Contrasting Conventional with Multi-Level Modeling Approaches to Meta-Analysis: Expectation Consistency in U.K. Woodland Recreation Values

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ABSTRACT. *The paper presents a variety of meta analysis models of woodland recreation benefit estimates, contrasting conventionally estimated models with those provided by novel, multi-level modeling (MLM) techniques (Goldstein 1995). Our conventional models suggest that studies carried out by certain authors are associated with unusually large residuals within our meta-analysis. However, the MLMapproach explicitly incorporates the hierarchical nature of meta-analysis data, with estimates nested within study sites and authors. These residuals are not a significant determinant upon values, suggesting that, at least in this aspect, estimates may be more robust than indicated by less sophisticated models.* (JEL Q26)

I. INTRODUCTION

The past two decades have witnessed an increasing reliance upon benefit-cost analysis (BCA) as a tool for project appraisal and to inform decision-making. In the United Kingdom, a typical example of this trend is provided by the 1995 Environment Act which brought into being the Environment Agency (EA) and imposed ''general duties'' upon the Agency to take account of the costs and benefits arising from its policies (H.M. Government 1995). For many agencies, particularly those which have explicitly environmental or public good responsibilities, the assessment of benefits necessitated by adopting BCA approaches has led to a growing interest in tools for the monetary valuation of preferences for environmental goods and services. Consequently, expressed preference methods such as contingent valuation (CV) and conjoint analysis (CA), together with revealed preference techniques such as hedonic pricing (HP) and individual and zonal travel cost (TC) have enjoyed an unprecedented increase in application. However, use of such methods raise theoretical, empirical, and practical issues. At a theoretical leve, certain of these various techniques yield different measures of value. Furthermore, the validity of certain modes of application and analysis have been subject to criticism and are associated with recognized biases, exhibited as empirical regularities within the published literature. These issues place an onus upon the analyst to explain to decision makers the consequences of adopting certain study designs. However, from a decision perspective, a further and pressing practical issue concerns the fact that individual applications incur both direct and time related costs. Consequently, the proliferation of valuation studies has coincided with increased interest in the potential for benefit transfer.

Rosenberger and Loomis (2000) define benefit transfer as ''the application of values and other information from a 'study' site with data to a 'policy' site with little or no data'' (1097). A number of approaches to undertaking transfers are available[1] including

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[1] For reviews of the issues raised by benefit transfer applications see Brookshire and Neill (1992), OECD (1994), Pearce and Moran (1994), Bergland, Magnussen, and Navrud (1995), van den Bergh et al. (1997) and Desvousges, Johnson, and Banzaf (1998).

TABLE 1
META-ANALYSIS STUDIES IN ENVIRONMENTAL AND RESOURCE ECONOMICS

Subject Area	Study Authors
Recreation benefits	Bateman, Lovett, and Brainard (1999), Bateman et al. (2000), Markowski, et al. (2001), Rosenberger and Loomis (2000), Shrestha and Loomis (2001), Smith and Kaoru (1990a), Sturtevant, Johnson, and Desvousges (1995), Van Houtven et al. (2001), Walsh, Johnson, and McKean (1990, 1992)
Price elasticity in TC studies	Smith and Kaoru (1990b)
CV versus revealed preference	Carson et al. (1996)
Multiplier effects of tourism	Baaijens, Nijkamp, and Monfort (1998), Van den Bergh et al. (1997, ch. 9)
Wetland functions	Brouwer et al. (1999), Woodward and Wui (2001)
Groundwater quality	Boyle, Poe, and Bergstrom (1994), Poe, Boyle, and Bergstrom (2001)
Price elasticity for water	Espey, Espey, and Shaw (1997)
Urban pollution valuation	Smith (1989), Smith and Huang (1993, 1995), Schwartz (1994), Van den Bergh et al. (1997, ch. 10)
Noise nuisance	Button (1995), Nelson (1980), Van den Bergh et al. (1997, ch. 4)
Congestion and transport	Button and Kerr (1996), Van den Bergh et al. (1997, ch. 13 and 14), Waters (1993)
Visibility and air quality	Desvousges, Johnson, and Banzaf (1998), Smith and Osborne (1996)
Endangered species	Loomis and White (1996)
Valuation of life estimates	Mrozek and Taylor (2002), Van den Bergh et al. (1997, ch. 11)

simple transfer of unadjusted point estimates, transfer of benefit demand functions and meta-analysis. As the simplest approaches cannot incorporate the characteristics of a given site within the transfer exercise, considerable attention is being given to the development of methods for transferring benefit demand functions (Loomis 1992; Bergland, Magnussen, and Navrud 1995; Loomis et al. 1995; Downing and Ozuna 1996; Kirchhoff et al. 1997; Brouwer and Spaninks 1999; Brouwer and Bateman 2000). However, results are mixed with some studies reporting considerable success while others indicate abject failure. Given this and the empirical difficulties of such studies, a substantial literature has developed regarding the applications of meta-analysis techniques as a basis for benefit transfer.

Meta-analysis is the statistical analysis of the summary findings of prior empirical studies for the purpose of their integration (Glass 1976; Wolf 1986). Developed over the last thirty years, it has most commonly been applied in the fields of experimental medical treatment, psychotherapy, and education. Typically, these experiments took place in well-controlled circumstances with standard designs. Deviation from such specifications increases the problems with any cross-analysis (Glass, McGaw, and Smith 1981).[2]

Despite problems, meta-analysis offers a transparent structure with which to understand underlying patterns of assumptions, relations and causalities, so permitting the derivation of useful generalizations (Hunter, Schmidt, and Jackson 1982). It permits the extraction of general trend information from large datasets gleaned from numerous studies which would otherwise be difficult to summarize. In comparison with other benefit transfer techniques, Rosenberger and Loomis (2000) identify three advantages of adopting a meta-analysis approach: 1) it typically collates information from a greater number of studies; 2) it is relatively straightforward to control for methodological differences between valuation source studies; 3) benefit transfer is readily affected by setting explanatory variable values to those at the desired target site be it a previously surveyed, unsurveyed or just proposed (i.e., currently nonexistent) site.

Table 1 extends reviews by Van den Bergh et al. (1997) and Smith and Pattanayak (2002) to provide a brief summary of meta-

[2] Meta-analyses also face the problem that studies published in the available literature may over represent that subset of all studies which produce ''positive'' or significant results if studies yielding ''negative'' or non-significant findings tend not to be published.

analysis studies in this area. As can be seen, while analyses have addressed a number of issues, the bulk of applications have been within the field of recreation benefits valuation.

The empirical applicability of meta-analysis to any given context is determined by the number, quality and comparability of studies available to the researcher (Desvousges, Johnson, and Banzaf 1998). Here there is a difficult trade-off between the desire to expand analyses so as to enhance the applicability of results to different goods, provision changes, locations, contexts, etc., and the consequent increase in data demands which such expansions entail. For example, Rosenberger and Loomis (2000) consider a wide range of outdoor recreation activities (10 separate categories ranging from fishing to rock climbing to snowmobiling) across a very extensive area, the United States and Canada. This analysis requires a large valuation dataset and their study utilizes 682 value estimates from 131 separate studies. By contrast, the meta-analysis presented in this paper considers just one type of activity, recreation in open-access woodlands, and just one geographical area, Great Britain, a land area just over 1% the size of that considered by Rosenberger and Loomis. Our analysis is initially restricted just to measures obtained by application of the CV method yielding a dataset of 44 value estimates from 11 studies. A second analysis supplements these data with results obtained from 6 TC studies, bringing the total number of value estimates to 77.[3] While this is less than the size of the Rosenberger and Loomis dataset (reflecting the fewer number of studies conducted in Great Britain), the much smaller geographical boundaries of our study, and its focus upon just one activity, mean that data are placed under considerably less stress, enhancing the reliability of resultant benefit transfer estimates. The disadvantage of this focus is that our results are not readily applicable to other activities or to areas outside Great Britain.

The study described here embraces two objectives. The minor of these concerns the extent to which meta-analysis confirms expectations, derived from theory and empirical regularities, regarding the relationship of values derived from the various permutations of study design represented in our assembled dataset. In so doing we seek to highlight to decision makers (and researchers) the influence upon value estimates of adopting different methods or analytical techniques and so directly address concerns regarding the variability of valuation estimates for apparently similar goods. As a direct extension of this investigation we address the issue of whether, after allowing for design choice, different authors are associated with significantly different valuation estimates. Evidence for such effects would constitute a substantial criticism of valuation studies raising the charge that authors tailor findings to the desires of those commissioning research. However, the principal objective of this study is analytical as we detail alternate approaches to the construction of meta-analysis models.

