155	18.6	16.3	-2.3	67.391	-80.3	-0.12366	-0.1320	0	1	0	1
10	498	7.8	25.2	17.4	28.621	574.2	2.23077	1.1727	1	0	1	0
10	239	11.4	21.0	9.6	24.896	311.0	0.84211	0.6109	1	1	1	0
10	153	11.4	13.8	2.4	63.750	60.5	0.21053	0.1911	1	1	1	0
10	94	7.8	25.2	17.4	5.402	574.2	2.23077	1.1727	0	0	1	0
10	464	11.6	16.4	4.8	96.667	134.4	0.41379	0.3463	1	0	0	0
10	259	10.9	14.4	3.5	74.000	88.6	0.32110	0.2785	1	1	0	0
10	117	10.9	11.8	0.9	130.000	20.4	0.08257	0.0793	1	1	0	0
10	162	11.4	16.4	5.0	32.400	139.0	0.43860	0.3637	0	0	0	0
11	-134	75.0	25.0	-50.0	2.680	-5000.0	-0.66667	-1.0986	0	0	0	1
11	-97	75.0	50.0	-25.0	3.880	-3125.0	-0.33333	-0.4055	0	0	0	1
11	-72	50.0	25.0	-25.0	2.880	-1875.0	-0.50000	-0.6931	0	0	0	1

Table 6-3

Regression Estimates of Equation 6.2 for All CV Studies with Dummy Variables for Differences in Studies

Variable	Coefficient	t-statistic
DVR	19.74	5.62
DIFSQ	-.17	-3.11
RANK	258.15	3.28
DIST	-91.41	-1.14
PRETEST	-5.23	-.10
WEST	-6.39	-.09

$N = 36$
$R^2 = .77$
$F = 16.33$

these studies, the value increases with bigger changes in visual range, but at a decreasing rate. This is consistent with the Tolley et al. findings. The RANK coefficient indicates significantly higher values when contingent ranking was used. This conclusion should be considered preliminary since only one study in the group used contingent ranking. The DIST coefficient indicates values are somewhat, but not statistically significantly, lower when visibility conditions are depicted as a distribution rather than a single average. It should be noted that the change in visual range has tended to be smaller when a distribution was used which could have resulted in the negative coefficient. PRETEST and WEST were not significant.

To test the sensitivity of these results to the Tolley et al. estimates, the equation was estimated without the Tolley et al. estimates. With the smaller sample size and the change in the group of studies, the dummy variables were not expected to be stable and were therefore left out. The results are shown in Table 6-4. To allow a consistent comparison, the equation was estimated with all studies without the dummy variables. The coefficients were slightly larger, but very similar. Estimated without the Tolley results the coeffients are practically identical. This is strong support that the Tolley et al. results are generally consistent with those of the other CV studies that have been conducted.

A third estimate of the equation was made excluding the Rae et al. estimates and is also shown in Table 6-4. Questions have been raised about the Rae et al. results due to difficulties in the interpretation of the contingent ranking responses and due to the relatively high values obtained. Without the Rae et al. results the coefficients are very similar to those shown in Table 6-3 when the dummy variables were included.

Table 6-5 shows some predicted values for changes in visual range based on the estimates of equation 6.2. At a base visual range of 10 miles, the values for a 1 mile increase in average annual visual range are \$16-18. As the increases in visual range get larger, the values per mile decline to about \$13-15 for a change of 20 miles. At a higher base level of visual range (15 miles is given as an example) the per mile values are somewhat smaller for each change in visual range. Values for preventing a 1 mile decrease in average visual range

Table 6-4

Regression Estimates of Equation 6.2 for Different Groups of CV Studies

All Studies

Variable	Coefficient	t-statistic
DVR	22.31	6.75
DIFSQ	-.19	-4.20

N = 36
R^2 = .64
F = 29.9

All Studies Except Tolley et al.

