Do Survey Results Systematically Differ from Hedonic Regression Results? Evidence from a Residential Property Meta-Analysis

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Abstract
In this paper, we evaluate the effect of environmental contamination situations on residential property values. Using the meta-analysis technique, conclusions are drawn about the effect of location, type of study conducted, empirical technique used, and economic conditions on various outcomes. Using observations extracted from 40 peer-reviewed articles, meta-regression analysis is used to identify the factors that explain variation in marginal willingness to pay for environmental amenities and disamenities as a percentage of the average unimpaired value of local residential properties. Our findings suggest that relatively similar property value diminution conclusions are obtained regardless of the methodological approach employed. Additionally, we find no evidence of "publication bias" in our results.

Empirical studies of the effect of environmental contamination on property values often find that contamination is negatively correlated with property values after controlling for other variables that may influence property values. The full spectrum of environmental contamination effects on property values spans findings of no correlation between contamination and property values (e.g., Jackson, 2001; Wilson, 2004; Kiel and Williams, 2007) to findings of strong association between disamenities and property values (Brown, 1976; Barnard, 1978; McCluskey and Rausser, 2001). This wide range of results raises an interesting question: What is the impact of different methodological approaches on determinations of the property value effects due to environmental contamination, ceteris paribus? Conventional wisdom suggests that the methodological approaches (e.g., regression analysis, contingent valuation, case studies) used by researchers may affect property value diminution results in systematic ways. To answer this question, we use meta-analysis to provide an empirical summary of the relationship between environmental contamination and property values across studies that use different methods of valuation.

The meta-analysis developed here summarizes information from articles that use several different methodological approaches to determine the effects of environmental contamination on property values. Our meta-analysis database is comprised of studies

that have used hedonic regression, case studies, travel cost, and survey techniques [e.g., contingent valuation (CV) and conjoint analysis]. Hedonic regression (83% of the observations) is the most common study type found within our meta-analysis, which is not surprising given the literature. There are advantages to using each approach; and the use of these methods in a single study can provide a significant degree of insight into how goods are valued. In fact, according to Stanley (2001, p. 132), "meta-regression analysis can identify the extent to which the particular choice of methods, design and data affect reported results." Also, Franke (2001, p. 186) states that this type of research "uses different methods with offsetting strengths and weaknesses to 'triangulate' on convergent patterns." We take advantage of these different methodological approaches to find whether or not they determine significantly different property valuations.

The rest of the paper follows. First, we review the literature on the meta-analysis technique. Then, we describe our data, methodological approach, and results. Finally, we draw some conclusions and discuss avenues of future research.

LITERATURE REVIEW

Meta-analysis is described by Stanley (2001, p. 131) as "a body of statistical methods that have been found useful in reviewing and evaluating empirical research results." In the fashion of Glass (1976), a meta-analysis is, in essence, an analysis of a series of analyses conducted by other researchers. Researchers have used this process to identify the extent to which the particular choices of empirical methods, research designs, and data affect the reported results. In fact, meta-analysis "has become the accepted practice for evaluating the current flood of conflicting scientific evidence. It is 'how science takes stock' [Stanley (2001), quoting Hunt (1997)]." Meta-analysis has been used widely in the medical, education, and social science fields.

Some meta-analyses are designed specifically to address estimation differences resulting from the utilization of different valuation techniques. List and Gallet (2001) developed a meta-analysis to determine the factors that influence differences between experimental and observed statements of willingness to pay (WTP). The data set included 29 willingness to pay studies, from which 174 observations of both hypothetical and actual valuations were extracted. The analysis used the natural logarithm of the minimum, median, and maximum calibration factors for three separate dependent variable constructs. Results from the meta-analysis provide insight into the characteristics of studies that lower the calibration factors. First, when comparing results across the three models, willingness to pay studies generally have a lower calibration factor than willingness to accept studies. Second, the results suggest that most people are better at valuing private goods than public goods. Third, calibration factors vary greatly across elicitation methods. This indicates that the use of some methods leads to more realistic responses than others. Lastly, the analysis recognized no significant difference in the use of laboratory or field experiments, which indicates that conducting laboratory experiments does not compromise willingness to pay estimates.

Other meta-analyses focus solely on the effects of specific amenities or disamenities on property values. One of the first meta-analyses used to evaluate environmental effects was conducted by Smith and Huang (1995) when they attempted to estimate how changes in air quality affect property values. The meta-analysis used 37 hedonic property value model studies, which generated 86 observations of the marginal willingness to pay for reductions in air pollution in different markets across the United States. The universe of Smith and Huang's study consisted of reports, Ph.D. dissertations, and published and unpublished papers. The model was estimated in two ways: (1) minimum absolute deviation (MAD) and (2) an ordinary least squares (OLS) estimator. The two models provided similar results, but the MAD estimator was slightly more accurate. Results from the hedonic property value studies used in the meta-analysis indicate that a reduction in PM_{10} (particulate matter less than 10 microns) to the daily maximum concentration standard of 150 micrograms per cubic meter warrants a mean marginal willingness to pay of $109.90. When comparing the individual results from the 18 cities across the country, the authors suggest that local conditions can cause a wide variation in the estimated marginal willingness to pay. However, they also realized that the use of a meta-analysis reduces sensitivity to any outliers that exist in the source articles used to create their meta-analysis database.

