A Meta-Analysis of Contingent Valuation Studies in Coastal and Near-Shore Marine Ecosystems

Liu, Shuang and Stern, David I.

CSIRO

23 November 2008

A Meta-Analysis of Contingent Valuation Studies in Coastal and Near-Shore Marine Ecosystems

Shuang Liu[1] and David I. Stern[2]

ABSTRACT

The ecosystem services provided by coastal and nearshore marine systems contribute significantly to human welfare. However, studies that document values of these services are widely scattered in the peer-reviewed literature. We collected 39 contingent valuation papers with 120 observations to conduct the first meta-analysis of the ecosystem service values provided by the coastal and nearshore marine systems. Our results show that over ¾ of the variation in Willingness to Pay (WTP) for coastal ecosystem services could be explained by variables in commodity, methodology, and study quality. We also used the meta-regression model to predict out-of-sample WTPs and the benefit transfer result showed that the overall median transfer error was 57%. Based on such results, one could argue that such meta-analyses can provide useful guidance regarding at least the general magnitudes of welfare effects. However, we also caution against the application of such a result in a broader context of benefit transfer as it is derived from a limited amount of data, and it may suffer from some degree of measurement error, generalization error, and publication selection error. Lastly, we discuss possible ways of minimizing these errors.

JEL CODES: Q25, Q51, Q57

KEY WORDS: Ecosystem services, valuation, meta-analysis, coastal

---

[1] Corresponding author: Division of Entomology, CSIRO, GPO Box 1700, Canberra ACT 2601, Australia; Fax: +61-2-6246-4000; E-Mail: shuang.liu@csiro.au

[2] 19/30 Watson Street, Turner ACT 2612, Australia; E-Mail: sterndavidi@yahoo.com

INTRODUCTION

Meta-analysis has been applied extensively in fields such as education and the medical sciences where applications involve studies conducted under controlled conditions with standardized experimental designs (van den Bergh et al., 1997). However, it is still used sparingly in ecosystem service valuation because of the heterogeneity of research methods in economics and a lack of standardized data reporting.

The transfer of estimates of environmental benefits from study sites to different policy locations has been heavily criticized (Spash and Vatn, 2006). Meta-analysis can provide information to allow researchers to more appropriately transfer benefit estimates despite remaining issues with the estimated benefits. Based on this potential, USEPA guidelines characterize meta-analyses as “the most rigorous benefit transfer exercises” (p. 87) (EPA, 2000). The focus of our paper is on meta-analysis rather than benefit transfer itself and so while we address the technical issues involved in accurately transferring benefits we do not address the deeper philosophical concerns regarding using valuation and cost-benefit analysis to make environmental decisions.

The purpose of this study is to 1) assess whether variation in WTP for coastal ecosystem services may be explained sufficiently by systematic variation in contextual variables to justify benefit transfer, 2) use the meta-regression model for out-of-sample benefit transfer and calculate the transfer error, and 3) discuss the sources for the transfer errors and how to minimize them in future research.

META-ANALYSIS AND FUNCTION TRANSFER

Gene V. Glass published his ground-breaking article on Meta Analysis (MA) in 1976. In that article, he laid out the fundamental rationale for the technique and defined many of the basic features of MA as it is known and used today. He also coined the term "meta-analysis", which he defined as:

> "…the statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings. It connotes a rigorous alternative to the casual, narrative discussions of research studies which typify our attempts to make sense of the rapidly expanding research literature (Glass, 1976, p3)".

In the field of environmental economics, *Meta-analysis* refers specifically to the practice of using a collection of formal and informal statistical methods to synthesize the results found in a well-defined class of empirical studies (Smith and Pattanayak, 2002). MA has three general purposes: 1) synthesize past research on a particular topic, 2) test hypotheses with respect to the effects of explanatory variables, and 3) use the meta-regression model in function transfer (Bergstrom and Taylor, 2006). Traditionally, MA has been used for the first two purposes but a more recent use is the systematic utilization of the existing value estimates from the source literature for the purpose of benefit transfer (e.g. Rosenberger and Loomis, 2000; Johnston, et al., 2005; Brander et al., 2006).

The first two meta-analyses in the field were by Walsh and colleagues on outdoor recreation benefits and by Smith and Kaoru on travel cost studies of recreation benefits in the late 1980s and early 1990s (Walsh et al., 1989; Walsh et al., 1992; Smith and Kaoru, 1990).

More recent applications of MA for similar purposes include groundwater (Boyle et al., 1994), air quality and associated health effects (Smith and Huang, 1995; Desvousges et al., 1998), endangered species (Loomis and White, 1996), air pollution and visibility (Smith and Osborne, 1996), and wetlands (Brouwer et al., 1997; Brouwer et al., 1999; Woodward and Wui, 2001).

In the context of benefit transfer, meta-analysis enables us to statistically explain the variation found across empirical studies. Once the basic model specification is complete, that is, if it includes the relevant explanatory variables in the correct functional form, then the net benefit estimate for the policy site can be estimated by inserting values of explanatory variables into the function (Walsh et al., 1992). Of course, the basic premise is the existence of an underlying valuation function.

Meta-analysis has two major conceptual advantages over other value transfer approaches such as point estimate and demand function transfers (Rosenberger and Loomis, 2000; Shrestha and Loomis, 2003):

1) Meta-analysis utilizes information from a greater number of studies, thus providing more rigorous measures of central tendency that are sensitive to the underlying distribution of the study site measures.
2) Methodological differences between different non-market valuation techniques can be controlled when calculating a unique value estimate from the meta-analysis function.

Based on this potential, USEPA guidelines characterize meta-analyses as "the most rigorous benefit transfer exercises" (p. 87) (EPA, 2000). On the other hand, many limitations of benefit transfers in general are also applicable to meta-analysis [3] and there are also some issues specific to using meta-analysis in benefit transfer (Desvousgese et al., 1998):

1) There should be sufficient original studies conducted so that statistical inferences can be made and relationships modeled.
2) A meta-analysis can only be as good as the quality of the research that is included. This includes the scientific soundness of the original research and the transparency in reporting results and summary statistics for the original data.
3) The studies included in the analysis should be similar enough in content and context that they can be combined and statistically analyzed.

In sum, the use of meta-analysis in value transfer is fairly new and very promising but it is not without its limitations. First and foremost, it depends heavily on the quality of the primary studies used. As the quality of information increases over time in the source literature, the accuracy of the resulting meta-analysis technique will likely improve.

METHOD

Data Selection

Empirical valuation data is often scattered throughout the scientific literature and is uneven in quality. We selected studies that deal *explicitly* with non-market coastal ecosystem services measured throughout the world and focused on peer-reviewed ones only because of their

[3] See Spash and Vatn (2006) for a general discussion of the problems with benefit transfer.

presumably higher quality. Our literature review yielded a total of 70 studies and most of them featured the contingent valuation (CV) technique (Wilson and Liu, 2008). Therefore, we selected this subset of studies for further analysis.

Only 39 of these studies reported benefit estimates or provided sufficient information to derive them. From these 39 studies we coded 120 observations for our meta-analysis. Several studies are responsible for multiple observations because they reported alternative results due to the use of split survey samples targeting different groups and/or testing different survey designs.[4] Care was taken not to double count benefit estimates reported by the same authors in more than one paper.

Data Coding

Based on the theory and findings in the literature, we expect that various attributes may be associated with systematic variations in WTP for coastal ecosystem services. Following Bergstrom and Taylor (2006) these attributes are categorized into those characterizing 1) commodity consistency, 2) methodology consistency, and 3) data quality consistency between study and policy sites. Commodity attributes characterize the subjects (i.e. income and density of the surveyed population), objects (e.g. ecosystem services type and land cover type), and marginal change in the valuation (type and degree of the change).

