Publication Selection of Recreation Demand Price Elasticity: A Meta-Analysis

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Abstract

A meta-regression analysis (MRA) of own-price elasticity of recreation demand estimates in the U.S. shows significant publication selection bias based on simple and multivariate MRA tests. However, these tests also reveal that there is genuine negative price elasticity. While the simple average of past reported research results exhibits nearly a unitary elasticity (-0.997), this average estimate is likely to be several times too elastic. Our results are based on nearly 600 estimates of own-price elasticity drawn from the recreation demand literature. One previous MRA was conducted on own-price elasticity estimates (Smith and Kaoru, 1990). A similar OLS MRA finds substantial consistency between our expanded research data and Smith and Kaoru's results according to sign and significance of moderator variables (i.e., determinants of elasticities). There is a high degree of heterogeneity in the recreation demand literature. When a multivariate MRA, which captures variations in elasticity estimated due to their standard errors and weights the data according to these standard errors, many of the moderator variables change in sign and/or significance. Regardless of changes in model results when correcting for publication selection bias, general conclusions that researcher modeling decisions and assumptions, along with theoretical expectations, do indeed matter.

JEL Classifications: C21; C51; Q26; Q51; R22

Keywords: Meta-analysis; Price Elasticity; Publication selection bias; Recreation Demand

Introduction

Recreation demand models have been empirically estimated for over a half-century using an indirect method proposed by Harold Hotelling in 1947. Collectively, there have been over 329 recreation demand studies providing over 2,700 empirical estimates of the access value to recreation resources from 1958 to 2006 (Rosenberger and Stanley 2007).[1] Yet, only one other study evaluated estimates of own-price elasticity of recreation demand. (Smith and Kaoru, 1990), involving many fewer estimates and studies— approximately 77 studies and 185 own price elasticity estimates from 1970 to 1986. Because adequate tests for publication bias are a more recent development (Egger et al., 1997; Stanley, 2005a, 2008), Smith and Kaoru (1990), did not formally test for publication selection bias in this area of research. This paper tests for publication selection bias among reported elasticity estimates and greatly expands the recreation demand literature covered.

Own-price elasticity measures the sensitivity of demand to changes in prices. Price elasticity is typically defined as the percentage change in quantity (e.g., recreation trips) resulting from a one-percentage change in price (e.g., travel costs). While price elasticities are unitless measures of demand's responsiveness to price changes, they are a function of an estimated price coefficient ($\delta q/\delta p$), when demand is linear, and the ratio of prices and quantities (p/q) typically evaluated at their mean values. If, on the other hand, a double-log demand model is estimated, it can easily be shown that the price coefficient is itself the elasticity.

Previous meta-regression analyses have been conducted on demand elasticity of many other goods and services, including private good brands/markets (Tellis 1988), money (Knell and

[1] This estimate includes only those studies that reported access values for recreation resources. Not included in this total are studies that estimated demand functions without providing consumer surplus estimates and studies providing estimates of marginal values or values per choice occasion.

Stix 2005), residential water (Espey et al. 1997; Dalhuisen et al. 2003), gasoline (Espey 1997, 1998), cigarettes (Gallett and List 2003), and prescription drugs (Gemmill et al., 2007). Dalhuisen et al. (2003) included a dummy variable identifying unpublished studies and found a significant difference between elasticity measures in published vs. unpublished studies, *ceteris paribus*. Gallett and List (2003) included a dummy variable identifying the top 36 journals, finding a significant difference in elasticity estimates for the top journals, *ceteris paribus.* Stanley (2005a) evaluated the residential water elasticity data using the funnel asymmetry and precision effect tests (FAT-PET) and uncovered significant publication bias defined as a function of the standard error of the price elasticity measures. As a result, price elasticities of water demand are exaggerated by three- to four-fold through publication selection bias (Dalhuisen et al. 2003; Stanley 2005a). Needless to say, the water board of a drought-stricken area will be greatly disappointed to find that a doubling of residential water rates reduces usage by a mere 10% and not the expected 40%. Similarly, Gemmill et al. (2007) found substantial publication biases using FAT-PET MRAs. However, Knell and Stix (2005) also apply the FAT-PET test on elasticities of money demand but found small and insignificant publication selection. Among 87 previously published meta-analyses in economics, approximately two-thirds contain 'substantial' to 'severe' publication bias (Doucouliagos and Stanley, 2008).

Publication Selection Bias Tests

Publication selection bias results from a literature of reported estimates that are not an unbiased sample of the actual empirical evidence. Researchers and reviewers are often predisposed to seek statistically significant results or desire results that conform to prior theoretical expectations, or both.[2] Publication selection has long been recognized as an important problem in economics (e.g. Card and Krueger 1995; De Long and Lang 1992; Feige 1975; Leamer 1983; Leamer and Leonard 1983; Lovell 1983; Roberts and Stanley 2005; Rosenberger and Johnston 2009; Tullock 1959, to cite but a few). In areas where the direction of an economic effect is accepted as fact—such as the 'Law' of demand—reporting of only statistically consistent findings that conform to this fact are reported. E.g., when primary survey data are used to estimate the price coefficient of a demand relation, the first estimated coefficient produced is not necessarily the one reported. Rather, economists will exert enough effort to ensure the estimated demand relation is 'valid.' Validity will require, at a minimum, that the price coefficient be negative and in many cases that it be statistically significant as well. Thus, the sample of reported estimates may not be random, and, if not, any summary of estimates will be biased. "Publication bias (aka 'file-drawer problem') is a form of sample selection bias that arises if primary studies with statistically weak, insignificant, or unusual results tend not to be submitted for publication or are less likely to be published" (Nelson and Kennedy 2009, p. 347).

Wide application of MRA in economics suggests that publication biases are often as large as or larger than the underlying parameter being estimated (Doucouliagos and Stanley 2009; Hoehn 2006; Krassoi Peach and Stanley 2009; Stanley 2005a, 2008). For example, the negative sign of own-price elasticity is often required to validate the researcher's estimated demand relation. Should random sampling error produce a positive coefficient, researchers feel obligated to re-specify the demand relation, find a different econometric estimation technique, identify and omit outliers, or somehow expand the dataset until a suitably negative price coefficient is found.

[2] 'Selection biases' or 'reporting biases' are more descriptive terms for the phenomena discussed in this paper. It is presumed that researchers recognize a preference for statistically significant findings and tend to selectively document these in any report, published or not.

Because the 'Law' of demand is so widely accepted, demand studies will ironically exhibit the greatest publication bias (Doucouliagos and Stanley, 2008).

