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Valuing Environmental Health Risks: From Preference Calibration to Estimation♣

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ABSTRACT

'Preference calibration' has been proposed as an approach for putting the 'fit' back into 'benefits transfer' by integrating summary measures of benefits from the literature within a specific utility function to calibrate parameters of a benefits function. What if the analyst can access complete micro data sets and macro point estimates – how does one consistently use this wealth of information? This paper draws on advances in micro-econometrics to propose a method of moments approach to estimate parameters of benefits function using multiple data sources on values for changes in environmental health risks. In addition to statistical efficiency, bias reduction and parameter identification, a generalized method of moments approach avoids the challenge of specifying a joint likelihood function in combined estimation of this type. As a 'proof of concept' of our methodology, we present two case studies – a simple single equation, single parameter estimation using a meta-data set on values for acute morbidity, and a three equation, three parameter example using three different unequal sized samples of labor supply, hedonic wages, and contingent valuation data on values for mortality risk changes.

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I. INTRODUCTION

Benefits of reduced environmental health risks are key components of environmental policy design and evaluation in the U.S. Policy analysts charged with the task of assessing the benefits of proposed policies typically rely on 'benefits transfer' – that is, they adapt and transfer benefit estimates (e.g. value of statistical life, or willingness to pay) derived from one set of individuals' choices to a different context (Desvouges et al., 1998). Benefits transfer is considered to be a cost-effective basis for using what has been established in the peer reviewed literature, thereby avoiding the need for primary research. Although it saves 'evaluation resources', it has also been criticized in many circumstances as an approach that lacks a well-defined theoretical foundation.

Recently, we have suggested a new strategy for benefits transfer, requiring the literature based benefits estimates be defined as a specific economic concept (e.g. a Marshallian consumer surplus) and interpreted within a specific preference function. This process establishes the theoretical conditions linking the value estimate from the literature to the variables specified to enter the preference function and the parameters relating each variable to utility. Therefore, in addition to maintaining some of the resource efficiency features of benefits transfer, the logic imposes conditions for theoretical consistency (Smith et al., 2002a; Smith et al., 2002b; Pattanayak et al., forthcoming). For example, the estimates of the benefits attributed to a policy will be bounded by the ability to pay and accommodate substitution effects. In addition, preference calibration requires the analysts to completely disclose analytic assumptions, leading to more transparent policy assessments. Most recently, we illustrated how this logic can be applied to calibrating benefits function for reductions in mortality risks (Smith et al., 2003).

In this paper, we consider conditions where multiple forms of data are available, and we move from calibration to estimation of preference parameters for evaluation of environmental policies that impact health risks. The primary distinction between the calibration and estimation logic is the access to multiple sources of benefit information in the latter. That is, as opposed to a few point estimates such as average willingness to pay, average income, and average risk from one or two studies (in the calibration case), we propose to combine single or sets of micro data on willingness to pay, mortality risks, wages, and health-related behaviors with macro or aggregate data on the same variables (e.g. as reported in meta-analyses or census). Compared to calibration with a few point estimates, which has in practice allowed preference parameters to be 'exactly identified', this extra information becomes the source of 'over-identification.' In other words, we can systematically use all this data to 'estimate' parameters of a generalized benefits function by ensuring all the data fit within a unifying theoretical structure. Moreover, calibrated parameters are by construction sensitive to the specific point estimates of the benefits applied, posing a choice problem when you have more than one set of starting values (see Smith et al. [2002] for an example of the income variable and corresponding parameter in their water quality example). By introducing estimation uncertainty in the form of error terms (be that attributed to method, investigator, or data), we develop a systematic method for using all the data.

As proposed, the methodology is therefore a form of 'structural' meta-analysis because we impose a theoretical structure on benefits estimates from other studies, treating these as data points for meta-regressions. That is, in this paper we are proposing a variation of typical meta-analysis for two reasons. First, we believe it is necessary to tie the meta-regressions to utility theory, a process that will result in a specification that is not reduced form. As we argue in Smith and Pattanayak (2002), such structural meta-analysis goes beyond simply imposing theoretical consistency by allowing the policy analyst to

- synthesize the seemingly disparate quantitative literature,
- test meta-hypotheses when different studies have investigated different elements of the same commodity (e.g. different amounts of mortality risks), and
- generate a benefits transfer function or a prediction formula.

Second, as described below, we envision not being limited in estimation to meta-data exclusively, but combining it with primary or micro data in the spirit of complementary samples (Angrist and Krueger, 1992; Imbens and Lancaster, 1994).

The reason for employing two or more samples is not purely because of the 'statistical efficiency' of using all the information and exploiting the correlation in error across multiple equations. As numerous applications of complementary or two-sample estimation have shown (Angrist and Krueger, 1992; Arellano and Meghir, 1992), one data set may not have all the relevant variables or the relevant variables may be measured with a lot of error. In such a situation, instead of looking for good instruments, it might be more appropriate to look for good data in another sample from different survey of different people (Lusardi, 1996). Thus, identification of parameters has also been the basis for using multiple data sets.[1]

Our proposal also ties to the small but growing literature on jointly estimating revealed preference (RP) and stated preference (SP) data on environmental benefits (Cameron, 1992; Adamowicz et al., 1994; Kling, 1997). Similar to our goals, the reconciliation of multiple, overlapping measures of benefits to accomplish 'convergent' and 'construct' validity and the treatment of contingent valuation and travel cost data as 'complementary' has been the overarching goal of this body of work (Loomis, 1997). This literature also shares many motivations with the complementary samples literature, including:

[1] Imbens and Lancaster (1994) link this idea of combining two data sets, particularly micro and macro data sets, to the endogenous stratification, missing variables, and bayesian econometrics literature in addition to research on estimation using two-samples.

