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Using structural restrictions to achieve theoretical consistency in benefit transfers

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Abstract

Analysts often extrapolate estimates of the value of environmental improvements reported in prior studies to evaluate new policy proposals, a practice sometimes referred to as “benefit transfer.” Benefit transfer functions are frequently specified based on statistical considerations alone. However, such a purely statistical approach can lead to willingness-to-pay functions that fail to satisfy some aspects of theoretical consistency that may be especially important for policy evaluations. In this paper, we examine several previous meta-analyses of nonmarket valuation studies in light of the adding-up condition, which is one important aspect of theoretical validity. We then use meta-regression to estimate a new willingness-to-pay function for surface water quality improvements intended to be used for benefit transfers. We estimate the meta-regression model using summary results from 51 previously published stated preference studies. An important feature of our approach is that we develop the meta-regression estimating equation to ensure that the resulting benefit transfer function will necessarily comply with the adding-up condition. This is achieved by first specifying a marginal willingness-to-pay function and then deriving an expression for total willingness-to-pay. This leads to a non-linear estimating equation, so we estimate the parameters of the model using non-linear least squares. We discuss the advantages and disadvantages of our approach relative to other structural approaches, and we compare our empirical results to a more traditional nonstructural meta-regression model. Finally, we examine the quantitative importance of imposing the adding-up condition in our case study by performing some illustrative calculations of willingness-to-pay for hypothetical water quality improvements using both structural and non-structural models.

1 Introduction

Environmental policies are often evaluated using a benefit transfer (BT) approach, which involves extrapolating results from previous non-market valuation studies to estimate benefits for new policy cases (Johnston *et al.* 2015). Benefit transfer is widely used for

evaluating water quality policies in particular. Several water quality BT functions have been estimated in previous studies (e.g., Johnston *et al.* 2005, Van Houtven *et al.* 2007, USEPA 2015b) using meta-regression, which is a form of meta-analysis that uses regression methods to examine the influence of study characteristics on estimated effect sizes among a collection of primary studies (Nelson and Kennedy 2009).

Some authors have recommended using a structural benefit transfer approach, which imposes theoretical consistency on the resulting value function by deriving an expression for willingness-to-pay (WTP) from assumed forms of the direct or indirect utility function (e.g., Smith *et al.* 2002). However, the most common approach to developing benefit transfer functions still relies mainly on atheoretic or nonstructural reduced-form estimating equations. As we show in this paper, a possible unintended consequence of a nonstructural approach is that the resulting WTP predictions may not satisfy some basic theoretical requirements for internal consistency. This can lead to implausible or nonsensical results when transferring values in an applied benefit-cost analysis. Smith *et al.* (2006) provided a concise statement of the basic problem: “There is nothing in the use of simple average unit values or in the predictions from a meta-regression analysis that necessarily ensures the results will be consistent with underlying theory... While these models may provide reasonable reduced form approximations of the value generating process, they do not impose the same level of theoretical consistency as a structural model would.” This is a main theme of the paper: we cannot expect theoretical consistency in a meta-analysis unless it is built-in *ex ante*.

In this study we use a structural approach to specify a meta-regression estimating equation for the purpose of developing a benefit transfer function. Our method is similar in spirit to previous studies that have used a structural benefit transfer approach (e.g., Pattanayak *et al.* 2007, Van Houtven *et al.* 2011, Phaneuf and Van Houtven 2015), but our estimation strategy is different. Our procedure involves specifying a functional form not for the direct or indirect utility function but for the Marshallian inverse demand curve for environmental quality, with the resource quality level as one explanatory variable and other explanatory variables acting as demand curve shifters. We then derive a compatible indirect utility function and from this an expenditure function. The difference in the expenditure function evaluated at the initial and final quality levels gives the willingness-to-pay for an incremental change in quality, so this is the function we use as our estimation equation in the meta-regression. A key advantage of a structural benefit transfer approach in general, including the strategy we pursue in this paper in particular, is that it can impose an important element of theoretical consistency on the BT function by ensuring that it will satisfy the adding-up condition (Diamond 1996).

Benefit transfers based on a constant unit value will automatically satisfy adding-up, but in the move from unit value transfer to function transfer it is possible to lose even this limited form of theoretical consistency. The basic motivation for using a functional rather than unit value transfer approach is to account for various forms of heterogeneity among study and policy cases that may be important determinants of value (Ready and Navrud 2005), and there is some empirical evidence that in fact function transfers tend to be more accurate than unit value transfers (e.g., Kaul *et al.* 2013, Rosenberger 2016). Imposing structure in the

move from unit value to function transfer is a way to ensure that we remain within the space of all possible functions that comply with whatever aspects theoretical consistency we want to maintain while still providing a policy evaluation tool that can account for the important dimensions of value heterogeneity.

In the remainder of this introduction, we first review Diamond's adding-up condition, which serves as the main theoretical insight that motivates our approach to benefit transfer function specification and estimation. We discuss the practical importance of the adding-up condition for applied nonmarket valuation problems, and we examine the functional forms of estimating equations used in several previous non-market valuation studies in light of the adding-up condition. We find several cases where otherwise carefully conducted meta-analysis studies have used functional forms that do not satisfy the adding-up condition, and we find that in many of these cases the adding-up condition can be severely violated in a quantitative sense. This review will set the stage for the heart of the paper in section 2, where we use meta-regression to estimate a new benefit transfer function for valuing water quality improvements following an approach that is guaranteed to add up. We also compare our results to those from an alternative estimating equation that is not constrained to satisfy the adding-up condition. In section 3 we examine several hypothetical policy examples, and in section 4 we discuss our results and summarize our main conclusions.

The main contributions of this paper pertain to the choice of functional form for a meta-regression estimating equation when developing a benefit transfer function. In our empirical application below, we use a very simple meta-regression estimation procedure that is almost certainly not the most statistically efficient approach possible. More sophisticated meta-regression approaches might be used to analyze these data,¹ but we believe that our relatively simple estimation strategy is sufficient to illustrate the key lessons of the paper and that these lessons will apply to any statistical approach used to estimate a meta-regression equation to be used for benefit transfers.

1.1 The adding-up condition

Diamond (1996) suggested a type of validity test based on an internal consistency condition that any willingness-to-pay function should satisfy. Let Y be an individual's baseline income, and let Q_j be the (exogenous) level of environmental quality in state j . Diamond's adding-up condition requires that for all Q_0 , Q_1 , and Q_2 :

$$WTP(Y, Q_0, Q_1) + WTP(Y - WTP(Y, Q_0, Q_1), Q_1, Q_2) = WTP(Y, Q_0, Q_2). \quad (1)$$

In words, the willingness to pay for a change from state 0 to 1 conditional on baseline income plus the willingness to pay for a change from state 1 to state 2 conditional on the income remaining after paying for the change from state 0 to state 1 must equal the

¹Specifically, if we could obtain estimates of the standard errors of each observation, this would allow us to weight the observations according to their precision in a fixed or random effects meta-analysis estimation approach, and test and possibly correct for certain forms of publication bias. For these and related meta-analysis approaches, see Borenstein *et al.* (2009), Cooper *et al.* (2009), Nelson and Kennedy (2009), Hedges *et al.* (2010), Nelson (2015), and Stanley and Doucouliagos (2015).

willingness to pay for a change from state 0 to 2 conditional on baseline income.² This type of path-independence is a basic requirement for internal consistency, and in our judgment should be viewed as a necessary condition for a valid benefit transfer function. If a benefit transfer function is inconsistent with the adding-up condition, and if the deviation from adding-up is found to be quantitatively important, then we would judge the function to be unsuitable for applied valuation work.

Diamond (1996) originally proposed the adding-up test for examining the validity of stated preference survey data. However, in this paper we do not use the test as a diagnostic for confirming or rejecting the internal validity of the primary stated preference data themselves. Rather, we assume that the primary SP estimates of willingness-to-pay are internally valid and we use the adding-up condition as a kind of constraint to impose external, or cross-study, validity on the synthetic benefit transfer function that is estimated using the SP results as data. This distinction is important because even if we are willing to assume (as we do here) or are able to confirm (through one or more validity tests applied to the original studies) that the primary estimates are themselves theoretically consistent, this does not in itself guarantee or imply that a benefit transfer function estimated by meta-regression will also be consistent with theory. Thus, the role for structural estimating equations in the development of benefit transfer functions—based on the adding-up condition or any other aspects of theoretical validity that we may want to maintain—can be distinguished from their role in examining the internal validity of primary stated preference data.