Ready (2010) developed a meta-analysis to study the effects of landfills on property values. First, two hedonic regression models are estimated using three landfills in Pennsylvania. The first regression model was used to determine the impact area and the second to estimate the price gradient for each of the landfills on a per mile basis. The author finds that two of the three landfills had significant negative impacts on nearby home values when compared to similar homes located further away. He then combines this hedonic estimate and all other available property value impact studies that focus specifically on landfill effects into a meta-analysis. The meta-analysis includes 15 different estimates from 13 landfills from six different states and Ontario, Canada. Results show that, on average, as the distance from a landfill increases, home values increase correspondingly. The volume of waste a landfill accepts has a significant negative impact on home values too. Property values of homes surrounding low-volume landfills are likely to increase on average by 1.3% per mile, while their higher-volume counterparts are likely to have value increases averaging 5.9% per mile.

Ready (2010) also conducts a meta-analysis to measure the impacts of landfills on adjacent properties. The results show that impacts from the landfill are dependent on the amount of waste the landfill accepts. Homes located adjacent to low-volume and high-volume landfills are expected to be worth 2.7% less and 13.7% less, respectively, than similar homes not located adjacent to a landfill. Results from both of Ready's meta-analyses reveal that virtually all of the high-volume landfills have some impact on surrounding property values, and that 20%–26% of low-volume landfills will have no impact on surrounding property values.

To determine the effect of waste sites on property values across North America, Braden, Feng, and Won (2011) conducted a meta-analysis using 46 hedonic studies yielding 129 observations (after the exclusion of outliers). The proportional price effect (PPE) was used as the dependent variable because it is robust to inflation and

variances among markets. The studies were coded according to four negative amenity categories that were mutually exclusive. The results indicate that within a 6.5-mile radius of a waste site, otherwise unimpaired property values demanded a 6.3% price discount. The analysis employed several estimation models, which reveal a few key insights. First, different cleanup stages have no effect on PPE estimates and some regions in North America produce larger PPE estimates than others. Second, sites on the National Priority List (NPL) provide smaller PPE estimates than terrestrial hazardous sites that are not included in the NPL. Similarly, terrestrial and aquatic hazardous waste sites produce larger PPE estimates than nuclear sites and non-hazardous waste sites,[1] with aquatic hazardous waste sites showing the greatest impact on PPE.

The meta-analysis method is also directly related to the method of benefits transfer. Braden, Feng, Freitas, and Won (2010) conducted a study that consolidated these methods. They defined the benefits transfer method as "the application of relationships derived from original research to predict outcomes in data contexts related to but not included among the background studies" (p. 101). In what the authors refer to as a "meta-functional" study, the value function used is derived from the results of the meta-analysis. A meta-functional transfer yields a more efficient account of policy site characteristics than simpler value transfer methods. The study encompassed the Great Lakes Areas of Concern (AOCs), and the model was designed to estimate the loss in property values associated with contamination of the area.

The benefits transfer model was also applied to a meta-analysis by Braden, Feng, and Won (2009). This study focused on hedonic property value studies in the Great Lakes AOCs. The meta-function estimation comprised a final sample of 129 observations that projected the average proportional diminution to property values to be 4.5%. From here, the function was calibrated to the policy sites to determine estimates of site values. After multiplying the PPE by the number of owner-occupied homes within two miles of the AOCs and their respective weighted median property values, the authors determined that property values (cumulatively) were diminished by $5.3 billion (in 2005 dollars). A few of the site-specific estimates were then compared to their hedonic site-specific studies and determined to be fairly accurate. The major problem that the authors noted about this analysis was that the meta-function was unable to easily make a distinction between policy sites. Thus, the need is apparent for an empirical analysis that allows for distinction between communities.

A meta-analysis conducted by Simons and Saginor (2006) is arguably one of the most comprehensive meta-analyses in the real estate literature as it measures the proximity influence of several different types of disamenities and amenities on residential property values and also compares results across multiple methodologies. The study reviewed 58 articles that represented negative amenities and 17 that represented positive amenities, producing 228 and 62 observations, respectively. The studies included within the meta-analysis applied hedonic regression, survey, case study, or some "other" type of methodology. The data set including only negative amenity studies was shown to have a mean loss of 9.5% on average unimpaired property value ($157,818), and the average proximity influence was determined to be slightly less than two miles. In other words, property values of homes within two miles of the

source of contamination/disamenity were affected. Outlier-free and five observation maximum models were also analyzed to test for problems with multicollinearity, heteroscedasticity, and a file drawer effect. No complications were discovered within the model; however, in the outlier-free model, parameter estimates varied considerably.

Simons and Saginor (2006) utilized only regression analysis studies in the meta-analysis of positive amenities. This model was run separately in order to ascertain the order of magnitude of the parameter estimates, as well as to establish any symmetry in proximity influence. Results from the positive amenities model suggested that there is little symmetry between positive and negative amenity proximity influences. All models established that regression analysis typically provides lower impaired estimates than other methods, and that further research needs to be conducted to analyze the effects of positive and negative influences. However, depending on which dependent variable was being used, some model results suggested that there was no significant difference in property value diminution between regression, case study, and survey methods. If anything, this is one of the motivations for the present study—to validate this particular result.