- improving statistical efficiency by exploiting correlation of two data sets, restricting parameters to represent same underlying preference structure, and externally 'adding' observations for small data sets,
- reducing bias by imposing theoretical restrictions and by including data on revealed preferences to balance the hypothetical nature of stated preferences, and
- identifying parameters of variables that are collinear or have little variation in any one of the data sets (e.g. scale parameter in discrete choice models).

There are at least two important ways in which our proposal is differs from the literature on combining revealed and stated preference data.[2] First, as Smith (forthcoming) discusses, the combined estimation methodology requires two complete sets of data, whereas our proposed approach requires "small scale *and complementary* data sources that are designed to search individual preferences in regions not observed with ordinary market choices". The power of the complementary samples logic is that we can work with two or more incomplete data sets at different levels of aggregation to fill in all the relevant information.[3] Second, we follow the complementary samples literature in using generalized method of moments (GMM) estimators for our preference parameters. Almost all of the joint estimation literature has relied on maximum

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[2] Cameron (1992) originally applied this approach to environmental valuation by combining CV and travel cost data to estimate recreation benefits. Around the same time similar work was being conducted in the field of transportation economics. For example, Ben-Akiva and Morikawa (1990) combined survey data on actual (past) and on future (stated) transportation mode choice and jointly estimated a random utility model. Other than the fact that one choice was based on actual behavior and the other on predicted behavior, the choice framework was essentially identical in the two contexts. Therefore a common preference structure and choice model were used to analyze the pooled data. When appropriately scaled to account for the different variances of the error terms in the SP and RP data, the preference parameter coefficients were found not to be significantly different. Although the SP data contained more random noise, combining the data improved the accuracy of the parameter estimates. Louviere (1996) summarizes the results of several similar studies and concludes that their findings are generally consistent with those of Ben-Akiva and Morikawa (1990).

[3] Our approach also parallels to recent developments in public economics and empirical industrial organizations. In both cases, a composite of micro and aggregate data is used to estimate the parameters of a common preference function. For example, Sieg et al. [2003] estimate hedonic price functions based on individual housing sales, derive price indexes at a community level and then use these price indexes as data along with aggregate data to estimate preferences. Berry et al. [1998] use micro data to estimate consumer preferences for automobiles based on their characteristics and then aggregate data to estimate unobserved product specific characteristics. This strategy is comparable to the complementary sample logic. In this case, the aggregation of predicted micro responses has a predictable relationship to the observed aggregate shares of purchases for each product. Differences between the estimated and observed shares provide can be interpreted as product specific unobserved heterogeneity parameters.

likelihood estimation, which requires the unambiguous specification of utility (preference) and error for each value and method. Closed form representations of multivariate probability distributions do not always exist and are rarely easy to specify. In addition to not having to specify the likelihood function, GMM presents a unifying framework for econometric estimation and a computationally convenient estimation strategy (Greene, 2003; Johnson and Di Nardo, 1996).

II. ANALYTICAL FRAMEWORK

The basic logic underlying our proposal is to treat information about individual choices involving environmental resources as sample information, be it samples of individual responses, pre-existing estimates of specific models, economic concepts like consumer surplus, or aggregate data. The central organizing principle is to use a single behavioral model, which is drawn from an underlying utility function, to describe how each type of response is linked to the parameters of the model. If there are two or more independent samples with individual behavior and different data, then there will be an advantage to joint estimation. These advantages exist only if the information relates to the same (or closely linked) choices and there are overlapping variables that can be causally linked to these choices.

To demonstrate this logic, we consider an example comprising of three possible sets of information derived from a budget constrained model of consumer choice – a demand for an observable good, a consumer surplus for use of the good, and a Marshallian virtual price. If equation (1) defines an indirect utility function with p the price of the good of interest, $\overline{p}$ a vector of prices for all other goods, m, income, q the quasi fixed good and β is a vector of parameters describing preferences, then equations (2) through (4) define the three measures we assume are observed.

$$\mathrm{V} = \mathrm{V}(\mathrm{p}, \overline{\mathrm{p}}, \mathrm{m}, \mathrm{q}, \beta) \tag{1}$$

$$x = -\frac{V_p}{V_m} \tag{2}$$

$$CS = \int_{p0}^{pc} \left(-V_p / V_m\right) dp \tag{3}$$

$$\mathrm{r_q} = \frac{\mathrm{V_q}}{\mathrm{V_m}} \tag{4}$$

p_c and p_0 correspond to the choke price (i.e. p_c satisfies $-\left(V_p\left(p_c, \overline{p}, m, z, \beta\right) / V_m\left(p_c, \overline{p}, m, z, \beta\right)\right) = 0$) and p_0 the baseline price so that equation (3) defines the Marshallian consumer surplus for access. We assume that r_q is some other basis for observing the virtual price. It could be through a hedonic model or, if we define it as an incremental approximation of value, through a contingent valuation study. What is important is that the three equations–(2), (3), and (4)--define relationships between measures of choice outcomes, variables describing an individual's circumstances, and

parameters of a common preference function. Different samples might lead to observations of the various outcome measures and our goal is to consistently link these so that we can estimate the common set of preference parameters.