Our interest in the adding-up condition is not merely academic. For example, the U.S. EPA regularly sets goals for impaired waterbodies using “total maximum daily load” (TMDL) requirements. In some cases, waterbodies cannot be cleaned to the targeted level under a single regulation (as illustrated by the on-going cleanup of the Chesapeake Bay), and several different policies must be used. For example, one policy may target point sources and another non-point sources. If the BT function does not adhere to the adding-up condition, then breaking the water quality change into multiple policies could increase or decrease the overall estimated benefits even when the final environmental outcomes are the same. Additionally, violation of the adding-up condition can frustrate benefit-cost comparisons of different versions of essentially the same policy. For example, if a policy is proposed to be implemented through the installation of abatement capital all in a single year, and this is compared to a variant proposal where installation will occur in stages over multiple years conditional on positive net benefit estimates for each stage, then the staged variant may appear more beneficial than the non-staged variant due to the non-additivity of the benefit function. Because regulations are sometimes staged and sequenced over time and possibly over space, it is important to be able to analyze the options—some of which may be nested versions of more comprehensive options—in an internally consistent way.³ If decision-makers wish to use a policy choice procedure that is rational in the classical decision-

²Desvousges *et al.* (2015) and Kling and Phaneuf (2016) use expenditure functions to explain the adding-up condition. We can re-state expression (1) in terms of expenditure functions by noting that $WTP(Y, Q_0, Q_1) = \alpha(Q_0, u_0) - \alpha(Q_1, u_0)$, $WTP(Y, Q_0, Q_1) - WTP(Y, Q_0, Q_1) = \alpha(Q_1, u_0) - \alpha(Q_2, u_0)$, and $WTP(Y, Q_0, Q_2) = \alpha(Q_0, u_0) - \alpha(Q_2, u_0)$. Adding the right hand sides of the first two of these equations gives the right hand side of the third, which verifies (1).

³A simple example with concrete numbers might help to further clarify the theoretical validity issues that are at stake here. To see how a benefit transfer function that does not add up can lead to irrational policy guidance, consider the following pair of policies: Policy A would increase water quality from Q_0 to Q_1 (WTP = \$11) and then from Q_1 to Q_2 (WTP = \$9) at a cost to polluting firms of \$17.5.

theoretic sense—i.e., where policy rankings are transitive and cycling is not possible (e.g., Gilboa 2009 p 62–63)—then the inconsistencies that can stem from failures to comply with the adding-up condition described above need to be ruled out by imposing some form of structure on the benefit transfer function estimating equation.⁴

More generally, failure to comply with the adding-up condition means that benefit estimates will not be invariant to logically equivalent alternative framings of the environmental changes that are anticipated from a policy. As we show in section 1.2, benefit transfer functions estimated in some previous studies give predictions of WTP for two subsequent quality changes, from Q_0 to Q_1 and then from Q_1 to Q_2 , that diverge significantly from their predicted WTP for the full change, from Q_0 to Q_2 . Furthermore, this discrepancy typically will grow with the number of times the full quality change is divided into smaller constituent parts. In some cases, a benefit transfer function may predict that marginal WTP increases without bound as the size of the quality change gets smaller. In these cases, the predicted benefits of a policy could be increased to as large a value as desired by artificially dividing the policy into arbitrarily many small increments.

As we indicated above, imposing structure on a benefit transfer function to ensure theoretical consistency in policy evaluations is distinct from the use of theoretical consistency criteria for judging the validity of primary stated preference studies. Kopp and Smith (1997) argued that “...strict adherence to the scope and adding-up conditions (of the Diamond *et al.* type) as internal consistency tests for CV estimates is inappropriate, even in cases where we ignore income effects.” One reason that strict adherence may be inappropriate is that survey respondents may not view the resource changes associated with the hypothetical policy scenarios as strictly additive to the baseline quantity or quality levels of the resource as described in the CV questionnaire, i.e., respondents may not view the improved or additional units, ΔQ , as perfect substitutes for the currently extant units, Q_0 . For example, rather than $Q_1 = Q_0 + \Delta Q$, the respondents might interpret the hypothetical scenario to imply that $Q_1 = (Q_0^\alpha + \Delta Q^\alpha)^{1/\alpha}$ (Kopp and Smith 1997 p 110). More generally, one might imagine any number of ways that respondents’ interpretation of the resource changes described in a stated preference survey might diverge from the explicit or implicit intent of the researchers. For example, the respondents might not believe that the plan would be as effective as claimed in the survey, or they might assume that other environmental improvements or costs not described in the survey also would occur if the plan were implemented. In these cases, failure of the estimated WTP function to comply with the adding-up condition could indicate a mismatch between the researchers’ intended meaning of the hypothetical scenarios and the respondents’ interpretation of the scenarios. Carson and Groves (2007) discuss several ways in which SP surveys that are not incentive compatible

Policy B would reduce water quality from Q_2 to Q_0 (WTP = −\$15) at a cost savings for polluting firms of \$17.5. Policy A has net benefits of \$11 + \$9 − \$17.5 = \$2.5, then policy B has net benefits of \$17.5 − \$15 = \$2.5, then policy A has net benefits of \$11 + \$9 − \$17.5 = \$2.5... and so on without end. Such cyclical policy rankings cannot occur if the adding-up condition is satisfied because in that case WTP for policy A = −WTP for policy B.

⁴Hsu (2011) describes “postmodernist” critics who argue that benefit-cost analysis is too often and too easily manipulated for partisan ends. Relaxing the traditional rationality constraints on the quantitative tools we use to analyze public policies, such as the adding-up condition, would expand the scope for such manipulation. This would undermine the role of benefit-cost analysis in serving as an organizing framework for objectively and systematically examining the potential consequences and weighing the advantages and disadvantages of proposed public policies.

could lead to responses that fail to exhibit sensitivity to scope, so it seems possible that survey data collected under these circumstances also could imply violations of the adding-up condition.

1.2 Adding-up in previous valuation studies

In this section we examine a convenience sample of six previous non-market valuation studies of water quality improvements that used or recommended estimating equations that violate the adding-up condition. Our review is neither systematic nor comprehensive, but it will serve to illustrate the potential limitations of nonstructural, or atheoretic, approaches to specifying benefit transfer functions. Each of the studies we review in this section is in most respects exemplary, so the prevalence of adding-up violations in such cases highlights the ease of overlooking this issue. We organize our review chronologically, starting with one of the earliest and most prominent water quality valuation studies in the environmental economics literature.

Carson and Mitchell (1993) estimated a willingness-to-pay function for improvements in water quality conditions across the U.S. based on data collected from a national contingent valuation survey. Theirs was an original valuation study, not a meta-analysis of previous studies, but it is instructive to discuss it here because the Carson and Mitchell estimating equation allows us to illustrate the distinction between failures to comply with the adding-up condition due to the income effect versus the quality effect.⁵ It is the latter effect that will be of most concern in the remainder of this paper. Carson and Mitchell's estimating equation took the following form:

$$WTP(Y, Q_0, Q_1) = e^Z Y^\sigma (Q_1^\alpha - Q_0^\alpha), \quad (2)$$

where Q_0 and Q_1 are the initial and final water quality levels, Y is the respondent's income, and Z is a reduced form parameter including all other control variables and their respective coefficients. This function will add up along the Q dimension but it fails to account for the income effect so will not strictly adhere to the adding-up condition in general. We can see this by using (2) to compare the sum of WTP for two subsequent changes in Q to WTP for the full change:

$$e^Z Y^\sigma (Q_1^\alpha - Q_0^\alpha) + e^Z (Y - e^Z Y^\sigma (Q_1^\alpha - Q_0^\alpha)^\sigma) (Q_2^\alpha - Q_1^\alpha) \neq e^Z Y^\sigma (Q_2^\alpha - Q_0^\alpha). \quad (3)$$

Note that if $\sigma = 0$ in equation (2), then expression (3) would be an equality. That is, if WTP were independent of income then this function would comply with the adding-up condition. However, there are good theoretical reasons to expect the income effect to be negligible when considering WTP amounts that are small fractions of income (Horowitz and McConnell 2003) and in many cases the income effect is empirically found to be small

⁵Another reason to examine the Carson and Mitchell study is that their results were used by EPA in benefit-cost analyses of most of its water regulations prior to 2009 (Griffiths *et al.* 2012).