Over the past decade, meta-analysis has become routinely employed to identify and correct publication selection in economics research (Ashenfelter et al. 1999; Card and Krueger 1995; Coric and Pugh 2010; Disdier and Head 2008; Doucouliagos 2005; Doucouliagos and Stanley 2009; Egger et al. 1997; Gemmill et al. 2007; Görg and Strobl 2001; Havranek 2010; Knell and Stix 2005; Krassoi Peach and Stanley 2009; Longhi et al. 2005; Mookerjee 2006; Roberts and Stanley 2005; Rose and Stanley 2005; Stanley 2005a, b, 2008; Stanley and Doucouliagos 2010). However, in environmental economics, meta-analysis has been widely applied but with limited focus on publication selection and other potential biases (Hoehn 2006; Nelson and Kennedy 2009; Rosenberger and Johnston 2009). Previous MRAs in environmental economics have treated publication selection bias as arising from the source of an estimate; a form of systematic heterogeneity among the metadata (Smith and Huang 1993, 1995; Rosenberger and Stanley 2006). Typically a dummy variable identifying the publication type is added as an independent variable in the MRA (Rosenberger and Stanley 2006) or a sample selection model is estimated as a form of model specification test (Smith and Huang 1993, 1995). However, more sensitive and robust tests of publication selection bias are available.

In economics, it has become standard practice to include the standard errors (or their inverse, precision) in a MRA to identify and correct for publication selection bias

$$effect_i = \beta_0 + \alpha_0 SE_i + \sum \beta_k \mathbf{Z}_{ki} + \varepsilon_i \qquad (1)$$

(Card and Krueger 1995; Doucouliagos 2005; Doucouliagos and Stanley 2009; Egger et al. 1997; Gemmill et al. 2007; Rose and Stanley 2005; Stanley 2005a, 2008). Where ε_i is a random error, $\mathbf{Z_i}$ is a matrix of moderator variables that reflect key dimensions in the variation of the 'true' empirical effect (heterogeneity) or identify large-sample biases that arise from model misspecification, and SE_i are the reported standard errors of the estimated effects.

Meta-regression model (1) provides a valid test for publication bias (H_1:$\alpha_0 \neq 0$), called 'funnel-asymmetry test' (FAT), and a powerful test for genuine empirical effect beyond publication selection (H_1:$\beta_0 \neq 0$), called a 'precision-effect test' or PET) (Stanley 2008). This approach works because the standard error serves as a proxy for the amount of selection required to achieve statistical significance. Studies with large standard errors are at a disadvantage in finding statistically significant effect sizes—effect sizes need to be proportionally larger than their standard errors in individual t-tests. Imprecise estimates will likely require further re-estimation, model specification, and/or data adjustments to become statistically significant, if at all possible. If statistical significance cannot be achieved, then it is presumed that results are not published, reported, or otherwise made available. Thus, greater publication selection is expected in estimates with larger SE, *ceteris paribus*. This correlation between reported effects and their standard errors has been observed in dozens of different areas of economics research and among thousands of published papers (Doucouliagos and Stanley 2008).

However, Eq (1) likely contains substantial heteroskedasticity because SE is an estimate of the standard error of the elasticity measure that varies from observation to observation. Eq (1) therefore needs to be estimated using weighted least squares (WLS) by dividing through by SE:

$$t_i = {effect_i}/{SE_i} = \alpha_0 + \beta_0 \, {1}/{SE_i} + \sum \beta_k \, {\mathbf{Z}_{ki}}/{SE_i} + v_i \qquad (2)$$

A simplified version of Eq (2) has been used as a test for publication selection bias:

$$t_i = \alpha_0 + \beta_0 \, {}^{1}\!/_{SE_i} + v_i \tag{3}$$

(Stanley 2005a; Stanley 2008). The null hypothesis of no publication selection bias (H_0: $\alpha_0 = 0$) is the test for publication selection bias. This method is related to funnel graphs and therefore is called a 'funnel-asymmetry test' (FAT) (Stanley 2005a; Stanley and Doucouliagos 2010). A funnel graph plots precision (1/SE) against the elasticity estimate. Figure 1 shows a funnel graph of union-productivity partial correlations where FAT tests show little sign of publication selection bias (Stanley 2005a). Compare Figure 1 with Figures 2 and 3 that show asymmetric distributions for elasticity measures of efficiency wage and residential water demand, respectively. In these latter two cases, the null hypothesis of no publication selection bias (H_0: $\alpha_0 = 0$) is easily rejected.

The meta-regression estimate of β_0 in Eq (3) is shown to serve as a test for a genuine empirical effect corrected for publication bias (Stanley 2008). Given 1/SE is a measure of the precision of the empirical effect, the test (H_0: $\beta_0 = 0$) is called the 'precision effect test' (PET), where the null hypothesis is no genuine empirical effect. Combining these two tests, Eq (3) is called the FAT-PET test.

FAT (H_0: $\alpha_0 = 0$) has low power as a publication selection bias test and PET (H_0: $\beta_0 = 0$) shows a downward bias in β_0 (Stanley 2008). However, in the presence of publication selection bias and when there is a genuine nonzero empirical effect, the observed effect and its standard error have a nonlinear relationship. It is easy to show that the truncation for statistical significance gives: $E(effect_i) = \beta_0 + \sigma_i \lambda(c)$; where $\lambda(c)$ is the inverse Mills ratio, which is a function of the cutoff for statistical significance, c, σ_i is standard error of $effect_i$, and SE_i is the empirical estimate of σ_i—Theorem 24.2 Greene (2008, p.866). This nonlinearity with respect to SE results from the fact that the inverse Mills ratio is itself a function of σ_i, and this forms the basis for the below corrected estimate, or precision-effect estimate with standard error (PEESE). Beginning with the simplest form:

$$effect_i = \beta_0 + \alpha_0 SE_i^2 + \varepsilon_i \tag{4}$$

Note, the square of SE (i.e., the variance of each estimated elasticity) is included. A WLS version of Eq (4) to control for heteroskedasticity is derived by dividing through by SE:

$$t_i = \alpha_0 SE_i + \beta_0 \, {}^{1}\!/_{SE_i} + v_i \tag{5}$$

Note that there is no intercept and a second independent variable (SE) is included as compared with Eq (3). In Eq (5), $\hat{\beta}_0$ is the estimate of the effect (elasticity) corrected for publication selection or the precision-effect estimate with standard error (PEESE), which simulations show can greatly reduce the potential bias of publication selection (Stanley and Doucouliagos 2007).

Determinants of Elasticity

Several factors are known to affect elasticity estimates, including presence of substitutes, income effect, necessity of the good, time dimensions of price changes and scope of the affected resource. These factors give rise to variation in elasticity estimates. For example, a demand model that evaluates price changes for a particular campground with substitutes will estimate a more elastic demand than a model that evaluates the demand for camping in general, where substitution across multiple sites holds demand fairly constant at the activity level with price changes at a particular site. In addition to these expected variations due to consumer behavior, researcher choices about experimental design and analysis of data may affect elasticity estimates (Smith and Kaoru 1990). In previous MRAs of price elasticities (Tellis 1988; Espey et al. 1997), determinants have been classified as demand specifications, environmental characteristics, data characteristics, and factors arising from estimation methods.

Demand specifications include the model's structure, variables, functional form, and type of travel cost method used. Environmental characteristics include measures of activity type, geographic region, presence of developed facilities at the recreation site, and land management agency. Dummy variables may also identify the resource type such as lake, river, ocean, etc, or differentiate warmwater and coldwater resources. Data characteristics include survey mode, scope, types of visitors, sample design, and types of trips. Estimation methods include measures of estimator types such as ordinary least squares (OLS), Poisson and negative binomial, corrections for endogenous stratification, ML-truncation, and censored models.