Applying the generalized method of moments (GMM) logic, we would re-write equations (2) through (4) in a general format in (5) through (7) and assume the equalities hold except for the errors, $\varepsilon_1, \varepsilon_2, \text{and}\, \varepsilon_3$.

$$y_1 - g_1(z_1, \beta) = x + (V_p / V_m) = \varepsilon_1 \tag{5}$$

$$y_2 - g_2(z_2, \beta) = CS - \int_{p_0}^{p_c} (-V_p / V_m) dp = \varepsilon_2 \tag{6}$$

$$y_3 - g_3(z_3, \beta) = r_q - (V_q / V_m) = \varepsilon_3 \tag{7}$$

If all the instruments (*z*'s) are exogenous, then we can define a method of moments estimator from these equations by stacking them, including enough equations to match the number of parameters to be estimated in the β vector.

Preference calibration has one observation per equation. Estimation has multiple observations per equation, although not necessarily the same number of observations. If the moment conditions can be solved for the parameters (i.e., they are invertible), then this is one way of estimating the β's. Generalized method of moments deal with cases where we wish to (a) reconcile the estimates of β across moment conditions and/or (b) deal with endogeneity, typically using instruments for the variables correlated with the errors hypothesized to be added to each moment condition.

To explain how this process would work, we begin with the assumption of equal sample sizes and use the subscript *i* to indicate observations; *n* is the number of observations; k is the number of equations; and *Z* is the set of instruments. Each moment $\overline{m}_k(\beta)$ then can be written with endogeneity as (with $\bar{z}$ including z_1, z_2, and z_3):

$$\bar{\varepsilon}_k(\bar{z}_i, \hat{\beta}) = y_{ki} - g_k(\bar{z}_i, \hat{\beta}) \qquad i = 1, \ldots, n \tag{8}$$

$$\overline{m}_k(\beta) = \frac{1}{n} \sum Z_i \, \varepsilon_{ki} \tag{9}$$

Stacking across moments we have:

$$\overline{m}_k(\beta) = \frac{1}{n} Z' \varepsilon(z, \beta) \tag{10}$$

GMM minimizes a weighted distance function (*d*) in terms of $\overline{m}_k(\beta)$ as given in equation (11).

$$d = \frac{1}{n} \varepsilon'(z, \beta) Z \left(\frac{Z' \sum Z}{n} \right)^{-1} \frac{1}{n} Z' \varepsilon(z, \beta) \tag{11}$$

The weighting function, ((Z′ΣZ) / n), is defined in terms of the errors for each moment condition as in equation (12).

$$\frac{1}{n}Z'\sum Z = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} Z_i\, Z_j'\mathrm{Cov}\big(y_i - g(z_i,\beta)\big)\big(y_j - g(z_j\beta)\big) \tag{12}$$

Here is where the independence of samples arises. If observations are independent within and across samples, equation (12) reduces to the variance weighted sum of the instruments' moment matrix because the 'off-diagonal' elements would be zero. Moreover, if we consider a case where instruments are not needed, then the weights are simply given in equation (13), a diagonal matrix with the variance for each moment (three in our example).

$$\frac{1}{n}\sum = \frac{1}{b}\begin{bmatrix} J_1^2 & & 0 \\ 0 & J_2^2 & \\ & & J_3^2 \end{bmatrix} \tag{13}$$

This implies that *d* can be written as the sum of three terms. It is weighted nonlinear least squares, estimated with restrictions because of the common parameters. If the errors are correlated across equations, it would be restricted nonlinear seemingly unrelated regressions.

At this point we can simply (as Angrist and Krueger [1992] suggest) use the individual sample sizes to weight the estimates. So, *d* reduces to *d** as the objective function.

$$d^* = \frac{1}{n_1}\sum_{i=1}^{n_1}\frac{1}{\sigma_1^2}\big(y_{1i} - g_1(z_{1i},\beta)\big)^2 + \frac{1}{n_2}\sum_{i=1}^{n_2}\frac{1}{\sigma_2^2}\big(y_{2i} - g_2(z_{2i},\beta)\big)^2 + \frac{1}{n_3}\sum_{i=1}^{n_3}\frac{1}{\sigma_3^2}\big(y_{3i} - g_3(z_{3i},\beta)\big)^2 \tag{14}$$

Following conventional practices, the σ_e^2's are computed in two stages by using the residuals for the parameter estimates derived from an unweighted objective function, recognizing that the parameters in the first stage of the estimation are consistent. The optimal weights are the inverse of the variance of the moment condition, so as to give least weight to the data that is measured with the least precision or most noise. If equation (4) for example represents a WTP function, the β_{GMM}, estimated as described, can then be plugged back into equation (4) to generate a generalized benefits function that has three desirable properties:

- maintains consistency with utility theory,
- synthesizes available micro and macro data, and
- provides a platform for benefits transfer.

Three features of this problem should be noted. First, the *y*'s and *z*'s need not be micro data. Some could be aggregate information, provided these can be consistently related to the model as described in detail in Imbens and Lancaster (1994). Second, the independence of samples greatly simplifies estimation – we do not have to deal with the covariance terms that would arise with

dependence and the issues related to unequal sample sizes. Third, the sample sizes could be different. For example, Smith et al. (1997) use focus group samples to estimate rank logit functions to characterize individuals' perceptions of beach quality. It should be possible, in principle at least, to include these convenience samples as complementary samples to larger micro data or aggregate data so that we can evaluate (a) if the two data sets imply consistent behaviors, and (b) capture specific features of behaviors or preferences not observed in the micro or aggregate data set. What is required is that the two data sets (micro and focus groups) provide a common set of variables, reflecting the same measure of behaviors.

To summarize, we can move from preference calibration to estimation in four steps. First, identify micro and macro data on benefits of changes in environmental health risks. Second, specify a utility function that is consistent with the available benefits. Third, derive the benefit measures from the utility function and therefore specify the moment conditions. Fourth, estimate the moment conditions, employing the relevant econometric methods including selection of instruments and weights as necessary.