(Kopp and Smith 1997 p 109, Desvousges *et al.* 2015), so failure to comply with the adding-up condition for this reason alone may lead to relatively minor violations of the adding-up condition.

We will use two sets of sequential water quality improvements to illustrate the potential size of the deviations from the adding-up condition that could be produced by this and other WTP functions examined in this section. First, we will apply each WTP function to a sequence of two relatively large water quality improvements, first from “boatable” (2.5 on Vaughan’s [1986] water quality ladder) to “fishable” (5.1 on the water quality ladder), then from “fishable” to “swimmable” (7.0 on the water quality ladder). Second, we will apply each function to a sequence of two much smaller water quality improvements, first from 5.0 to 5.1, then from 5.1 to 5.2 on the water quality ladder.

Carson and Mitchell (1993 p 2450) reported the following parameter estimates: $\hat{Z} = 0.834$, $\hat{\sigma} = 0.959$, and $\hat{\theta} = 0.819$, and average income for the sample was $\bar{Y} = 24.2$ thousand dollars per year. Using these parameter estimates and the willingness-to-pay function in equation (2), we calculate $WTP(2.5, 5.1, \bar{Y}) + WTP(5.1, 7.0, \bar{Y}) - WTP(2.5, 7.0, \bar{Y}) = \126.82 , whereas $WTP(2.5, 7.0, \bar{Y}) = \126.95 . These are not exactly equal—the ratio of these values is 0.999—so the adding-up condition is violated. However, the discrepancy is less than one percent, which seems negligible for practical policy purposes. The discrepancy is a bit larger for the sequence of smaller changes—the ratio of the sum of values of the two changes in series to the value of the full change is 0.952—but this is still arguably within the range of tolerable error for practical purposes.

The next five studies we examine are water quality valuation meta-analysis studies wherein one or more of the estimated or recommended WTP functions fail to comply with the adding-up condition due to the quality effect, which as we will see can lead to much more severe discrepancies than those due to the income effect. We will discuss the first of these studies in some detail, but the others will be discussed more briefly. The key results of our review are summarized in Table 1.

Johnston *et al.* (2005) conducted a meta-analysis of 81 primary estimates of willingness-to-pay for hypothetical water quality improvements reported in 34 stated preference studies to examine which factors exert the strongest influence on the WTP estimates and to develop a value function that could be used for benefit transfers. Among the functional forms estimated by the authors were trans-log and semi-log models. The trans-log form can be written as

$$\ln WTP = \alpha Q + \beta \ln \Delta + Z. \quad (4)$$

where Q is the initial water quality level, Δ is the change in quality being valued, and Z is the sum of a constant and all other explanatory variables multiplied by their respective coefficients. To see why this estimating equation will violate the adding-up condition, first note that (4) implies the following total willingness-to-pay function:

$$WTP_i = e^{Z + \alpha Q} \Delta^\beta. \quad (5)$$

This functional form has several attractive features: it contains the magnitude of the water quality change and the baseline level of water quality, both of which would naturally be expected to influence a household's willingness-to-pay for the change, and it implies that predicted WTP necessarily will equal 0 when the water quality change equals 0. However, this functional form does not in general satisfy the adding-up condition because

$$e^{Z + \alpha Q_0} (Q_1 - Q_0)^\beta + e^{Z + \alpha Q_1} (Q_2 - Q_1)^\beta \neq e^{Z + \alpha Q_0} (Q_2 - Q_0)^\beta. \quad (6)$$

Furthermore, a well-behaved utility function would imply that willingness to pay grows or shrinks nearly linearly with small increases or decreases in the quantity or quality of a resource. However, the WTP function in (5), with $0 < \beta < 1$ as estimated by Johnston *et al.* (2005), implies that the marginal willingness to pay for water quality improvements grows very large as Q gets very small, i.e., as Q approaches zero, WTP approaches ∞ . Therefore, willingness-to-pay will shrink far more slowly than linearly as the change in quality shrinks towards zero, and so the more times an incremental change is divided into smaller components for sequential valuation, the larger will be the estimated WTP. In other words, the estimated WTP for any incremental water quality improvement could be made arbitrarily large by dividing the increment into progressively more constituent increments. This behavior is another manifestation of the failure of the WTP function to satisfy the adding-up condition. To be well-behaved and satisfy the adding-up condition, the WTP function must take the form of a difference in (possibly nonlinear) functions of the quality levels, not a nonlinear function of the difference in quality levels.

The second row of Table 1 shows the parameter estimates for the trans-log model reported by Johnston *et al.* (2005) for cases where the survey indicated that the water quality improvement would benefit only finfish and the results of applying the WTP function to our two illustrative sequences of water quality improvements. The resulting benefit ratios are 1.47 and 1.70. That is, dividing the improvement from 2.5 to 7.0 into a sequences of two improvements, from 2.5 to 5.1 then from 5.1 to 7.0, increases the estimated benefits by 47%. Dividing the improvement from 5.0 to 5.2 into a sequence of two improvements, from 5.0 to 5.1 then from 5.1 to 5.2, increases the estimated benefits by 70%.

The semi-log model estimated by Johnston *et al.* (2005) can be written as

$$\ln WTP = \alpha Q + \beta \Delta + Z. \quad (7)$$

The reported parameter estimates and our calculations of benefit ratios for the two water quality improvement sequences are shown in the third row of Table 1. In this case breaking the water quality improvements into two parts increases the total benefit estimates by 9% and 95%.

Van Houtven *et al.* (2007) also conducted a meta-analysis of water quality stated preference valuation studies using both semi-log and trans-log estimating equations. In this case breaking the water quality improvements into two parts increases the benefit estimates by between 58% and 98%. So for all of the benefit transfer functions examined so far—by Carson and Mitchell (1993), Johnston *et al.* (2005), and Van Houtven *et al.* (2007)—summing the benefits of smaller sequential increments produces a more severe violation of the adding-up condition.

Johnston and Thommasin (2010) used a semi-log estimating equation in their meta-analysis study, which also leads to violations of the adding-up condition. However, unlike the studies examined above, the Johnston and Thommasin (2010) results give a lower total benefit estimate when the larger water quality improvement is decomposed into two sequential parts, whereas decomposing the smaller improvement into two parts still gives a larger total benefit estimate. This shows that functional forms that fail to comply with the adding-up condition may lead to larger or smaller benefit estimates when a quality improvement is decomposed into smaller constituent improvements, depending on the size of the increments. For the semi-log and trans-log functional forms examined here, there is a unique for which the sum of benefits for two sequential equal-sized increments will be equal to the benefits of the corresponding full change; below (above) this value the benefits of the two half changes will be larger (smaller) than the full change. This “pivot” value of $\frac{1}{2}\Delta$ for each reviewed study is shown in the final column of Table 1.⁶

Johnston and Wainger (2015) discussed concepts and methods of ecosystem service valuation and provided some recommendations for developing benefit transfer functions. The authors provided two examples of willingness-to-pay functions—one linear and one quadratic in Q and (see Table 1)—that might be fit to data from one or more study sites and then transferred to a policy site. These functions will comply with the adding-up condition only if all coefficients save the coefficient on are zero.

Following the example of Johnston *et al.* (2005), Alvarez *et al.* (2016) also used a semi-log functional form in a meta-analysis of water quality valuation studies intended for benefit transfers in the state of Florida. As we found for the Johnston and Thommasin (2010) study, applying the Alvarez *et al.* WTP function to our two illustrative water quality improvement sequences gives benefit ratios less than one for the large improvement and greater than one for the small improvement.