Data

Empirical estimates of own-price elasticity of recreation demand were derived from the published literature as part of a larger project (Rosenberger and Stanley 2007). Empirical recreation demand studies were identified through previous bibliographies, electronic database searches, and formal requests sent to graduate programs and listservers. Each document was screened for inclusion in the database using the following criteria—(1) written documentation must be available; (2) studies must evaluate recreation resources in Canada or the United States; (3) estimate(s) of use value must be provided; (4) use values must be for outdoor recreation related activities; and (5) use value estimates must be measures of access value (all-or-nothing, not marginal values). Although these selection criteria do not directly target demand functions and elasticity measures, the resulting database does cover the vast majority of recreation demand studies.

Our research database currently contains 329 documents that jointly provide 2,705 estimates of recreation use values. The studies were documented from 1958 to 2006 based on data collected from 1956 to 2004. Own-price elasticity measures are only derived from travel cost studies, including individual and zonal, and were either directly coded from estimates provided in the documents, or were calculated when enough information was provided to do so. The price elasticity database contains 119 studies documented from 1960 to 2006 and collectively providing 610 estimates of own-price elasticity.

Table 1 provides variable definitions and descriptive statistics. Own-price elasticity of recreation demand (P_ELAST) is the dependent variable in all subsequent analyses. ELAST_SE is the standard error of the elasticity estimate. The independent variables account for potential factors that affect the variation in price elasticity estimates. Model specification variables include the presence and number of site characteristic variables in the demand model (SITEVR and NSITEVAR, respectively); the presence of substitute site price (SUBPRICE) and whether the value of time was included in the travel cost variable (TIMECOST). Functional form is captured by a linear-linear (LINLIN) and log-linear (LOGLIN) forms, with double log and linear-log the omitted category. A dummy variable also identifies whether outliers were removed from the data prior to model estimation (OUTLIER).

Environmental characteristics factors include several activity types (the omitted category include all other recreation activities that individually have low sample sizes) and geographic region (NEAST and SOUTH, with other regions omitted due to correlations with other variables). These factors also identify sites with developed facilities (DEVREC) and sites located on national forests (USFS) and state parks (STPARK) (omitted categories include other public agencies and private lands). Resource types are identified, including LAKE, BAY (or estuary), OCEAN and RIVER, with land being the omitted category. Water temperature was also coded as warmwater (WARMWAT) and coldwater (COLDWAT).

Data characteristics include MAIL surveys (all other modes are omitted due to correlation with other factors) and single site models (SSITE). Visitor type includes resident visitors (RESIDENT) with non-resident and mixed visitors as omitted. ONSITE identifies studies that derived their sample on-site (other sampling designs such as user list and general population are omitted). Models that only include single destination trips (SINGDEST) or primary purpose trips (PRIMARY) are also identified, as well as models based on day trips only (DAYTRIP).

Estimation methods include OLS, Poisson/negative binomial count data models (POISNB), and estimators that corrected for truncation (TRUNC), censoring (CENSOR), and endogenous stratification (ENDOGST). Other independent variables include a TREND variable and whether the elasticity measure was calculated (ELASTC), not directly reported in the primary documents.

Results

Figure 4 plots the funnel graph for elasticity estimates against their precision (1/SE). The plot is asymmetric with more precise estimates corresponding to inelastic measures. The raw average elasticity is unitary elasticity (-0.997), while the median elasticity is inelastic (-0.567). Table 2 reports the simple FAT-PET and PEESE MRA models without explanatory moderator variables. FAT rejects the null hypothesis, H_0: $\alpha_0 = 0$ ($p<.01$), signaling publication selection bias. The size of $\hat{\alpha}_0$ (-5.95) represents very severe publication selection bias (Doucouliagos and Stanley, 2008). PET, on the other hand, tests the null hypothesis that $\beta_0 = 0$, which is also rejected ($p<.01$), meaning that there is a genuinely negative price elasticity for outdoor recreation. The PEESE estimate of own-price elasticity ($\hat{\beta}_0$) is -0.158. Thus, correcting for publication selection reduces the average elasticity from nearly -1 to one-sixth this value (-0.158). Accounting for the variation in an estimate's precision (or standard error) is essential. The conventional fixed-effect weighted average (Sutton et al. 2000) is -0.169, which uses optimal weights (the inverse of an estimate's variance), and is largely consistent with the PEESE estimate. However, these simple FAT-PET and PEESE MRA models and averages ignore heterogeneity of consumer behavior and the effect of alternative estimation methods. Thus, we need to account for likely heterogeneity to ensure that these results remain representative of this area of intense research.

Nelson and Kennedy (2009) note that MRAs should account for heteroskedasticity, dependence and heterogeneity of metadata. Heteroskedasticity is captured through the use of standard error weights in the models. Hausman tests for dependency among the data emerging as intrastudy correlation among observations derived from the same study reject the classical regression in favor of a fixed or random effects panel model (Rosenberger and Loomis 2000). Further, Lagrange Multiplier tests favor a random effects specification that captures intrastudy dependence in the error term. Heterogeneity is captured through the use of moderator variables as determinants of variation in reported elasticity estimates.

Four estimated models are provided in Table 3, including an OLS model with White's heteroskedastic consistent coefficient standard errors (Model A) that is directly comparable to Smith and Kaoru's (1990) model; an OLS unweighted FAT-PET-MRA (Model B) to illustrate the heteroskedastic nature of the model; a WLS FAT-PET-MRA with standard errors of elasticity measures as weights (Model C), which corrects for heteroskedasticity; and the preferred random effects FAT-PET-MRA with standard errors of elasticity measures as weights

(Model D). Our primary focus will be on Models C and D; however, Models A and B are provided for general comparisons.

Model A contains several more variables in addition to those in Smith and Kaoru's (1990) full specification model of recreation demand elasticities. A comparison of Model A (n = 594) with Smith and Kaoru's (SK) model (n = 185) shows them to be quite similar. Model performance as measured by R^2 is close (Model A, R^2 = 0.58, adj-R^2 = 0.54; SK, R^2 =0.65). The effects of per trip vs. per day measures of use, state parks, and linear demand were positive and significant in both models. The effects of forest, presence of substitute price, log-linear demand, and trend were negative and significant in both models. The variables for lake, river, value of time, regional travel cost models[3], semi-log dependent variable, and OLS are consistent in sign, but not in level of significance. Truncation is the only variable in both models that had an inconsistent sign, although this variable is significant in Model A but not in SK.