Table 1 summarizes this set of 50 independent variables. The majority are qualitative dummy variables coded as 0 or 1, where 0 means the study does not have that characteristic and 1 means that it does. One of the biggest limitations of meta-analysis is the lack of comparability

[4] We coded all value estimates reported in a single study, which exposes the dataset to the danger of selection bias as estimates from the same study were likely more similar.

across studies (Woodward and Wui, 2001). Characteristics of valuation are often reported in such a diverse manner that the best a meta-analyst can do is to use a binary variable to indicate whether an attribute is associated with each observation.

Sometimes these explanatory variables were not explicitly reported at all in the source papers because they define the context of the valuation, and therefore, were treated as constants in the original studies. As a result, external sources have to be used to extract such information. In particular, income data for the survey respondents is not reported in most cases. In these cases we used the mean GDP per capita adjusted for purchasing power parity (PPP) (Penn World Table, http://pwt.econ.upenn.edu/php_site/pwt_index.php) in the country in which the surveyed sample resides to account for people's capacity to pay. For the U.S. studies, regional income information was gathered from the US Department of Commerce's online database (http://bea.gov/regional/index.htm#state).

Survey year was adopted as a surrogate for quality of a valuation study. Another possible indicator of quality is the survey response rate, but about one quarter of our studies did not report this, and in those studies that did report it is often unclear what these response rates actually represent or which criteria may have been used to exclude responses from further analysis (Brouwer et al., 1999).

All of the WTP measures were converted to 2006 USD dollars (by using the Consumer Price Index) per household per year. We created the binary variable "*Whether primary data only"* to identify those studies that gave enough information for the conversion. 0 means external sources were used to during the conversion.

Model Construction

Meta-analyses have utilized a range of statistical models including *Ordinary Least Squares* (OLS) (e.g. Rosenberger and Loomis, 2000; Schlapfer, 2006; and Brander et al., 2006) and the *multilevel model* (e.g. Bateman and Jones, 2003; Johnston et al., 2005), leaving researchers to make *ad hoc* judgments regarding the most appropriate statistical specification for meta-models.

Our general model is:

$$f(y_i) = \alpha + \sum_j \beta_j g(x_{ji}) + \sum_k \gamma_k z_{ki} + \varepsilon_i$$

where f () and g () are the functions used to transform the dependent variable y and continuous explanatory variables x respectively. z are the qualitative explanatory variables (dummies), and ε is the error term. α, β_j, and γ_k are regression coefficients and individual observations are indexed by i.

We used OLS and a nonlinear Box-Cox procedure to estimate our model.[5] We estimated a number of OLS regressions with different functional forms to search for a model with residuals with desirable properties. These included a linear model, a model with a logarithmic dependent variable, a model where the continuous explanatory variables were in logarithms but the dependent variable was not, and a log-log model. The qualitative variables were not transformed in any of these specifications. We also tried a fairly general specification search using Box-Cox transformations for the continuous variables. This showed that the Box-Cox parameter was not significantly different from zero and, therefore, the model could be approximated by a log-log

[5] A multi-level model was considered but not adopted. This approach allows for the often unrealistic assumption of independence between estimates to be relaxed by using dummy variables for each group within each level (e.g. study sites, author, method and study). But this approach is only feasible when the data set is homogenous or there are a large number of observations available to run the model. Unfortunately, neither is the case for our dataset.

model. In order to test if omitting irrelevant variables might help reduce multi-collinearity, we then applied a stepwise regression procedure to the log-log model by stepping out variables.

Function Transfer

Following Brander et al. (2006), we predicted the WTP for each of the 120 observations by using the value transfer function estimated on the other 119 observations. Then we compared the predicted WTP to the "actual" WTP in the original study to calculate the transfer error, defined as $|(WTP_{act}-WTP_{prd}) / WTP_{act}|$.

TABLE 1 ABOUT HERE

RESULTS

Summary Statistics

The mean annual per household WTP in the sample of studies is about $766 (USD2006). The median however is $88.50 per household per year, showing that the distribution is skewed with a tail of high values. As expected, the mean WTP varies considerably depending on the coastal ecosystem services considered, the land cover, the spatial area of the study site, and the valuation method used. Table 2 presents the breakdown of WTPs by 1) ecosystem service, 2) land cover, 3) geopolitical region, and 4) CV elicitation method.

The wide range of WTP values by ecosystem service is striking though not unexpected for coastal ecosystems (Costanza et al., 1997; Costanza et al., 2007). Average annual per household willingness to pay ranges from $0.30 for provisioning of food to $3,268 for aesthetic services. It is worthwhile to notice that we only have one observation for both food and disturbance services, and the Standard Deviation (SD) of aesthetic services is quite high as well.

In terms of land cover type, saltwater wetland, marsh, or pond has the highest average WTP of \$2189 household^{-1} year^{-1}(again with a high SD), and near-shore islands and beaches have values at the lower end of the spectrum (\$37 and \$38 household^{-1} year^{-1}, respectively). Compared to a recent study (Costanza et al., 2007) where the total ecosystem service value of beaches in the State of New Jersey was estimated as \$42,147 acre^{-1} year^{-1}(USD 2004), this beach value seems low at first glance. But the value in the New Jersey study was the value of an acre of beach aggregated across all relevant households, while the value in the current study is the WTP of a single household.

Average WTP values are highest in the North America, followed by Asia, Oceania, South America, and Europe. 78% of our data points refer to North America. The geographical distribution of observations in our sample reflects the availability of valuation studies rather than the distribution of coastal and near-shore marine ecosystems.

When grouped by elicitation format, studies using contingent ranking produce the highest values, followed by those using contingent behavior (including both contingent behavior and combined CV and RP studies), and dichotomous choice. On the other end of the spectrum, iterative bidding studies have the lowest WTP values. These results are in line with the literature, as it is well known that different ways of asking preference questions yield different estimates of willingness to pay (e.g. Desvousges et al., 1987). Open-ended, payment card, and iterative bidding approaches are all believed to open the possibility of free-riding, therefore leading to an understatement of WTP (Bateman and Jones, 2003). On the other hand, WTP value estimates from a contingent ranking exercise have been recently found to be greater than those elicited through CV (Stevens et al., 2000; Bateman et al., 2006).

TABLE 2 ABOUT HERE

Meta-Regression

We estimated a number of regressions with different functional forms to see if we could find a model with residuals having desirable properties. Table 3 presents coefficients, significance level (for the continuous variables only for the sake of brevity), the results of diagnostic tests, and some statistics of the transfer errors for each model.

First, we estimated a regression where all variables enter linearly. The last variable in each group of dummies was dropped from the regression to avoid collinearity (marked with an asterisk in Table 1). The standard errors were estimated using the ROBUSTERRORS option in the RATS (Regression Analysis for Time Series) econometrics package so that the standard errors of the coefficients would take into account potential heteroskedasticity of unknown form. Income and survey year are non-significant and both even have the wrong sign. Density is significant but unexpectedly has a negative sign. Area of the study has the expected result. The residuals have very strong kurtosis (a fat-tailed distribution) though skewness is not significant. Therefore, the Jarque-Bera normality test rejects the null that the residuals are normally distributed. The Breusch-Pagan heteroskedasticity test checks the correlation between the squared residuals and the full set of explanatory variables. It strongly rejects the null of homoskedasticity. The transfer errors for this model are very large on average with a median value of 1,327%. However, because of the large standard deviation, the mean of 35,333% is only significantly different from zero at the 11% significance level.