Variable	Coefficient	t-statistic
DVR	22.37	3.20
DIFSQ	-.19	-2.42

N = 15
R^2 = .50
F = 6.46

All Studies Except Rae

Variable	Coefficient	t-statistic
DVR	20.34	6.67
DIFSQ	-.17	-4.23

N = 28
R^2 = .70
F = 29.67

Table 6-5

Predicted Values from Equation 6.2 for Changes in Visual Range*

	Base Level Visual Range (Miles)	Visual Range Change (Miles) -5	-1	1	5	10	20
1. All Studies (with dummies)	10	-111	-17	16	78	147	261
	15	-120	-15	14	69	130	224
2. All Studies	10	-126	-19	18	88	165	292
3. All Studies Except Tolley et al.	10	-126	-19	18	88	167	297
4. All Studies Except Rae et al.	10	-114	-17	17	80	152	269

* Assuming 0 value for RANK DIST PRETEST and WEST

are somewhat higher than for obtaining an increase. Values for preventing a 5 mile decrease indicate a higher per mile value for preventing additional decreases in visual range. This last result should be tempered by the finding in the Rowe et al. study that per mile values are lower for preventing larger decreases in visual range.

The results reported in Table 6-3 can be used to estimate values for changes in visual range that could be expected to result from alternative pollution control policies. These estimates would reflect the average estimates obtained to date in CV studies concerning values to residents of visibility in urban areas. If used for such estimates, however, the range of the data should be kept in mind. For example, the smallest change in average visual range considering in any of the studies was about 1 mile, while the average change was about 5 miles and most of the changes were 20 miles or less. The equation would therefore be less reliable for predicting values for changes in average visual range of less than 1 mile or greater than 20 miles. The base level of visual range is also important. The average in these studies was about 15 miles, with most of them falling between 7 and 19 miles. The equation would be less reliable for areas where the current average visual range is less than 7 or more than 19 miles.

Two other forms for the bid function were also estimated that give some sense of the sensitivity of the results to different forms. The first was a simple linear function:

$$BID = aDVR \qquad 6.3$$

Equation 6.3 is consistent with a value function of

$$Value = aVR + f(X)$$

and a utility function of

$$U = aVR + bY + cf(X,Y)$$

The results of this estimation with and without Tolley et al. are shown in Table 6-6. In both cases the coefficients are statistically significant. With all studies, the coefficient implies an average bid of $10 per mile. Without Tolley et al. the average bid is $6.5 per mile. These are lower than the per-mile values at visual range levels of 10 and 15 shown in Table 6-5.

The second form that was estimated implies that the bid is constant for a given percentage change in visual range. The percentage change in visual range may be a good way to characterize a person's perception because it takes into account the starting point and the size of the change. The estimated function was

$$BID = a \ln (VR_2/VR_1) + b_1 RANK + b_2 DIST + b_3 PRETEST + b^4 WEST \qquad 6.4$$

This bid function is consistent with a visibility value function of .

$$Value = a \ln VR + cf(X)$$

The estimated results for equation 6.4 are shown in Table 6-7. The coefficient for the VR term is statistically significant and the fit seems to be as good or better that with equation 6.2.

Predicted values for estimated equation 6.4 are shown in Table 6-8. These are very similar to the predicted values reported in Table 6-5, although the decrease in average per mile value is somewhat greater as the change in visual range increases.

6.2 PROPERTY VALUE STUDIES

Several property value studies have been conducted that estimate values for different levels of air quality based on differences in residential property values across areas with different levels of air quality. (These have been reviewed by Rowe and Chestnut, 1982; and Freeman, 1979.) In general, these studies have found a significant relationship between property values and air quality when other factors affecting property values are held constant. This

Table 6-6

Estimation Results for Simple Linear Bid Function

Variable	Coefficient	t-statistic
	All Studies	
CHANGE	10.02	5.36
$N = 36$ $R^2 = .45$ $F = 28.70$		
	All Studies Except Tolley et al.	
CHANGE	6.46	2.29
$N = 15$ $R^2 = .27$ $F = 5.22$		

36 19

Table 6-7

Estimation Results for Equation 6.4 with All Studies

Variable	Coefficient	t-statistic
LOGRAT	195.10	7.77
RANK	253.59	3.50
DIST	-94.96	-1.34
PRETEST	21.88	.42
WEST	-5.33	-.11

N = 36
R^2 = .78
F = 21.42

Table 6-8

Predicted Values from Equation 6.4

	Base Visual Range (Miles)	Change in Visual Range (Miles)					
		-5	-1	1	5	10	20
Value	10	-135	-20	19	79	135	214
(1984 $)	15	-79	-13	13	56	100	165

provides evidence that people not only say they prefer to live in areas with less air pollution, these preferences are reflected in actual market behavior.