The only difference between Model A and Model B (adj-R^2 = 0.67) is the inclusion of the FAT-PET measure of publication selection bias (i.e., the standard error (SE) of the elasticity measures). This result demonstrates that SE is an important, but omitted variable in Model A, and individually accounts for 13% of the variation in elasticity estimates (adj-R moves from 0.54 for Model A to 0.67 for Model B). The unweighted FAT-PET-MRA (Model B), when accounting for heterogeneity among the data still rejects the FAT null hypothesis (H_0: $\alpha_0 = 0$) of no publication selection bias and rejects the PET null hypothesis (H_0: $\beta_0 = 0$) of no genuine empirical effect, although the magnitude of these coefficients differ, as they should, from the unweighted simple FAT-PET in Table 2.

[3] In Model A, we coded for individual travel cost models whereas SK coded for regional travel cost models. However, the opposite sign on these variables is consistent with expectations and comparable.

Model C differs from Model B in that it weights the data by the SE of elasticity measures. Adj-R^2 further improves to 0.79 due to the introduction of SE weights. However, inferences about specific variables change from Model B, signaling substantial heteroskedasticity among the data related to varying standard errors of elasticity measures (Figure 4). Of the 41 variables excluding SE, 21 remained of the same sign and significance, 19 changed in significance, and one variable (SUBPRICE) switched sign but remained significant. The weighted FAT-PET-MRA, when accounting for heterogeneity among the data, still rejects the FAT null hypothesis (H_0: $\alpha_0 = 0$) of no publication selection bias and rejects the PET null hypothesis (H_0: $\beta_0 = 0$) of no genuine empirical effect, although the magnitude of these coefficients differ, as they should, from the simple FAT-PET in Table 2. The simple FAT-PET-MRA estimates the overall effects for the typical study, while those in Table 3 are conditional on all of the moderator variables being zero.

Model D (adj-R^2 = 0.55), the random effects FAT-PET-MRA is our preferred model based on the Hausman and Lagrange Multiplier specification tests.[4] The estimated coefficients are mostly consistent with Model C, and are interpreted based on the direction of the effect—a positive sign means more inelastic (i.e., decreases elasticity) while a negative sign means more elastic (i.e., increases elasticity). Interpretations of elasticity determinants or moderator effects are restricted to Model D, because we have statistical reasons to believe that this specification is superior. Seven out of eight demand model characteristics factors are statistically significant, with five having a positive effect (more inelastic) and two having a negative effect (more elastic). Three of these demand characteristics are consistent with SK's model. However, the

[4] In the random effects model, a panel effect parameter, μ_{ij}, is added to the FAT-PET-MRA of equation (2): $t_{ij} = {effect_i}/{SE_i} = \alpha_0 + \beta_0 \, 1/SE_i + \Sigma \beta_k \, \mathbf{Z}_{kij}/SE_i + v_i + \mu_{ij}$, where μ_{ij} is the panel-specific disturbance component and j stratifies by study.

most notable exception, and contrary to theoretical expectations, is the sign switch on substitute price—studies with substitute prices included in them provide more inelastic measures, although the overall elasticity is still elastic, *ceteris paribus*. Including site characteristic measures (SITEVAR) in the demand model increases the elasticity measure, while increases in the number of site characteristic variables (NSITEVAR) in the demand model specification decreases the elasticity measure (each additional site characteristic variable decreases elasticity by 0.186). A linear-linear (LINLIN) functional form provides more inelastic elasticities than other functional forms, as does including the value of time in the travel cost measure (TIMECOST). Individual travel cost models (TCMIND) likewise provide more inelastic elasticities than zonal travel cost models, as expected given zonal travel cost models better capture substitution effects. Removal of outlier observations from the data (OUTLIER) increases the elasticity, where these outliers may either be uncharacteristically large prices or number of trips.

Nine out of 19 environmental characteristics factors are statistically significant, with the majority leading to more elastic elasticities. Two factors (forest and lake) are consistent with SK's model, while two factors (state park and river) are not consistent. Camping (CAMP) and motorized boating (MBOAT) provide more elastic elasticities whereas fishing (FISH) and general recreation (GENREC) studies provide more inelastic measures. Studies conducted in the northeastern (NEAST) and southern (SOUTH) U.S. provide more elastic measures relative to other regions. Sites with developed recreation facilities (DEVREC) show less price responsive demands. National forest studies (USFS) showed more elastic measures, while studies of ocean (OCEAN) resources have less elastic measures.

Overall, data characteristics factors did not influence elasticity measures with only resident samples (RESIDENT) being statistically significant and positive (less elastic demands).

Estimation method factors are mostly significant in determining elasticity measures (three out of five). OLS models (OLS) and censored models (CENSOR) provide less elastic estimates, while truncated models (TRUNC) provided more elastic estimates. Two of the factors consistent with SK's model specification are similar. There is a general trend in more elastic elasticity estimates over time (TREND), also consistent with SK's results. Those studies that did not report elasticities but provided enough information for them to be calculated tend to be more inelastic demand models (ELASTC), which is consistent with publication selection for significantly negative price elasticities.

Conclusions

The recreation demand literature shows substantial publication bias in estimates of own-price elasticity based on the simple FAT-PET tests, but does demonstrate that there is a genuine price effect on outdoor recreation demand. However, based on a simple PEESE test, the precision effect estimate with standard errors shows the standard error-corrected empirical elasticity is -0.158—recreation demand is not very price responsive (i.e., inelastic). Compared with this PEESE estimate, the raw average elasticity measure (-0.997) is six-fold more elastic while the raw median elasticity measure (-0.567) is four-fold too elastic. If this corrected overall elasticity accurately reflects the demand for outdoor recreation, then raw (or average) research results will greatly exaggerate the price responsiveness of recreation demand, and management decisions and policies based on them will likely inefficiently allocate resources. For example, pricing decisions based on these raw measures will underestimate potential revenue from price increases, or will overestimate the reduction in use due to increases in prices. Similarly, value calculations based on these raw research results will likely underestimate the value of a given project or expansion. Recall, that value is often inversely related to the price coefficient (Adamowicz et al. 1989; Haab and McConnell 2002; Hanemann 1984, 1989).

Including elasticity measure standard errors as a moderator variable shows marked improvement in model performance. This suggests that not including this measure of precision results in models with a substantial omitted variable bias. Even after weighting the data and accounting for the substantial heterogeneity in this recreation demand literature, there is still substantial publication selection bias and many genuine empirical effects present in this literature based on the multivariate random effects FAT-PET-MRA.

Smith and Kaoru (1990) estimated a meta-regression model of own-price elasticities of recreation demand for the early literature. Their MRA is consistent with our unweighted OLS model (Model A). The demand model, environment and data characteristics factors were the same in sign and significance for those factors included in both models. However, compared with the random effects FAT-PET-MRA that accounts for publication selection and data dependency, the results are mixed. The model structure, environment, and data characteristics factors were consistent for some factors (e.g., linear demand models, including value of time in the travel cost price, individual travel cost models, and forest and lake resources), but not all (e.g., substitute price, state parks, measurement units, and river resources). Most notably, the estimated coefficient on inclusion of substitute site price in the demand model specification was estimated to be significant and negative in Smith and Kaoru's (1990) model, as it was in our replication model (Model A). However, when the data are weighted by the standard errors of the elasticity measures, the sign switches to positive and significant (weighted and random effects FAT-PET-MRA models). The estimation method factors were consistent with Smith and Kaoru's (1990) model for OLS and semi-log demand models, and truncated models.