To data, we are familiar with two previous examples of applying this approach to environmental valuation— visibility changes in national parks (Smith and Pattanayak, 2002) and oil spills impacts on recreational beach use (Smith, forthcoming). While both applications illustrate the strategy by working with limited data and simplifying analytical assumptions, they do not necessarily present generalizable benefits transfer function for policy analysis.

Smith and Pattanayak (2002) consider values for visibility changes by combining contingent value data described in Brookshire et al. (1982) with hedonic rents reported in Beron et al. (2001). Both studies consider approximately the same environmental service – air quality for recreation and aesthetic uses as measured by 'miles of visibility'. Because the Beron et al (2001) sample in many orders of magnitude larger than the CV sample, Smith and Pattanayak (2002) draw ten random samples of sizes equal to the Brookshire et al. (1982) sample. Starting with a modified CES indirect utility function, they derive marginal rent and willingness to pay functions as two moment equations in two unknown common preference parameters. These are estimated using data from the complementary samples, including income and visibility as independent variables. The estimation results are stable across the ten hedonic samples, with one of the two preference parameters being statistically significant.

In the other application of this logic, Smith (forthcoming) considers oil spills in Western California recreational beaches. He combines contingent valuation data discussed in Carson et al (1996) and travel cost data collected as part of Public Area Recreation Visitors Survey (Leeworthy and Wiley, 1993). As in the previous case, three contingent valuation data sets of sizes equal to the travel costs data are drawn by random sampling and by matching on two recreation data characteristics (type of beach use and travel). Starting with a linear recreational visit demand function, a corresponding indirect utility and WTP function are derived. The visit demand and WTP equations become the two moment conditions for estimating four parameters, including the

income parameter that is common to both moments and an environmental quality parameter only identified by the recreation equation. The results are stable across the three CV samples and the primary statistical gain lies in the ability to identify the environment quality parameter.

III. METHOD OF MOMENT APPLICATIONS

We present two cases of applying the method of moments approach to environmental health risks, reflecting different degrees of complexity in estimating preference parameters for benefits transfer. The first case study, which is the simpler of the two, addresses valuation of acute morbidity using a single meta-data and represents an example of 'structural' meta-analysis (as compared to reduced form meta-regressions). The second more complex case considers valuation of mortality risk changes using three different samples – two micro data sets and one macro or meta data set.

Case I: Valuing Changes in Acute Morbidity

Van Houtven et al. (2003) present the utility theory underlying WTP for acute morbidity and derive a value function from a specified preference structure that is QALY based. This derivation is synthesized in Appendix A. The specific form of the resulting WTP function is as follows:

$$\text{WTP} = Y - Y\left(\frac{1-\Delta q L_1{}^{\beta}}{1-\Delta q L_2{}^{\beta}}\right)^{1/\alpha} \tag{15}$$

where Y is annual income, q is a health index for acute condition, L_1, and L_2 are fractions of a year spent with the acute condition, Δq is equal to 1 – q, and α and β are the preference parameters.

The estimation of the parameters α and β relies on collecting sufficient WTP estimates in the literature that can be linked to values for Δq, Y, L_1, and L_2. As shown in Van Houtven et al. (2003a), it is possible to *calibrate* the two preference parameters using information from just two morbidity valuation studies. However, our goal here is to fully utilize the information available in the much larger number of WTP estimates for avoided acute effects in the current literature. Introducing estimation uncertainty and rewriting equation (15) as a moment condition, we have the following moment equation for estimation:

$$\overline{m}_1(z,\alpha,\beta) = E\left[\text{WTP} - Y + Y\left(\frac{1-\Delta q L_1{}^{\beta}}{1-\Delta q L_2{}^{\beta}}\right)^{1/\alpha}\right] = 0 \tag{16}$$

To identify studies and construct the meta-analysis dataset for this estimation, first we conducted an extensive review of the literature, acquired and reviewed studies (see Van Houtven et al., 2003b for details). We began by selecting the 53 observations included in the Johnson et al. (1997) study. These values were taken from five CV studies conducted in the United States in the

late 1970s and 1980s. The studies were predominantly conducted for cardio-respiratory health effects associated with air pollution. We then supplemented these data with 165 additional values taken from 11 other studies. These additional studies were, for the most part, conducted after 1990, and they include research conducted both in the United States and in other countries.

The final sample for this case study constitute WTP values if

- they were estimated for well-defined acute health effects,
- they were estimated using stated preference methods,
- the severity of the acute health effect could be expressed as and converted to a Quality of Well-Being (QWB) score, and
- the change in duration or frequency of the acute effect could be quantified in terms of discrete days and/or episodes.

For the 218 selected values, Table 1 summarizes the key variables used in the analysis. WTP, the dependent variable, represents individuals' WTP to avoid or to reduce the duration or frequency of a specific acute condition over the course of a year. All WTP estimates were converted to 2000 dollars using the consumer price index (CPI) and, if they were originally measured in a foreign currency, we first converted the estimates to dollars using the purchasing power parity (PPP) index (Pattanayak et al., 2001). Most of the selected studies estimate and report average WTP values. If only median WTP values were reported, we included these estimates in WTP.

Following the approach used by Johnson et al. (1997), we characterized the change in acute health outcomes associated with each WTP value in two main dimensions. First, we used the QWB index to characterize the severity of the acute health effect. The QWB index characterizes health outcomes in four dimensions—symptoms, mobility, social activity, and physical activity—each of which can be scored separately. Using the health effect descriptions from the valuation studies and following the approach by Johnson et al. (1997), we assigned each health effect to a defined level for all four dimensions. We then used the premeasured QWB weights (Kaplan et al., 1996) to assign a numerical score to each level.