One difficulty in comparing the results of property value studies to the CV studies for visibility is that typically air quality is measured by levels of ambient pollutants in the property value studies. Although ambient pollutants are related to visual range, the relationship is complex and confounded by correlations among the levels of different pollutants in the area. Although people can be expected to be judging air quality based on what they see, it is difficult to say that a change in visual range is worth $X when the estimates have been made in terms of ozone or particulates.

Another difficulty is that estimates from property value studies can be expected to reflect concerns about health effects as well as visual aesthetics and due to the correlation between the two it is difficult to identify separate values for these concerns. Two CV studies have asked about both and found that 34% (Brookshire et al.) and 50% (Loehman et al.) of the total values for changes in air quality were for visual aesthetics. For this comparison of CV results to property value results an average of 42% is used.

Two property value studies provide some direct comparisons to changes in visual range and a third provides some indirect information. Trijonis et al. used light extinction (a measure directly related to visual range) as the pollution measure in property value studies in Los Angeles and San Francisco. Some illustrative results are reported in Table 6-9. Using the 42% adjustment on the assumption that the estimated values will reflect concern about health effects as well as aesthetics, the findings imply household values per mile change in average annual visual range of $38 to $96, with the authors placing the greatest confidence in the $38 to $47 range. The average per mile values found by Tolley et al. ranged from $3 to $65, with the majority falling between $10 and $50.

Brookshire et al. found estimates of household values for a 30% change in air quality of about $550 (see Table 6-9). The author suggest that the scenarios used in the CV portion of their study also reflect a 30% change in air quality. Based on this and the 42% estimate for the aesthetics portion, their

Table 6-9

Values for Changes in Visibility from Property Value Studies

Study (Year $)	Change in Air Quality	Reported Annual Household Value Estimates	Estimate of Implied WTP per Mile (1984 $)[a]
Brookshire et al.[b] (1978 $)	30% Improvement in Air Quality	$528 to $588	$ 27 to $ 30
Loehman et al.[c] (1980 $)	30% Improvement in Air Quality	$ 82	
Trijonis et al. (1978-79 $)			
Los Angeles[d] (Mean VR = 9.5)	10% Improvement from Mean VR	$ 57 to $153	$ 38 to $ 96
San Francisco (Mean VR = 17)	10% Improvement from Mean VR	$115 to $128	$ 43 to $ 47

[a] Assumes that 42% of total value is for visibility aesthetics, based on findings of Brookshire et al. (34%) and Loehman et al. (50%).

[b] Calculation of WTP per mile assumes that a 30% change in air quality is related to a 13-mile change in visual range, since this is the average change in visual range presented in the CV survey, which the authors report is roughly comparable to a 30% change in air quality.

[c] The authors did not report any comparability between the change in visual range in the CV survey and the 30% change in air quality. A per mile value was therefore not calculated.

[d] Subsequent analysis suggests that more confidence should be placed in the low range of these results ($57 to 62 for the reported estimates).

property value results imply values per mile of about $27 to $30. These should be treated as very rough estimates, but they give an idea of the order of magnitude involved. Loehman et al. found an estimate of value for a 30% change in visual range an order of magnitude smaller for San Francisco. It is not possible to related this estimate directly to the CV scenarios used in that study.

This comparison of results of property value studies to CV studies suggests that the CV results are "reasonable" in that they are generally on the same order of magnitude.