The first and second meta-analyses presented here are conducted by applying conventional regression techniques to, initially, the subset of CV estimates and subsequently to the full set of CV and TC estimates. These analyses provide a basis for illustrating the limitations of such conventional regression techniques in comparison with a third analysis obtained through application of multilevel modeling (MLM) methods (Goldstein 1995) to the full dataset of CV and TC observations. As discussed in detail subsequently, the MLM approach allows the researcher to explicitly incorporate potential nested structures within the data, permitting examination of a number of key issues and criticisms of both meta-analysis and valuation studies. Crucially, the MLM approach allows the researcher to relax strong and commonly adopted assumptions regarding the independence of estimates with respect to the numerous natural hierarchies within which they reside. For example, we might expect estimates derived for a given forest to be more similar than those obtained from different forests. Furthermore, whilst not in accord with any theoretical expectation, it might be observed

[3] Details of all of these estimates are given in Table A1 in Bateman et al. (2000).

that estimates produced within the same study (or, as highlighted above, by the same author) were more similar than other estimates.[4] While many previous meta-analyses have failed to acknowledge this issue by implicitly assuming independence between estimates (e.g., see some of the studies reported in Van den Bergh et al. 1997), others have adopted weighting approaches, typically by dividing the data associated with each estimate by the number of estimates within the study concerned (e.g., Markowski et al. 2001; Mrozek and Taylor 2002).[5] However, both approaches are flawed; independence ignores the real possibility of similarity between nested estimates, while weighting schemes such as those described here result in all studies receiving equal weight, irrespective of the fact that we have more information about those containing higher numbers of valuation estimates. Furthermore, such studies typically only address the nesting of estimates within studies and ignore other equally plausible hierarchies such as the nesting of estimates within sites or within authors.

By explicit incorporation of data hierarchies within the analysis, the MLM approach both provides insight into areas in which the independence assumption fails to hold and, through improved modeling of such nesting, ensures that standard errors on parameter estimates are correctly estimated and the significance of explanatory variables accurately assessed. Such a meta-analysis can then defensibly be used to investigate the extent to which valuation estimates conform to expectations. This then links together our analytical objectives with the validity aims of the paper. We can used our refined MLM model to examine both expected differences, such as those associated with different methods and analytical techniques, and unexpected differences, such as the clustering of estimates within authors as described above.

The remainder of the paper is organized as follows. In Section 2 we provide some background to the case study and detail the theoretical and empirical expectations embraced by this application. Section 3 sets out and reports conventional meta-analyses of our data. Section 4 repeats this process for our MLM based model discussing in detail the nature of his approach and how it differs from the conventional approach. Section 5 concludes by highlighting advantages and limitations of the MLM approach, examining the implications of our findings for the validity of valuation exercises and distilling messages for policymakers within this area.

II. THE RECREATIONAL VALUE OF FORESTS

Background and Data

In terms of land use, British forestry has always been the poor cousin of agriculture. A history of deforestation meant that, by 1900, only 4% of England and Wales and 2% of Scotland and Ireland was forested, by far the lowest level in Europe (Rackham 1976). The establishment of the FC in 1919 has done much to reverse this trend and over 10%[6] of the land area of Great Britain is under woodland today. This constitutes the largest single source of open-access land, generates approximately 24–32 million recreational visits per annum (NAO 1986; Benson and Willis 1990, 1992), and produces a national aggregate consumer surplus value estimated at between £40 million (Bateman 1996) and well over £50 million (Benson and Willis 1992) at current prices. From an eco-

[4] As discussed subsequently, value estimates may also be "cross classified," for example, where different authors conduct studies at the same, as well as differing, forest sites.

[5] Markowski et al. (2001) clearly describe the weighting procedure used as follows: "For these models we weight the data to reflect the "oversampling" of estimates associated with studies with a large number of observations relative to others with just a few or one observation. To do this, we first determine how many estimates (k_j) in the sample are associated with each study (j) to define a study weight. We then divide the data associated with each observation (dependent variable and explanatory variables) by the weights (k_j) for each study. Thus, rather than all observations having equal weights in the estimation, which is the case for the basic model, each study has an equal weight in this estimation for models of per-day and per-trip welfare estimates." (12)

[6] This decomposes into 14.7% of Scotland, 12.0% of Wales, and 7.4% of England. However, this is still well below an EU average of about 25% of land area under forestry (FICGB 1992).

TABLE 2
STUDIES OF OPEN-ACCESS WOODLAND RECREATION VALUE IN GREAT BRITAIN

Value Type	Recreation Value Unit	Valuation Method	No. of Studies	Date Conducted[1]	No. of Value Estimates	Value Range (in £, 1990) (m = million)
Use	Per person per visit	CV	8[a]	1987–1993	28	£ 0.28–£ 1.55
Use + option	Per person per visit	CV	3[b]	1988–1992	16	£ 0.51–£ 1.46
Use	Per person per visit	ZTC	3[c]	1976–1988	17	£ 1.30–£ 3.91
Use	Per person per visit	ITC	3[d]	1988–1993	16	£ 0.07–£ 2.74
Use	Per person per year	CV	3[e]	1989–1992	7	£ 5.14–£ 29.59
Use	Per household capital[2]	CV	3[f]	1990	3	£ 3.27[3]–£ 12.89
Use	FC forests/conservancy[4]	TC	1[g]	1970	13	£ 0.1m–£ 1.1m
Use	Total UK value	TC	6[h]	1970–1998	6	£ 6.5m–£ 62.5m
—	All studies	—	30	1970–1998	106	—

Notes:
1 = Dates refer to the year of study survey rather than publication date.
2 = These studies use a once-and-for-all willingness to pay per household question.
3 = We have recalculated this figure by including those who refused to pay as zero bids.
4 = The FC at the time divided the area of Great Britain into a number of Forest Conservancies and large forests to which these estimates relate.
Study references:
a = Whiteman and Sinclair (1994); Hanley and Ruffell (1991); Bishop (1992); Willis and Benson (1989); Hanley (1989); Willis, Benson, and Whitby (1988); Bateman and Langford (1997); Bateman, Lovett, and Brainard (forthcoming).
b = Bishop (1992); Willis and Benson (1989); Willis, Benson, and Whitby (1988).
c = Benson and Willis (1992); Hanley (1989); Everett (1979).
d = Willis and Garrod (1991); Bateman (1996); Bateman et al. (1996).
e = Whiteman and Sinclair (1994); Bishop (1992); Bateman (1996).
f = Hanley and Munro (1991); Hanley and Ecotec (1991); Hanley and Craig (1991).
g = H.M. Treasury (1972).
h = H.M. Treasury (1972); Grayson, Sidaway, and Thompson (1975); NAO (1986); Willis and Garrod (1991); Benson and Willis (1992); Bateman (1996).

nomic perspective, the recreational value of forestry is therefore one of its most important benefit streams.

The initial stage of any meta-analysis involves a survey of the relevant literature to identify potential base data studies. Table 2 presents summary details from some 30 studies of U.K. woodland recreation value yielding over 100 benefit estimates. As can be seen these studies embrace a diversity of recreation value units including per annum, capitalized and per forest values. This variety is not readily incorporated within a meta-analysis and so our study concentrates upon the largest single group of estimates; the per person per visit values.

As outlined above, an initial analysis focused solely upon those estimates obtained from applications of the CV method. Here survey respondents were asked to state their willingness to pay (WTP) for the recreational value of the forests concerned.[7] Table 2 indicates that there are 8 studies yielding 28 estimates of the direct ''use value'' of the recreational services provided by forests. Three studies also asked respondents about their WTP for both the present and possible future use (or ''option value''; Weisbrod 1964; Pearce and Turner 1990) of forests providing a further 16 estimates of this wider recreational value. In total therefore, these studies yield 44 value estimates.[8]

A second analysis was conducted by expanding the dataset to include a further 23 per person per visit value estimates obtained from TC studies. These estimates can be further subdivided. There are 16 individual TC estimates of which 9 use ordinary least squares (OLS) estimators. A further 7

[7] Note that CV studies can be adapted to ask either WTP or willingness to accept compensation questions in respect of either gains or losses of the resource concerned (Mitchell and Carson 1989), although only the WTP format was used in the studies concerned.