Second, we created variables to capture the changes in the duration or frequency of the health effect. In most cases, the variables L_1, and L_2 are based on the number of days over the course of a year (before and after the change), that one experiences a given condition, such as shortness of breath, nausea, or headache. In a relatively small number of cases (N = 17), the variables are based on the number of acute events, such as asthma, angina, or allergy attacks. The INCOME variable represents the average income of the sample used to estimate WTP. All income estimates were converted to 2000 dollars using the same approach as was used for the WTP estimates. The SAMPLESIZE variable represents the number of respondents used to estimate each WTP estimate.

Finally, we estimate equation (16) in STATA using weighted nonlinear least squares regression. We use weighted regression to account for the fact that the 318 WTP values were estimated using different sample sizes (see Table 1 for summary of SAMPESIZE) and that those based on larger

sample sizes provide relatively more information. The regression weights, therefore, correspond to the size of the underlying sample for each WTP estimate.

The results are summarized in Table 2. Both of the coefficient estimates have a positive sign, as expected, and both are statistically significant at a 0.01 level.

Applying these parameter estimates to equation (15) in effect defines a benefit transfer function for avoided cases of acute illness. What is unique about this transfer function is that it is explicitly linked to the assumed preference structure described by equation (A.1). With this function it is possible to estimate WTP for any number of combinations of Δq, Y, L_1, and L_2.

Table 3 illustrates how this structural, meta-analytic function can be used for benefit transfer, and presents an example of what we would call 'structural benefits transfer'. It reports WTP estimates based on the function for values of Δq ranging between 0.2 and 0.5, values of Y between $25,000 and $50,000 and duration changes between 1 and 20 days. The resulting WTP estimates range from $15 to avoid 1 day of a relatively minor acute condition (with income of $25,000) to almost $720 for avoiding 20 days of very severe illness (e.g., requiring hospitalization) with $50,000.

Case II: Valuing Changes in Mortality Risks

Smith et al (2003) show how data from labor supply, hedonic wages, and contingent valuation studies can be integrated within a unifying utility structure to derive a WTP function for changes in mortality risks. Appendix B summarizes the set up for this case study, particularly the identification of the relevant data, specification of a utility function, and derivation of estimating equations. To summarize this derivation, we begin with the specification of a semi-log labor supply equation (equation [17]) and derive 'value of statistical life' (equation [18]) and 'willingness to pay' (equation [19]).

$$\ln(h) = \alpha + \beta r + \mu m \tag{17}$$

$$VSL = \frac{1}{(1-p)\beta} \tag{18}$$

$$WTP = \frac{1}{\mu}\ln\left[1 + \frac{\mu}{\beta} \bullet (p_0 - p_1) \bullet e^{(\alpha+\beta r+\mu m)}\right] \tag{19}$$

where h is the annual labor supply, r is the hourly wage rate, m is the annual non-wage income, VSL is the value of statistical life, p is the probability of death on the job, WTP is the willingness to pay, and p_0 and p_1 are baseline and policy induced mortality risks (probabilities), described as part of the CV study. α,β, and μ are the preference parameters.

Following the logic presented in Section 2 (equations [2] – [7]), that is, introducing estimation errors into each equation, restating them as moment conditions, and rearranging terms for implementation convenience, we get the following three moments.

$$\overline{m}_1(z,\alpha,\beta,\mu) \quad = E\,[\ln(h) - \alpha - \beta r - \mu m] = 0 \tag{20}$$

$$\overline{m}_2(z,\alpha,\beta,\mu) \quad = E\left[VSL - \frac{1}{(1-p)\beta}\right] = 0 \tag{21}$$

$$\overline{m}_3(z,\alpha,\beta,\mu) = \quad E\left[e^{\mu WTP} - 1 - \frac{\mu}{\beta} \bullet (p_0 - p_1) \bullet e^{\alpha+\beta r+\mu m}\right] = 0 \tag{22}$$

Method of moments allows us to estimate three preference parameters - α,β, and μ - from these three equations. These parameters can be used in equation (22) to generate a generalized benefits function, and they can be combined with location or policy specific data on wage, non-wage income, and risk probabilities for structural benefits transfer. Estimating the parameters of this system of equations requires data on labor supply, VSL, and WTP, in addition to the other independent variables described above.

As discussed previously, it is not necessary for this information to come from a single data set because we can consider multiple complementary data sets to identify this system of parameters. In this case we consider estimation of preference parameters using three data sets – a contingent valuation of changes in mortality risks (Gerking et al., 1988), a meta-analysis of hedonic wage values (Mrozek and Taylor, 2002), and labor supply (Health and Retirement Survey – HRS – Wave 5). The data on annual hours worked, hourly wage rates, and non-wage 'capital' income for equation (20) come from Wave 5 of the HRS (see Smith et al. [2002] for uses of this data). This sample has 125 observations. The data on VSL and death probabilities for equation (21) come from a meta-analysis of hedonic wage studies of mortality risks (Mrozek and Taylor, 2002). There are 33 studies in this meta-data. Finally, data on WTP, mortality risk change, wage and non-wage income for equation (22) are drawn from a CV survey conducted by Gerking et al. (1988). This survey includes 462 observations. The values for all monetary variables are put in constant dollars (1983) and the descriptive statistics for all variables are presented in Table 4.