Next, we report the results of the general specification search applying the Box-Cox transformation to the dependent variable and the continuous explanatory variables (RATS Manual, 280).[6] We estimated the models using maximum likelihood. The result showed the value of λ is not significantly different from zero, which indicates that the model is close to log-log. All the key continuous explanatory variables have positive and highly significant coefficients. The residuals are now homoskedastic but skewness and kurtosis have deteriorated. We didn't estimate transfer errors for this model as estimating the model one time took a large number of iterations and, therefore, estimating it 120 times for different data sets would be very labor intensive.

The third model we present is a log-log model where both the dependent variable and continuous independent variables are transformed into natural logarithms. The coefficients of the continuous variables have the expected sign but only that of area is significantly different from zero. Though there is no heteroskedasticity, the residuals are still highly non-normal. The median transfer error of 57.3% is similar to values found in other studies (see summary table of transfer validity tests in Rosenberger and Stanley, 2006). The mean transfer error is, however, significantly different from zero at the 3% level.

In order to see if omitting irrelevant variables might help reduce multi-collinearity, we optimized the model by retaining only those variables that were significant at a 20% level of confidence or better based on t-statistics using the STWISE procedure in RATS. The procedure started with the full vector of explanatory variables and "stepped out" non-significant variables.

---

[6] The Box-Cox transformation f(x) is given by: $f(x) = \frac{x^{\lambda} - 1}{\lambda}$ where λ is a parameter to be estimated. This function is nonlinear in the parameters and therefore λ cannot be estimated by OLS. When the dependent variable is also subject to Box-Cox transformation an explicit maximum likelihood estimation procedure is required (RATS Manual, 280).

We estimated this final model using the ROBUSTERRORS option for the standard errors of the regression coefficients. As expected, compared to the log-log model, the adjusted R-squared increases. The t-statistics also increase a little to be somewhat more significant. The residual properties are also slightly better than the full model but are still non-normal. The transfer errors are similar to those of the full log-log model and though the maximum error is somewhat greater there are fewer high values as reflected in a lower mean transfer error that is significant at the 10% level.

TABLE 3 ABOUT HERE

TABLE 4 ABOUT HERE

Table 4 lists the coefficients and significance levels of all the explanatory variables of the step-wise model. For the dummy variables, the coefficients indicate the percentage change in the dependent variable for the presence of the characteristic indicated by the dummy variable relative to the value of the dependent variable in the base case. For the continuous variables, the coefficients should be interpreted as elasticities, that is, the percentage change in the dependent variable given a small percentage change in the explanatory variable.

The R^2 for this model is 0.79. Furthermore, the signs of the significant parameters generally conform to prior theoretical and empirical expectations where these exist. In other words, as documented in more detail in the following subsections the model passes the test of "construct validity" (Spash and Vatn, 2006).

Commodity Consistency: The Subject of the Valuation

Coefficients on the *income* of survey respondents *and population density* are both positive, and the former is significant at 6% and latter only at the 16% level. The coefficient for income is 0.42, suggesting a 10% increase in income leads to roughly a 4% increase in WTP for coastal ecosystem services. This finding echoes the usual empirical result from CV studies where a positive income elasticity of WTP was found to be substantially less than one for environmental commodities (Kristrom and Riera, 1996; Carson et al., 2001; Horowitz and McConnell, 2003).

Commodity Consistency: The Object of the Valuation

Compared to the baseline service of water supply, the WTPs for *food* provision and for *spiritual* services are both significantly lower (p=0.0000 and 0.078, respectively). This corresponds with past meta-analysis where the value of provisioning service and non-use value were found to be small (Brander et al., 2006; Johnston et al., 2005). However, the first part of the result has to be interpreted with caution because there is only one observation for food services in our dataset.

Separation of direct, indirect use and non-use benefit is difficult sometimes. Brouwer et al. found only in a third of all CV studies could a single benefit flow be identified, in all other cases wetlands provided multiple benefits (1999). In order to take account of this effect we created a dummy variable of *Bundled service* to investigate whether it can explain variations in WTP. The coefficient turned out to be negative and significant at an 11.2% level, which makes intuitive sense because a package of goods should be valued less than the sum of its independently valued constituents.

The coefficient on the size of the study *area* is positive and very significant and a coefficient of 0.17 indicates that doubling of the study area size will only lead to a 17% increase in WTP, which signals decreasing returns to scale or a nonlinearity as documented in past research (Woodward and Wui, 2001; Brander et al., 2006; Barbier et al., 2008).

Compared to the baseline of *Asia* as the study location, people seemed to be more willing to pay for coastal ecosystem services in *Europe* but less so in the *Oceania* area (both significant at 5% level). The coefficient for South America is also positive and significant but given the paucity of observations (n=1), it is possible that the significance of the coefficient is entirely due to this single study and has nothing to do with a fundamental difference.

WTPs for beach, estuary, and the open ocean are lower than that of the semi-enclosed sea (baseline). Again the beach value is surprisingly low, compared to the result of our recent study (Costanza et al., 2007) where the total ecosystem service value of beach in the State of New Jersey was estimated as the highest among coastal and marine systems (other land cover valued include coastal shelf, estuary and saltwater wetland).

Commodity Consistency: Variables for Marginal Change

The default category here is a negative change in the service. For these studies the valuation is the *willingness to accept* (WTA) a deterioration in the ecosystem service in question. Compared to this baseline, lower valuations are associated with *no change, 100%, and 200% positive changes*.[7] The no change case is the WTP to maintain current ecosystem functioning, while the remaining two categories are the willingness to pay for improvements. As is found in most studies (Spash and Vatn, 2006) and is supported by theory (Stern, 1997; Amiran and Hagen, 2003), willingness to accept is systematically greater than willingness to pay. Furthermore, the

[7] Because it is impossible to compare changes over different ecosystem services studies, the changes here are relative compared to their own baseline of *status quo*. For instance, for water quality studies, a 100% water quality improvement means moving up a step along the water quality ladder. For recreation fishing studies this means 100% increase of fish population.

coefficients show that WTP is higher for 100% positive change than for 200% change, which indicates WTP is sensitive to the scope of improvement. Indeed for many environmental goods the public may have sharply declining marginal utility after a reasonable amount of it has been provided (Rollins and Lyke, 1998).

Methodology Consistency

The contingent ranking method (CR) is used as the baseline category in the regression analysis in order to avoid collinearity. The negative coefficients for the other five *elicitation formats* indicate that these formats generate lower WTP values than the baseline (all highly significant). Corresponding to previous research results, other elicitation formats produced significantly lower WTP than contingent ranking (Stevens et al., 2000; Bateman et al., 2006). Stevens et al. (2000) provide three reasons why CR and CV results may differ. 1) substitutes are often made more explicit in the ranking format and. therefore, respondents are encouraged to explore their preferences and trade-offs in greater depth, 2) the psychological process of ranking in the CR format is somewhat different than that of the CV format, 3) non-response and protest zero-bidding behavior may be less of a problem for CR because it is easier to express indifference to the choices by ranking them equally.

Among different CV elicitation formats, the results also correspond to past empirical research conclusions that WTP estimates from binary discrete choice formats tend to be higher than those from other formats (Boyle et al., 1994; Carson et al., 2001).

Interview (including both face to face and phone interview) has a negative and statistically significant coefficient ($p< 0.05$) compared to the default of mail surveys. This finding contradicts the previous empirical evidence where “warm glow” has been offered as a possible explanation why interview-based WTP might be higher. Respondents in a face-to-face CV survey may attempt to please an interviewer by agreeing to pay some amount when they would not do so otherwise (Carson et al., 2001).