Our review in this section demonstrates that compliance with Diamond’s adding-up condition is not guaranteed by the use of atheoretic estimating equations. This is true even if the estimating equations seem reasonable from a statistical perspective and include among the regressors the key variables expected to influence WTP, namely the size of the quality change being valued, the baseline quality level, and income. The basic lesson we take from

⁶These pivot values are useful for diagnosing why some cases in Table 1 lead to benefit “inflation” while some lead to “deflation,” but they have no broader significance. For example, if the functions were used to estimate benefits for a sequence of two improvements of unequal size, or more than two improvements of equal or unequal size, then the $\frac{1}{2}\Delta$ values would no longer be pivotal.

these examples is that analysts should examine the implications of their estimating equations in the model specification stage to ensure that the resulting WTP function will comply with the adding-up condition and to consider alternative functional forms as needed. To appropriately inform policy analysis, this lesson is critical. The examples reviewed above show that failure to satisfy adding-up can result in significant deviations in the estimated benefits of environmental quality improvements, with magnitudes that could easily alter policy recommendations.

Compliance with the adding-up condition will be guaranteed if the WTP function is derived from an assumed form of the direct or indirect utility function, as recommended by Smith *et al.* (1999) and Smith *et al.* (2006), but this “structural benefit transfer” approach is still uncommon in practice (Bergstrom and Taylor 2006). In the next section, we describe an approach that is very much in the spirit of the structural benefit transfer approach developed by Smith and colleagues, but uses a different implementation strategy.

2 Application

In this section we describe and illustrate an approach for specifying and estimating a benefit transfer function that will necessarily satisfy the adding-up condition. We use a meta-dataset that was developed for the benefit-cost analysis of the U.S. Environmental Protection Agency’s effluent guidelines for steam electric power facilities (USEPA 2013). The meta-dataset comprises 140 observations of sample average estimates of willingness-to-pay for hypothetical water quality improvements from 51 stated preference studies. Each study represented in the meta-dataset reported one or more estimates of total (use + nonuse) willingness-to-pay per household for quality changes in U.S. water bodies, including rivers, lakes, wetlands, and estuaries. A wide range of potential explanatory variables also are recorded in the meta-dataset. These include variables describing study design characteristics (e.g., choice experiment, thesis, year, voluntary, outliers, non-parametric, non-reviewed, lumpsum, median wtp), respondent attributes (e.g., nonusers, average income), resource attributes (e.g., multiple water bodies, river, swim, fish, boat), and geospatial variables (e.g., region, agricultural area, affected area/resource counties, among others). Summary statistics for the meta-data are provided in Table 2. Our main goal here is to use this dataset to illustrate our key points about the specification and estimation of benefit transfer functions, so for further detail on the development of the meta-dataset we refer the reader to the original source documents (USEPA 2015a, 2015b).

An important feature of the dataset is that all baseline water quality levels and water quality changes valued in each study are represented on a common scale: a 100-point water quality index (WQI) developed by the EPA (2015c). Of the 140 estimates in the dataset, 44 were reported in studies that used the RFF water quality ladder (Vaughn 1986) in their survey design. The remaining 96 estimates were reported in studies that used a different scale or set of water quality measures and so were translated to the 100-point water quality index based on an inferred correspondence between the descriptions of the water quality conditions and the native measurement scale in each survey (USEPA 2015b Section 3.3). The purpose of these translations onto a common scale is to achieve the “commodity consistency” that is needed for benefit transfer models (Bergstrom and Taylor 2006).

2.1 Specification of the estimating equation

The approach we use to develop a meta-regression estimating equation involves specifying a functional form for the marginal willingness-to-pay function—i.e., the Marshallian inverse demand curve—which can then be used to derive a total WTP function. In the application below, we contrast the results based on our recommended approach to an alternative estimating equation not constrained to satisfy the adding-up condition. We will refer to our recommended approach as the “structural model” and the alternative approach as the “nonstructural model.”

The nonstructural model, which is similar to models estimated in previous meta-analysis studies by Johnston *et al.* (2005), Van Houtven *et al.* (2007), and USEPA (2015a), specifies the expected value of WTP as an exponential function of a linear combination of explanatory variables,

$$E[WTP_i] = \exp(\beta_H H_i + \beta_Y \ln Y_i + \beta_Q \ln Q_{0i} + \beta_\Delta \ln \Delta_i), \quad (8)$$

where WTP_i is the average or median stated (total, not marginal) willingness to pay for observation i , H_i is a column vector containing a constant plus factors associated with the source study for observation i that are believed to influence stated WTP and β_H is a conformable row vector of parameters, Y_i is average household income for the sample, Q_{0i} is the baseline water quality level, and $\Delta_i = Q_{1i} - Q_{0i}$ is the water quality change associated with observation i . β_H , β_Y , β_Q , and β_Δ are parameters to be estimated by meta-regression. Income, baseline quality, and the quality change are entered as natural logs, so this function has a Cobb-Douglas form. The estimating equation in (8) is similar to the trans-log model used by Johnston *et al.* (2005), reviewed in section 1 above and summarized by equation (4), and so will not in general satisfy the adding-up condition for the same basic reason: it implies that WTP is a nonlinear function of the difference in water quality levels, rather than a linear function of the difference in (possibly a nonlinear transformation of) the initial and final water quality levels.

We can ensure that the WTP function will comply with the adding-up condition by following a three-step procedure. First, we specify a Marshallian inverse demand curve for environmental quality that includes income and the baseline quality level as arguments; second, we derive a compatible indirect utility function; and third, we derive from the indirect utility function the associated expenditure function. The difference in the expenditure function evaluated at the initial and final quality levels gives a total WTP function, which can then be used as the meta-regression estimating equation. This procedure will guarantee that the WTP function will satisfy the adding-up condition along the quality dimension and account for the income effect.

Note that our strategy differs from the approach developed by Smith *et al.* (2002), which involves first specifying a direct or indirect utility function and then deriving the associated Marshallian demand and willingness-to-pay functions. The parameters of the model can be calibrated using data on observed behaviors and the derived demand functions. Our strategy also differs from the approach developed by Larson (1991), building on the work of

Hausman (1981), which involves first specifying a demand function for a complementary market good then integrating the implied partial differential equation and invoking weak complementarity to derive an expenditure function that can be used value changes in the quality of the complementary good. So our approach represents a third option for selecting a function to recover information about people's preferences for non-market amenities.

To implement this approach, we used the following form for the Marshallian inverse demand function for water quality:

$$wtp_i = \exp(\beta_H H_i + \beta_Y \ln Y_i + \beta_Q Q_i), \quad (9)$$

where wtp_i is marginal willingness-to-pay, H_i is a vector of demand shifters including resource characteristics and design features of the primary study, Y_i is the average income of the survey respondents, and Q_i is the water quality index level for observation i .⁷

Next we want to derive an indirect utility function, $V(\cdot)$, that is consistent with our assumed form for the marginal willingness-to-pay function. To this end, we assume that $V_Q =$

$e^{\alpha + \beta_Q Q}$, where $\alpha = \beta_H H + \varepsilon$, and $V_Y = e^{-\beta_Y \ln(Y)}$. This gives $V = \frac{1}{\beta_Q} e^{\alpha + \beta_Q Q} + K_1$ and

$V = \frac{1}{1 - \beta_Y} e^{(1 - \beta_Y) \ln(Y)} + K_2$, and so we find that

$$V = \frac{1}{\beta_Q} e^{\alpha + \beta_Q Q} + \frac{1}{1 - \beta_Y} e^{(1 - \beta_Y) \ln(Y)} + K, \quad (10)$$

where the K 's are constants of integration.⁸ We can confirm this result by taking the derivatives of (10) with respect to Q and Y and dividing these, which will return our assumed demand function in (9).

Before proceeding further, we note that the prices of complementary market goods, such as outdoor recreation trips, do not appear explicitly in equation (10). The role of prices could be represented by specifying the constant of integration, K , as a function of prices and possibly other arguments, analogous to the strategy of Larson (1992) and Eom and Larson (2006) for specifying the role of environmental quality in the expenditure function derived by integrating the demand curve for a complementary market good. In the absence of relevant data on prices, we must assume that the joint distribution of prices and the measured control variables among the study cases is sufficiently similar to that among the policy cases to which the benefit transfer function will be applied to allow treating K as a constant that can be transferred without adjustment. We will return to this issue in section 4.