[8] Further details of these studies are provided in Bateman et al. (2000).

use maximum likelihood (ML) estimators.[9] There are also 17 zonal TC (*ZTC*) estimates all of which use OLS estimators.

Taken together, these CV and TC studies yield 77 value estimates across 21 forests (methods were well represented across these forests).[10] The following list of variables which might potentially influence value estimates were identified.

Method: A set of four binary variables indicating the method/estimation technique adopted to produce the value estimate.
- *CV* = 1 for contingent valuation method used, 0 otherwise.
- *ITCols* = 1 for individual travel cost method with ordinary least squares estimators used, 0 otherwise.
- *ITCml* = 1 for individual travel cost method with maximum likelihood estimators used, 0 otherwise.
- *ZTC* = 1 for zonal travel cost method with ordinary least squares estimators used, 0 otherwise.

Option (CV studies only): 1 = use value plus option value requested in WTP question, 0 = use value alone.

Elicit (CV studies only): A set of five binary variables identifying the WTP elicitation method employed (variable names as follows: *OE* = open ended, *IB* = iterative bidding, *PC* = payment card, *PCH* = high range payment card, *DC* = dichotomous choice).

Forest: A set of 21 binary variables identifying each of the forests included in at least one of the studies (variable/forest names as follows: *Mercia, Thames Chase, Gt. Northern Forest, Aberfoyle, Derwent Walk, Whippendell Wood, New Forest, Cheshire, Loch Awe, Brecon, Buchan, Newton Stewart, Lorne, Ruthin, Castle Douglas, South Lakes, North York Moors, Durham, Thetford, Dean, Dalby*).

Author: A set of six binary variable identifying authors common to a set of studies (studies can be identified via notes to Table 2; variable names as follows: *Bateman, Bishop, Everett, Hanley, Whiteman, Willis*).

Year: Continuous variable; the number of years before (negative) or after (positive) the base year (1990).

Table 3 reports summary descriptive statistics for the value estimates disaggregated by the various *Method* and *Author* variables. All values were adjusted to a common base year (1990) set roughly in the middle of the density of collated estimates. The table highlights two important features of the dataset that are the subject of subsequent investigation. First, the data is dominated by estimates derived from studies conducted by Willis, Benson, and Whitby (1988), reflecting their leading role in this field. Second, while the number of estimates is too small to permit calculation of confidence intervals, values do appear to vary by *Method* (e.g., the *ZTC* estimates appear to be substantially higher than those from other approaches) and possibly by *Author* (although it is clearly important to control for the effect of *Method* here). These initial observations provide focal points for the analyses described subsequently.

Theoretical and Empirically Derived Expectations

Taken together, theory and empirical regularities reported in the valuation literature provide a rich set of expectations regarding how our valuation estimates may vary according to the differing combinations of valuation methods and analytical techniques from which they were obtained. This means that we can use our various meta-analyses to examine the extent to which value estimates conform to these expectations. If we were to assume that all our meta-analyses were equally robust, we could use them to provide a commentary upon the validity of our valuation estimates. However, as highlighted pre-

[9] For a discussion of ML estimators see Maddala (1983).

[10] The distribution of estimates by forests and methods is as follows: 44 CV estimates across 20 forests; 9 ITCols estimates across 7 forests; 7 ITCml estimates across 7 forests; 17 ZTC estimates across 16 forests.

TABLE 3

Per Person Per Visit Woodland Recreation Value Estimates (in £, 1990) Disaggregated by Study Author and Valuation/Estimation Method

Method	Whiteman and Sinclair	Hanley et al.	Bishop	Willis et al.	Bateman et al.	Everett	All
CV	3	6	4	28	3	0	44
	0.78	1.30	0.89	0.71	1.08	—	0.84
	(0.66–0.93)	(0.85–1.55)	(0.46–1.46)	(0.28–1.29)	(0.47–1.55)	—	(0.28–1.55)
	[0.14]	[0.27]	[0.46]	[0.27]	[0.55]	—	[0.36]
ITCols	0	0	0	6	3	0	9
	—	—	—	1.46	1.35	—	1.42
	—	—	—	(0.47–2.74)	(1.07–1.58)	—	(0.47–2.74)
	—	—	—	[0.84]	[0.26]	—	[0.68]
ITCml	0	0	0	6	1	0	7
	—	—	—	0.57	1.20	—	0.66
	—	—	—	(0.07–1.13)	(1.20–1.20)	—	(0.07–1.20)
	—	—	—	[0.47]	[—]	—	[0.49]
ZTC	0	1	0	15	0	1	17
	—	2.14	—	2.53	—	1.30	2.43
	—	(2.14–2.14)	—	(1.58–3.91)	—	(1.30–1.30)	(1.30–3.91)
	—	[—]	—	[0.66]	—	[—]	[0.71]
All	3	7	4	55	7	1	77
	0.78	1.41	0.89	1.27	1.21	1.30	1.24
	(0.66–0.93)	(0.85–2.14)	(0.46–1.46)	(0.07–3.91)	(0.47–1.58)	(1.30–1.30)	(0.07–3.91)
	[0.14]	[0.40]	[0.46]	[0.95]	[0.38]	[—]	[0.83]

Cell contents are as follows:
Number of estimates
Mean value (£/person/visit)
(Range: minimum to maximum value)
[StDev of values]

viously, we have good reason to suspect that our MLM meta-analyses provide a superior alternative to conventionally estimated models. Therefore, we can reverse the direction of our test by examining the differing extents to which our various meta-analyses provide results which conform to expectations. Here improved conformity with expectations may be taken as indicating superior performance of a given meta-analysis technique.

What then are the relationships that we might expect to observe within our valuation estimates? Considering the subset of CV studies first, an initial expectation is that questions seeking to elicit the sum of option plus use value should yield higher values than those addressing use values alone (Pearce and Turner 1990).

Staying within the CV studies, theory also provides clear guidance regarding the impact of changing WTP elicitation method across the various permutations identified in our list of variables. Carson, Groves, and Machina (1999) extend earlier work by Hoehn and Randall (1987) to provide a comprehensive critique of the incentive compatibility of differing WTP elicitation approaches. They note that a simple open ended (OE) WTP question, such as "what are you willing to pay?" is liable to free-riding behavior, typically leading to understatement of WTP. Conversely, following the work of Farquharson (1969), Gibbard (1973) and Satterthwaite (1975), Carson, Groves, and Machina show that "no response format with greater than a binary responses can be incentive compatible without restrictions on preferences" (11).[11] This provides a powerful argument in favor

[11] While the DC method is incentive compatible, whether or not it is in practice also demand revealing (i.e. produces unbiased estimates of true WTP) is an ongoing source of debate (Green et al. 1998; Carson, Groves, and Machina 1999).

of CV studies adopting the single bound dichotomous choice (DC) format wherein respondents may only choose to accept or reject an interviewer specified discrete WTP sum. For our purposes, the DC approach also provides a useful benchmark for testing the theoretical compatibility of our various meta-analyses. For example, we can expect that estimates of WTP derived from OE elicitation techniques should be below those provided by the DC format. Similarly, the iterative bidding (IB) approach, in which respondents can bid up or down from a given starting point, opens the possibility of free riding again resulting in values which are lower than those derived from DC designs. However, these theoretical expectations can be modified in the light of empirical regularities, repeatedly observed in the literature. So, for example, IB studies have been shown to exhibit significant starting point biases (Roberts, Thompson, and Pawlek 1985; Boyle, Bishop, and Welsh 1985) and in comparative tests have provided value estimates which lie below those given by DC methods but above those derived from OE formats (Bateman et al. 1995). The situation with payment card (PC) approaches, in which respondents choose values from a range presented to them, is equally complex. While recent years have seen a renaissance in the use of PC approaches (Rowe, Schultze, and Breffle 1996), they fail an incentive compatibility test and in the face of free-riding are again likely to yield under-estimates of true WTP. Furthermore, changes in the PC range given to respondents may induce psychological effects resulting in further biases. It is an examination of one such possible bias which yields our high range payment card (PCH) study (Bateman 1996; Bateman, Lovett, and Brainard forthcoming) which compares various payment cards including those deliberately designed to stretch well beyond the distribution of woodland WTP measures as obtained by a more typical PC range. This test found that measures derived from the PCH were significantly higher than those obtained from other, conventionally designed, PC approaches.