However, our contradictory result may be because we pooled together face-to-face with phone interview studies. In the future they should be separated and at least one other meta-analysis shows that both face-to-face interviews and mail surveys have positive and significant coefficients in comparison to telephone surveys (Johnston et al., 2005).

The coefficient estimated for the dummy variable '*payment vehicle*' reflects, *ceteris paribus*, an almost 30% higher average WTP when the payment vehicle is an increase in tax than the baseline payment type of donation (p=.107). This result is comparable to that of Brouwer et al (1999), where the difference was about two times larger. One possible explanation is that to use taxation as a payment vehicle is expected to prompt responses which consider the benefits for society at large and not just restricted to private use only. Another way to explain it is that the unwillingness among respondents to offer large voluntary payments is due to their fear that others will ride for free.

WTP values for the majority of studies included in the analysis were based on a series of annual payments over an indefinite duration. However, a small number of studies estimate WTP for one-time payments. The variable *lumpsum* identifies studies in which payments were to occur other than on an annual basis. The positive and statistically significant parameter for lumpsum reveals sensitivity to the payment schedule. Studies that ask respondents to report an annual payment (as opposed to a one time lump-sum payment) have lower nominal WTP estimates ($p < 0.01$).

The variable of *Sub-sample* was used to investigate the influence of dropping outliers when calculating the central tendency of WTP in the CV studies. As expected, smaller WTP estimates are associated with studies that eliminate or trim outlier bids ($p<0.05$).

Variables for Study Quality

In the absence of a better proxy, *Survey Year* was adopted as an indicator for quality of the study (Johnston et al., 2005). The premise is that stated preference survey design improves over time, resulting in a reduction of survey biases that would otherwise result in an overstatement of WTP. The negative sign of the coefficient means that later studies are associated with lower WTP ($p=0.036$).

However, this variable might also reflect whether ecosystem services are growing more or less scarce over time. Unfortunately, the influence of systematic refinements in methodology over time cannot be distinguished from a scarcity-related trend in the availability of ecosystem services relative to demand (Smith and Kaoru, 1990).

Function Transfer

Figure 1 plots the observed and predicted natural log values of the dependent variable. Following Piñeiro et al. (2008), we regress the observed values of lnWTP on the values predicted by the model to test for model consistency. As can be seen the regression line deviates a little from the 1:1 relationship indicated by the 45 degree line. The regression slope is 0.91 (standard deviation 0.06) while the regression constant is 0.38 (0.30). The slope is, therefore, not significantly different from unity and the constant is not different from zero at the 5% level of significance, assuming conventional significance tests apply. These results indicate that the model is unbiased. The regression R^2 is 0.65.

Figure 2 shows the relationship between the transfer error associated with each observation and ln WTP. As shown in Table 3 the median transfer error is 57%. Clearly, the most extreme transfer errors are associated with very low WTP values. 26 out of 120 transfer errors are greater than 100% while 28 out of the 120 are less than 25%. The median transfer error for each of the quartiles of the transfer errors ordered by "actual" WTPs in ascending order is 87%, 58%, 53% and 51%, respectively. This indicates that the fit for low ecosystem service values is poor compared to medium to high values.

The larger errors might also be related to the low incidence of specific characteristics associated with these three data-points. In other words, their attributes are under-represented in our meta-database. The observation with the highest transfer error, for instance, is from a study on food provision service, for which service we only have this single data point. Indeed, if we view each empirical study included in the meta-analysis as a sample of this meta-function, then this function becomes an envelope of study site functions that relate WTP and the context variables. If some variables of the policy site are outside this envelope to start with, then one can predict a large transfer error.

Essentially, this is the type of generalization error discussed by Rosenberger and Stanley (2006). It arises when estimates from study sites are adapted to represent policy sites with very different conditions. These errors are inversely related to the degree of similarity between the study and the policy site. Rosenberger and Stanley also discussed another two general types of errors in benefit transfer: measurement and publication bias errors. Measurement error occurs when a researcher's decisions affect the accuracy of transferability, publication bias error happens when the empirical literature included in the meta-analysis is not an unbiased sample of empirical evidence. They both relate to issues in ecosystem service valuation in general and will be covered in detail in the next section.

FIGURE 1 ABOUT HERE

FIGURE 2 ABOUT HERE

DISCUSSION

Measurement Error: More than a Problem of Original Studies

Measurement error stems from the judgments and the methods used in the original study. During meta-analysis, a portion of measurement error will be ‘passed through’ if effort is not taken to minimize it (Wilson and Cohen, 2006). Put another way, the accuracy of benefit transfer is subject to the measurement of original studies. As Brookshire and Neill (1992) state: “Benefit transfers can only be as accurate as the initial benefit estimates”.

Fifteen dummy variables were used in order to maintain methodological consistency in our model and 9 of them turned out to be significant in the step-wise model. However, there are a couple of limitations in this approach: 1) any model estimated using a large number of dummies will quickly become large and complex and, therefore, the degrees of freedom and the efficiency of parameter estimates will decrease. In this case, one has to somehow reduce the number of dummy variables in a meaningful way. The combining of the face-to-face and phone interview categories is one such an attempt. 2) Critical information needed for data-coding is missing from the original studies.

This problem of incomplete information is not only restricted to methodology related variables. Brouwer et al. (1999) found in their meta-analysis research that two-thirds of their original studies contained no information about the size of the area involved. This is rather unfortunate considering that, along with other researchers (e.g. Woodward and Wui, 2001; Brander et al, 2006), we found that the size of the study area has significant explanatory power for WTP variations.

When no information is readily available from the original study, meta-analysis researchers are forced to use external sources during their data coding process. For instance, another category of information that is often not reported in papers is the socio-economic profile of the user population. In the most comprehensive benefit transfer exercise on recreational service, only 3% of the 131 included studies reported the average income for their samples, less than 1% reported the average education level, about 16% reported the gender composition, and 61% reported their sample size (Rosenberger and Stanley, 2006). Users of primary studies must then find proxies for population characteristics - Rosenberger and Loomis (2000) use U.S. Census data for the state in which each study was conducted.

When there is not even a proxy variable available an "N vs. K' dilemma is posed: should the researcher discard explanatory variables that are not common to all studies (thus preserving N – the number of observations - at the cost of K – the number of explanatory variables) or discard observations that do not include key regressors (thus preserving K at the cost of N) (Moeltner et al., 2007)? This is a difficult question and it is every researcher's judgment call.

We attempted to maintain a balance between the two. We resort to external information sources for income, population density, and the size of study area in order to preserve N. On the other hand, in order to preserve K we did not delete those variables with only one observation including food provision service, disturbance control service, or the dummy for South America. It is likely that any other idiosyncratic factors that affect a single observation may be attributed spuriously to these characteristics. In this sense, the measurement error is not only due to the original research but could also come from the meta-analysis process itself.

In addition to the use of dummy variables, another way to minimize measurement error is to control the quality of the original studies used in the meta-analysis. As is common practice, we selected peer-reviewed studies only whereas Johnston et al. (2005), for example, focused on those studies with methods "generally accepted by journal literature (p223)".[8]

Though it is possible that quality control results in a meta-model with higher explanatory power, it also may expose researchers to selection bias error.

Publication Selection Bias: How to Avoid the Inevitable?