⁷Higher order Q terms also could be added to allow a more flexible shape for the demand curve, which would accommodate a non-concave WTP function. We estimated models with both Q and Q^2 terms, but these did not significantly improve the fit over models that excluded Q^2 , so throughout this paper we discuss only models with first-order Q terms for brevity.

⁸Note that this result implies that water quality and market goods and services are additively separable, which follows from our assumption that Q and Y enter the demand function in (9) separately. If an interaction between water quality and income were included in the demand function, then the indirectly utility function would not be additively separable.

Now that we know the form of the indirect utility function, we can derive the minimum expenditure function, denoted in what follows as $Y_e(Q)$, which indicates the level of expenditures on market goods and services required to achieve a reference utility level given an exogenous level of environmental quality, Q . Holding utility constant at $V_0 \equiv V(Y_0, Q_0)$, we can write

$$\frac{1}{\beta_Q} e^{\alpha + \beta_Q Q_0} + \frac{1}{1 - \beta_Y} e^{(1 - \beta_Y) \ln(Y_0)} = \frac{1}{\beta_Q} e^{\alpha + \beta_Q Q} + \frac{1}{1 - \beta_Y} e^{(1 - \beta_Y) \ln(Y_e(Q))}, \quad (11)$$

which can be solved explicitly for the minimum expenditure:

$$Y_e(Q) = \left[(1 - \beta_Y) \left(\frac{1}{\beta_Q} e^{\alpha + \beta_Q Q_0} - \frac{1}{\beta_Q} e^{\alpha + \beta_Q Q} + \frac{1}{1 - \beta_Y} Y_0^{1 - \beta_Y} \right) \right]^{\frac{1}{1 - \beta_Y}}. \quad (12)$$

The willingness-to-pay for an improvement in quality from Q_0 to Q_1 is the difference in the minimum expenditure required to reach the reference utility at the initial and final quality levels:

$$WTP(Q_0, Q_1, Y_0) = Y_e(Q_0) - Y_e(Q_1) = Y_0 - Y_e(Q_1). \quad (13)$$

Equation (13) is a total willingness-to-pay function that is guaranteed to satisfy the adding-up condition along the Q dimension while accounting for the income effect. This is the function we used as the estimating equation in our meta-regression, and this is a benefit transfer function that an analyst could use in applied policy work for valuing proposed water quality improvements.

2.2 Model selection and parameter estimation

We began by estimating both the nonstructural and structural models including the same set of regressors used by USEPA (2015a). The full specifications contain 25 and 24 parameters, respectively, and the dataset includes 140 observations from 51 studies. The studies are assumed to be independent, but we do not assume that multiple observations drawn from a single study are independent, so there are somewhere between 51 and 140 independent observations, or between 2 and 6 independent observations per parameter. With so few observations per parameter, we have some fear that the models based on the full specifications may suffer from over-fitting and therefore have substantially lower out-of-sample predictive power than indicated by their nominal measures of fit (e.g., Breiman 1992).

To address this possibility, we used backward step-wise regression and leave-one-out cross validation to select variables for inclusion in more parsimonious versions of each model.⁹ This approach selects the model that minimizes the quadratic loss from predictive errors, i.e.,

$$\hat{\beta}^* = \operatorname{argmin} \left\{ \frac{1}{N} \sum_{i=1}^N [y_i - \hat{y}_i(\hat{\beta}_{-i})]^2 \right\}, \quad (14)$$

where $\hat{y}_i(\hat{\beta}_{-i})$ is the predicted value of y_i based on parameters fit to all data excluding observation i (Hastie *et al.* 2009 p 241–249). The intuition for this approach follows from the tradeoff between bias and variance (Breiman 1992). Beginning with a null model—e.g., including only a constant term in a standard linear regression—out-of-sample predictive performance typically will initially increase as regressors drawn from a set of candidate explanatory variables are added to the model. But as more regressors are added to the model, the variance of the model predictions eventually will become so large that the mean squared error of the out-of-sample predictions will increase even as the mean squared error of the in-sample predictions and the bias of the out-of-sample predictions continue to decrease. Minimizing out-of-sample predictive errors is a natural objective for meta-regression models intended to be used for benefit transfers, which by definition involve out-of-sample predictions.

To estimate the parameters of the candidate model specifications we used weighted nonlinear least squares,¹⁰ where each observation was weighted by the reciprocal of the number of observations drawn from its parent study.¹¹ This approach gives each study rather than each observation equal weight in the regression (e.g., Mrozek and Taylor 2002, Van Houtven *et al.* 2007). To measure the fit of the models, we report the squared correlation coefficients, r^2 , between the weighted observed and predicted values for each model for both in-sample and out-of-sample predictions (Haessel 1978). In all cases, we report cluster-robust standard errors (Cameron and Miller 2015) and clustered-bootstrapped standard errors (Ren *et al.* 2010). It is well known that nominal standard error estimates will be biased low when data mining procedures such as step-wise regression are used because the formulas do not account for the degrees of freedom used up in the variable selection process (Ye 1998). We note this shortcoming but set it to one side; developing improved variance estimates is a larger task that would take us too far afield from the main theme of the paper.¹²

⁹Backward step-wise regression begins by including all candidate explanatory variables in the model, then iteratively drops the variable with the lowest t -statistic and repeats the process until the model contains only a constant term. We select the model from those considered along the backward step-wise path that achieves the highest out-of-sample predictive power according to the leave-one-out cross validation criterion in equation (14). The procedure is path-dependent and does not consider all possible models, so is not guaranteed to identify the globally optimal model. This approach is similar in spirit to that of Auffhammer and Carson (2008), who conducted a specification search using the mean squared forecasting error as one selection criterion to develop a model to forecast CO₂ emissions from China.

¹⁰In an earlier version of this paper we estimated the parameters of the nonstructural model by regressing $\ln WTP_i$ on H_i , $\ln Y_i$, $\ln Q_i$, and $\ln \beta_i$ using (weighted) linear least-squares. We thank an anonymous reviewer for pointing us to the paper by Santos Silva and Tenreiro (2006), which shows that such an estimation approach will produce biased coefficient estimates in the presence of heteroscedasticity. The non-linear least-squares estimator does not suffer from this deficiency.

¹¹When using weighted least squares, the leave-one-out cross-validation criterion in equation (14) must be modified by pre-multiplying the term $[y_i - \hat{y}_i(\hat{\beta}_{-i})]^2$ by a weight, w_i , equal to the reciprocal of the number of observations drawn from the same study as observation i . For comparison, we also estimated all models using OLS, in which case equation (14) applies without modification. Those results were qualitatively similar and so are excluded for brevity.

¹²To correct for the over-optimism of the nominal standard errors, it is possible to estimate standard errors by bootstrapping the data many times and re-running the entire model selection algorithm on each bootstrap sample (Hastie *et al.* 2009). The sampling distributions estimated in this way would account for the uncertainty associated with selecting the parsimonious model specification plus the sampling uncertainty conditional on the selected specification. Because the models were estimated using non-linear least

2.3 Results

Results for the full and parsimonious specifications of the structural and nonstructural models are shown in Table 3 and Table 4, respectively. The tables show that a majority of the variables included in the models are statistically significant at the 5% level according to the cluster-robust standard errors. However, the bootstrapped confidence intervals are substantially larger than the cluster-robust standard errors, so by the bootstrap measures far fewer variables are statistically significant. For data sets of small to modest size such as this one, we generally view bootstrapped statistics as more credible because they do not rely on asymptotic assumptions or parametric assumptions about the error terms (Efron 1979, Efron 2003, Horowitz 2003). It is not clear to us why the bootstrapped confidence intervals are larger than the cluster-robust standard errors in this case, so we report both measures for comparison and we flag this divergence for closer examination in future research.