1 Each of the positive values is an estimate of the maximum willingness to pay to obtain an improvement in visual range. Each of the negative values is an estimate of the maximum willingness to pay to prevent a deterioration in visual range. The former is a CS measure while the latter is an ES measure. One of two possible assumptions must be made to group these CS and ES estimates together. The ES function that can be derived from equation 6.1 suggests that the ES estimates could be grouped with the CS estimates by entering them as positive values and subtracting the smaller VR from the larger VR.

$$ES = [(b/a)(V1 - V2) + (c/a)(V1^2 - V2^2)]f(x)$$

Although this is consistent with the simple utility function given in 6.1, it implies that the direction of the change does not affect the value. For example, it implies that the value for a change in visual range from 10 miles to 5 would be the same as a value for a change from 5 miles to 10. Subjects may, however, respond differently to potential gains than to potential losses. This makes sense intuitively and has been supported by empirical evidence (Loehman et al., 1981; and Tversky and Kahneman, 1981).

The second potential assumption is to treat the ES responses as if they are CS responses. This means entering them as negative values and treating the changes in visual range as negative changes. What this implies is that the question asked was really, "How much would you have to be compensated in order to accept this decrease in visual range?" Studies that have asked this type of CS question have found that the values are larger than the ES values for a similar decrease in visibility, but the high percentage of protest responses has raised questions about the usefulness of the CS estimates. This remains an unresolved methodologicial question.

For this analysis we chose the second assumption and the ES responses were entered as negative values. This can be expected to result in a flatter function than would be obtained if CS estimates for decreases in visual range were available, but it allows for differences between values to prevent decreases and values to obtain improvements.

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APPENDIX

Table A.1

Atlanta

BID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	23603848.45	1475240.53	18.474	0.0001
ERROR	436	34817021.39	79855.55365		
C TOTAL	452	58420869.84			

ROOT MSE	282.5872	R-SQUARE	0.4040
DEP MEAN	184.2538	ADJ R-SQ	0.3822
C.V.	153.3685		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > ITI
INTERCEP	1	-34.77826888	26.08371926	-1.333	0.1831
DVR	1	36.42341697	8.93946699	4.074	0.0001
DVR2	1	-0.65075288	0.24376860	-2.670	0.0079
East	1	9.78118681	4.18935211	2.335	0.0200
West	1	6.66065934	4.18935211	1.590	0.1126
Income	1	0.20721583	0.10011183	2.070	0.0391
Hsldsiz	1	1.33121001	0.47677086	2.792	0.0055
Hohed	1	0.36510069	0.43375141	0.842	0.4004
Hohage	1	-0.41732738	0.09863290	-4.231	0.0001
Exview	1	-4.33375832	2.45098876	-1.768	0.0777
Badeyes	1	12.90804176	3.52020744	3.667	0.0003
Actcindx	1	0.02510654	0.19756242	0.127	0.8989
Prop	1	-2.39729706	6.48513482	-0.370	0.7118
Femhoh	1	4.59393892	2.67920782	1.715	0.0871
Own	1	-4.73339020	2.70487294	-1.750	0.0808
Rural	1	4.52385366	3.70669587	1.220	0.2230
Nonwhite	1	-4.91211948	2.55690085	-1.921	0.0554

Estimates of Equation 5.2.1

810

Table 5.3.2

Boston

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	14057321.16	878582.57	20.653	0.0001
ERROR	557	23695361.51	42541.04401		
C TOTAL	573	37752682.67			

ROOT MSE	206.2548	R-SQUARE	0.3724
DEP MEAN	117.2615	ADJ R-SQ	0.3543
C.V.	175.893		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > |T|
INTERCEP	1	-18.19365256	16.94879034	-1.073	0.2835
DVR	1	30.69402731	6.62039456	4.636	0.0001
DVR2	1	-0.62757696	0.15830700	-3.964	0.0001
East	1	4.95944352	2.71425480	1.827	0.0682
West	1	3.54300000	2.70825825	1.308	0.1913
Income	1	0.19820984	0.04636010	4.275	0.0001
Hsldsiz	1	1.05344484	0.46713784	2.255	0.0245
Hohed	1	-0.28464751	0.27792216	-1.024	0.3062
Hohage	1	-0.17777120	0.06116826	-2.906	0.0038
Exview	1	-2.90878034	1.50057000	-1.938	0.0531
Badeyes	1	1.15291731	2.07340872	0.556	0.5784
Actcindx	1	-0.001870091	0.11293902	-0.017	0.9868
Prop	1	3.05438509	1.91764545	1.593	0.1118
Femhoh	1	4.08284041	1.55263335	2.630	0.0088
Own	1	-7.83039064	1.88815008	-4.147	0.0001
Rural	1	-1.96569258	2.03341118	-0.967	0.3341
Nonwhite	1	0.56652765	4.62309692	0.123	0.9025