Publication selection bias, or the 'file drawer problem', has been a major concern regarding the use of meta-analysis in economics (Stanley, 2001; Stanley, 2005). A sample of value estimates that approximates a random draw is assumed, but this assumption is unlikely to be met because meta-data are often subject to various forms of selection bias. For instance, researchers and reviewers are predisposed to treat statistically significant results more favorably and as a result they are more likely to be published. Studies that find relatively 'non-significant' effects tend to be left in the 'file drawer'.

For this reason, meta-analysts are encouraged to mitigate the selection bias by including grey literature and any unpublished reports they can find. "It is best to err on the side of inclusion," as Stanley put it (2001). Next, statistical methods can be employed to identify and/or accommodate these biases (Stanley, 2005; Hoehn, 2006).

[8] Their selection included non-peer reviewed literature as well. This paper did not adopt their approach because to decide what is "acceptable for journal literature" meant another layer of subjective judgment, which was to be avoided as much as possible.

Several recent economic meta-analyses attempted to overcome this problem by including an extra dummy variable that identifies the publication type (whether peer-reviewed or not). Woodward and Wui (2001) did not find a significant effect from publication type in explaining variation in their wetland WTP data. However, Rosenberger and Loomis (2000) showed that not only do journal publications have a smaller aggregate mean estimate than non-journal publications, but there is also greater variation in estimates across published studies.

One possible explanation is the accuracy of the reported estimates in the peer-reviewed literature may be less than ideal (Rosenberger and Stanley, 2006). This is because most journals are not interested in publishing new estimates for their own sake and the current institutional incentives are biased towards methodological and theoretical contributions (Smith and Pattanayak, 2002). In this sense, publication selection bias is more a matter of methodological innovation than statistical significance in the area of ecosystem service valuation (ESV) (Loomis and Rosenberger, 2006).

Another layer of selection bias in the ESV field is introduced by funding availability. Valuation research is costly and such costs limit the feasibility of carrying out a large number of original studies (though it also promotes benefit transfer). Decisions to fund research are linked to human awareness of the importance of ecosystem services and the magnitude of the policy decisions made in response to conflicts over resource use (Hoehn, 2006). Such decisions are certainly not random. As Woodward and Wui noticed (2001), wetlands that are considered valuable *a priori* are much more likely to be evaluated. On the other hand, our results show that *Marquee Status* was not significant in the step-wise model.

Although selection bias does not necessarily lead to errors in estimation of the valuation function, given the limitations of available data, the likelihood of such bias should be taken into account in future benefit transfer exercises. What is particularly important is to avoid measurement error and publication selection bias working in the same direction. In the next section the possible selection bias of our dataset will be discussed, and then a plan sketched for future research.

Panel Data Issues

As mentioned above, the values in our data are also not independent draws because the data has panel characteristics because some studies and authors generate multiple WTP estimates (Smith and Kaoru, 1990).

There have been two ways to deal with the issue of panel data in the literature: to use corrective procedures (Smith and Kaoru, 1990, Rosenberger and Loomis, 2000), or to statistically check and test for, and model this potential panel effect (Brouwer et al., 1999; Bateman and Jones, 2003; Johnston et al., 2005). In this study, we decided to adopt a corrective procedure by using the ROBUSTERROR option to correct the standard errors of the regression coefficients for potential heteroskedasticity. But this still does not account for common effects due to several studies or WTP estimates being produced by a single author or group of authors. Therefore, *one potential future direction* is to statistically test for these effects by using a panel data model or multi-level model. A daunting challenge of constructing a panel data model though, is to identify the possible source of these effects because sources of heterogeneity and correlation may not be based on a single dimension such as study and researcher. A multi-level model requires a much larger and/or more homogeneous dataset, which is unavailable.

CONCLUSION

In this study we collected 39 contingent valuation papers with 120 observations to conduct the first meta-analysis of the ecosystem service values provided by the coastal and nearshore marine systems. Our results show over ¾ of the variation in WTP for coastal ecosystem services could be explained by variables in commodity, methodology, and study quality. The sign and magnitude of the estimated effects of these variables is generally consistent with theoretical and prior empirical expectations.

We also used the meta-regression model to predict out-of-sample WTPs and the benefit transfer result showed that the median transfer error was 57%. These errors are similar to those of other meta-analyses. The most extreme errors were associated with the lowest WTP values in the sample. Based on such results, one could argue that such meta-analyses can provide useful guidance regarding at least the general magnitudes of welfare effects. However, we also caution against the application of such a result in a broader context of benefit transfer as it is derived from a limited amount of data, and it may suffer from some degree of measurement error, generalization error, and publication selection error.

ACKNOWLEDGEMENTS

This work was supported in part by Contract No. SR04-075, "Valuation of New Jersey's Natural Capital" from the New Jersey Department of Environmental Protection. We thank Matthew Wilson for his generous help in conducting the research.

REFERENCES

Amiran, E. Y. and Hagen, D. A. 2003. Willingness to pay and willingness to accept: How much can they differ? American Economic Review, 93(1): 458-463.

Barbier, E. B., Koch, E. W., Silliman, B. R., Hacker, S. D., Wolanski, E., Primavera, J., Granek, E. F., Polasky, S., Aswani, S., Cramer, L. A., Stoms, D. M., Kennedy, C. J., Bael, D., Kappel, C. V., Perillo, G. M. E. and Reed, D. J. 2008. Coastal ecosystem based management with nonlinear ecological functions and values. Science, 319: 321-323.

Bateman, I. J., Cole, M. A., Georgiou, S. and Hadley D. J. 2006. Comparing contingent valuation and contingent ranking: A case study considering the benefits of urban river water quality improvements. Journal of Environmental Management, 79(3): 221-231.

Bateman, I. J. and Jones, A. P. 2003. Contrasting conventional with multi-level modeling approaches to meta-analysis: Expectation consistency in UK woodland recreation values. Land Economics, 79(2): 235-258.

Bergstrom, J. C. and Taylor, L. O. 2006. Using meta-analysis for benefits transfer: Theory and practice. Ecological Economics, 60(2): 351-360.

Boyle, K. J., Poe, G. L. and Bergstrom, J. C .1994. What do we know about groundwater values - Preliminary implications from a meta-analysis of contingent-valuation studies. American Journal of Agricultural Economics, 76(5): 1055-1061.

Brander, L. M., Florax, R. J. G. M. and Vermaat, J. E. 2006. The empirics of wetland valuation: A comprehensive summary and a meta-analysis of the literature. Environmental and Resource Economics 33(2): 223-250.

Brookshire, D. S. and Neill, H. R. 1992. Benefit transfers - Conceptual and empirical issues. Water Resources Research, 28(3): 651-655.

Brouwer, R., Langford, I. H., Bateman, I., Crowards, T. C. and Turner, K. 1997. A Meta-Analysis of Wetland Contingent Valuation Studies. Norwich: CSERGE, University of East Anglia.

Brouwer, R. and Spaninks, F. A. 1999. The validity of environmental benefits transfer: Further empirical testing. Environmental and Resource Economics, 14(1): 95-117.

Carson, R. T., Flores, N. E. and Meade, N. F. 2001. Contingent valuation: Controversies and evidence. Environmental and Resource Economics, 19(2): 173-210.

Costanza, R., dArge, R., deGroot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., ONeill, R. V., Paruelo, J., Raskin, R. G, Sutton, P. and van den Belt, M. 1997. The value of the world's ecosystem services and natural capital. Nature, 387(6630): 253-260.

Costanza, R., Wilson M. A., Troy, A., Voinov, A., Liu S. and d'Agostino, J. 2007. The Value of New Jersey's Ecosystem Services and Natural Capital. New Jersey Department of Environmental Protection.