The objective function for these three moments is the weighted sum of the squared moments, where the weights are the inverse of the variance or the precision with which each moment is estimated. In combining unequal samples, we also consider the relative sample sizes by weighting

each moment by its relative sample size.[4] In order to obtain these weights we take the usual two stage procedure. That is, we first minimize the objective function to obtain consistent estimates of α,β, and μ, then use these parameter estimates to compute the squared error for each observation and each moment, and then calculate the variance as the average sum of square errors. These variances then provide the weights for the second stage minimization of the weighted sum of squared moments.

The results of the method of moments estimation are reported in Table 5. While stage one proceeded as planned, our model did not converge in the second stage. The results presented in Table 5 thus reflect the outcome of minimizing the 'equal weights' distance function and not an 'optimal' weights distance function, and therefore should be treated as preliminary.[5] Note, while the size and sign of the estimated parameters is not expected to change with the optimal weights estimation, their statistical significance will.

The general model statistics suggest that the overall model is highly significant. We find that the statistically significant wage parameter (β) equals 0.00058. The positive sign and small size is consistent with the estimates in the literature and provided by our calibration model. The constant in the labor supply equation (α) equals 7.45. The non-wage parameter is, however, insignificant. This is not surprising, given that the quality of the non-wage variable. Both HRS and Gerking et al. (1988) data include imprecise estimates of non-wage. Instruments and optimal weights might solve this problem.

Table 3 from Case I illustrates how we could, in principle at least, use these estimated parameters in equation (22) to make out of sample predictions. Given that the logic has already been described in Case I and that the parameter estimates are imprecise, this exercise would be somewhat premature at this early stage in the development of the methodology.

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[4] For example, in equation (21) we use a weight equal to 33 / (33 + 125 + 462). Arellano and Meghir (1992) provide additional details on weighting by sample sizes. These equations are estimated in LIMDEP, which unfortunately cannot utilize unequal complementary samples. We create multiples of the smaller data sets (e.g. Mrozek and Taylor) so that this multiple data set is equal in observations to the largest data (Gerking et al.). To compensate for the multiplicity of the smaller data sets, we down-weight the corresponding equations by the inverse of the multiple. For example, we created 14 multiples of the VSL meta-data and therefore pre-multiplied equation (21) by $\sqrt{(1/14)}$. This procedure is certainly not a requirement of the method. It was done to be able to work with LIMDEP to implement method of moments with unequal samples.

[5] One problem with the estimation of the second stage is the form of equation (22), which includes a parameter, μ, in the left hand side. The first stage estimates of this parameter result in small residuals and a significantly larger weight in the 'optimal weight' second stage minimization of the distance function. By itself this equation is highly non-linear and unstable, and by assigning it the largest weight in the system, we get a system that is non-linear and unstable.

IV. CONCLUSION

This paper develops a methodology for moving from preference calibration (*per se*) to preference estimation for benefits transfer, using the method of moments estimation approach. The primary motivation for this methodology is to synthesize disparate estimates of the value for changes in environmental health risks within a unifying utility structure. The 'preference calibration' research showed how aggregate or point estimates could be integrated using utility theory. In this paper, we draw on recent advances in the micro econometric literature to show how multiple observations and data sets can be combined, be they from the same sample, similar samples or micro and macro samples,. Consequently, as suggested in the research on combining revealed and stated preference, such an approach offers several econometric benefits, including statistical efficiency, bias reduction, and parameter identification of parameters. The additional gain is that data do not have to come from the same sample or even two samples of the same scale (i.e., it is possible to combine large micro data set with a macro data set of completely different size). Additionally, GMM does not require the specification of joint likelihood function – the primary strategy taken in the literature on combining SP and RP data. Moreover, we show that these methods can be applied using accessible econometric software such as STATA and LIMDEP.

We provide a 'proof of concept' of our methodology with two case studies on valuing environmental health risks –acute morbidity and changes in mortality risks. The first case represents a simple case with the estimation of a single equation to recover a single parameter from a meta-data set of values for acute morbidity. The second case requires combining three disparate data sets on labor supply, hedonic wages, and contingent valuation to estimate three equations for three parameters. The GMM approach achieves the econometric gains described above. For example, it is impossible to estimate the parameters of the WTP function in equation (19) by itself because the parameters are not identified. Joint estimation using GMM (see Table 5) shows the benefit of using data from multiple samples. Moreover, unlike preference calibration, which produced point estimates for each parameter, estimation provides parameter distributions and confidence intervals. Collectively these show how extra information (*e.g.* more observations, more samples, aggregate data) can be utilized consistently.

What has been described in this paper, is a preliminary assessment of the logic of combining multiple data sets on non-market values. We have not exploited the full range of benefits of using method of moments for combining data sets. For example, we have not used instruments in the estimation. The challenge, of course, would be to identify the appropriate set of instruments (*e.g.,* education or other forms of human capital) and to use them systematically. Additionally, we have used a convenient fix for the problem of unequal samples to be able to work with LIMDEP. We have already begun work in other optimizing software such as MATLAB to develop a general solution to the problem. Finally, these caveats imply that our estimated parameters and the benefits function they populate are not yet ready for benefits transfer. While these qualifications suggest the need for more research, we hope that the methodology and case studies presented in

this paper offer a road map and innovative ideas for valuation of environmental health risks using multiple data sources.