Overall, Smith and Kaoru's (1990) general implications still hold even in the presence of publication selection bias. They conclude that "modeling assumptions do matter" (p.271). With over half of the moderator variables being related to the magnitude of the elasticity estimated, researcher decisions and assumptions continue to affect this literature beyond what is theoretically expected. However, not accounting for levels of precision in reported measured effects in a literature or properly weighting the data may result in incorrect inferences. Future research should endeavor to account for publication selection effects when estimating meta-regression models to a body of literature.

Table 1. Data Description (N = 610)

Variable	Definition	Mean	Std Dev	Min	Max
P_ELAST	Own price elasticity of demand	-0.997	1.040	-5.981	-0.006
ELAST_SE [a]	Std error of elasticity	0.208	0.269	0.003	3.161
SITEVAR	1 = Site characteristics variables in demand model	0.238	0.426	0	1
NSITEVAR[b]	# of site characteristics variables in demand model	0.387	0.919	0	5
LINLIN	1 = Linear-linear demand model functional form	0.251	0.434	0	1
LOGLIN	1 = Log-linear demand model functional form	0.359	0.480	0	1
SUBPRICE	1 = Price of substitute site included in demand model	0.500	0.500	0	1
TIMECOST	1 = Cost of time included in travel cost variable	0.608	0.488	0	1
TCMIND	1 = Individual travel cost model	0.597	0.491	0	1
OUTLIER	1 = Outlier observations removed from data	0.311	0.463	0	1
BIKE	1 = Bicycling	0.034	0.182	0	1
CAMP	1 = Camping	0.046	0.209	0	1
FISH	1 = Fishing	0.323	0.468	0	1
NMBOAT	1 = Non-motorized boating	0.043	0.202	0	1
HIKE	1 = Hiking	0.070	0.256	0	1
HUNT	1 = Hunting	0.090	0.287	0	1
MBOAT	1 = Motorized boating	0.067	0.250	0	1
GENREC	1 = Generalized recreation	0.144	0.352	0	1
NEAST	1 = Northeast region	0.105	0.307	0	1
SOUTH	1 = Southern region	0.236	0.425	0	1
DEVREC	1 = Developed recreation facilities available on-site	0.516	0.500	0	1
USFS	1 = National forest land	0.139	0.346	0	1
STPARK	1 = State park	0.136	0.343	0	1
LAKE	1 = Lake resource	0.306	0.461	0	1
BAY	1 = Estuary or bay resource	0.090	0.287	0	1
OCEAN	1 = Ocean resource	0.044	0.206	0	1
RIVER	1 = River or stream resource	0.148	0.355	0	1
WARMWAT	1 = Warm water resource (lake, river, etc.)	0.128	0.334	0	1
COLDWAT	1 = Cold water resource (lake, river, etc.)	0.090	0.287	0	1
MAIL	1 = Mail survey mode	0.397	0.490	0	1
SSITE	1 = Single site evaluated	0.695	0.461	0	1
RESIDENT	1 = Resident visitors only	0.439	0.497	0	1
ONSITE	1 = Sample drawn on site	0.441	0.497	0	1
SINGDEST	1 = Single destination trips only modeled	0.454	0.498	0	1
PRIMARY	1 = Primary purpose visitors only modeled	0.416	0.493	0	1
DAYTRIP	1 = Day trips only modeled	0.479	0.500	0	1
OLS	1 = Ordinary least squares estimator	0.693	0.461	0	1
POISNB	1 = Poisson/Negative Binomial estimator	0.184	0.387	0	1
TRUNC	1 = Observations truncated in demand model	0.380	0.486	0	1
ENDOGST	1 = Demand model corrected for endogenous stratification	0.134	0.341	0	1
CENSOR	1 = Censored demand model	0.115	0.319	0	1
TREND	Trend (1 = 1960, 2 = 1961,…, 44 = 2003)	25.448	9.355	1	44
ELASTC	1 = Elasticity measure calculated by researcher	0.415	0.493	0	1

[a]N = 558
[b]N = 594

Table 2. Publication Bias Tests (n=558)

Coefficient	**FAT-PET**		**PEESE**
	No Weights	**Weights[a]**	**Weights[a]**
β_0	-0.552*** (0.047)	-0.048*** (0.012)	-0.158*** (0.012)
α_0	-2.151*** (0.137)	-5.946*** (0.295)	----
ELAST_SE (α_0)	----	----	-7.273*** (0.933)
Adj-R^2	0.30	0.42	0.10
F	246***	407***	61***

Dependent variable = P_ELAST.
Coefficient standard errors in parentheses.
*** = p-value ≤ 0.01
** = p-value ≤ 0.05
* = p-value ≤ 0.10
[a]Weights = 1/ELAST_SE

Table 3. FAT-PET and PEESE Meta-Regression Analysis Models.

Variable	**Model A** OLS MRA unweighted[a]	**Model B** FAT-PET-MRA unweighted[a]	**Model C** FAT-PET-MRA weighted[b]	**Model D** Random Effects FAT-PET MRA weighted[c]
β_0	-1.601*** (0.248)	-1.399*** (0.195)	-0.743*** (0.150)	-0.778*** (0.099)
α_0	----	-1.326*** (0.111)	-4.064*** (0.586)	-4.615*** (0.480)
SITEVAR	-0.370** (0.175)	-0.274* (0.145)	-0.299*** (0.095)	-0.350*** (0.074)
NSITEVAR	0.335*** (0.066)	0.267*** (0.053)	0.186*** (0.038)	0.167*** (0.027)
LINLIN	0.289** (0.114)	0.365*** (0.103)	0.413*** (0.075)	0.305*** (0.050)
LOGLIN	-0.140 (0.127)	-0.078 (0.115)	0.087 (0.092)	0.048 (0.070)
SUBPRICE	-0.289*** (0.087)	-0.154** (0.069)	0.101* (0.053)	0.078** (0.038)
TIMECOST	0.054 (0.076)	0.103 (0.068)	0.078* (0.039)	0.066*** (0.026)
TCMIND	0.699*** (0.117)	0.669*** (0.096)	0.526*** (0.080)	0.485*** (0.051)
OUTLIER	-0.176 (0.108)	-0.060 (0.089)	-0.194*** (0.051)	-0.115*** (0.040)
BIKE	0.248 (0.218)	0.301 (0.249)	0.144 (0.165)	0.116 (0.117)
CAMP	-0.344 (0.264)	-0.310 (0.200)	-0.342*** (0.119)	-0.307*** (0.078)
FISH	0.383* (0.219)	0.329** (0.164)	0.289*** (0.100)	0.209*** (0.072)
NMBOAT	-0.072 (0.337)	-0.082 (0.219)	-0.090 (0.117)	-0.035 (0.082)
HIKE	-0.199 (0.206)	-0.387** (0.172)	-0.052 (0.090)	0.040 (0.055)
HUNT	0.116 (0.163)	0.090 (0.150)	0.012 (0.085)	-0.002 (0.064)
MBOAT	-0.948*** (0.235)	-0.900*** (0.221)	-0.615*** (0.150)	-0.444*** (0.116)
GENREC	0.070 (0.181)	0.156 (0.152)	0.185* (0.099)	0.188*** (0.065)
NEAST	0.404** (0.170)	0.013 (0.165)	-0.155** (0.064)	-0.347*** (0.078)
SOUTH	0.317*** (0.114)	0.343*** (0.090)	-0.058 (0.056)	-0.150*** (0.051)