In summary, we have a variety of theoretically and empirically derived expectations regarding elicitation effects in CV studies. If we rely solely upon theoretical expectations then, in the presence of strategic free-riding within non-incentive compatible formats, we might expect DC derived measures to exceed those obtained from other formats. However, if we temper these theoretical expectations with observed empirical regularities then, while we would still expect OE estimates to be below those from DC studies we would expect IB values to lie between these values. PC measures also suffer incentive incompatibility although we expect those obtained from the PCH format to exceed those from other PC analyses.

Widening our analysis to include the TC estimates again both theory and practice provide some guidance regarding expectations. Comparing these with CV estimates, while the latter yield direct Hicksian welfare measures of WTP, TC methods provide Marshallian consumer surplus estimates. The relationship of these measures depends upon the relative shape of the underlying compensated and uncompensated demand curves for the goods and provision changes concerned (Just, Hueth, and Schmitz 1982; Boadway and Bruce 1984). Carson et al. (1996) review 83 studies from which 616 comparisons of CV to revealed preference (RP; including TC) estimates are drawn, yielding a whole sample mean CV:RP ratio of 0.89 (95% CI = 0.81 to 0.96), that is, CV estimates were found to be significantly lower than TC values.

As noted in the preceding section, we can identify a number of distinct types of TC analysis. Certain of the TC based estimates of woodland recreation value rely upon theoretically inappropriate OLS estimation techniques (labeled above as *ITCols* measures). Such techniques are liable to lead to over-estimates of benefits due to an inability to reflect the truncation of non-visitors within an on-site TC survey sample. In contrast, other estimates (labeled as *ITCml* measures) have been derived using appropriate maximum likelihood estimators which explicitly model the truncation of non-visitors and are not upwardly biased in this respect. There are also a number of zonal TC (*ZTC*) estimates. These are also likely to yield over-estimates of values both because, in this instance, all used OLS estimators and because of a systematic upward bias in most zonal estimates of travel time and distance (and hence consumer surplus) recently identified by Bateman et al. (1999).

Taken together, these theoretical and empirical factors lead to clear expectations regarding the relationships that should hold in our meta-analyses. In summary, these are that, within CV estimates those derived from OE methods should yield the lowest values and that IB estimates should lie above these but below those from DC formats. The relation with PC estimates is less clear other then PCH estimates should exceed those from other PC designs. A general expectation is that TC studies should produce higher values than CV analyses and that within TC estimates those from ZTC and *ITCols* designs should be higher than *ITCml* measures.

Considering the remaining variables identified from our set of estimates, the *Forest* variables are included to identify any influences that variations in the nature of individual sites (e.g. facilities) may have upon stated WTP. We have no theoretical expectations regarding these variables, however empirical work by Brainard, Lovett, and Bateman (1999) and Brainard, Bateman, and Lovett (2001), examining the drivers of demand for forest recreation found that site facilities had very little discernable impact upon observed demand for woodland recreation which was instead driven primarily by locational factors (a result which supports the use of TC methods). This would suggest that the *Forest* variables are likely to prove relatively weak predictors of variation between value estimate. The *Year* variable seems most likely to reflect perceived changes in the availability or desirability of open-access woodland recreation over time and therefore as no prior expectation (although its observed sign is clearly of policy interest). Finally, while we have no theoretical expectation that the *Author* variables should impact significantly upon values, if this did prove to be the case it would constitute a problem for valuation research, giving support to the criticism that some authors yield unusually high or low value estimates.

Together these expectations provide a basis for validating and comparing our various meta-analyses. As outlined above these open, in Section 3, with conventionally modeled analyses initially for just our CV estimates after which we expand to include the TC estimates. Section IV then re-estimates the latter model using MLM techniques.

III. CONVENTIONALLY ESTIMATED META-ANALYSIS

Conventional Meta-Analysis of the CV Per Person Per Day Values

Our initial meta-analysis applied conventional regression methods to our set of CV derived value estimates. This restriction removed the *Method* variables defined previously. However, all other variables were considered within this analysis. Within the *Elicit* variables the *DC* dummy was omitted as an incentive compatible base case against which all other elicitation effects could be observed. Collinearity between the *Author* and *Forest* variables was too high to permit their simultaneous inclusion within a single model (e.g., all studies by Hanley and Craig 1991; Hanley and Ecotec Ltd. 1991; Hanley and Munroe 1991; and Hanley and Reffell 1991 were conducted in Aberfoyle forest although others also undertook studies in this forest). When tested separately the *Forest* variables proved, as per expectations outlined above, to be almost always insignificant predictors of WTP. Given this, the first model reported in this paper concentrates instead upon the *Author* variables. Here we hold the Bateman et al. studies as the base case (as these fall roughly in the middle of values reported by other researchers) and include all other *Author* dummies. Inspection of the *Year* variable indicated little variation across CV estimates relative to our wider dataset and this variable was reserved for subsequent analysis. Tests indicated that a linear model performed better than other functional forms yielding the model given in Table 4.[12]

[12] Bateman, Lovett, and Brainard (1999) use a reduced form of the model reported in Table 4 in their GIS based benefit transfer analysis of woodland recreation values.

TABLE 4
CONVENTIONALLY MODELED META-ANALYSIS OF CV ESTIMATES OF PER PERSON PER VISIT RECREATION VALUES (IN £, 1990) FOR OPEN-ACCESS WOODLAND IN GREAT BRITAIN

Variable	Coefficient	95% CI	p
Intercept	1.061	0.999–1.684	<0.001
Option	0.419	0.290–0.549	<0.001
OE	−0.443	−0.784– −0.102	0.032
IB	−0.419	−0.901– −0.064	0.144
PC	−0.129	−0.53–0.276	0.589
PCH	0.489	−0.052–0.971	0.090
Bishop	0.065	−0.303–0.434	0.764
Hanley	0.497	0.156–0.838	0.017
Whiteman	0.161	−0.215–0.537	0.466
Willis	−0.118	−0.443–0.208	0.538

R^2 = 0.718; R^2 (adj.) = 0.643; N = 44.

The model detailed in Table 4 fits the data well and conforms well with our theoretical and empirical expectations. The *Option* variable provides a strong, positive, and highly significant influence upon stated WTP; as expected respondents facing a "use plus option value" question stated higher WTP sums than those facing "use value alone" questions. The *Elicit* variables also conform well with prior expectations. Compared to the incentive compatible *DC* base case all methods yield negative departures (suggesting the anticipated presence of free-riding strategies) except for the *PCH* method (where the psychological pressure exerted by the high range payment card seems to have raised stated WTP above that predicted via the *DC* approach; a result which is just significant at the 10% level). The size and significance of estimated coefficients also conforms well with expectations with the *OE* method exerting the largest downward pressure upon estimates (this being the only effect which is clearly significant at the 5% level), while the *IB* approach results in a lesser negative effect followed by the *PC* results, with both of these proving insignificant. Overall, this ordering conforms in all aspects with our prior expectations providing some considerable support for this model. However, this is not the case for our set of *Author* variables. Here, the expectation is of no significant effect and while this is generally the case, this is not true of the *Hanley* variable which yields a clearly significant positive effect. This latter result is somewhat worrying as it appears to suggest that reported valuation estimates are partly dependent upon the researcher carrying out the study. We therefore move to our wider dataset, boosted by the TC estimates and re-examine this and the other issues raised above.

Conventionally Estimated Meta-Analysis of the CV and TC Per Person Per Day Values

The analysis was subsequently expanded by the addition of the 23 estimates of per person per visit woodland recreation values obtained using TC methods. In addition to increasing the total observations to 77, this also adds the set of *Method* variables which defines the four method/estimation combinations used (*CV, ITCols, ITCml,* and *ZTC*, of which the *CV* studies are held as the base case in subsequent analyses).[13] The *Elicit* variables were omitted from this analysis as they did not apply to the TC studies, however the expanded period covered by the wider dataset permitted inclusion of the *Year* variable. Models were estimated using conventional regression technique.[14] Table 5 details results for a number of model specifications.

[13] In addition, we have one further *Author* category (*Everett*) and one extra *Forest* study site (*Dalby*).

[14] Equation (A1) in Bateman et al. (2000) details such a model showing effects for individual forests.