Measures of fit for all models are shown in Table 5. Our motivation for estimating the parsimonious models was to try to improve predictive performance by excluding those explanatory variables that reduce the precision more than they increase the accuracy of the predictions. Table 5 shows that the out-of-sample measures of fit for the parsimonious models are larger than those for their corresponding full models. Figure 1 shows the in-sample and out-of-sample predictive fit curves for the structural and nonstructural models. The in-sample fit curves increase monotonically as more variables are included, as they must, but the out-of-sample fit curves reach a maximum before all variables are included. The selected parsimonious models correspond to the maximum points on the test fit curves. The measures of statistical fit indicate that the correlation between the out-of-sample predicted and observed values is higher for the nonstructural model than the structural model. This should not be surprising considering that the nonstructural model can take advantage of one extra free parameter when being fit to the data: the water quality change is included on the right-hand side of the nonstructural estimating equation but is excluded from the structural estimating equation. This reflects a tradeoff between improved statistical fit that can be achieved by allowing additional model flexibility on the one hand, and consistency with theoretical restrictions that might require reduced model flexibility on the other.

For the structural model, if the coefficient on Q is equal to zero this would imply a flat inverse demand curve—i.e., marginal WTP for water quality improvements would not depend on the level of water quality. The estimated coefficients on Q are negative in both versions of the structural model, indicating a downward sloping inverse demand curve. The estimated magnitudes of the coefficient on Q vary by a factor of nearly two across the two versions of the structural model, which indicates a fair degree of model uncertainty. Figure 2 shows the estimated marginal WTP curves over the entire domain of the water quality index for the full and parsimonious versions of the structural model. When creating these curves, all variables in H were set at their (study-level) mean values in the sample.¹³ The dotted red lines are the corresponding 5th, 50th, and 95th percentiles of bootstrapped marginal

squares, it was too computationally cumbersome to bootstrap the entire model selection procedure for this study. We are investigating more computationally efficient estimation methods that might allow us to implement the bootstrap procedure encompassing the entire model selection algorithm.

willingness to pay predictions at the mean values of H . The estimated demand curves in Figure 2 suggest that, at the means of the explanatory variables, marginal WTP declines from between \$6 and \$8 per index point at $Q = 0$ to around \$2 per index point at $Q = 100$. For comparison, Van Houtven *et al.* (2007) estimated average willingness to pay by users of \$5.6–\$5.8 per point using a linear function and \$3.2–\$3.7 per point using a log-linear function in an earlier meta-analysis study.¹⁴

3 Hypothetical policy examples

To demonstrate the practical implications of the alternative benefit transfer functions estimated in the previous section, we conducted two sets of illustrative benefit calculations. These exercises were designed to explore differences across the benefit transfer functions that might arise in real-world benefit-cost analyses. First, we applied the models to two sequential water quality improvements directly analogous to those we used in section 1.2 to demonstrate the potential deviations from the adding-up condition in previous non-market valuation studies. Specifically, we examined sequential improvements from 25 to 51 and 51 to 70 and then 50 to 51 and 51 to 52 on the 100-point water quality index. The results of these calculations are shown in Table 6. By construction, the structural models always comply with the adding-up condition, so for both versions of the structural model the sequential benefit ratios are equal to one. The sequential benefit ratios for the nonstructural models are around 1.5 to 1.6 for both versions and for both policy scenarios.

Second, we applied the models to a hypothetical national water quality policy using water quality data from the regulatory impact analysis of a recently promulgated regulation under the Clean Water Act (USEPA 2009). These data represent national baseline water quality conditions at the time of the rule and include estimates of the average levels of six water quality constituents for all fresh surface water bodies in the U.S. affected by the rule: dissolved oxygen, fecal coliform, biological oxygen demand, nitrogen, phosphorus, and total suspended solids. We applied a simple transformation to these data to simulate a hypothetical water quality improvement and then used the meta-analysis benefit transfer functions estimated in section 2 to calculate and compare benefits. First, we examined a one percent improvement in the levels of all water quality constituents in all waterbodies.¹⁵ Second, we split the one percent improvement into two one-half percent improvements applied in sequence. Third, we split the one percent improvement into three one-third percent improvements applied in sequence. We abstract from any time lags between the successive water quality improvements in these examples, so in principle splitting the one percent improvement into two or three (or any number of) constituent parts should not influence the total benefits.

¹³The means of the explanatory variables were chosen for transparency and ease of interpretation for this illustration. In a real application, only one of the regional dummy variables would be set to 1, the use indicators would be set to 0 or 1 depending on the context, and the analyst may choose to set the some or all of the methodological variables in H at alternative theoretically preferred values rather than the sample means. For example, 'thesis' and 'non-reviewed' might be set to 0. Preliminary experiments with alternative settings of these study attributes suggest that they can have a large influence on the height of the curve, so it will be important to examine these alternatives more closely in future research.

¹⁴Van Houtven *et al.* used a water quality index defined on a 10-point scale, so we have divided their reported WTP estimates by 10 to make them comparable to our estimates, which are based on a 100-point scale.

¹⁵Note that the baseline water quality levels differ across waterbodies, so the absolute changes in the constituent parameters and the water quality index will also differ across waterbodies.

To calculate the benefits of the simulated water quality improvements, we followed the approach used by the EPA in its analysis of the Steam Electric Effluent Limitations Guidelines (USEPA 2015a). The benefit transfer functions were used to estimate willingness-to-pay for all households in the United States. The water quality level assigned to each household was the average water quality index, which is a weighted combination of all six water quality constituents, among all water bodies within 100 miles of the centroid of the household's census block group.¹⁶

The results of this exercise appear in Table 7. The first two columns of the table describe the water quality change. For example, the first row contains benefit estimates for a one percent increase in each water quality constituent relative to their respective baseline levels. The second and third rows contain benefit estimates for successive changes equal to one-half percent of the baseline levels, with the first change added to the baseline level and the second change added on top of the first change. Columns 3–6 contain the estimates from the four benefit transfer functions.

There are two striking features of the results displayed in Table 7. First, the nonstructural model produces far larger benefit estimates than does the structural model. This is due to a feature of the nonstructural model that was highlighted earlier: marginal WTP decreases far more slowly than linearly as the change in quality being valued shrinks towards zero. And here we are valuing water quality improvements that are much smaller than those examined in the primary studies from which the meta-data were obtained. Since both models fit the meta-data reasonably well, if the models were used to estimate benefits for water quality changes closer to the middle of the range of water quality changes represented in the meta-data, then they would produce comparable benefit estimates. The structural model does not exhibit the same dramatic out-of-sample extrapolation divergence as the nonstructural model because the meta-data indicate that marginal WTP decreases at only a modest rate over the observed range of water quality changes. As a consequence, extrapolating the structural model towards very small water quality improvements increases the predicted marginal WTP much less dramatically.

Second, the nonstructural model produces benefit estimates that severely violate the adding-up condition. The results shown in column 3 of Table 7 indicate that a one percent change (valued all at once) produces benefits of \$3,264 million in the full nonstructural model. If that same one percent change is broken into two pieces and those are valued sequentially and added together, then the nonstructural model produces \$5,304 million in total benefits (\$2,654 + \$2,650), or nearly double the estimate of \$3,264 shown in the first row. Similarly, if the change is broken into three parts, the bottom of the table shows that each will be worth roughly \$2,349 for a total of \$7,047 million. In each case, the final water quality conditions are exactly the same as the original one percent change, but the full nonstructural BT function produces benefit estimates ranging from roughly \$3 billion to \$7 billion. Importantly, the variation in these benefit estimates is not due to any real differences in

¹⁶Since the purpose of this example is to compare the benefit transfer methods, we did not re-estimate any of the household-level spatial variables used in the meta-analysis (ln ar ratio, ln ar agr, and sub frac) and instead assigned the meta-dataset study-level means to all households.

water quality outcomes, it is solely due to the functional form that has been applied. The situation is similar for the parsimonious nonstructural model. Breaking the rule into multiple parts implemented in sequence yields a substantial increase in estimated benefits.