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Table 1. Summary Statistics for Variables Used in Case I – Acute Morbidity

Variables	N	Mean	sd	min	max
WTP	218	$287.21	$329.01	$2.70	$2,927.69
1-QWB (Δq)	218	0.380	0.112	0.170	0.572
DURATION BEFORE(L1)	218	0.041	0.066	0.003	0.247
DURATION AFTER (L2)	218	0.007	0.024	0.000	0.127
INCOME (Y)	218	$47,335	$13,711	$21,891	$88,020
SAMPLE SIZE	218	308.17	150.28	20	832

Table 2. Method of Moments Estimation of Parameters for Valuing Acute Morbidity (Weighted Nonlinear Least Squares)

	Dependent Variable: WTP	
	Coef. Estimate	t-stat
α	12.538	7.11
β	0.379	10.47
R^2	0.47	

Table 3. WTP for Avoided Acute Illness: Estimates Based on Structural Meta-Analytic WTP Function

Annual Income (Y)	Health Status Change (Δq)	Before Change Duration (L1))	After Change Duration (L2))	Annual WTP Estimate
$25,000	0.2	20	0	$137
$25,000	0.2	10	0	$104
$25,000	0.2	5	0	$80
$25,000	0.2	1	0	$43
$25,000	0.2	20	15	$15
$25,000	0.2	20	10	$33
$25,000	0.2	20	5	$57
$25,000	0.5	20	0	$360
$25,000	0.5	10	0	$271
$25,000	0.5	5	0	$205
$25,000	0.5	1	0	$109
$25,000	0.5	20	15	$41
$25,000	0.5	20	10	$90
$25,000	0.5	20	5	$156
$50,000	0.2	20	0	$274
$50,000	0.2	10	0	$209
$50,000	0.2	5	0	$160
$50,000	0.2	1	0	$86
$50,000	0.2	20	15	$29
$50,000	0.2	20	10	$65
$50,000	0.2	20	5	$114
$50,000	0.5	20	0	$720
$50,000	0.5	10	0	$542
$50,000	0.5	5	0	$411
$50,000	0.5	1	0	$218
$50,000	0.5	20	15	$81
$50,000	0.5	20	10	$179
$50,000	0.5	20	5	$312

Table 4. Summary Statistics for Variables Used in Case II – Mortality

Variables	N	mean	stdev	min	max
Hours Worked	125	7.40	0.57	3.91	8.05
Hourly Wage ($)	125	9.64	5.23	4.25	44.00
Non-Wage Income ($)	125	1712.05	4210.11	0.00	27822.00
VSL (millions of $)	33	6.02	4.53	0.24	16.55
Probability of death	33	1.95E-04	2.14E-04	2.90E-05	1.10E-03
WTP ($)	462	1099	1868	0	6001
Hourly Wage ($)	462	13.53	11.40	1.92	153.85
Non-Wage Income ($)	462	15483	4075	2500	49080
Baseline death probability	462	1.51E-03	1.30E-03	6.25E-04	6.25E-03
Lowered death probability	462	8.82E-04	1.30E-03	-1.40E-11	5.63E-03

Table 5. Method of Moments Estimation of Parameters for Valuing Mortality Risk Changes

	Coefficient Estimate	Probability Value
α	7.45	0.000
β	0.58 E-03	0.000
μ	0.14 E-05	0.998
F (objective function value)	2928104	
χ^2 (3)	5856208	0.000

APPENDIX A. Derivation of Moment Equations for Valuation of Changes in Morbidity Risk

To estimate parameters of a utility function that are consistent with WTP estimates for avoiding acute illness, the first step is to specify a preference structure. To do this, we assume that acute conditions last for one year or less, and we specify the following function to represent annual utility:

$$U(Y,q,L) = Y^{\alpha}(1-L^{\beta}) + Y^{\alpha}qL^{\beta} = Y^{\alpha}(1-\Delta qL^{\beta}) \tag{A.1}$$

where Y is annual income, q is a health index for acute condition ($0<q<1$), L is a fraction of a year spent with the acute condition, and Δq is equal to $1 - q$.

According to this specification, if an individual spends the entire year with the acute condition ($L=1$), then annual utility can be written as:

$$U(Y,q,1) = Y^{\alpha}q \tag{A.2}$$

Therefore, q can be thought of as the SG or visual analog utility score corresponding to 1 year in the health state.

If, on the other hand, the individual spends the entire year in perfect health ($q=1$), then annual utility can be expressed as

$$U(Y,1,0) = Y^{\alpha} \tag{A.3}$$

Otherwise, annual utility is like a weighted average of utlity in perfect health and utility with acute illness, where the weights are $1\text{-}L^{\beta}$ and L^{β} respectively. If $\beta<1$, this implies marginal disutility is decreasing with respect to the length of acute illness.

The second step is to derive an expression for WTP that is based on this assumed preference structure. According to this utility specfication, WTP for a nonmarginal reduction in the length of acute illness (from L_1 to L_2) can be expressed as:

$$Y^{\alpha}(1-\Delta qL_1{}^{\beta}) = (Y-WTP)^{\alpha}(1-\Delta qL_2{}^{\beta}) \tag{A.4}$$

Rearranging this expression, WTP can then be expressed by the following equation:

$$WTP = Y - Y\left(\frac{1-\Delta qL_1{}^{\beta}}{1-\Delta qL_2{}^{\beta}}\right)^{1/\alpha} \tag{A.5}$$

APPENDIX B. Derivation of Moment Equations for Valuation of Changes in Mortality Risks

Assume that an individual's "hours worked" (**h**) to be a function of the wage rate (**r**) and non-wage income (**m**) as in Eq. (B.1).

$$\ln(h) = \alpha + \beta r + \mu m \tag{B.1}$$

α, β, and μ are parameters of this equation and also the eventual parameters of the preference function that we wish to calibrate. For algebraic convenience we can translate Eq. (B.1) into its exponential form and apply Roy's Identity in Eq. (B.2). Recognize that labor supply is a "bad " and therefore we need to insert a negative sign in front of it.