TABLE 5

Conventional Meta-Analyses of CV and TC Estimates of Per Person Per Visit Recreation Values (in £, 1990) for Open-Access Woodland in Great Britain

		Models				
		A	B	C	D	E
Intercept		1.1980 (0.1057) [11.34] {0.000}	0.8368 (0.0764) [10.95] {0.000}	0.6687 (0.0862) [7.75] {0.000}	0.6796 (0.0886) [7.67] {0.000}	0.7697 (0.0910) [8.46] {0.000}
Option				0.2717 (0.1436) [1.89] {0.063}	0.2626 (0.1469) [1.79] {0.078}	0.3414 (0.1434) [2.38] {0.020}
Forest	*Cheshire*	−1.3780 (0.3839) [−0.98] {0.328}		−0.4029 (0.2163) [−1.86] {0.067}	−0.4153 (0.2203) [−1.88] {0.064}	−0.3962 (0.2109) [−1.88] {0.065}
	Loch Awe	0.5653 (0.4881) [1.16] {0.251}		0.4379 (0.2760) [1.59] {0.117}	0.4212 (0.2812) [1.50] {0.139}	0.4154 (0.2690) [1.54] {0.127}
	Aberfoyle	0.4445 (0.3104) [1.43] {0.156}		0.5491 (0.1799) [3.05] {0.003}		
Method	*ZTC*		1.5973 (0.1447) [11.04] {0.000}	1.6988 (0.1378) [12.33] {0.000}	1.7253 (0.1418) [12.17] {0.000}	1.8461 (0.1427) [12.94] {0.000}
	ITCols		0.5876 (0.1854) [3.17] {0.002}	0.8005 (0.1767) [4.53] {0.000}	0.7910 (0.1805) [4.38] {0.000}	0.7994 (0.1727) [4.63] {0.000}
	ITCml		−1.1811 (0.2062) [−0.88] {0.383}			
Author	*Hanley*				0.4926 (0.1955) [2.52] {0.014}	0.4390 (0.1881) [2.33] {0.023}
	Year					0.0755 (0.0276) [2.74] {0.008}
	R^2 (adj.)	0.020	0.531	0.690	0.678	0.705
	N	77	77	77	77	77

Cell contents are: Estimated coefficient
(s.e.)
[*t*-value]
{*p*-value}

where:

Dependent variable = recreational value (£) per person per visit.

Option = 1 where the value estimate relates to the sum of use plus option value, and 0 where the value estimated is use value alone. Note that all TC studies relate to use values alone.

Cheshire = 1 for studies conducted at Cheshire forest, and 0 otherwise.

Loch Awe = 1 for studies conducted at Loch Awe forest, and 0 otherwise.

Aberfoyle = 1 for studies conducted at Aberfoyle forest, and 0 otherwise.

ITCols = 1 if study uses the individual travel cost method with an OLS estimator, and 0 otherwise.

ITCml = 1 if study uses the individual travel cost method with a ML estimator, and 0 otherwise.

ZTC = 1 if study uses the zonal travel cost method (all employ OLS estimators), and 0 otherwise.

Hanley = 1 if study conducted by Hanley et al., and 0 otherwise.

Year = Continuous variable; the number of years before (negative), or after (positive) the base year (1990).

In each case, tests of functional form indicate that the linear specification performs roughly as well as other standard forms and is retained for comparability and ease of interpretation.

In Table 5, Model A restricts investigation to the 21 *Forest* variables referring to study site effects, reporting only the three most significant of these dummies. Even these prove highly insignificant, a result which conforms to our expectations as set out previously. In model B these variables are removed in favor of the *Method* dummies which yield a dramatic increase in explanatory power. Perhaps more important, the sign and significance of these variables conforms well with our prior expectations. Remembering that CV studies form our base case, we find no significant effect from the *ITCml* variable (a result which persisted throughout our analysis such that we omit this variable from subsequent analyses in Table 5 for which the base case now becomes *CV* and *ITCml* estimates), but strongly significant and positive effects associated with the *ITCols* and *ZTC* variables. This result again confirms our prior expectations, suggesting that these latter estimates are upwardly biased.

Model C adds the Option and previously considered *Forest* variables producing a further substantial improvement to model fit which does not change substantially in remaining models. As expected the *Option* variable yields a positive and significant ($\alpha = 10\%$) effect upon values. Interestingly, two of the *Forest* variables also prove significant. However, as mentioned previously, one of these, the site variable for *Aberfoyle* forest, is strongly correlated with the author variable *Hanley* (all of the Hanley et al. studies were conducted at Aberfoyle although other authors also provide estimates for this forest). Given the insignificance of all but one other of the *Forest* variables and our results of Table 4 it seems reasonable to investigate the possibility that it is this *Author* variable which is the root of this effect. Accordingly the move from Model C to Model D exchanges the *Aberfoyle* variable with that for *Hanley*, the latter also proving significant.

Taken together, the results of Model D and that reported in Table 4 could be seen as supporting the argument that valuation estimates may be subject to authorship effects. An alternative explanation is that the Hanley et al. estimates are elevated because of some characteristics of the Aberfoyle site for which they were estimated. Yet a further explanation might be that this result is in some way a product of the conventional modeling approach adopted in this meta-analysis. All of these possibilities are explored subsequently.

Model E adds the final variable *Year* into the analysis. This yields a small, positive, and significant coefficient. The result is not particularly robust, becoming insignificant ($p = 0.181$) when the oldest estimate (that provided by Everett [1976]) is omitted, yet even then the sign and size of the coefficient remain similar ($\beta = 0.0526$). This suggests that, given a longer data period, a positive trend in valuations might become more clearly established. While emphasizing statistical uncertainties regarding this result, its general message seems plausible, suggesting an increasing relative interest in outdoor, environmentally based recreation over the last three decades and echoing the seminal work of Krutilla and Fisher (1975).

In summary, with the exception of the *Hanley* variable, the relationships detailed in Model E conform well to expectations. Values are positively related to the *Option* variable which in this best fit model is now significant at the 5% level. Similarly, the *Method* variables *ITCols* and *ZTC* both have significant and positive coefficients reflecting their expected relationship with the CV and *ITCml* values which form the base case of this analysis. Here the only *Forest* variable to prove significant ($\alpha = 10\%$) is that for *Cheshire*. The negative coefficient on this variable may reflect the high visitor congestion observed in studies of this forest (Willis and Benson 1989).[15] As noted, the positive and significant *Year* variable also seems

[15] By contrast, the *Loch Awe* coefficient is positive (although not statistically significant) reflecting its somewhat remote and secluded location attracting a more 'dedicated' woodland user (as noted by Willis and Benson 1989).

highly plausible. Model E also provides the best fit to our data and, given the generally desirable characteristics noted above, provides a typical example of a meta-analysis estimated using conventional statistical modeling approaches. We now consider an alternative to this approach and examine the extent to which this may provide superior insight into the nature and robustness of these postulated relationships.

IV. AN MLM APPROACH TO META-ANALYSIS

The various models reported in Tables 4 and 5 all assume independence between estimates. However, in recent years a suite of ''Multilevel Modeling'' (MLM) techniques have been developed within the fields of epidemiology and education research to allow the researcher to relax this assumption and develop models which explicitly incorporate natural hierarchies or ''levels'' within which data is clustered (Goldstein 1995). This is achieved by modeling the residual variance of estimates in two parts; that due to the effect of given levels upon estimates, and that remaining due to true unexplained error. In effect, this approach allows for the possibility that variation within value estimates may differ between levels thus violating the independence assumption. In order to relax this assumption and examine the advantages of an MLM approach, this technique is now applied to our meta-analysis of woodland recreation estimates.[16]

A potential limitation of the application of conventional regression techniques in meta-analysis occurs if the observations being modeled possess an inherent hierarchy. Within conventional estimation strategies, some of the variables used to predict recreation may be specific to each individual study (examples being the study design and elicitation method used). However, others, such as the author, study, or forest to which a given estimate pertains may be constant across a set of such estimates. These former categorizations can be conceptualized as higher level variables, and in this sense the data may be viewed as possessing a hierarchical structure. The data structure from the above examples can be seen as actually corresponding to a range of hierarchical levels; of value estimates (level 1) within studies (level 2), of value estimates (level 1), within forests (level 2), or alternatively of value estimates (level 1) within authors (level 2).[17] Given sufficient data, this hierarchy could be extended with further levels representing, for example regions or even nations.