Variable	**Model A** OLS MRA unweighted[a]	**Model B** FAT-PET-MRA unweighted[a]	**Model C** FAT-PET-MRA weighted[b]	**Model D** Random Effects FAT-PET MRA weighted[c]
DEVREC	0.124 (0.096)	-0.015 (0.096)	0.311*** (0.056)	0.200*** (0.049)
USFS	-0.291* (0.176)	-0.121 (0.132)	-0.179* (0.095)	-0.145* (0.077)
STPARK	0.476*** (0.125)	0.456*** (0.121)	0.034 (0.056)	-0.020 (0.062)
LAKE	-0.469*** (0.146)	-0.537*** (0.131)	-0.085* (0.050)	-0.046 (0.041)
BAY	0.002 (0.168)	-0.190 (0.147)	-0.112 (0.069)	0.034 (0.062)
OCEAN	-0.257 (0.246)	-0.245 (0.212)	0.058 (0.097)	0.135* (0.071)
RIVER	-0.291 (0.184)	-0.580*** (0.152)	0.054 (0.042)	0.049 (0.037)
WARMWAT	-0.544** (0.214)	-0.317** (0.154)	-0.179 (0.110)	-0.095 (0.076)
COLDWAT	-0.186 (0.256)	0.001 (0.172)	-0.137 (0.112)	0.018 (0.075)
MAIL	0.399*** (0.123)	0.306*** (0.106)	-0.014 (0.056)	0.012 (0.046)
SSITE	0.229** (0.116)	0.245** (0.101)	0.008 (0.069)	-0.005 (0.058)
RESIDENT	-0.340*** (0.116)	-0.198** (0.090)	-0.102 (0.084)	0.112** (0.055)
ONSITE	-0.209* (0.118)	-0.289*** (0.082)	-0.158** (0.064)	-0.027 (0.054)
SINGDEST	-0.034 (0.206)	-0.030 (0.138)	0.014 (0.088)	0.049 (0.074)
PRIMARY	-0.574*** (0.204)	-0.355*** (0.134)	-0.224*** (0.081)	-0.098 (0.074)
DAYTRIP	0.372*** (0.120)	0.173** (0.088)	0.042 (0.078)	-0.018 (0.057)
OLS	0.705*** (0.136)	0.682*** (0.103)	0.235** (0.116)	0.190*** (0.060)
POISNB	0.510** (0.210)	0.452** (0.178)	0.063 (0.169)	0.069 (0.106)
TRUNC	0.515*** (0.148)	0.499*** (0.097)	-0.011 (0.112)	-0.153*** (0.042)
ENDOGST	-0.086 (0.172)	-0.032 (0.137)	0.150 (0.101)	-0.001 (0.076)

Variable	Model A OLS MRA unweighted[a]	Model B FAT-PET-MRA unweighted[a]	Model C FAT-PET-MRA weighted[b]	Model D Random Effects FAT-PET MRA weighted[c]
CENSOR	-0.146 (0.206)	-0.214 (0.139)	0.306** (0.143)	0.404*** (0.097)
TREND	-0.022*** (0.007)	-0.019*** (0.007)	-0.009** (0.004)	-0.008** (0.004)
ELASTC	0.371*** (0.119)	0.299*** (0.100)	0.127** (0.056)	0.187*** (0.040)
Adj-R^2	0.54	0.67	0.79	0.55
N	594	542	542	542

Dependent variable = P_ELAST.
Coefficient standard errors in parentheses.
*** = p-value ≤ 0.01
** = p-value ≤ 0.05
* = p-value ≤ 0.10
[a]White's robust heteroskedasticity corrected covariance matrix
[b]Weights = 1/ELAST_SE with cluster robust SE_β
[c]Weights = 1/ELAST_SE

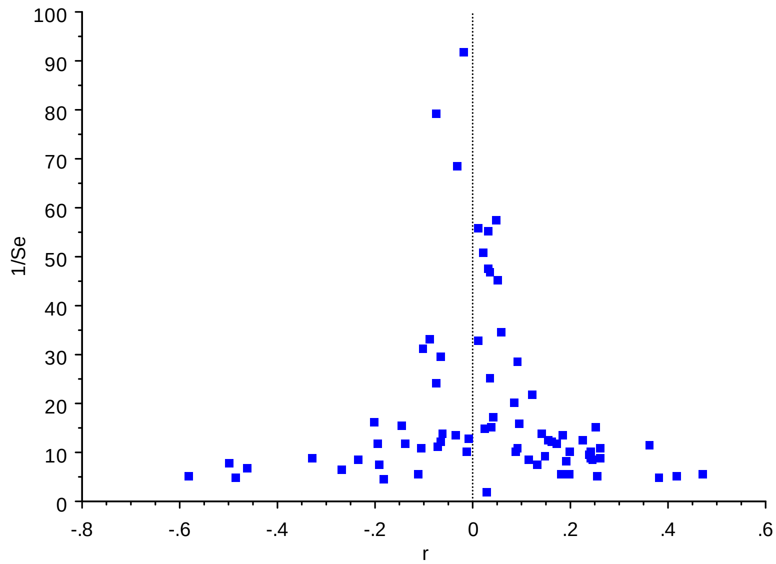

Figure 1: Funnel Graph of Union-Productivity Partial Correlations (r) (Source: Doucouliagos and Laroche (2003)).