$$-e^{\alpha+\beta r}e^{\mu m} = -\frac{\partial V(r,m)}{\partial r}\Big/\frac{\partial V(r,m)}{\partial m} = \frac{dm}{dr} \tag{B.2}$$

To derive the indirect utility function we use the implicit function theorem to re-write Eq. (B.2) as in Eq. (B.3).

$$e^{\alpha+\beta r}dr = -e^{-\mu m}dm \tag{B.3}$$

Solving this differential equation, i.e., integrating on both sides we get equation (4), where c is the constant of integration.

$$\frac{e^{(\alpha+\beta r)}}{\beta} = \frac{e^{-\mu m}}{\mu} + c \tag{B.4}$$

As in Burtless and Hausman (1978), c is our measure of cardinal utility, which in this case is the indirect utility function (V[r, m]) we desire. By rearranging terms we get indirect utility in Eq. (B.5)

$$V(r,m) = \frac{\exp(\alpha+\beta r)}{\beta} - \frac{\exp(-\mu m)}{\mu} \tag{B.5}$$

This function can then be used in our definition for the expected utility of jobs varying in risk. Let *p* designate the probability of a fatal accident on the job. Following conventional practice (see Viscusi [1993]), we assume an individual's ex ante choice among alternative jobs treats each choice as a lottery with the state "life" (and the utility given by Eq. [B.5]) and the state "death" as the two outcomes being considered when jobs with varying risks of fatal accidents are evaluated. Death is conceptualized in advance so the utility attached to this outcome is usually assumed to be associated with bequest motives. In our case, we maintain this is captured by the second term

including the non-wage income (m).[6] Formally, these contributions are introduced through the specification of the expected utility function as given in Eq. (B.6).

$$EU = (1-p)\left(\frac{\exp(\alpha+\beta r)}{\beta} - \frac{\exp(-\mu m)}{\mu}\right) + p\left(-\frac{\exp(-\mu m)}{\mu}\right) \tag{B.6}$$

To derive the value of statistical life or the change in wages associated with a unit change in probability (dr/dp), we can totally differentiate Eq. (6) and set it equal to 0. Re-arranging terms, we get our equation for VSL. These steps are described in the equations below.

$$\begin{aligned} dEU = 0 &= \left(-\frac{\exp(\alpha+\beta r)}{\beta} + \frac{\exp(-\mu m)}{\mu} - \frac{\exp(-\mu m)}{\mu}\right)dp + \left((1-p)\frac{\exp(\alpha+\beta r)}{\beta} * \beta\right)dr \\ \Rightarrow \quad & \left((1-p)\exp(\alpha+\beta r)\right)dr = \frac{\exp(\alpha+\beta r)}{\beta}dp \\ \Rightarrow \quad & \frac{dr}{dp} = VSL = \frac{1}{(1-p)\beta} = \frac{r}{(1-p)\eta} \end{aligned} \tag{B.7}$$

where η is the labor supply elasticity with respect to wage. For the semi-log case, note that η equals βr.

To derive the WTP equation that measures non-marginal changes, we return to the expected utility function in Eq. (B.6) and introduce the concept of an option price. That is, we measure WTP as the amount of money that an individual is willing to give up and be just as well off with a lower non-wage and lower mortality risk. There is an important distinction between this WTP concept, as used in Eq. (B.8), and in the conventional logic. It is subtracted from the non-wage or exogenous income to capture the idea that it represents the amount of money that an individual can give away (presumably from exogenous income sources) to be better off (see the Appendix on "Welfare Measures for Consumer-Laborer's" in Just, Heuth, and Schmitz, 1982). This logic and derivation points to a potentially important insight that the VSL using wage income to estimate an ex ante marginal rate of substitution may not be the appropriate welfare concept. Instead, monetary measures of the value of a risk change should be expressed in terms of the *exogenous* income, *m*, that is not related to choices made with respect to the 'commodity' being valued, as was implicit in our definition in Eq. (B.5).

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[6]This formulation simplifies the final expression for the expected utility, but is not essential to the logic. The rationale for this selection follows from interpreting m as non-wage, exogenous income available to the household. When added considerations are introduced for this state they require new information to augment the preference calibration.

$$(1-p_0)\left(\frac{\exp(\alpha+\beta r)}{\beta}-\frac{\exp(-\mu m)}{\mu}\right)+p_0\left(-\frac{\exp(-\mu m)}{\mu}\right)=$$
$$(1-p_1)\left(\frac{\exp(\alpha+\beta r)}{\beta}-\frac{\exp(-\mu[m-WTP])}{\mu}\right)+p_1\left(-\frac{\exp(-\mu[m-WTP])}{\mu}\right) \tag{B.8}$$

After opening out brackets and canceling terms we get

$$\frac{\exp(-\mu m)\bullet[\exp(\mu WTP)-1]}{\mu}=\frac{\exp(\alpha+\beta m)\bullet[p_0-p_1]}{\beta}$$
$$\Rightarrow \quad \exp(\mu WTP)-1=\frac{\mu\bullet\exp(\alpha+\beta m+\mu m)\bullet[p_0-p_1]}{\beta} \tag{B.9}$$

Further simplifying and re-arranging terms, we obtain an expression for WTP as in Eq. (B.10).

$$WTP=\frac{1}{\mu}\ln\left[1+\frac{\mu}{\beta}\exp(\alpha+\beta r+\mu m)(p_0-p_1)\right] \tag{B.10}$$

Note, we could also derive WTP from the expenditure function implicit in Eq. (B.5) and solved for a change in expenditures that holds utility constant at two levels of job risks. We would start by re-writing Eq. (B.5) in terms of m. See Smith et al. (2003) for additional details.