Hierarchical data structures cannot be easily accommodated within the traditional regression framework. Here, the values of author or study location related variables must be collapsed to the level of the individual value estimate and simply replicated across all observations sharing those characteristics. This procedure is problematic in that it provides no information on, for example, the probability of estimates made in the same forests, or by the same authors producing similar value estimates. This limitation may be circumvented, as employed in the examples given in Tables 4 and 5, by the use of dummy variables to indicate forest location or authorship. However, this solution can present difficulties. With the present data, there are only a limited number of authors and forest sites, and hence the number of dummy variables that need to be added to the models are manageable. However, it is readily apparent that any model estimated using dummies will quickly become extremely

[16] We initially develop this approach in Brouwer et al. (1999). However, this earlier analysis is restricted to CV studies alone, considers only one form of potential data hierarchy and is complicated by the necessity of drawing upon studies of diverse resources taken from a number of countries; factors which make interpretation of findings problematic. The present study examines a single resource within a single country but considers three potential data hierarchies (while also providing a fuller account of the MLM modeling structure).

[17] If no two authors undertake a study in the same forest, then this may be extended to a three level hierarchy of WTP estimates (level 1) within forests (level 2) within authors (level 3). If multiple authors do study the same forests, then a more complex structure (known as cross-classified) exists wherein estimates (level 1) are nested within a cross-classified level (2) of forests and authors. Such a case is not considered here (although it is the subject of ongoing research by the authors), but the theory of cross-classified hierarchies is discussed in detail by Goldstein (1995).

large and complex if the dataset contains numerous observations at each level of the hierarchy.[18]

An alternative to the use of dummy variables to model hierarchical data structures is to fit a series of separate regression models. For example, separate models could be fitted for each forest or author. However, this approach defeats the objective of meta-analyses when the variables found to be significant may differ between models. Furthermore, unreliable results may be produced due to small sample sizes when there are relatively few estimates for each forest, as in the present case.

Aside from methodological considerations, a further limitation of traditional analyses stems from the fact that they may contain poorly estimated parameters and standard errors (Skinner, Holt, and Smith 1989). Problems with standard error estimation arise due to the presence of intra-unit correlation; the fact that recreation value estimates from studies within the same forest, or by the same author, may be expected to be more similar than those drawn from a random sample. If intra-unit correlation is small, then reasonably good estimates of standard errors may be expected (Goldstein 1995). However, where intra-unit correlation is significant then conventional regression strategies will tend to under-estimate standard errors, meaning that confidence intervals will be too short and significance tests will too often reject the null hypothesis.

For simplicity, a two level hierarchy of i value estimates (at level 1) within j authors (at level 2) is considered in the examples below. As with a traditional generalized linear model, the observed responses y_{ij} are the published mean per person per visit recreation value estimates in 1990 pounds sterling. Considering a situation with just one explanatory variable, *OPTION* (defined as before) being tested, a simple model may be written as:

$$y_{ij} = \beta_{0j} + \beta_1 OPTION_j + \in_{ij}. \qquad [1]$$

Here the subscript i takes the value from 1 to the number of value estimates in the model, and the subscript j takes the value from 1 to the number of authors in the sample. Using this notation, items with two subscripts ij vary from estimate to estimate. However, an item that has a j subscript only varies across authors but is constant for all the estimates made by each author. If an item has neither subscript it is constant across all studies and authors.

As the authors included in the analysis are treated as a random sample from a population, Equation [1] may be re-expressed as:

$$\beta_{0j} = \beta_0 + \mu_j$$
$$\hat{y}_{ij} = \beta_0 + \beta_1 OPTION_{ij} + \mu_j. \qquad [2]$$

Where β_0 is a constant and μ_j is the departure of the j-th author's intercept from the overall value. This means that it is an author level (level 2) residual that is the same for all estimates nested within an author. In other words this term describes, after holding constant the effect of the explanatory variables within the model, the residual influence of the author in determining the outcome for each individual mean WTP estimate they published.

The notations expressed in equation [2] can be combined. Introducing an explanatory variable *cons*, which takes the value 1 for all estimates (and hence forms a constant or intercept term), and associating every term with an explanatory variable, the model becomes as shown in equation [3]:

$$y_{ij} = \beta_0 cons + \beta_1 OPTION_{ij} + \mu_{0j} cons + \in_{0ij}. \qquad [3]$$

Finally, the coefficients can be collected together and written as:

$$y_{ij} = \beta_{0ij} cons + \beta_1 OPTION_{ij}$$
$$\beta_{0ij} = \beta_0 + \mu_{0j} + \in_{0ij}. \qquad [4]$$

In equation [4], both μ_j (the level 2 or author level residuals) and $\in_{ij}$ (the level 1 or estimate level residuals) are random quantities whose means are estimated to be equal

[18] An example might be an international dataset of value estimates nested within hundreds of study locations.

to zero. A comparison between the multilevel model expressed in equations [3] and [4] and the original non-hierarchical structure depicted in Table 4 illustrates the tenet of multilevel models. Traditionally the residual error term of a model, $\in$, is seen as an annoyance and the aim of the modeling process is to minimize its size. With multilevel models, the error term is of pivotal importance in model estimation. Rather than a single error term being estimated, it is stratified into a range of terms, each representing the residual variance present at each level of the hierarchy. Viewed in this sense, μ_j represents author level effects, while $\in_{ij}$ represents those operating at the level of the value estimate.

If, after holding constant the influence of the x_{ij} explanatory variables in the model, $\mu_j > \in_{ij}$, then this would suggest that some factors associated with the authors themselves are of greatest importance in explaining the residual variation in WTP estimates. If instead $\mu_j < \in_{ij}$ then some un-modeled factor associated with the elicitation of each estimate (which, for example, could be associated with the characteristics of each specific study, or might simply be random variation in each elicited WTP value) is more important. A common scenario is that, while both μ_j and $\in_{ij}$ are large in a model containing few x_{ij} explanatory variables, both will decrease as further explanatory variables are added and the residual variance in the model is explained.

The structure presented in equation [4] is known as a variance components model (Lin 1997). For ease of interpretation, the estimated parameters may be classified as either being of a *fixed* or *random* nature. The fixed parameters are those for which a just single coefficient is estimated, and hence correspond to those that would be found in a conventional analysis. In this example both *CONS* and *OPTION* are fixed. In contrast, the random parameters are those where individual estimates are made for every unit at each level of the hierarchy. Here, both μ_j and $\in_{ij}$ are random, as a value of $\in_{ij}$ is estimated for each value estimate (at level 1 of the model) and a value of μ_j is estimated for each author (at level 2 of the model). Hence, in terms of model interpretation, it is the stratification of the error term to form these random parameters that differentiates a multilevel model from more traditional regression analysis techniques. Remembering that $OPTION_{ij}$ is a dummy variable that represents whether the elicited WTP requested use plus option value ($OPTION = 1$) or use value alone ($OPTION = 0$), the variance components model depicts the relationship between *OPTION* and the value estimate as being constant, but (provided $\mu_j > 0$) recreation values are modeled as being higher for some authors than others.

While there are various methods available for parameter estimation in multilevel models, an approach known as Iterative Generalized Least Squares (IGLS) was adopted in our subsequent analysis. The statistical theory underpinning IGLS is described in detail by Goldstein (1995). Briefly, initial estimates of the fixed parameters are derived by traditional regression methodologies ignoring the higher-level random terms. The squared residuals from this initial fit are then regressed on a set of variables defining the stricture of the random part to provide initial estimates of the variances/covariances. These estimates are then used to provide revised estimates of the fixed part, which is in turn employed to revise the estimates of the random part, and so on until convergence. Crucially, a difficult estimation problem is decomposed into a sequence of linear regressions that can be solved efficiently and effectively, providing maximum-likelihood estimates.[19]

It is important to note that the slopes and intercepts which are estimated for units within level 2 and above of the hierarchy will not be the same as those that would be obtained from a traditional generalized linear solution. They are in fact residuals which have, to a greater or lesser extent, been shrunken towards the average regression line giving the predicted relationship between mean WTP and the explanatory variables

[19] A limitation of IGLS for models with a binomial or Poisson distributed response variable (neither of which were used in the present application) is that is uses a method based on either marginal or penalized quasi-likelihood. This requires assumption of normally distributed variance above level one of the hierarchy.