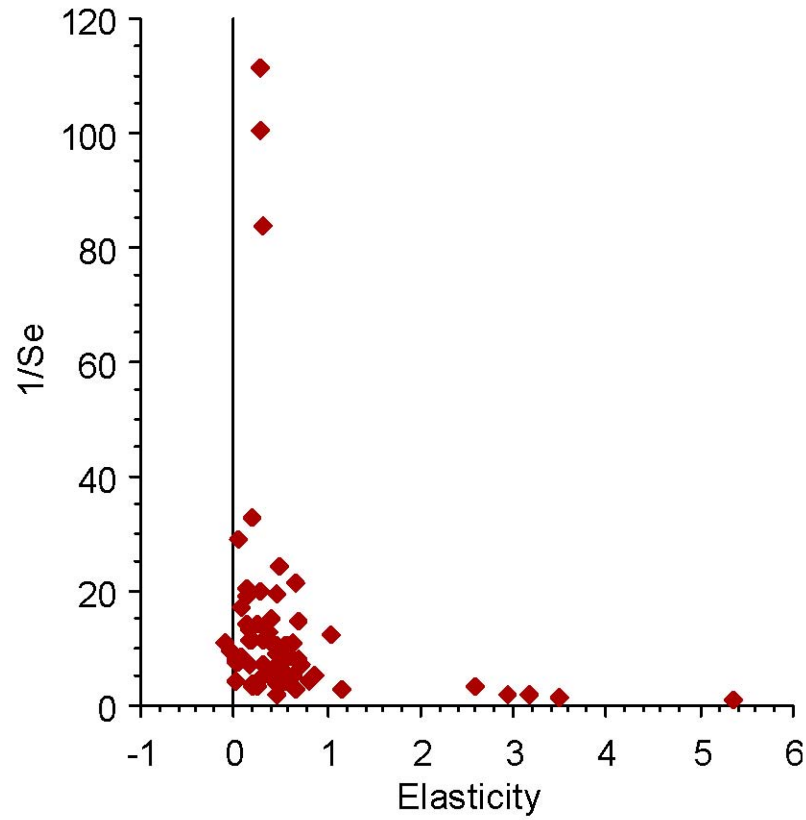

Figure 2: Funnel Graph of Efficiency Wage Elasticities (Source: Stanley and Doucouliagos (2007)).

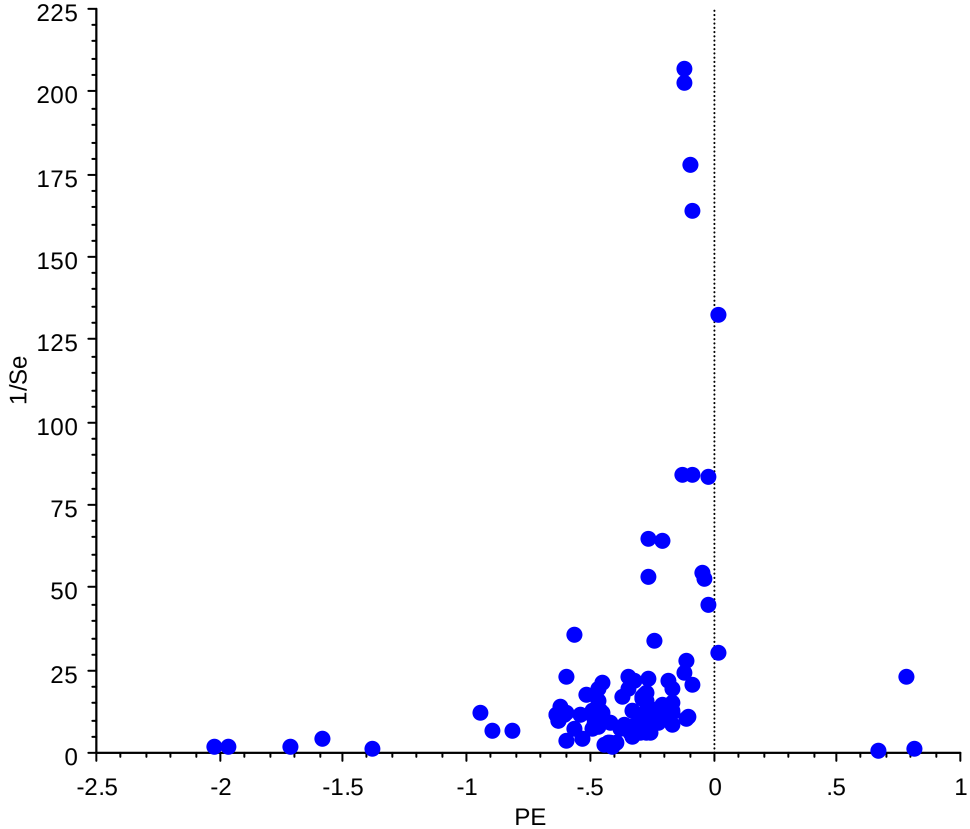

Figure 3: Funnel Graph of Price Elasticities (PE) for Water Demand (Source: Stanley (2005a)).

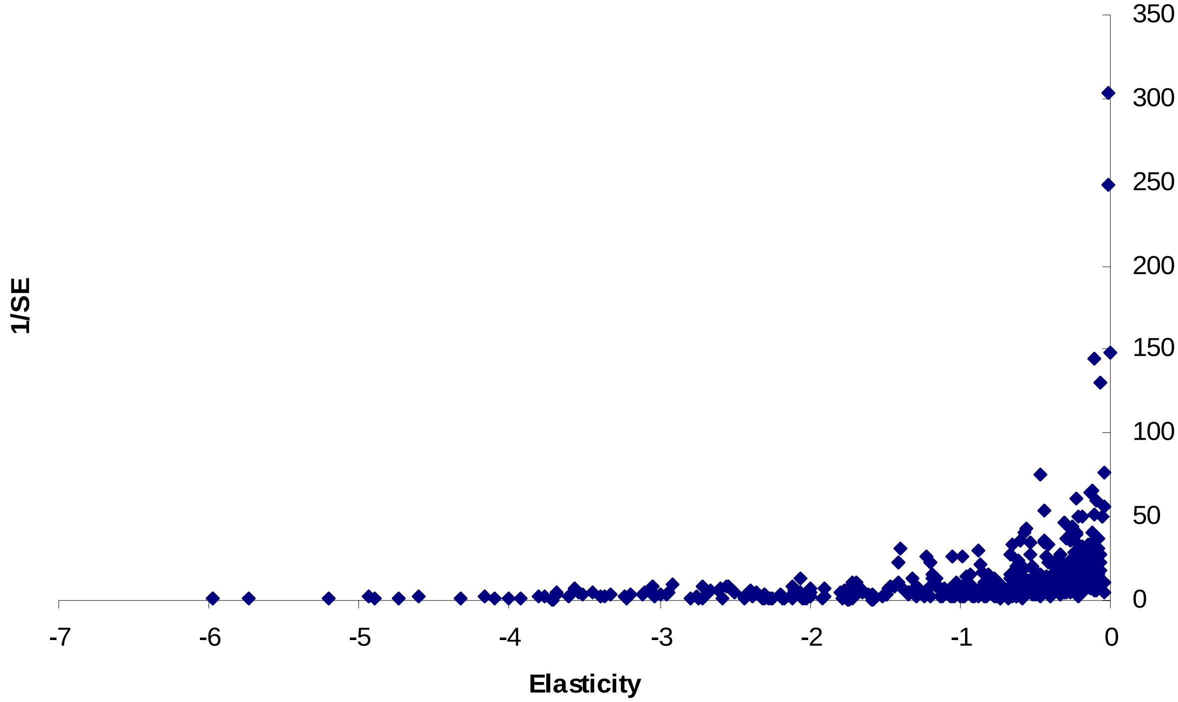

Figure 4: Funnel Graph of Recreation Demand Own Price Elasticities.

References

Adamowicz WL, Fletcher JJ, Graham-Tomasi T (1989) Functional forms and the statistical properties of welfare measures. Am J Agric Econ 71(2):414-421

Ashenfelter O, Harmon C, Oosterbeek, H (1999) A review of estimates of the schooling/earnings relationship, with tests for publication bias. Labour Econ 6(4):453-470.