The first two columns of numbers in the table show that the structural model does not suffer from similar anomalous behaviors when decomposing the rule into smaller increments. A one percent improvement in all water quality constituents produces benefits of \$235.7 million for the full model and \$238.8 million for the parsimonious model, whether or not the rule is broken into smaller parts. Since these functional forms satisfy the adding-up condition, they do not exhibit the divergent total benefit estimates that the nonstructural models produce.

4 Discussion and conclusions

The main goal of this paper was to highlight the potential role of structural assumptions when specifying meta-regression estimating equations intended to be used for benefit transfers. We showed that traditional atheoretic, or nonstructural, approaches may produce benefit transfer functions that fail to satisfy the adding-up condition. Our review of several previous studies showed that in some cases the quantitative departures from adding-up can be very large. In our judgment, severe failures to comply with the adding-up condition would render a benefit transfer function unsuitable for applied policy evaluation work. Use of such a function could lead to implausibly large estimates of willingness-to-pay for very small environmental quality changes, would give divergent estimates of WTP for a change in environmental quality depending on how the change was decomposed into smaller parts, and could lead to intransitive or cyclical policy recommendations. Consistency with the adding-up condition can be guaranteed by specifying a structural meta-regression estimating equation that is derived from a set of assumptions that comply with standard rational choice theory. The specific strategy we used in this paper was to first specify a marginal willingness-to-pay function for environmental quality, including the quality or quantity level but not the change in quality or quantity on the right-hand-side with other potential demand shifters, and then deriving the associated indirect utility, minimum expenditure, and total willingness-to-pay functions.

Our study raises several important questions that we have not addressed here but should be subject to further research. Previous studies that have used a structural benefit transfer approach have specified either the indirect utility function or a demand function for a complementary market good and derived the willingness-to-pay function from there. In contrast, we began by specifying the marginal WTP function for environmental quality. So one area for further investigation would involve assessing the relative advantages and disadvantages of these alternative approaches. This comparison might be influenced by how much and what kind of structure we want to impose on people's preferences. For example, one constraint we might *not* want to impose on the marginal willingness-to-pay function is monotonicity. We can imagine a setting where marginal values are initially low (incremental improvements in highly degraded waters may have little value), then high (incremental improvements in modestly degraded waters may bring those waters back across important recreational use thresholds, such as "fishability" or "swimmability," and so may have

disproportionately high values), then low again (because eventually diminishing marginal returns will set in, e.g., improving clarity from 20 ft to 21 ft might be much less valuable than from 3 ft to 4 ft). This would imply an initially increasing then decreasing marginal willingness-to-pay curve. In this case, we would not want to require that the total WTP function be everywhere concave. However, as long as the marginal WTP function is uniquely defined in $\$-Q$ space, then the derived total WTP function will comply with the adding-up condition. So one potential advantage of our approach is the ease of allowing greater flexibility in the shape of the marginal WTP function than if the analyst started by specifying the indirect utility function itself.

Also recall that we ignored the prices of complementary goods in our benefit transfer function. What are the implications of this omission and how might it be addressed in future research? The conceptual importance of this issue has to do with the distinction between use and nonuse values. Use values may comprise a substantial fraction of the total value represented by the primary WTP estimates. If so, then the prices of complementary market goods should appear in the indirect utility function. If the omitted prices are correlated with other included variables, then we will have biased estimates of the associated coefficients. And if the distribution of the unobserved prices among policy cases differs substantially from that among the study cases, then the application of the estimated benefit transfer function could produce large transfer errors. A possible way to account for prices would be to extract from the primary studies, or develop using extraneous information, a direct or proxy measure of the travel costs that a representative respondent would face to access the affected water bodies and their potential substitutes in the original surveys. This might be relatively straightforward in cases where there is little variation in travel costs among respondents and affected water bodies (e.g., a single water body far outside of an urban center is affected, and only residents in the urban center were surveyed). But in many cases the survey respondents and the affected water bodies may be distributed across space in a more or less clumpy pattern. This would complicate the calculation of any single representative access price to associate with the summary WTP value(s) reported in the primary studies.

As emphasized by Heberlein *et al.* (2005) and Haab *et al.* (2013), tests of validity are most useful when they can help to diagnose the causes of any failures of those tests and potentially lead to further research on strategies for avoiding or correcting such outcomes. So what are the potential causes for the meta-data to be inconsistent with the adding-up condition? One obvious possibility is that at least some of the underlying stated preference-based estimates are contaminated by hypothetical bias. But this is not the only possible explanation. Another possibility is a noisy mapping between the water quality measures used in the primary studies onto the 100-point water quality index (Boyd and Krupnick 2013 p 18). This conjecture is analogous to the suggestion discussed in section 1 for why stated preference results might fail an adding-up test, except in that case the hypothesized cause was a mismatch between the water quality measures implicitly used by the survey respondents relative to that intended by the researchers. This possibility highlights the importance (and difficulty) of ensuring commodity consistency among the value estimates included in a meta-analysis.

Finally, our study also raises a set of questions relating to detecting and responding to adding-up violations in primary non-market valuation data. Is it possible to devise one or more formal tests for compliance with the adding-up condition or other theoretical consistency conditions that follow from rational choice theory? One or more formal statistical tests for such violations could be informative, but a purely statistical test would be incomplete. We also would need criteria for judging whether the magnitude of the observed violations of theoretical consistency are economically or substantively significant. A related question is, what are the implications of imposing theoretical consistency through the use of a structural estimating equation when meta-analyzing value estimates from studies whose own raw data or estimating equations themselves may not be consistent with such restrictions? We do not have a complete answer to this question, but we can offer one relevant observation. Even if a primary study used an estimating equation that failed to comply with the adding-up condition, the model predictions still could provide reliable estimates of willingness-to-pay—we would think especially near the center of the mass of observational data—for the same reasons that good predictive models do not always correspond exactly to good explanatory models (Shmueli 2010).

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Figure 1.

In-sample and out-of-sample prediction fit curves based on backward step-wise regression: a) structural model, and b) nonstructural model. Full models correspond to right-most points on blue curves, where in-sample predictive fit is maximized. Parsimonious models correspond to maximum points of red curves, where out-of-sample predictive fit is maximized.

Figure 2. Estimated water quality demand curves for the structural model: a) full specification, b) parsimonious specification.

Table 1

Violations of the adding-up condition in a selection of previous non-market water quality valuation studies.

Study	Benefit transfer function	$\frac{[2.5, 5.1] + [5.1, 7.0]}{[2.5, 7.0]}$	$\frac{[5.0, 5.1] + [5.1, 5.2]}{[5.0, 5.2]}$	$\frac{1}{2}\Delta$ pivot point
Carson and Mitchell (1993)	$WTP = e^{0.834_{24.2} 0.819 (Q_1^{0.959} - Q_0^{0.959})}$	0.999	0.952	NA
Johnston <i>et al.</i> (2005)	$\ln WTP = -0.129Q + 0.2274 \ln + Z$	1.47	1.70	13.7
	$\ln WTP = -0.124Q + 0.2095 + Z$	1.09	1.95	2.60
Van Houtven <i>et al.</i> (2007)	$\ln WTP = 0.113Q + 0.2212 + Z$	1.68	1.98	9.34
	$\ln WTP = 0.091Q + 0.6245 \ln + Z$	1.77	1.58	-14.4
Johnston and Thommasin (2010)	$\ln WTP = -0.1085Q + 0.914 + Z$	0.246	1.82	0.717
Johnston and Wainger (2015)	$WTP = \alpha Q + \beta + Z$	--	--	--
	$WTP = \alpha + \beta Q + \theta^2 + Z$	--	--	--
Alvarez <i>et al.</i> (2016)	$\ln WTP = -0.249Q + 0.201 + Z$	0.993	1.94	2.25

Table 2

Summary statistics for water quality stated preference valuation meta-data. All summary statistics calculated using un-weighted observations.