Data, Methods, and Results

Using a meta-analysis to provide an empirical summary of the literature related to a particular kind of environmental contamination situation requires several different kinds of data. These include the geographical study area, the kind of analytical method used (e.g., hedonic regression, travel cost, contingent valuation, case study), general economic conditions during the study period, and other metrics that may affect the results reported in each of the analyses. Like any other method, meta-analysis has advantages and disadvantages. Some of its advantages are that it covers a broad range of goods, allows for testing of convergent validity between different valuation methods, allows for a more comprehensive measurement of property values because of its pluralistic approach, allows for diagnostic testing (multicollinearity, heteroscedasticity, outliers) of the underlying meta-regression model, and can examine the effects of various sources of contamination on property values. Some of its disadvantages are that researchers may disagree over which characteristics are important to include in the analysis, the study may be subject to publication bias, the geographic extent of property value effects cannot always be determined depending on the amount of information presented in the source article, and results may be different depending on which valuation techniques are used in the meta-analysis. Stanley (2001, p. 137) commented that: "However, because the number of studies is limited and most studies entail a unique combination of techniques, independent variables, data, time periods and other research choices, not every study characteristic can be coded and analyzed. Nor should a researcher wish to do so. Variation due to minor modeling choices may be treated as part of the random study-to-study background."

Despite the criticisms of meta-analysis procedures, we believe that this method is a useful tool that can tease out any systematic differences in property value diminution across different valuation methodologies. For academic researchers, meta-analysis

provides support for the features of particular empirical studies that correlate to higher or lower willingness to pay estimates. That may influence how researchers modify their research questions and methods over time. In a litigation context, meta-analysis provides empirical support of the property value diminution conclusion. The meta-analyses conducted by Smith and Huang (1995), List and Gallet (2001), Gen (2004), Simons and Saginor (2006), Sirmans, MacDonald, Macpherson, and Zietz (2006), and Ready (2010) provide examples of how this technique can be used.

Following the academic literature on meta-analysis, we extracted information from peer-reviewed articles to construct a valuation meta-analysis. This meta-analysis can best be described as a "quantitative literature review." This method uses information from previous empirical research that is then summarized, analyzed, and evaluated using conventional statistical methods and criteria. The meta-analysis guidelines developed by Stanley (2001) are important to consider when using this technique. We have organized the rest of this section around Stanley's (2001) five steps to create a meta-analysis: (1) include all relevant studies from a standard research database; (2) choose a summary statistic and reduce the evidence to a common metric; (3) choose moderator variables; (4) conduct a meta-regression analysis; and (5) subject the meta-regression analysis to specification testing.

STEP 1: SELECT ARTICLES TO INCLUDE IN THE META-ANALYSIS

Stanley (2001) suggests including published and unpublished studies in the meta-analysis. Since the results from unpublished studies often change prior to publication in standard research databases, we have limited our analysis to published research. Published research in this area is often included in research databases such as EconLit. After conducting a search of EconLit for articles using the keywords "hedonic pricing," "travel cost," and "contingent valuation," we ended up with a list of articles that included some of the articles used by Gen (2004) in his meta-analysis and most of the articles referenced in Simons and Saginor (2006). This gave us a preliminary universe of 2,614 articles. We screened articles to make sure they addressed property values, or in two cases,[2] were reflective of property value losses. After removing articles that did not reflect influences on residential property values, we extract enough observations to give us an approximately 5% margin of error at a 95% confidence level. After we extracted observations from the 40th article, we had 325 observations. The margin of error with 325 observations from an approximate universe of 10,000 observations (if we coded all 2,614 articles and averaged 5 observations per article) is 5.3% at a 95% confidence level. This compares favorably to the margin of error of $\pm$ 7% reported in Rosenberger and Loomis (2001). For transparency, the Appendix shows how we extracted observations from three different articles.

STEP 2: CHOOSE A SUMMARY STATISTIC

For our meta-regression analysis, we followed the published literature on the subject. We considered two different dependent variables: effect size and marginal willingness to pay as a percentage of the unimpaired value. Effect size is the same dependent

variable used by Gen (2004), and marginal willingness to pay is the primary dependent variable used by Simons and Saginor (2006). The latter study used multiple dependent variables, including the dollar value of property loss and diminution as a percentage of the average unimpaired property value in each article. According to Stanley (2001, p. 136), effect size is the preferred variable to calculate and use as the dependent variable in a meta-analysis regression model because it "allows diverse studies, potentially even with different outcome variables, to be compared directly on the same dimensionless scale." Stanley suggested that a great advantage of using effect size is that the researcher obtains an increase in statistical power of the results. In other words, when the effect sizes from a number of independent studies are combined, statistical power increases corresponding to the sum of the sample sizes across all of those studies. Meta-analyses with more statistical power have more reliability. Stanley (2001, p. 142) also added that "If there is a genuine underlying empirical effect, rather than the exploitable artifacts of econometric misspecification, then the empirical literature should exhibit a significantly positive relation between the normalized test statistic which is used as the dependent variable and the study's degrees of freedom."

One of the difficulties of using effect size as the dependent variable is that it complicates the interpretation of the results. One important use of our meta-regression model is to predict a range of property value effects for different environmental contamination situations. So, while we acknowledge the importance of using effect size as the dependent variable, for ease of interpretation, we report the results from the regression models where the absolute value of the percentage effect is employed as the dependent variable. But, because the directions of impact are mostly the same regardless of dependent variable chosen, our results have higher statistical power. Also, we control for observations that involve amenities that have a positive effect on property values through the use of a dummy variable, an approach similar to that described by Simons and Saginor (2006).

STEP 3: CHOOSE MODERATOR VARIABLES

The moderator (or independent) variables in this analysis were selected based on previous meta-analyses. Gen (2004) found that only 29 of his more than 200 studies (12.7%) reported any measure of income. We have similar reports of income in our randomly selected 40 articles. Therefore, income was not used as a moderator variable. Also, we did not use race because a large majority of studies do not report the racial composition of households included in their samples. The definitions and descriptive statistics for the dependent and moderating variables are reported in Exhibit 1.