Estimates of Equation 5.2.1

BID

Table A.3

Cincinnati

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	2431455.85	151965.99	23.191	0.0001
ERROR	452	2961895.28	6552.86567		
C TOTAL	468	5393351.13			

ROOT MSE	80.94977	R-SQUARE	0.4508
DEP MEAN	43.48401	ADJ R-SQ	0.4314
C.V.	186.1599		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-5.32462400	7.33583971	-0.726	0.4683
DVR	1	0.79900683	2.78619674	0.287	0.7744
DVR2	1	-0.27779333	0.06866400	-4.046	0.0001
East	1	1.65957447	1.18077379	1.405	0.1606
West	1	0.61914894	1.18077379	0.524	0.6003
Income	1	0.22275098	0.02310216	9.642	0.0001
Hsldsiz	1	-0.55330831	0.19870082	-2.785	0.0056
Hohed	1	0.39312089	0.12773834	3.078	0.0022
Hohage	1	-0.009122077	0.02735066	-0.334	0.7389
Exview	1	-0.94923819	0.79551242	-1.193	0.2334
Badeyes	1	0.80442247	0.81861876	0.983	0.3263
Actcindx	1	-0.04897608	0.06576689	-0.745	0.4568
Prop	1	-2.01111471	1.51523394	-1.327	0.1851
Femhoh	1	-0.72881145	0.74447335	-0.979	0.3281
Own	1	0.59178755	1.01727515	0.582	0.5610
Rural	1	0.16333981	0.83279396	0.196	0.8446
Nonwhite	1	4.26152287	1.11557554	3.820	0.0002

Estimates of Equation 5.2.1

Table A.4

Mobile

BID -

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	11688902.20	730556.39	32.152	0.0001
ERROR	434	9861437.76	22722.20682		
C TOTAL	450	21550339.96			

ROOT MSE	150.7389	R-SQUARE	0.5424
DEP MEAN	133.3969	ADJ R-SQ	0.5255
C.V.	113.0003		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-10.96694351	14.00428346	-0.783	0.4340
DVR	1	33.51903562	3.80060643	8.819	0.0001
DVR2	1	-0.75039363	0.13099916	-5.728	0.0001
East	1	4.67188340	2.24738205	2.079	0.0382
West	1	2.38681319	2.23470168	1.068	0.2861
Income	1	0.04577254	0.04206529	1.088	0.2771
Hsldsiz	1	-1.14848424	0.42998131	-2.671	0.0078
Hohed	1	-0.13358811	0.08625439	-1.549	0.1222
Hohage	1	-0.12168698	0.04412216	-2.758	0.0061
Exview	1	-1.48846542	1.39993644	-1.063	0.2883
Badeyes	1	0.19234079	1.67765863	0.115	0.9088
Actcindx	1	0.39993254	0.12595252	3.175	0.0016
Prop	1	8.61416020	1.72303743	4.999	0.0001
Femhoh	1	-0.64986707	1.24665233	-0.521	0.6024
Own	1	-1.88324048	1.45004252	-1.299	0.1947
Rural	1	-4.68719825	2.57423529	-1.821	0.0693
Nonwhite	1	-2.69037117	1.54556331	-1.741	0.0824

Estimates of Equation 5.2.1

Table A.5

Miami

BID -

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	3262312.64	203894.54	13.508	0.0001
ERROR	218	3290461.24	15093.85891		
C TOTAL	234	6552773.88			