Card D, Krueger AB (1995) Time-series minimum-wage studies: a meta-analysis. Am Econ Rev 85(2):238-243.

Coric B, Pugh G (2010) The effects of exchange rate variability on international trade: a meta-regression analysis. Appl Econ 42(20):2631-2644.

Dalhuisen J, Florax RJGM, deGroot HLF, Nijkamp P (2003) Price and income elasticities of residential water demand: a meta-analysis. Land Econ 79(2):292-308.

De Long JB, Lang K (1992) Are all economic hypotheses false? J Polit Econ 100(6):1257-1272.

Disdier A, Head K (2008) The puzzling persistence of the distance effect on bilateral trade. Rev Econ Stat 90:37-48.

Doucouliagos C (2005) Publication bias in the economic freedom and economic growth literature. J Econ Surv 19(3):367-388.

Doucouliagos C, Laroche P (2003) What do unions do to productivity: a meta-analysis. Industrial Relations 42(4):650-691.

Doucouliagos C, Stanley TD (2008). Theory competition and selectivity. Deakin Working Paper 2008-06.

Doucouliagos C, Stanley TD (2009) Publication selection bias in minimum-wage research? A meta-regression analysis. British J Industrial Relations (in press).

Egger M, Davey Smith G, Schneider M, Minder C (1997) Bias in meta-analysis detected by a simple, graphical test. British Med J 315(7109):629-634.

Espey, M (1997) Explaining the variation in elasticity estimates of gasoline demand in the United States: A meta-analysis. Energy J 17:49-60.

Espey, M (1998) Gasoline demand revisited: An international meta-analysis of elasticities. Energy Econ 20:273-295.

Espey, M, Espey J and Shaw WD (1997) Price elasticity of residential demand for water: A meta-analysis. Water Resources Research 33(6):1369-1374.

Feige EL (1975) The consequence of journal editorial policies and a suggestion for revision. J Polit Econ 83(6):1291-1295.

Gallett CA, List JA (2003) Cigarette demand: A meta-analysis of elasticities. Health Econ 12(10):821-835.

Gemmill MC, Costa-Font J, McGuire A (2007) In search of a corrected prescription drug elasticity estimate: a meta-regression approach. Health Econ 16(6):627-643.

Görg H, Strobl E (2001) Multinational companies and productivity: a meta-analysis. Econ J 111(475):723-739.

Greene WH (2008) *Econometric Analysis*, Sixth Edition. New Jersey: Prentice-Hall.

Havránek T (2010) Rose effect and the euro: is the magic gone? Rev World Econ 146(2):241-261.

Haab TC, McConnell KE (2002) Valuing environmental and natural resources: The econometrics of non-market valuation. Cheltenham: Edward Elgar.

Hoehn JP (2006) Methods to address selection effects in the meta regression and transfer of ecosystem values. Ecol Econ 60(2):389-398.
Hanemann WM (1984) Welfare evaluations in contingent valuation experiments with discrete responses. Am J Agric Econ 66(3):332-341.
Hanemann WM (1989) Welfare evaluations in contingent valuation experiments with discrete responses: reply. Am J Agric Econ 71(4):1057-1060.
Hotelling H (1947) Letter to National Park Service, in: An economic study of the monetary evaluation of recreation in the National Parks. Washington, DC: U.S. Department of the Interior, National Park Service and Recreational Planning Division.
Knell M, Stix H (2005) The income elasticity of money demand: a meta-analysis of empirical results. J Econ Surv 19(3):513-533.
Krassoi Peach E, Stanley TD (2009) Efficiency wages, productivity and simultaneity: a meta-regression analysis. J Labor Res 30: 262-268.
Leamer EE (1983) Let's take the con out of econometrics. Am Econ Rev 73(1):31-43.
Leamer EE, Leonard H (1983) Reporting the fragility of regression estimates. Rev Econ Stat 65(2):306-317.
Longhi S, Nijkamp P, Poot J (2005) A meta-analytic assessment of the effect of immigration on wages. J Econ Surv 19(3):451-477.
Lovell MC (1983) Data mining. Rev Econ Stat 65(1):1-12.
Mookerjee R (2006) A meta-analysis of the export growth hypothesis. Econ Letters 91(3):395-401.
Nelson JP, Kennedy PE (2009) The use (and abuse) of meta-analysis in environmental and natural resource economics: an assessment. Environ Resour Econ 42(3):345-377.
Roberts CJ, Stanley TD (eds) (2005) Meta-regression analysis: issues of publication bias in economics. Blackwell, Oxford.
Rose AK, Stanley TD (2005) A meta-analysis of the effect of common currencies on international trade. J Econ Surv 19(3):347-365.
Rosenberger RS, Johnston RJ (2009) Selection effects in meta-analysis and benefit transfer: avoiding unintended consequences. Land Econ 85(3):410-428.
Rosenberger RS, Loomis JB (2000) Panel stratification in meta-analysis of economic studies: an investigation of its effects in the recreation valuation literature. J Agric Appl Econ 32(2):459-470.
Rosenberger RS, Stanley TD (2006) Measurement, generalization, and publication: sources of error in benefit transfers and their management. Ecol Econ 60(2):372-378.
Rosenberger RS, Stanley TD (2007) Publication effects in the recreation use value literature: a preliminary investigation. Paper presented at the American Agricultural Economics Association Annual Meeting, Portland, 29 July-1 August 2007. http://purl.umn.edu/9883.
Smith VK, Huang JC (1993) Hedonic models and air pollution: Twenty-five years and counting. Environ Resour Econ 3(4):381-394.
Smith VK, Huang JC (1995) Can markets value air quality? A meta-analysis of hedonic property value models. J Polit Economy 103(1):209-227.
Smith VK, Kaoru Y (1990) What have we learned since Hotelling's letter: A meta-analysis. Econ Letters 32:267-272.
Stanley TD (2005a) Beyond publication bias. J Econ Surv 19(3):309-345.

Stanley TD (2005b) Integrating the empirical tests of the natural rate hypothesis: a meta-regression analysis. Kyklos 58(4):587-610.
Stanley TD (2008) Meta-regression methods for detecting and estimating empirical effect in the presence of publication selection. Oxford Bull Econ Stat 70(1):103-127.
Stanley TD, Doucouliagos H (2007) Identifying and correcting publication selection bias in the efficiency-wage literature: Heckman meta-regression. School working paper – Economic Series 2007, SWP 2007/11. Victoria, Australia: Deakin University.
Stanley TD, Doucouliagos H (2010) Picture this: a simple graph that reveals much ado about research. J Econ Surv 24:170-191.
Sutton AJ, Abrams KR, Jones DR et al (2000) Methods for meta-analysis in medical research. Chichester: John Wiley and Sons.
Tellis GJ (1988) The price elasticity of selective demand: A meta-analysis of econometric models of sales. Journal of Marketing Research XXV:331-341.
Tullock G (1959) Publication decisions and tests of significance – a comment. J Am Stat Assoc 54(287):593.