Our meta-analysis provides a great deal of insight into the factors that influence value estimates. Our data set comprises 40 articles, yielding 325 observations that reflect the effects from both amenities and disamenities on property values. Descriptive statistics suggest that, on average, contamination events that involve water, Superfund sites, air sources, linear sources, and urban disamenities result in 6.1%, 11.4%, 2.5%, 10.4%, and 5.7% decreases in property values, respectively. Amenities or improvement programs, on average, result in an 11.8% increase in property values.

Exhibit 1
Descriptive Statistics of the Moderator Variables

Name	Definition	Descriptive Statistics
ABSDIMPERC	The absolute value of *DIMPERC*, calculated as marginal impact (*REALVAR*) on prices or values of an amenity or disamenity divided by *REALVAL*	Mean = 0.10, Std. Dev. = 0.15
REALVAL	Unimpaired property value identified within the study	Mean = 90,415, Std. Dev. = 51,106
URBAN	= 1 if data from study represents an urban area, 0 otherwise	Studies located in an urban area = 55%
SUBURBAN	= 1 if data from study represents a suburban area, 0 otherwise	Studies located in a suburban area = 14%
MIXED	= 1 if data from study is a mix of intra-urban locations, 0 otherwise	Studies located in a mix of intra-urban locations = 17%
REGIONAL	= 1 if geographic location of the study is regional, 0 otherwise	Studies with regional observations = 2%
NATIONAL	= 1 if geographic location of the study is national, 0 otherwise	Studies with national observations = 4%
INTERNATIONAL	= 1 if geographic location of the study is international, 0 otherwise	Studies with international observations = 13%
NUKEMANUF	= 1 if source of contamination is a nuclear power plant or manufacturing facility, 0 otherwise	Nuclear power plants or manufacturing facilities = 3%
LANDFILL	= 1 if source of contamination is a landfill, 0 otherwise	Landfills = 2%
SUPERSITE	= 1 if source of contamination is a hazardous waste or superfund site, 0 otherwise	Hazardous waste or Superfund sites = 7%
LINEAR	= 1 if source of contamination is a linear source (power lines, railroad tracks, etc.), 0 otherwise	Linear source of contamination = 13%
WATER	= 1 if source of contamination is groundwater or surface water pollution, 0 otherwise	Groundwater or surface water pollution = 35%
AIRCAFO	= 1 if source of contamination is some type of air pollution, 0 otherwise	Air pollution = 9%
URBANDIS	= 1 if source of contamination is an urban disamenity (airport noise etc.), 0 otherwise	Urban disamenity = 4%
POSITIVE	= 1 if source is a positive amenity (views, proximity to water, etc.) or a prevention program, 0 otherwise	Positive amenity = 42%
LITIG	= 1 if observation is involved in litigation, 0 otherwise.	Mean = 0.003, Std. Dev. = 0.055

Exhibit 1 (continued)
Descriptive Statistics of the Moderator Variables

Name	Definition	Descriptive Statistics
INFO	= 0 if no information was disclosed about the contamination, = 1 if there was an announcement of something bad, = 2 if there was an announcement that the contamination source was closing, and = 3 if information about the event is common knowledge	No information = 59%, Announced bad = 11%, Announced closing = 0.31%, Common knowledge = 30%
UNEMP	Unemployment rate of the closest metropolitan statistical area (or state) during the years of the study	Mean = 6.58, Std. Dev. = 1.37
LNSAMPLE	Natural log of the sample size of the study	Mean = 6.06, Std. Dev. = 1.98
LNDIST	Natural log of the distance (in feet) from the contamination source; adjacent properties are assigned a value of 0.0001.	Mean = 5.67, Std. Dev. = 4.43
STUDY_SURV	= 1 if the study uses contingent valuation or conjoint analysis, 0 otherwise	CV/Conjoint Study = 1.2%
LOTSOFOBS	= 1 if the study has at least 13 extracted observations, 0 otherwise	Observations part of a study with 13+ observations = 22.3%
YEAROFDATA	Year or average from the range of years that data was collected for the study	Mean = 1990, Std. Dev. = 7.64

The average distance of all of the included observations to the contamination source was 6,999 feet, or approximately 1.32 miles.

We included a dummy variable (*LOTSOFOBS*) to control for articles from which we extracted more than 13 observations, which corresponds to the 75th percentile of the number of observations distribution. This allows us to test for a kind of publication bias (to determine whether articles from which we extract more than 13 observations unduly influence the results).

Another important issue to address when constructing a meta-analysis is the inter-coder reliability. When multiple researchers are looking through articles and extracting observations to be analyzed, without proper training it is possible that different researchers could extract a different number of observations, which would decrease the credibility of any results. To eliminate this concern, we underwent extensive training on how to extract observations from articles. Ten articles were used as examples. Our research assistants coded the articles independently, results were compared, and any differences in how the articles were coded were reconciled. At least once a week during the coding process, the lead author verified the observations being extracted from articles to make sure there were no inter-coder reliability concerns. Finding none, the process continued until all 40 articles were coded.