Desvousges, W. H., Johnson, F. R. and Banzhaf, H. S. 1998. Environmental Policy Analysis with Limited Information: Principles and Application of the Transfer Method. Cheltenham: Edward Elgar.

Desvousges, W. H., Smith, V. K. and Fisher, A. 1987. Option price estimates for water quality improvements: A contingent valuation study for the Monongahela river. Journal of Environmental Economics and Management, 14(3): 248-267.

EPA, U. S. 2000. Guidelines for Preparing Economic Analyses. EPA 240-R-00-003. . Washington, D.C., U.S. Environmental Protection Agency.

Glass, G. V. 1976. Primary, secondary, and meta-analysis of research. Educational Researcher, 5:

3-8.
Hoehn, J. P. 2006. Methods to address selection effects in the meta regression and transfer of ecosystem values. Ecological Economics, 60(2): 389-398.
Horowitz, J. K. and McConnell, K. E. 2003. Willingness to accept, willingness to pay and the income effect. Journal of Economic Behavior and Organization, 51(4): 537-545.
Johnston, R. J., Besedin, E. Y., Iovanna, R., Miller, C. J., Wardwell, R. F., Ranson, M.H. 2005. Systematic variation in willingness to pay for aquatic resource improvements and implications for benefit transfer: a meta-analysis. Canadian Journal of Agricultural Economics-Revue Canadienne d' Agroeconomie, 53(2-3): 221-248.
Kristrom, B. and Riera, P. 1996. Is the income elasticity of environmental improvements less than one? Environmental and Resource Economics, 7(1): 45-55.
Loomis, J. B. and Rosenberger, R. S. 2006. Reducing barriers in future benefit transfers: Needed improvements in primary study design and reporting. Ecological Economics, 60(2): 343-350.
Loomis, J. B. and White, D. S. 1996. Economic benefits of rare and endangered species: Summary and meta-analysis. Ecological Economics, 18(3): 197-206.
Moeltner, K. et al. 2007. Meta-analysis and benefit transfer for resource valuation-addressing classical challenges with Bayesian modeling. Journal of Environmental Economics and Management, 53(2): 250-269.
Piñeiro, G., Perelman, S., Guerschman, J. P. and Paruelo, J. M. 2008. How to evaluate models: Observed vs. predicted or predicted vs. observed. Ecological Modelling, 216: 316-322.
Rollins, K. and Lyke, A. 1998. The case for diminishing marginal existence values. Journal of Environmental Economics and Management, 36(3): 324-344.
Rosenberger, R. S. and Loomis, J. B. 2000. Benefit Transfer of Outdoor Recreation Use Values. USDA Forest Service.
Rosenberger, R. S. and Stanley, T. D. 2006. Measurement, generalization, and publication: Sources of error in benefit transfers and their management. Ecological Economics, 60(2): 372-378.
Schlapfer, F. 2006. Survey protocol and income effects in the contingent valuation of public goods: A meta-analysis. Ecological Economics, 57(3): 415-429.
Shrestha, R. K. and Loomis, J. B. 2003. Meta-analytic benefit transfer of outdoor recreation economic values: Testing out-of-sample convergent validity. Environmental and Resource Economics, 25(1): 79-100.
Smith, V. K. and Kaoru, Y. 1990. Signals or noise - explaining the variation in recreation benefit estimates. American Journal of Agricultural Economics, 72(2): 419-433.
Smith, V. K. and Osborne, L. L. 1996. Do contingent valuation estimates pass a "scope" test? A meta-analysis. Journal of Environmental Economics and Management, 31(3): 287-301.
Smith, V. K. and Pattanayak, S. K. 2002. Is meta-analysis a Noah's ark for non-market valuation? Environmental and Resource Economics, 22(1-2): 271-296.
Spash, C. L. and Vatn, A. 2006. Transferring environmental value estimates: Issues and alternatives. Ecological Economics, 60: 379-388.
Stanley, T. D. 2001. Wheat from chaff: Meta-analysis as quantitative literature review. Journal of Economic Perspectives, 15(3): 131-150.
Stanley, T. D. 2005. Beyond publication bias. Journal of Economic Surveys, 19(3): 309-345.
Stern, D. I. 1997. Limits to substitution and irreversibility in production and consumption: a neoclassical interpretation of ecological economics. Ecological Economics, 21: 197-215.

Stevens, T. H., Belkner, R., Dennis, D., Kittredge, D. and Willis, C. 2000. Comparison of contingent valuation and conjoint analysis in ecosystem management. Ecological Economics, 32(1): 63-74.

van den Bergh, J. C. J. M., Button, K. J. and Nijkamp, P. 1997. Meta-Analysis in Environmental Economics,. Kluwer Academic Publishers.

Walsh, R. G., Johnson D. M. and McKean, J. R. 1989. Issues in nonmarket valuation and policy application: a retrospective glance. Western Journal of Agricultural Economics, 14: 178-188.

Walsh, R. G., Johnson D. M. and McKean, J. R. 1992. Benefit transfer of outdoor recreation demand studies, 1968- 1988. Water Resources Research, 28(3): 707-713.

Wilson, M. A. and Liu, S. 2008. Evaluating the non-market value of ecosystem goods and services provided by coastal and nearshore marine system. In: M. G. Patterson and B. C. Glavovic (Editors), The Ecological Economics of the Oceans and Coasts. Edward Elgar.

Wilson, M. A. and Hoehn, J. P. 2006. Valuing environmental goods and services using benefit transfer: The state-of-the art and science. Ecological Economics, 60(2): 335-342.

Woodward, R. T. and Wui, Y. S. 2001. The economic value of wetland services: a meta-analysis. Ecological Economics, 37: 257-270.

Table 1: Explanatory variables of meta-analysis

Variable	Description	Data type
Commodity consistency **--Objects of valuation**		
(Ecosystem services)		
BUNDLED_ES	Multiple services	Binary (0 or 1)
ES_AES	Aesthetic service	Binary (0 or 1)
ES_DIS	Disturbance control	Binary (0 or 1)
ES_FOOD	Food	Binary (0 or 1)
ES_HAB	Habitat	Binary (0 or 1)
ES_REC	Recreation	Binary (0 or 1)
ES_SPR	Spiritual	Binary (0 or 1)
ES_WAS*	Water supply	Binary (0 or 1)
(Land cover)		
LC_BCH	Beach	Binary (0 or 1)
LC_CRL	Coral Reefs and atolls	Binary (0 or 1)
LC_EST	Estuary	Binary (0 or 1)
LC_FWT	Nearshore freshwater wetland	Binary (0 or 1)
LC_ILD	Nearshore Islands	Binary (0 or 1)
LC_50M	Nearshore Ocean--50m depth or 100km offshore	Binary (0 or 1)
LC_OPS	Open ocean	Binary (0 or 1)
LC_SWT	Saltwater wetland, marsh or pond	Binary (0 or 1)
LC_GRS	Seagrass beds or kelp forests	Binary (0 or 1)
LC_SMI*	Semi-enclosed seas	Binary (0 or 1)
(Geopolitical region)		
SP_OCE	Oceania	Binary (0 or 1)
SP_NA	North America	Binary (0 or 1)
SP_SA	South America	Binary (0 or 1)
SP_EU	Europe	Binary (0 or 1)