ROOT MSE	122.8571	R-SQUARE	0.4979
DEP MEAN	65.5394	ADJ R-SQ	0.4610
C.V.	187.4553		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-14.46229787	15.71386460	-0.920	0.3584
DVR	1	0.76360743	4.94347749	0.154	0.8774
DVR2	1	-0.43677957	0.14729288	-2.965	0.0034
East	1	2.70638298	2.53434778	1.068	0.2868
West	1	0.28085106	2.53434778	0.111	0.9119
Income	1	0.04762071	0.06545457	0.728	0.4677
Hsldsiz	1	0.50566804	0.44295104	1.142	0.2549
Hohed	1	0.66301606	0.23516999	2.819	0.0053
Hohage	1	0.12380060	0.05223968	2.370	0.0187
Exview	1	-6.52826722	1.70467715	-3.830	0.0002
Badeyes	1	-6.37441256	1.62425303	-3.925	0.0001
Actcindx	1	0.49219292	0.12416138	3.964	0.0001
Prop	1	4.77497072	2.43096812	1.964	0.0508
Femhoh	1	-3.52830484	1.96618778	-1.794	0.0741
Own	1	-3.48571298	1.69339610	-2.058	0.0407
Rural	1	-1.58248843	4.84636655	-0.327	0.7443
Nonwhite	1	-2.49403685	2.15996042	-1.155	0.2495

Estimates of Equation 5.2.1

Table A.6

Washington

BID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	16	39485960.73	2467872.55	21.609	0.0001
ERROR	417	47622742.21	114203.22		
C TOTAL	433	87108702.94			

ROOT MSE	337.9397	R-SQUARE	0.4533
DEP MEAN	218.9748	ADJ R-SQ	0.4323
C.V.	154.3281		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-25.19184034	31.83824959	-0.791	0.4293
DVR	1	47.29147443	11.47006692	4.123	0.0001
DVR2	1	-0.99471782	0.29797330	-3.338	0.0009
East	1	11.97793103	5.12382801	2.338	0.0199
West	1	6.37931034	5.12382801	1.245	0.2138
Income	1	0.73672927	0.11094113	6.641	0.0001
Hsldsiz	1	-2.12968373	0.88665586	-2.402	0.0167
Hohed	1	-1.77754028	0.50850310	-3.496	0.0005
Hohage	1	-0.09021901	0.11302970	-0.798	0.4252
Exview	1	-4.88647016	2.96355955	-1.649	0.0999
Badeyes	1	-1.84553101	3.07117808	-0.601	0.5482
Actcindx	1	1.22293635	0.26638177	4.591	0.0001
Prop	1	0.50375528	3.59181152	0.140	0.8885
Femhoh	1	10.91309305	2.92962159	3.725	0.0002
Own	1	-10.55305051	3.52457825	-2.994	0.0029
Rural	1	-34.69249738	13.60213546	-2.551	0.0111
Nonwhite	1	-10.27841666	3.14565267	-3.267	0.0012

Estimates of Equation 5.2.1

Table A.7

Atlanta

BID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	16923273.50	3384654.70	36.459	0.0001
ERROR	447	41497596.34	92835.78601		
C TOTAL	452	58420869.84			

ROOT MSE	304.6897	R-SQUARE	0.2897
DEP MEAN	184.2538	ADJ R-SQ	0.2817
C.V.	165.3641		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-35.97247220	41.45670036	-0.868	0.3860
DVR	1	35.61222664	3.87958976	9.179	0.0001
DVR2	1	-1.23777166	0.19712656	-6.279	0.0001
INCOME	1	6.52122119	2.73235165	2.387	0.0174
INCOME2	1	-0.10306562	0.03539320	-2.913	0.0038
DVRINC	1	0.10446114	0.10474743	0.997	0.3192

A-7

Estimates of Equation 5.2.2

Table A.8

Boston

SID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	10886663.97	2177332.79	46.033	0.0001
ERROR	568	26866018.70	47299.32869		
C TOTAL	573	37752682.67			