STEPS 4 AND 5: CONDUCT META-REGRESSION ANALYSIS AND MODEL SPECIFICATION TESTS

The final steps suggested by Stanley (2001) were that the researcher should calibrate the meta-regression model and test different functional form specifications of it. This means that the researcher should conduct the usual diagnostic tests of the regression model (heteroscedasticity, functional form misspecification, multicollinearity, and outlier detection). We coded a total of 325 observations, some of which had missing data elements on some variables. When we eliminated observations with missing data elements, 295 observations remained. Then, using the Hadi (1994) method of outlier detection, we noticed that 22 observations had a much higher value of *REALVAL* and tended to be classified more often as local (the baseline location) compared to all other observations. Using the remaining 273 observations, we ran several preliminary regression model specifications with different functional forms of the interval level variables (untransformed and transformed using the natural log function). Including more than one type of methodological approach (e.g., including both dummy variables to indicate a hedonic regression analysis and a contingent valuation analysis) resulted in excessive multicollinearity, which we mitigated by only including the dummy variable *STUDY_SURV* in the final model specification.

The results of our baseline ordinary least squares (OLS) regression model are presented as Model 1 in Exhibit 2. Using the variance inflation factor (VIF) for each independent variable, we found no extreme multicollinearity. In fact, the highest VIF is 7.00 (*INTERNATIONAL*), which is well below the general rule of thumb of 10. Then, using the Breusch-Pagan/Cook-Weisberg test, we found the presence of heteroscedasticity in the error terms (χ^2 = 112.47, prob. = 0.000). To resolve this issue, we used two different methods for correcting the standard errors for heteroscedasticity. First, we used the Huber-White heteroscedasticity correction to obtain robust standard errors. Second, we noticed that observations are 'clustered' in the sense that many of them come from a single article. This clustering of observations means that the standard errors obtained from the baseline OLS regression model are biased. To correct the bias, a bootstrapping method that clusters the observations into strata (meaning that groups of observations are extracted from the same article) was used. Models 2 and 3 in Exhibit 2 show the regression results with the corrected standard errors, which affect the test statistics used to determine whether or not a variable is a significant predictor of the dependent variable. Note that these remedies for heteroscedasticity do not affect the regression coefficients; this is why only one set of regression coefficients is reported in Exhibit 2.

Next, we tested for any remaining heteroscedasticity by plotting the regression model error terms against the dependent variable to see if any unusual patterns emerge. No discernible pattern emerged, suggesting that heteroscedasticity was corrected by the bootstrapping process.

For all three models, the effective number of observations is 273. The overall *F*-statistic is 4.84 (prob. = 0.000). The rounded R^2 and adjusted-R^2 values are 0.31 and 0.25, respectively. At the 95% level of confidence, the statistically significant predictors of the dependent variable (*ABSDIMPERC*) in the baseline model (Model

Exhibit 2
Meta-Regression Analysis Results (DV = Absolute Value of Percentage Effect)

	(1)			(2)		(3)		
	OLS Regression Results			Robust Regression Results		Bootstrapped Regression Results		
Variable	Coeff.	Std. Err.	*T*-Stat.	Std. Err.	*T*-Stat.	Std. Err.	*Z*-Stat.	VIF
CONSTANT	−4.8938	2.376	−2.060	3.892	−1.260	1.489	−3.290	na
REALVAL	−0.0000	0.000	−1.210	0.000	−0.900	0.000	−1.960	2.86
URBAN	−0.0157	0.027	−0.590	0.040	−0.390	0.016	−0.980	6.13
SUBURBAN	0.0898	0.036	2.470	0.053	1.700	0.021	4.250	4.91
MIXED	0.0167	0.033	0.510	0.055	0.300	0.021	0.800	4.46
REGIONAL	0.0320	0.065	0.490	0.083	0.390	0.054	0.590	2.76
NATIONAL	−0.0800	0.096	−0.830	0.092	−0.870	0.050	−1.590	4.78
INTERNATIONAL	−0.0641	0.045	−1.410	0.057	−1.130	0.028	−2.270	7.00
NUKEMANUF	0.0196	0.071	0.280	0.043	0.460	0.036	0.540	3.83
LANDFILL	−0.1882	0.101	−1.870	0.080	−2.340	0.042	−4.440	2.65
SUPERSITE	0.0178	0.032	0.550	0.044	0.410	0.015	1.190	2.62
LINEAR	−0.0302	0.039	−0.770	0.033	−0.900	0.020	−1.480	5.21
WATER	−0.0127	0.025	−0.510	0.023	−0.560	0.015	−0.870	5.23
AIRCAFO	−0.0181	0.036	−0.500	0.033	−0.550	0.028	−0.650	4.16
URBANDIS	0.1779	0.060	2.980	0.049	3.670	0.037	4.820	1.85
POSITIVE	−0.0062	0.021	−0.300	0.025	−0.250	0.014	−0.450	3.79
LITIG	0.3061	0.133	2.290	0.048	6.330	0.036	8.440	2.33
INFO	0.0168	0.009	1.980	0.010	1.600	0.009	1.890	4.80
UNEMP	0.0327	0.010	3.220	0.019	1.740	0.006	5.450	6.56
LNSAMPLE	−0.0013	0.005	−0.270	0.005	−0.250	0.004	−0.370	3.04
LNDIST	−0.0015	0.003	−0.530	0.003	−0.470	0.003	−0.590	3.53
STUDY_SURV	0.1046	0.055	1.910	0.050	2.110	0.019	5.650	1.55
LOTSOFOBS	−0.0215	0.019	−1.120	0.041	−0.520	0.012	−1.740	3.30
YEAROFDATA	0.0024	0.001	2.010	0.002	1.260	0.001	3.190	2.78

Notes: The number of observations is 273. F-statistic = 4.84 [prob. = 0.000]; R^2 = 0.3091; Adj. R^2 = 0.2453; RMSE = 0.0873.