SP_AS*	Asia	Binary (0 or 1)
MARQUEE_STATUS	Whether a national park, RAMSAR site etc.	Binary (0 or 1)
URBAN	Whether an urban area	Binary (0 or 1)
STUD_AREA	Area of the study site	Continuous
--Situation of valuation		
(Type of change)		
MG_OTHER	Change in other areas	Binary (0 or 1)
MG_WATER	Change in water resource management	Binary (0 or 1)
MG_FISH	Change in fish population etc.	Binary (0 or 1)
MG_WILD	Change in wildlife management	Binary (0 or 1)
MG_INFRA*	Change in infrastructure	Binary (0 or 1)
(Degree of change)		
CHG_0	No change	Binary (0 or 1)
CHG_1	Improvement step 1	Binary (0 or 1)
CHG_2	Improvement step 2	Binary (0 or 1)
CHG_-1*	Undesirable change	Binary (0 or 1)
--Subject of valuation		
INCOME	Income	Continuous
POP_DEN	Population density	Discrete
Methodology consistency		
(Elicitation method)		
ELI_DM	Dichotomous choice	Binary (0 or 1)
ELI_OD	Open end	Binary (0 or 1)
ELI_ITR	Iterative bidding	Binary (0 or 1)
ELI_PCD	Payment card	Binary (0 or 1)
ELI_CB	Contingent behavior or combined CV& Revealed Preference (RP)	Binary (0 or 1)
ELI_CK*	Contingent ranking	Binary (0 or 1)

INTERVIEW	Whether phone or impersonal interview was applied	Binary (0 or 1)
(Payment vehicle)		
VHC_MKT	Market based payment e.g. water bill	Binary (0 or 1)
VHC_TAX	Tax	Binary (0 or 1)
VHC_DNT*	Donation	Binary (0 or 1)
NONUSERS_ONLY	Whether the sample population only including nonusers	Binary (0 or 1)
LUMPSUM	Whether it is a lump sum payment	Binary (0 or 1)
SUBSAMPLE	Whether outliers was excluded	Binary (0 or 1)
MEDIAN	Whether it is a median value	Binary (0 or 1)
STUBSTITUTION	Whether substitution included	Binary (0 or 1)
Quality of the study		
PRIMARY_DATA_ONLY	Whether external data used in calculating per unit value	Binary (0 or 1)
SURVEY_YEAR	Year of the study	Discrete

* These variables were omitted from all regressions in order to avoid collinearity due to dummy variables summing to unity. Therefore, all effects are measured relative to a base case with these characteristics.

Table 2: Mean, median and Standard Deviation (SD) of WTP estimates by service, land cover, geopolitical region, and elicitation method (Unit: 2006 US \$ household^{-1} year^{-1})

Variable (number of observations)	Mean WTP	Median	SD
Ecosystem services			
Aesthetic (20)	3268	600	6024
Disturbance control (1)	27	27	36
Food (1)	0.3	0.3	0
Habitat (18)	51	48	28
Recreation (50)	426	121	932
Spiritual (9)	39	32	36
Water quality (21)	192	112	207
Land cover			
Beach (25)	38	19	33
Coral Reefs and atolls (9)	812	766	574
Estuary (16)	1222	195	3964
Nearshore freshwater wetland (6)	152	110	185
Nearshore Islands (4)	37	35	9
Nearshore Ocean--50m depth or 100km offshore (28)	522	137	1169
Open ocean (6)	310	83	392
Saltwater wetland, marsh or pond (21)	2189	127	5201
Seagrass beds or kelp forests (3)	179	24	279
Semi-enclosed seas (2)	53	53	6
Geopolitical region			
Oceania (4)	105	89	76
Americas (95)	939	112	3044
Europe (9)	48	48	28
Asia (12)	151	40	277
Elicitation method			
Dichotomous choice (45)	349	109	935

Open end (23)	88	32	150
Iterative bidding (11)	37	19	38
Payment card (13)	60	48	41
Contingent behavior (16)	702	758	508
Contingent ranking (12)	5149	806	7273

Table 3: Comparison of different models

	Linear		Box-Cox		Log-log		Stepwise log-log	
	Coeff		**Coeff**	**p**	**Coeffi**	**p**	**Coeff**	**p**
Income	-0.009	0.46	0.35	0.00	0.37	0.43	0.42	0.06
Density	-1.22	0.00	0.11	0.00	0.11	0.37	0.09	0.17
Area	0.004	0.05	0.18	0.00	0.19	0.00	0.17	0.00
Survey year	31.46	0.77	-0.05	0.00	-0.052	0.36	-0.05	0.04
Constant	149056	0.01	4.12	0.00	3.81	0.53	3.94	0.19
Lambda	NA	NA	0.004	0.19	NA	NA	NA	NA
Residual Statistics								
Skewness	0.32	0.16	-0.64	0.00	-0.66	00.0	-0.64	00.0
Kurtosis	1.63	0.00	2.78	0.00	2.88	0.00	2.44	0.00
Jarque-Bera	15.21	0.00	46.86	0.00	50.2	0.00	37.8	00.0
Breusch Pagan heteroskedasticity Test								
Chi-Squared	75.09	0.006	57.19	0.15	57.2	0.15	30.88	0.19
Transfer Error Statistics (Percent)								
Mean	35,333%	0.11	NA	NA	381%	0.03	329%	0.10
Median	1,327%	NA	NA	NA	57.3%	NA	57.6%	NA
Maximum	2,320,000%	NA	NA	NA	16,090%	NA	22,954%	NA
Minimum	0.08%	NA	NA	NA	0.2%	NA	0.3%	NA
Standard Deviation	237,921%	NA	NA	NA	1,866%	NA	2,161%	NA

Table 4: Meta-regression result of the step-wise log-log model

(N=120, df = 94, R^2 = 0.79)

	Variable	**Coeff**	**Significance Level**
1	LNINCOME	0.42	0.060
2	LNDENSITY	0.09	0.165
3	LNAREA	0.17	0.000
4	Constant	3.94	0.189
5	SURVEY_YEAR	-0.05	0.036
6	ES_FOOD	-5.44	0.000
7	ES_SPR	-0.76	0.078
8	BUNDLED_SERVICES	-0.36	0.112
9	SP_OCE	-1.22	0.001
10	SP_SA	2.71	0.000
11	SP_EU	0.85	0.024
12	LC_BCH	-1.48	0.000
13	LC_EST	-0.45	0.092
14	LC_OPS	-0.60	0.027
15	CHG_0	-0.98	0.010
16	CHG_1	-1.24	0.001
17	CHG_2	-0.93	0.024
18	ELI_DM	-2.30	0.000
19	ELI_ODD	-2.50	0.000
20	ELI_ITR	-3.00	0.000
21	ELI_PCD	-4.21	0.000
22	ELI_CVBR	-1.82	0.000
23	INTERVIEW	-0.43	0.049
24	VHC_TAX	0.27	0.107
25	LUMPSUM_PAYMENT	1.37	0.000
26	SUBSAMPLE	-0.42	0.048