TABLE 6
MLM Model Estimates

Variable	Coefficient	95% CI	p
	Fixed Effects		
Constant	0.703	0.952–0.954	<0.001
Option	0.391	0.083–0.699	0.013
CVOE	−0.593	−1.081–−0.105	0.018
CVPCH	0.887	−0.089–1.863	0.075
ZTC	1.917	1.609–2.220	<0.001
ITCols	0.823	0.452–1.193	<0.001
ITCml	0.041	−0.355–0.436	0.841
Year	0.071	0.010–0.132	0.021
	Random (Hierarchical) Effects		
Level 1 (Value estimate)			
Variance σ^2_{e0}	0.218	0.142–0.295	<0.001
Level 2 (Author)			
Variance σ^2_{u0}	0.021	−0.021–0.121	0.673

Note: −2*loglikelihood (IGLS) = 86.759 (N = 77).

across all authors. Taking our example of a two-level model, at the author level, if $\sigma^2_{e0} = \text{var}(\in_{0ij})$ and $\sigma^2_{u0} = \text{var}(u_{0j})$ then each author level residual is estimated using equation [5]:

$$\hat{u}_j = \frac{n_j\sigma^2_{u0}}{n_j\sigma^2_{u0} + \sigma^2_{e0}}\,\tilde{y}_j. \qquad [5]$$

Here, n_j is the total number of estimates produced by author j, $\tilde{y}_j$ is the raw residual associated with the author (the mean estimate level residual for all estimates made by author j) and $\hat{u}_j$ is the shrunken residual. From this, it can be seen that if n_j is large and there are many value estimates made by an author, then the predicted level 2 residuals will be closer to the raw residual than when n_j is small. If n_j is small, then the residual will be shrunken towards the mean. Similarly if σ^2_{e0} is large and there is a high variability in the recreation value estimates produced by an author, then the predicted residual will also be shrunken. In this sense, the MLM approach provides conservative estimates of variability at different levels of the hierarchy where units based on a small sample or a very variable outcome are considered to provide little information. This is particularly pertinent here because, as has already been considered, the statistically significant positive coefficient observed for *Hanley* in Table 5 was based on studies that were all conducted at a single forest (Aberfoyle).

A multilevel re-analysis of the meta-analysis data was undertaken using the MLwiN package (Rasbash et al. 2000) developed by the Multilevel Models Project at the Institute of Education, London. Three sets of model were produced; one with a hierarchy of WTP estimates nested within authors, one of estimates within study locations, and finally one of estimates within published studies. The results of the model of estimates nested within authors are given in Table 6. Here, those CV elicitation techniques which produced estimates which were insignificantly different from the incentive compatible DC approach have been merged with the latter to yield a base case set of estimates from which departures are estimated. This leaves two CV elicitation techniques; the variable *CVOE* identifying those CV estimates produced using the OE format, while *CVPCH* refers to CV studies using the PCH format.

Although technically different, the fixed parameters in the model in Table 6 can be interpreted in the same way as an ordinary regression. The results detailed in the fixed part of the model now conform entirely with our theoretically and empirically derived expectations. As before, the *Option* variable yields a significant and positive effect. Considering the CV elicitation variables and remembering the DC results form our base case, the CVOE variable is associated with a clear negative effect that the coefficient on

CVPCH is strongly positive; both results conforming to expectations. Turning to the *Method* variables, as expected the ZTC and *ITCols* variables both produce strong positive effects while, as observed previously, the *ITCml* variable is statistically insignificantly different to the DC base case; given that these are the most theoretically and methodologically defensible of the TC and CV methods this seems a reassuring result. Finally, the positive and significant coefficient on the *Year* variable is reconfirmed.

In summary therefore, the fixed part of the multilevel model reported in Table 6 conforms entirely with our prior expectations. However, one of the prime objectives of fitting such a model was to determine if, after controlling for the variables in the fixed part, there was still statistically significant variation in WTP estimates between authors. These random effects are shown in the lower part of Table 6. This part of the model is relatively simple. Although the multilevel methodology involves estimating a separate intercept value for each author (μ_j) and a separate residual for each value estimate ($\in_{ij}$), the variance between the two levels of the model may be neatly summarized by the two parameters σ^2_{u0} and σ^2_{e0}. These are the same parameters used in the calculation of the shrinkage factor illustrated in Equation [5] and are known as variance parameters, as they indicate the variance in the μ_j and $\in_{ij}$ terms respectively. Hence a comparison of the values of σ^2_{u0} and σ^2_{e0} shows the relative importance of author (level 2) and estimate (level 1) effects in determining the variability of WTP values that is not explained by the fixed parameters in the model.

The parameter estimates for both σ^2_{u0} and σ^2_{e0} are greater than zero, suggesting that variability between estimates and between authors remains after controlling for the explanatory variables that were included in the fixed part of the model. Taking the ratio of these estimates suggests that approximately 9% of unexplained variation in elicited recreation value is associated with author effects. However, the calculation of t-statistics for each coefficient shows that while statistically significant residual variation remains between estimates at level 1 ($t = 5.59$, $p < 0.001$) the effect of authorship at level 2 does not reach statistical significance ($t = 0.41$, $p > 0.05$). In other words, the multilevel analysis suggests that an author effect is present but is not statistically significant.

Although in conflict with the earlier findings from the conventional regression analysis, such a result accords with theoretical expectations that recreation values should not vary significantly according to study authorship. This provides substantial (if, on its own, insufficient) support for the practice of placing monetary values upon preferences for non-market environmental goods. The author specific results are illustrated in Figure 1 where the value of u_j estimated for each individual author is presented in rank order along with corresponding 95% confidence intervals. The figure shows that, in the multilevel analysis, studies by *Hanley et al.* are still predicted to give the highest recreation values and those by *Willis et al.* the lowest. However, the confidence intervals clearly overlap. This represents a reduction in variance from the situation observed in Tables 4 and 5 where estimates provided by *Hanley et al.* were found to significantly differ from that of other authors. The reduction of variance is due to the effects of the conservative estimation strategy implemented in equation [5] where residuals are shrunken towards the mean value. The contrast between Tables 4 and 5 and the findings of Table 6 provides a clear justification for the application of MLM techniques to meta-analysis studies.

The shrinkage illustrated by Figure 1 has interesting implications for the comparison of results between multilevel and non-multilevel models. The message from the multilevel model is that variation is present between authors but, because of the magnitude of the variance and the size of the sample, it cannot be said to be statistically significant. Hence, we are making a statement about the importance of context (in this case authorship) and composition (the remaining unexplained variation in between WTP estimates). The traditional regression approach used previously did the opposite; it told us little about the overall roles of context and composition, but it did highlight two authors with rather different patterns of responses from the rest of the sample. From this comparison, it is clear that, whilst the conclu-

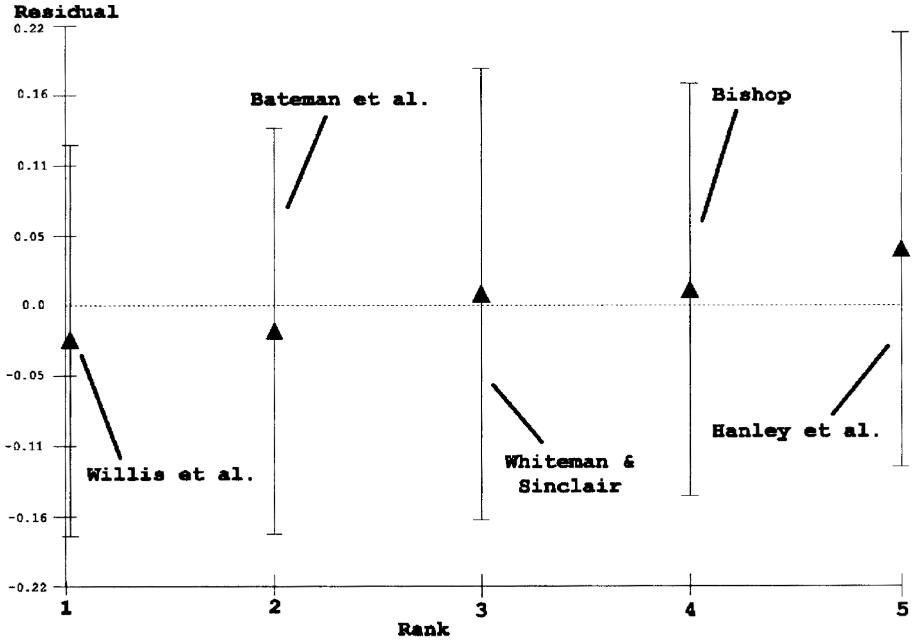

FIGURE 1
MLM AUTHOR LEVEL RESIDUALS

sions reached may be different from those of a conventional analysis, the multilevel approach is prudent if the intention of the analysis is to quantify whether there are overall contextual influences (in this case associated with different authors) on the measured outcome (recreation value).