1) are *SUBURBAN*, *URBANDIS*, *LITIG*, *INFO*, *UNEMP*, and *YEAROFDATA*. In Model 2 with robust standard errors, additional independent variables become significant predictors of *ABSDIMPERC*; these are *LANDFILL* and *STUDY_SURV*. In Model 3 with the bootstrapped standard errors, additional independent variables become significant predictors of the dependent variable (compared to Model 1); these are *REALVAL*, *INTERNATIONAL*, *LANDFILL*, and *STUDY_SURV*.[3]

Overall, we see that Model 3 corrects the biased standard errors in Model 1 for clustering effects. We found that a $10,000 change in the average unimpaired value is associated with an approximate 0.3% increase in the percentage diminution (*ABSDIMPERC*). This suggests that higher-valued properties have higher property value diminution percentages, holding all other variables constant. Also, observations that are based on suburban locations, all else constant, are associated with an 8.98% higher diminution. Observations that are national and international in scale are associated with an 8.0% and 6.41% lower diminution, all else held constant. Observations from mostly nuclear power plants and a few other manufacturing facilities are associated with an effect that is not significantly different from zero. Observations that involve landfills (*LANDFILL*) are associated with an 18.82% lower diminution. Also, Superfund sites are associated with a 1.78% higher diminution relative to the baseline. Observations based on linear contamination sources, such as pipelines, are associated with 3.02% lower diminution relative to the baseline. Water observations, all else constant, are associated with a 1.27% lower diminution. Observations based on air pollution, such as that from a concentrated animal feeding operation (*CAFO*), are associated with a 1.81% decrease in property value diminution relative to the baseline scenario (Model 1). Urban disamenities, such as noise, are associated with a 17.79% increase in property value diminution, all else held constant. Observations drawn from situations that involve litigation are associated with a 30.61% higher diminution. *INFO* has a positive association with property value diminution of 1.68%, but is significant in the baseline model only. All else being equal, a 1% increase in the unemployment rate is associated with a 3.27% increase in property value diminution. This variable controls for general economic conditions at the time and location of the individual studies. Observations that came from survey studies are associated with a 10.46% property value diminution when compared to the baseline models (regression, travel cost, etc.). Finally, the year of data collection has a significant impact on property values as each additional year is associated with a 0.24% increase in property value diminution.

Interestingly, the natural log of the number of observations used in each of the source articles, the natural log of distance of the farthest property in each source article, as well as observations that come from articles where we extracted 13 or more observations, are insignificant predictors of *ABSDIMPERC*. Arguably the most interesting results here are that (1) relative to the baseline (regression, travel cost, etc.), the use of survey methods produces significantly different property value diminution percentages of approximately 10% and (2) there is no evidence of publication bias. The first result is important as it suggests that we might expect to see close to a 10% discrepancy in the property value diminution percentages determined by different methods (e.g., hedonic regression and surveys). At the heart of this result is the debate concerning knowledge differences between buyers and sellers in the marketplace, the timing of new knowledge that might affect buying behaviors, and the difference between stated preference and revealed preference methods. Lipscomb et al. (2011) discuss the role of information asymmetry and how it can be mitigated through the use of the CV method. The second result tests the hypothesis that one might expect a different set of results if many observations are being extracted from only a few articles. Our results suggest that this is not problematic.

Also of importance is the error rate associated with these results. One measure of error, which improves upon error being measured by the standard deviation (because it is based on deviation from the mean, not deviation from zero), is the root mean square error (RMSE). RMSE, which is a more meaningful measure of the predictive accuracy of our regression model, is calculated as $\sqrt{\Sigma[f(x_i) - y_i]^2/n}$. This formula means that for each observation, the predicted value $f(x_i)$ of the dependent variable (*ABSDIMPERC*) is calculated using the regression coefficient estimates. The squared differences of the predicted values and the actual values (y_i) of *ABSDIMPERC* are summed and divided by the number of observations used in the regression analysis (273). Finally, the square root of the sum is determined. The RMSE for this model is 0.08, which means that the model's average error in predicting the dependent variable is 8%.

As a final step, we can use the results of the meta-regression analysis to predict the property value diminution of a given situation. To illustrate, we can use the regression coefficients to predict the diminution percentage in two different scenarios. In the first scenario, water contamination occurred in an area where (1) the average unimpaired value of a residence is $47,300, (2) the location is rural (the baseline scenario), (3) the contamination source is linear (e.g., a gas pipeline), (4) the medium is water, (5) the properties are involved in litigation, (6) there was a public announcement of contamination in the area, (7) the unemployment rate is 6.5%, (8) the study area has 100 properties (natural log of 100 is 4.605), (9) the maximum distance from the contamination source to a property is one mile (natural log of 5,280 feet is 8.571), and (10) the data were collected as of 2008. Using these inputs, the following formula calculates the diminution percentage:

$$\begin{aligned} ABSDIMPERC = {} & ((-4.893768) + (-0.000000268 * 47{,}300) + (-0.0301824) \\ & + (-0.0127081) + (0.3060878) + (0.0168142) + (0.0326509 * 6.5) \\ & + (-0.0013003 * 4.605) + (-0.0015268 * 8.571) \\ & + (0.0024109 * 2008)) = 40.78\% \end{aligned}$$