Variable	Mean	St. dev.	Min	Max	Description
WTP	102.73	83.74	2.84	404.19	Reported estimate of willingness-to-pay per year for specified water quality change
choiceexp	0.11	0.31	0	1	Study used choice experiment survey design
thesis	0.11	0.32	0	1	Study was PhD thesis
lnyear	2.21	0.93	0	3.43	$\text{Log}(\text{year} - \min(\text{year}) + 1)$, where year is publication year of study
volunt	0.09	0.28	0	1	Payment vehicle described as voluntary
outtrim	0.19	0.4	0	1	Outlier bids excluded from estimation in original study
nonpar	0.43	0.5	0	1	WTP estimated using nonparametric method
nonrev	0.24	0.43	0	1	Study non published in peer-reviewed journal
nonann	0.19	0.39	0	1	Hypothetical payments not annual
northeast	0.07	0.26	0	1	Study conducted in northeast region of US
central	0.36	0.48	0	1	Study conducted in central (midwest or mountain plains) region of US
south	0.16	0.37	0	1	Study conducted in southeast or southwest regions of US
nonusers	0.09	0.28	0	1	All survey respondents were nonusers
multitype	0.08	0.27	0	1	Study included multiple water body types
river	0.69	0.47	0	1	Studied system includes rivers
lncounty	-1.13	2.61	-8.48	6.65	$\text{Log}(\text{sampled area} / \text{area of all counties that intersect resource})$
lnag	-1.43	0.9	-4.26	-0.08	$\text{Log}(\text{affected shoreline} / \text{area of all counties that intersect resource})$
swim	0.26	0.44	0	1	Changes in swimming use emphasized in survey
fish	0.06	0.23	0	1	Changes in game fishing emphasized in survey
boat	0.11	0.32	0	1	Changes in boating uses emphasized in survey
sametype	0.19	0.29	0	1	Proportion of waterbodies of same type affected by change
medWTP	0.07	0.26	0	1	WTP reported was median
lnincome	10.75	0.17	10.44	11.27	Log of median US income in year of data collection [2007\$]
lnbase	3.59	0.67	1.61	4.38	Log of baseline WQI
lnchange	2.91	0.6	0.92	4.05	Log of WQI change

Table 3

Structural model estimation results.

Variable	Full model			Parsimonious model		
	β	se_{CR}	se_{BS}	β	se_{CR}	se_{BS}
constant	-5.2	5.0	11	-3.3	4.5	13
choiceexp	0.93	0.22 *	0.72	0.81	0.19 *	0.81
thesis	1.0	0.30 *	0.65	0.95	0.30 *	1.0
lnyear	-0.30	0.11 *	0.056 *	-0.26	0.11 *	0.37
volut	-1.0	0.13 *	0.54	-0.96	0.12 *	1.5
outtrim	-0.34	0.23	0.13 *	-0.41	0.22	0.67
nonpar	-0.58	0.14 *	0.22 *	-0.56	0.12 *	0.45
nonrev	-0.82	0.26 *	0.26 *	-0.71	0.24 *	0.78
nonann	0.83	0.18 *	0.56	0.81	0.19 *	0.41
northeast	-0.42	0.29	1.1	-0.38	0.23	0.83
central	0.075	0.14	0.31			
south	0.97	0.18 *	0.51	0.93	0.17 *	0.56
nonusers	-0.84	0.20 *	0.45	-0.77	0.19 *	0.46
multitype	0.044	0.21	0.33			
river	-0.91	0.25 *	0.28 *	-0.86	0.22 *	0.53
lncounty	-0.13	0.031 *	0.16	-0.11	0.022 *	0.081
lnag	-0.55	0.095 *	0.15 *	-0.53	0.10 *	0.26 *
swim	0.30	0.12 *	0.34	0.32	0.11 *	0.33
fish	-0.025	0.22	0.64			
boat	-0.69	0.25 *	1.0	-0.63	0.26 *	0.61
same type	-0.25	0.29	0.48			
medWTP	-0.95	0.62	0.47 *	-0.76	0.56	1.8
lnincome	0.74	0.46	1.0	0.55	0.39	1.2
Q	-0.018	0.0057 *	0.019	-0.017	0.0061 *	0.013

Coefficients with t -statistics greater than 1.96 are indicated with a “*”.

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Table 4

Nonstructural model estimation results.

Variable	Full model			Parsimonious model		
	β	se_{CR}	se_{BS}	β	se_{CR}	se_{BS}
constant	4.6	3.7	14	4.9	0.68 *	1.5 *
choiceexp	0.44	0.15 *	0.69	0.41	0.16 *	0.51
thesis	0.61	0.16 *	0.78	0.75	0.11 *	0.43
lnyear	-0.32	0.095 *	0.30	-0.35	0.097 *	0.25
volunt	-0.76	0.19 *	1.2	-0.67	0.14 *	0.47
outtrim	-0.39	0.16 *	0.61	-0.41	0.12 *	0.33
nonpar	-0.43	0.11 *	0.35	-0.41	0.11 *	0.29
nonrev	-0.52	0.14 *	0.64	-0.50	0.11 *	0.38
nonann	0.59	0.17 *	0.45	0.63	0.16 *	0.36
northeast	0.34	0.27	0.82	0.53	0.21 *	0.56
central	0.51	0.17 *	0.63	0.57	0.18 *	0.38
south	1.2	0.15 *	0.64	1.3	0.15 *	0.38 *
nonusers	-0.63	0.16 *	0.22 *	-0.65	0.12 *	0.18 *
multype	-0.51	0.15 *	0.63	-0.51	0.15 *	0.48
river	-0.44	0.22 *	0.52	-0.41	0.20 *	0.40
lncounty	-0.047	0.042	0.090			
lnag	-0.37	0.10 *	0.22	-0.32	0.078 *	0.19
swim	0.13	0.099	0.29	0.15	0.078	0.18
fish	0.13	0.22	0.56			
boat	-0.53	0.27	0.62	-0.55	0.22 *	0.39
same type	0.51	0.24 *	0.91	0.62	0.16 *	0.59
medWTP	-0.30	0.35	0.65			
lnincome	0.02	0.32	1.2			
lnQ	-0.27	0.16	0.38	-0.30	0.14 *	0.26

Variable	Full model			Parsimonious model		
	β	se_{CR}	se_{BS}	β	se_{CR}	se_{BS}
ln	0.30	0.093 *	0.23	0.31	0.094 *	0.19

Coefficients with *t*-statistics greater than 1.96 are indicated with a “*”.

Table 5

In-sample and out-of-sample r^2 measures of fit for the structural and nonstructural full and parsimonious meta-regression benefit transfer models.

	<i>WTP</i>	
	In-sample	Out-of-sample
Structural		
Full	0.76	0.56
Parsimonious	0.76	0.62
Non-structural		
Full	0.81	0.57
Parsimonious	0.80	0.66

Table 6

Sequential adding-up benefit ratios. Results shown for the nonstructural model are means and bootstrapped 95 percent confidence intervals (in square brackets).

	$\frac{[2.5, 5.1] + [5.1, 7.0]}{[2.5, 7.0]}$	$\frac{[5.0, 5.1] + [5.1, 5.2]}{[5.0, 5.2]}$
Structural		
Full	1	1
Parsimonious	1	1
Nonstructural		
Full	1.49 [1.00, 2.13]	1.62 [1.16, 2.06]
Parsimonious	1.47 [1.07, 2.07]	1.61 [1.22, 2.00]

Table 7
Illustrative sequential benefit estimates [millions of \$ per year] for a hypothetical national water quality policy.

Baseline	Increase	Structural		Nonstructural	
		Full	Pars.	Full	Pars.
Q_0	$.01 Q_0$	235.7	238.8	3,264	3,162
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Q_0	$\frac{.01}{2} Q_0$	118.1	119.7	2,654	2,559
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$\left(1 + \frac{.01}{2}\right) Q_0$	$\frac{.01}{2} Q_0$	117.6	119.1	2,650	2,555
Sum:	$.01 Q_0$	235.7	238.8	5,304	5,114
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Q_0	$\frac{.01}{3} Q_0$	78.8	79.8	2,351	2,261
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$\left(1 + \frac{.01}{3}\right) Q_0$	$\frac{.01}{3} Q_0$	78.6	79.6	2,349	2,259
<hr/>					
$\left(1 + \frac{.02}{3}\right) Q_0$	$\frac{.01}{3} Q_0$	78.3	79.4	2,347	2,257
Sum:	$.01 Q_0$	235.7	238.8	7,047	6,777