ROOT MSE	217.4841	R-SQUARE	0.2884
DEP MEAN	117.2515	ADJ R-SQ	0.2821
C.V.	185.4693		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	-28.45720178	29.84273577	-0.954	0.3407
DVR	1	21.37307403	2.62604316	8.139	0.0001
DVR2	1	-0.93131688	0.12507433	-7.446	0.0001
INCOME	1	2.82358019	1.40777407	2.006	0.0454
INCOME2	1	-0.03251362	0.01267169	-2.566	0.0105
DVRINC	1	0.20725460	0.06396647	3.240	0.0013

Estimates of Equation 5.2.2

Table A.9

Cincinnati

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	2235198.27	447039.65	65.538	0.0001
ERROR	463	3158152.86	6821.06450		
C TOTAL	468	5393351.13			

ROOT MSE	82.58974	R-SQUARE	0.4144
DEP MEAN	43.48401	ADJ R-SQ	0.4081
C.V.	189.9313		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	27.41654845	11.70808819	2.342	0.0196
DVR	1	6.01466543	1.08488859	5.544	0.0001
DVR2	1	-0.36473017	0.05251400	-6.945	0.0001
INCOME	1	-1.94805081	0.55332661	-3.521	0.0005
INCOME2	1	0.02584634	0.00490899	5.265	0.0001
DVRINC	1	0.18038975	0.02752095	6.555	0.0001

Estimates of Equation 5.2.2

Table A.10

Mobile

SID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	9512762.78	1902552.56	70.333	0.0001
ERROR	445	12037577.16	27050.73523		
C TOTAL	450	21550339.96			

ROOT MSE	164.4711	R-SQUARE	0.4414
DEP MEAN	133.3969	ADJ R-SQ	0.4351
C.V.	123.2945		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	21.64359989	20.82710716	1.039	0.2993
DVR	1	26.95637100	2.08225598	12.946	0.0001
DVR2	1	-1.01260959	0.10655590	-9.503	0.0001
INCOME	1	-0.29115004	1.08568565	-0.268	0.7887
INCOME2	1	-0.000292332	0.009677557	-0.030	0.9759
DVRINC	1	0.11659911	0.05557947	2.098	0.0365

Estimates of Equation 5.2.2

Table A.11

Miami

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	2065719.77	413143.95	21.100	0.0001
ERROR	229	4486054.11	19589.75593		
C TOTAL	234	6552773.88			

ROOT MSE	139.9634	R-SQUARE	0.3154
DEP MEAN	65.5394	ADJ R-SQ	0.3004
C.V.	213.5561		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0	PROB > |T|
INTERCEP	1	0.48894086	36.38165639	0.013	0.9893
DVR	1	10.29779739	2.73342502	3.767	0.0002
DVR2	1	-0.56330440	0.12572848	-4.480	0.0001
INCOME	1	0.05941793	2.72634746	0.022	0.9826
INCOME2	1	-0.005321032	0.04469626	-0.119	0.9053
DVRINC	1	0.28469294	0.08194976	3.474	0.0006

Estimates of Equation 5.2.2

Table A.12

Washington

BID

ANALYSIS OF VARIANCE

SOURCE	DF	SUM OF SQUARES	MEAN SQUARE	F VALUE	PROB>F
MODEL	5	27440366.68	5488073.34	39.356	0.0001
ERROR	428	59668336.26	139412.00		
C TOTAL	433	87108702.94			

ROOT MSE	373.3792	R-SQUARE	0.3150
DEP MEAN	218.9748	ADJ R-SQ	0.3070
C.V.	170.5124		

PARAMETER ESTIMATES

VARIABLE	DF	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0	PROB > |T|
INTERCEP	1	30.31979524	65.49772852	0.463	0.6437
DVR	1	34.34950857	5.45227123	6.300	0.0001
DVR2	1	-1.66793500	0.24679965	-6.758	0.0001
INCOME	1	-1.14276896	3.80093007	-0.301	0.7638
INCOME2	1	0.04205556	0.05247726	0.801	0.4233
DVRINC	1	0.44313216	0.13300645	3.332	0.0009

Estimates of Equation 5.2.2