In the second scenario, oil contamination to the soil occurred in an area where (1) the average unimpaired value of a residence is $350,000, (2) the location is rural (the baseline scenario), (3) the contamination source is linear, (4) the properties are involved in litigation, (5) there was a public announcement of contamination in the area, (6) the unemployment rate is 4.5%, (7) the study area has 100 properties (natural log of 100 is 4.605), (8) the maximum distance from the contamination source to a property is one-half mile (natural log of 2,640 feet is 7.878), and (9) the data were collected as of 2006. Using these inputs, the following formula calculates the diminution percentage:

$$\begin{aligned} ABSDIMPERC = {} & ((-4.893768) + (-0.000000268 * 350{,}000) + (-0.0301824) \\ & + (0.3060878) + (0.0168142) + (0.0326509 * 4.5) \\ & + (-0.0013003 * 4.605) + (-0.0015268 * 7.878) \\ & + (0.0024109 * 2006)) = 27.04\% \end{aligned}$$

CONCLUSION

We tested whether different methodological approaches used to determine diminution percentages produced statistically different results. As sometimes there is more information in sales that do not occur than sales that did occur (Kinnard, 1992), arguably we learned more from variables that do not significantly predict property value diminution percentages. First, after using a bootstrapping method to correct the standard errors obtained from OLS regression, we found that a few articles from which we extracted more than 13 observations did not significantly influence the results (i.e., no publication bias).

Second, we found a significant difference in diminution conclusions from studies that use survey methods. There are some caveats to this result, however. First, our random sample of the literature only resulted in one survey-based study included in the study. This is not surprising given that the use of survey research to estimate property value diminution is not as prevalent in the literature as, say, hedonic regression studies. While our result is inconsistent with other studies that have found generally that stated preference methods yield lower benefit estimates than revealed preference methods (Carson, Flores, Martin, and Wright, 1996; Rosenberger and Loomis, 2001), the small sample size issue (i.e., only one survey article in the meta-analysis) will need to be overcome in future research. One way to manage this issue is to use stratified random sampling; however, the relatively small number of studies using survey research to estimate property value diminution remains an issue. By addressing issues related to the randomness of the sample and statistical power, we have improved the generalizability of our results to other residential areas. We used two scenarios to illustrate the generalizability of our results. This will be a useful tool for researchers who do not have the time or budget to conduct their own residential meta-analysis studies.

More research is warranted to address the impact of different methodologies, different sample sizes, etc. on *non-residential* property value diminution. At least one article (Saginor, Simons, and Throupe, 2011) has addressed non-residential property value effects using the meta-analysis method. Additional research would externally validate their findings.

APPENDIX

ARTICLES USED TO CREATE THE META-ANALYSIS DATABASE

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THREE CODING EXAMPLES

EXAMPLE 1: HAMILTON AND SCHWANN (1995)

Hamilton and Schwann (1995) provide several different circumstances that allowed us to break out the data into six observations. First, the sample size was distributed according to distance from the high-voltage towers. Only properties within 200 meters of the power lines or properties adjacent to the transmission lines were used as part of the final sample. Using these two distance zones (adjacent to the transmission lines and within 200 meters), Hamilton and Schwann used regression analysis to determine the effect of removing the *visual externality* of the transmission lines on property value. So, our first observation is based on the effect of removing the visual externality for properties adjacent to the transmission lines; our second observation is based on the effect of removing the visual externality for properties within 200 meters of the power lines. Next, the effect on property values due to the *proximity* to the high-voltage towers was tested for each of the distance zones. This produced the third and fourth observations. Finally, tests were conducted to determine the effect on property values from removing *both* the visual externality of the transmission lines and the proximity effect to the towers, giving us our fifth and sixth observations.

After determining the number of observations in the study, we extracted data on each observation from the articles. First, the variable explaining property value diminution (*REALVAR*) was given for each of the observations in Hamilton and Schwann (1995, Table 6). Property values for each observation (*REALVAL*) were determined by dividing the diminution amount by the percent diminution. This percentage diminution value was used to code the independent variable, *ABSDIMPERC*. Since this study was based in Vancouver, British Columbia, Canada, the geographic location (GEO)—a vector containing the variables *REGIONAL*, *NATIONAL*, and *INTERNATIONAL*—of the study was coded as International. As described earlier, the distance to the contamination (*LNDIST*) was determined to be either adjacent to or within 200 meters of the transmission lines. Adjacent properties were assigned a distance value of 0.0001. Since the type of contamination was from the high-voltage power lines, the variable *LINEAR* was assigned a value of 1 in our meta-analysis. These observations were also coded as positive because the authors attempt to measure the increase in property value that result from removing the transmission line externality, or increasing the distance from the transmission line. Thus, the observations are considered to be an improvement from their current state. The unemployment rate (*UNEMP*) of 8.53 was determined by averaging the unemployment rates in British Columbia, Canada, for the years 1989 to 1991, toward the end of the whole time span (*YEAROFDATA*) in which the study took place. The study occurred in an urban area (*URBAN*) because it was based in metropolitan Vancouver. For all observations that correspond with the properties adjacent to the high-voltage towers, a sample size of 426 was used (and transformed via the natural log function to compute *LNSAMPLE*), and for those properties within 200 meters of the transmission lines, a sample size of 2,364 was used. The study technique (*STUDY_REG*) was determined to be a regression analysis, thus by default the variable *STUDY_SURV* was coded as "0."