The earlier conventional analyses also found evidence of a *Forest* (site) effect where recreation values for *Cheshire* were significantly lower than the rest of the sample, and those for *Loch Awe* and *Aberfoyle* were relatively higher (see Table 5). To test if any evidence of between-site heterogeneity remained after a multilevel approach was taken, the model presented in Table 6 was refitted, but this time authorship at level 2 was replaced by *Forest* identifiers. The fixed effect coefficient values and levels of significance were not found to differ greatly from the previous example and are hence not replicated here. However in this case the values of σ^2_{u0} (now for forests) and σ^2_{e0} (for value estimates) were estimated at 0.010 ($t = 0.73$, $p > 0.05$), and 0.212 ($t = 5.63$, $p < 0.01$) respectively. In similar fashion to the model for authors, these results show strong variation between estimates, but only a limited forest site effect (accounting for under 5% of the total residual variance). Figure 2 shows the forest level residuals ranked with 95% confidence intervals. In order to maintain legibility only those forests mentioned previously are identified. As with the original non-multilevel analysis, *Cheshire* shows the greatest negative residual (and hence correspondingly lower than predicted WTP values), while *Loch Awe* and *Aberfoyle* yield the highest positive residual values. However, again confidence intervals clearly overlap, thus conforming to our empirically derived prior expectation that forests do not exert significant impacts upon recreation values (although as noted before, their location may influence the quantity of visits).

Finally, we also considered the possibility of significant between-study heterogeneity (i.e., looking at the clustering of estimates within studies). As per our examination of author effects, we do not expect variance

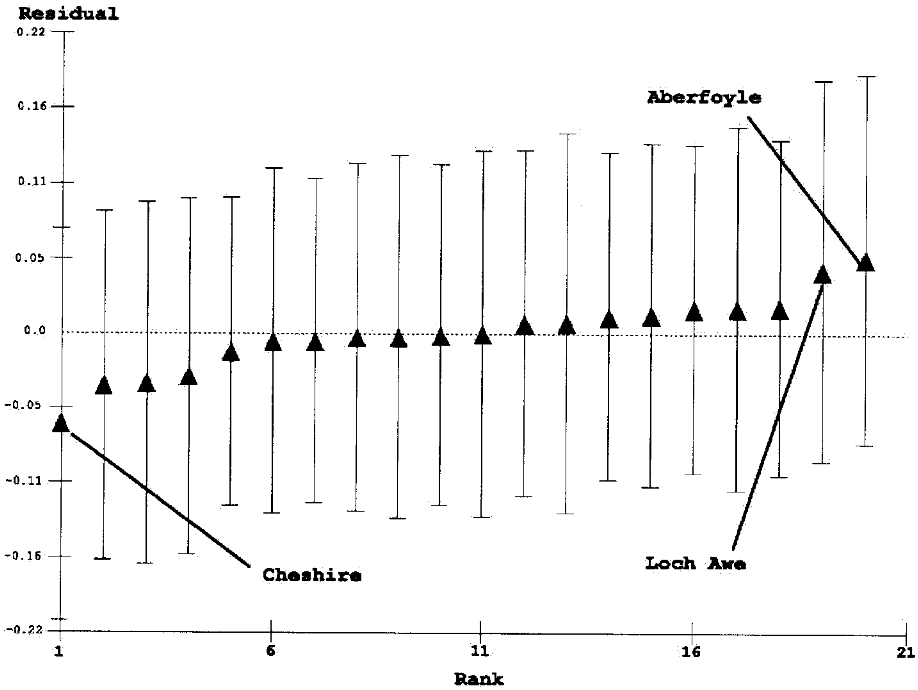

FIGURE 2
MLM FOREST LEVEL RESIDUALS

within estimates to differ significantly between studies. Analysis clearly confirmed this expectation with values of σ^2_{u0} (between study variance) and σ^2_{e0} (for value estimates) estimated at 0.017 ($t = 0.55, p > 0.05$), and 0.216 ($t = 5.68, p < 0.01$) respectively.

V. DISCUSSION AND CONCLUSIONS

There are a numerous routes through which benefit transfer and meta-analysis research may be taken forward. These include improvements in the conduct and reporting of new studies, the specific incorporation of benefit transfer and meta-analysis requirements within their design, and the re-analysis of past work. The present paper goes some way towards highlighting a novel way in which this latter aim might be best realized. We have compared the application of traditional regression and novel MLM methodologies to meta-analyses of British woodland recreation values. While both sets of results generally conform well to expectations derived from either theoretical considerations or empirical regularities, our conventional regression findings suggest that certain authors and forests are associated with large recreation value residuals. However, the more sophisticated and conservative MLM approach shows that these residuals are not large enough (or are not based on a large enough sample size) to be differentiated from variation that might be expected by chance. In so doing it is only these MLM based models which conform in all respects to prior expectations, a finding which underscores the importance of adopting such approaches which explicitly model the hierarchical nature of almost all meta-analysis datasets.

Here we have fitted only simple two-level MLM models. More complex structures have not been implemented here for a number of reasons. No significant variation was observed between authors or survey site locations, and it is highly unlikely that a more detailed model hierarchy would have contradicted these findings. A second limitation to the use of more complex hierarchies concerns sample size; as models become more complicated there is an associated loss of degrees of freedom. In particular, the conservative estimation strategy used means that the presence of a small amount of level 2 variation in a simple two-level model may be shrunken to zero if a more complex structure is attempted. While the dataset we have studied is comprehensive, it is based on a sample of just 77 observations, and hence has somewhat limited power. The increased number of observations that will result from more studies being undertaken would allow a greater complexity of models to be fitted.

Although the essential ideas of multilevel models were developed over 20 years ago, it is only recently that improvements in computing power and advances in our understanding of effective model implementation have meant that their execution has become a practical proposition (Bull et al. 1998). We are currently on a wave of innovation as use spreads from the original developers to the wider research community. Having said that, the multilevel approach retains some of the limitations of more traditional quantitative techniques, as well as introducing new ones.

In the MLM models presented here, influences on recreation values are modeled more powerfully than traditional techniques allow, yet the random parameters can ultimately offer only limited insight into the reasons behind between-author and between-forest variations in outcome. Preferences for complex, non-market environmental goods such as open-access recreation involve a detailed interplay between a wide range of factors that are difficult to quantify and may be subject to random variation. This unpredictability will undoubtedly introduce uncertainty into any model, multilevel or not, developed to identify and predict the important influences on such preferences. However, while multilevel models cannot remove this uncertainty, they can allow it to be more richly quantified and accounted for, and hence allow for systematic factors to be assessed.

Finally, our MLM estimated meta-analysis has some clear messages for both policy makers and economists who work within the applied policy arena. As noted, our results conform well with prior theoretically and empirically derived expectations. However, these expectations are not that value estimates will be invariant to choice of study methodology or analytical approach. Indeed the reverse is true. For example, as predicted by considerations of incentive compatibility, we show that CV estimates of recreation value derived from an OE elicitation technique will be significantly lower than those obtained by a DC approach. Similarly we show that TC values derived through inappropriate OLS estimators will be upwardly biased in comparison with those derived from maximum likelihood estimators or from CV studies using DC elicitation techniques. It is the responsibility of the economist to highlight these expected differences to the policymaker and to advise upon the most theoretically and methodologically appropriate approach to the issue at hand. That said, the absence of significant author or study level impacts within our MLM meta-analyses is encouraging providing an argument against criticisms that, for example, certain authors produce unusually high or low valuation estimates. This analysis also has some specific messages for policy makers within the U.K. Forestry Commission. In particular, while some evidence for site effects was found in the conventionally estimated models reported in Table 5, these do not persist within the more sophisticated MLM analysis given in Table 6. As noted previously, this finding is in line with other research showing that, while visitor arrivals at UK woodlands are highly responsive to a variety of locational factors, they are somewhat less responsive to the facilities on offer at these sites (Brainard, Lovett, and Bateman1999; Brainard, Bateman, and Lovett 2001).[20] Given this, the onus upon woodland policymakers within the

[20] This is not to suggest that site facilities are irrelevant in attracting visitors. However, as shown by Brainard, Lovett, and Bateman (1999) and Brainard, Bateman, and Lovett (2001), locational factors provide much stronger predictors of demand. In part this may be because virtually all U.K. sites provide the basic walking and recreational amenities that characterize woodlands visits and are thus relatively little differentiated in terms of further cogent attributes.

U.K. context, appears to be upon using scarce resources to optimize site location rather than to extend the diversity of facilities within woodlands.

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