Figure 1: Actual and predicted WTP values

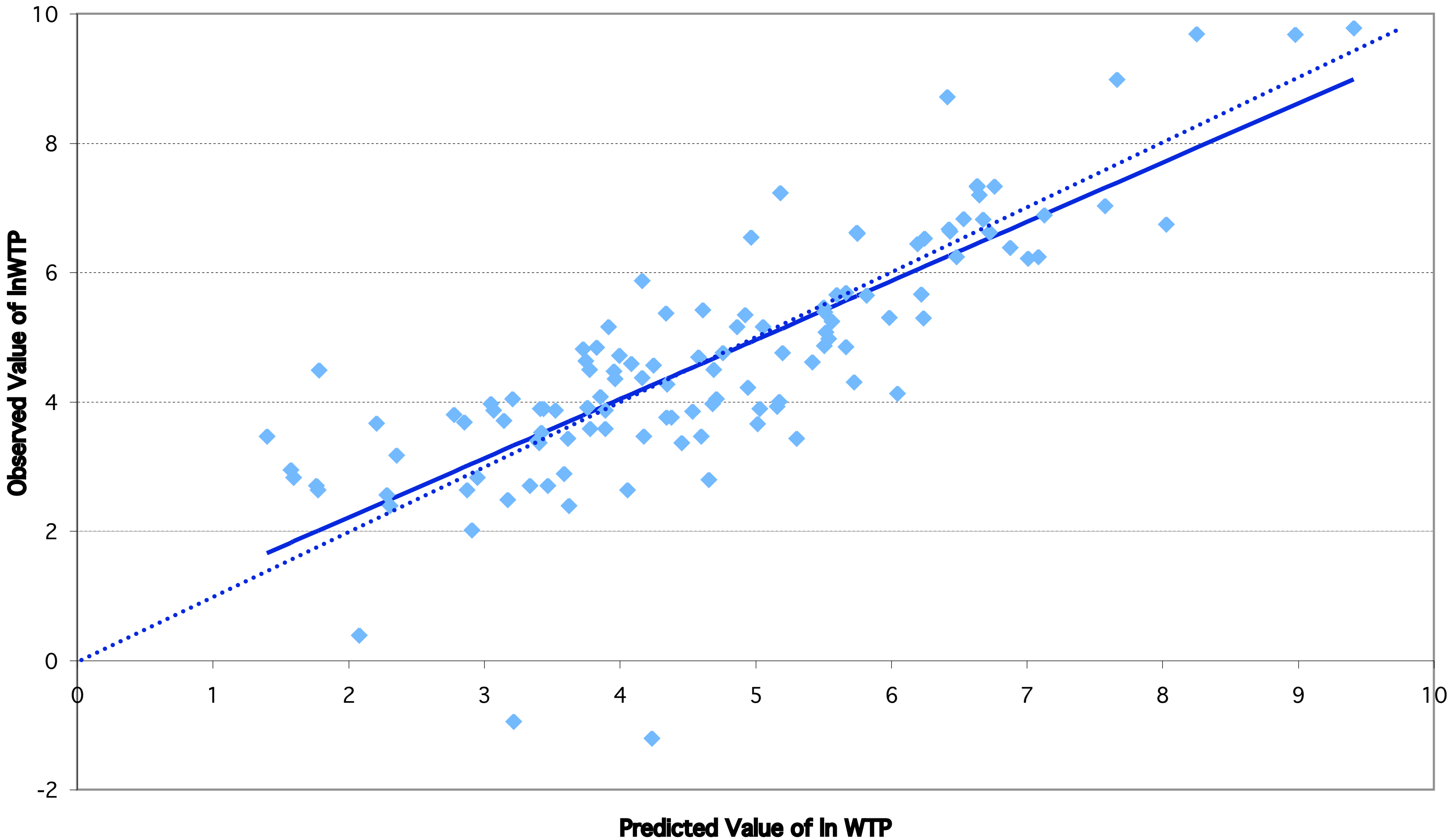
INSERT FIGURE 1 HERE, FOLLOWING TEXT TO APPEAR BELOW THE GRAPHIC

The dotted line is the 45 degree line that indicates a consistent relations between predicted and observed values. The solid line if the regression line of observed on predicted values.

Figure 2: Transferred error associated with each observation ranked in an ascending order of WTP

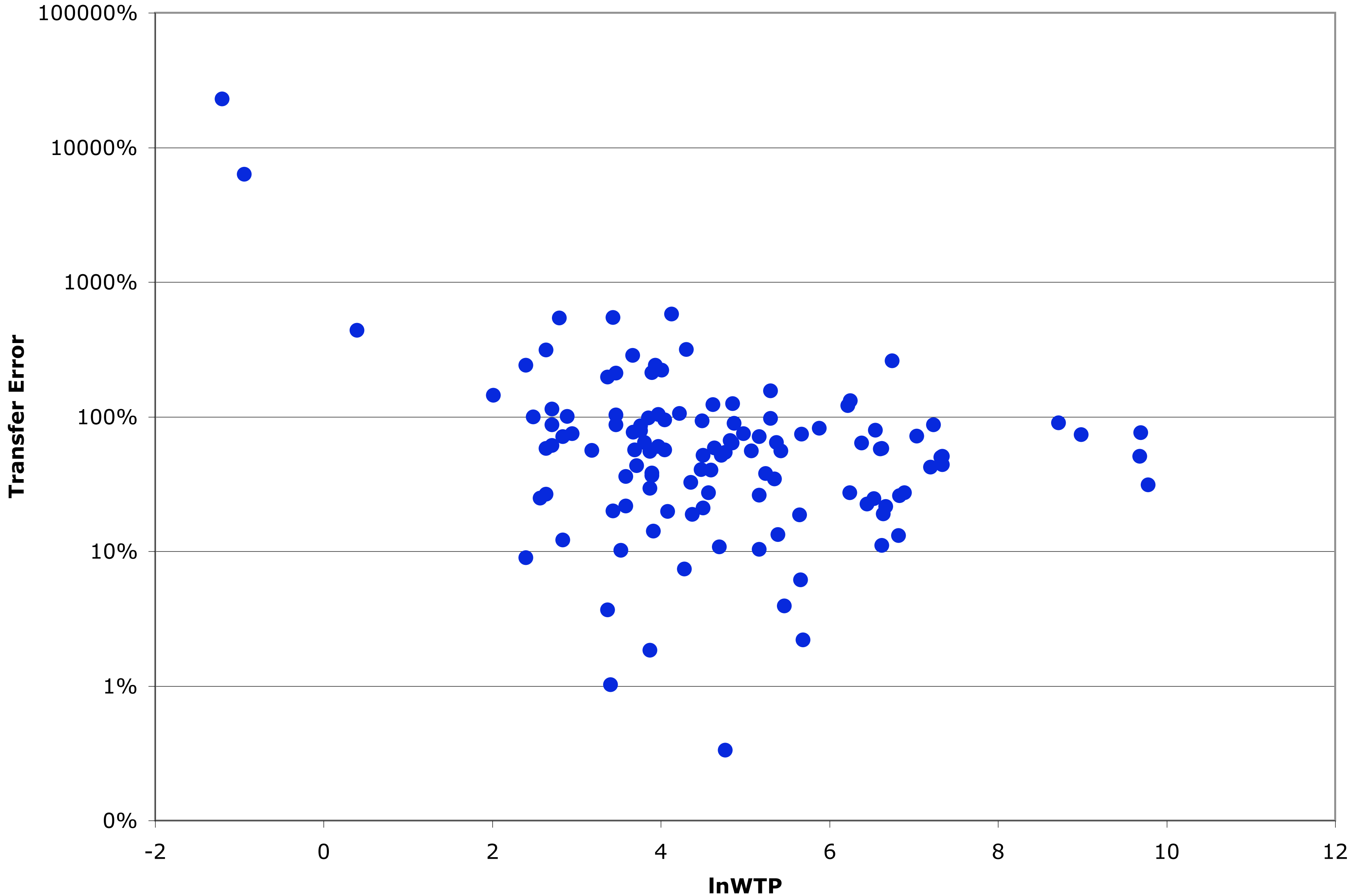
INSERT FIGURE 2 HERE

Figure 1



10
8
6
4
2
0
-2
0
1
2
3
4
5
6
7
8
9
10
Observed Value of lnWTP
Predicted Value of ln WTP

Figure 2


100000%
10000%
1000%
100%
10%
1%
0%
Transfer Error
-2
0
2
4
6
8
10
12
lnWTP