From the information provided in the study, there is no indication that this work was in any way related to litigation, therefore the variable *LITIG* was assigned a value of "0." Additionally, the variable *INFO* was coded as "0," as there was no indication that information was disclosed to the public regarding the impacts of the transmission lines on property values. Finally, the variable *LOTSOFOBS* was assigned a value of "0" since only six observations were extracted from this study.

EXAMPLE 2: NELSON, GENEREUX, AND GENEREUX (1992)

From a study by Nelson, Genereux, and Genereux (1992), we extracted one observation: a regression analysis (*STUDY_REG*). Thus, a value of "0" was assigned to *STUDY_SURV* by default, using a sample size of 708 properties, which was transformed to the natural log function to provide a value for *LNSAMPLE*. Since there was only one observation, the variable *LOTSOFOBS* was assigned a value of "0." The study was conducted in the suburban area of Ramsey, Minnesota, which we considered to be a local observation when coding the vector GEO. Since the observation was considered to be local, no value was coded for the *REGIONAL*, *NATIONAL*, or *INTERNATIONAL* variables within that vector. The study identified contamination from the Anoka Regional Landfill (*LANDFILL*) as the source. The *YEAROFDATA* variable can be described by the study taking place between 1979 and 1989; the associated unemployment rate (*UNEMP*) was calculated to be 7.85 by using the midpoint unemployment rate for the state of Minnesota during those years. The data used in the study was within 0.35 and 1.95 miles of the center of the landfill, which gave us our distance (*LNDIST*) to the source of contamination. The value of diminution (*REALVAR*) was based on the 6.2% increase in property values for each mile away from the landfill. Table 2 in Nelson, Genereux, and Genereux shows the mean value of homes used in the study, which became the variable describing property value (*REALVAL*). The absolute value of the *REALVAR* variable divided by *REALVAL* provided the value to be assigned to the independent variable, *ABSDIMPERC*. There was no indication that this observation was involved with any type of litigation, so the variable LITIG was assigned a value of "0." Finally, the variable *INFO* was coded as a "3" for common knowledge because the authors discuss how previous studies in the same area also determined that the landfills had negative impacts on nearby property values.

EXAMPLE 3: BOLITZER AND NETUSIL (2000)

We extracted 18 observations from Bolitzer and Netusil (2000). These observations are based on three models used to investigate the relationship between the sales prices of homes in the study area and open spaces within 1,500 feet of a home. In Model A, the effect of any type of open space within 1,500 feet of a home was estimated. Model B refined the analysis by distinguishing between the four open-space types. Model C focused on the effect of distance from an open space by introducing six dummy variables. Finally, each model was estimated using a linear and semi-log functional form. More specifically, they measured the price effect when a property is located 1,500 feet from an open space, park, or golf course. Next, the authors

measured the impact on sales prices at different distances from open space using six distances: within 100 feet, from 101 to 400 feet, 401 to 700 feet, 701 to 1,000 feet, 1,001 to 1,300 feet, and 1,301 to 1,500 feet.

The *REALVAR* variable was derived from Models A–C. *REALVAL* values were based on the average real sales price for the area in Table 1 in Nelson, Genereux, and Genereux. The absolute value of *REALVAR* divided by *REALVAL* provided us with the values for our independent variable, *ABSDIMPERC*. The entry for the GEO vector was "local" because it took place in Portland, Oregon, thus *REGIONAL*, *NATIONAL*, and *INTERNATIONAL* were all coded as zeros. *LNDIST* was determined by whether the effects estimated were within 1,500 feet (8 observations), corresponding to one of the dummy variable distances from Model C. Since the study focused on open spaces, the *POSITIVE* variable was coded accordingly. The *YEAROFDATA* entry is 1990 to 1992. The *UNEMP* value was determined by using the Portland, Oregon Metropolitan Statistical Area unemployment rates for 1992. The *URBAN* value was coded accordingly because the study occurred in a metropolitan area. For all observations, the sample size was 16,402; the natural log transformation of this number assigned a value to *LNSAMPLE* and the article was classified as a regression analysis (*STUDY_REG*). Because this was classified as a regression analysis study, *STUDY_SURV* was assigned a value of "0" by default. There was no indication that this study was involved in litigation, so the variable *LITIG* was coded "0" as well. There was no public information disclosure, which is normal for a study that focuses on positive impacts on property values; therefore, the variable *INFO* was coded as "0." Finally, since 18 observations were extracted from this study, the variable *LOTSOFOBS* was assigned a value of "1" for each observation.

ENDNOTES

1. This study suggests no significant difference between PPE estimates for nuclear sites and non-hazardous waste sites.
2. Two of the randomly selected studies were included in the meta-analysis (Caulkins, Bishop, and Bouwes, 1986; and Folland, Owen, Ward, and Colman, 1991) that did not deal exclusively with residential property values. The study by Caulkins, Bishop, and Bouwes examines the demand for lake recreation using travel cost models. We included this in our analysis because we wanted to include travel cost studies as one of the types of studies in our database, and lost recreational values are often reflective of property value diminution. The study by Folland, Owen, Ward, and Colman was included to account for any residential properties that might also include agricultural land; by coding this article, we were able to account for any agricultural and residential overlap.
3. Stanley (2001) recommends effect size as the most appropriate dependent variable to use when conducting meta-regression analysis. Our results suggest that the independent variables in the meta-regression models have similar directions of impact regardless of the choice of dependent variable. When there are exceptions, there is never a change in both sign and significance. In other words, the results are generally the same whether we use effect size (the preferred dependent variable) or marginal willingness to pay as a percentage of the unimpaired value (the easiest to interpret).

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