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Meta-regression of NDIs around airports: NDIs for Asian Airports

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Abstract: The external costs of aviation noise are an important input in policy assessment for cost-benefits analysis. The Noise Depreciation Index (NDI) is used to capture the externality costs through measuring the depreciation of property prices exposed to aviation noise. This paper summarizes existing studies on NDI and examines the underlying differences in order to transfer these NDI values to other parts of the world, where NDI estimates are not directly available. We find that higher wealth, expressed in terms of property prices, relative property prices or income, result in higher values of NDI. This means that wealthier households de-value the property prices more than the average in the presence of aircraft noise. The income dependence allows the NDI estimates to be transferred to other locations using local property prices or income for cost-benefit analysis. Estimates of NDI for some Asian countries using the meta-regression results are also provided.

Key words: Noise Depreciation Index, Hedonic Price method, Meta-analysis, airport noise costs

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1. INTRODUCTION

Noise near the airports has long dominated the environmental externality of the aviation sector (Schipper 2004). These noise externalities gives rise to economic externalities through annoyance costs, measures to avoid the annoyance (such as adding triple glazing windows, moving to new residences, etc.) and in some cases, significant health impacts and associated medical costs. Although the noisier aircrafts of earlier years have been phased out, the frequency of flights have increased manifolds. The number of flights in high density cities in developing countries is also increasing rapidly, increasing the number of people and properties exposed to aircraft noise. There are a range of policies that can affect noise exposures in and around the airports, ranging from individual airport expansion to system wide implementation of silent aircrafts or advanced open rotors, to simple changes in operational procedure (*e.g.* continuous descent approach, lower thrust take-off). In appraising any such policy that can alter the level of noise, economic valuation of noise is an important issue. System wide implementation of a policy also requires the estimation of noise costs around different regions in the world, where noise sensitivities of people, and therefore noise costs, could be different.

Noise Depreciation Indices (NDI's) are used to determine the annoyance costs related to noise. NDI's are defined as the per cent increase in the loss of property values due to a unit increase in noise exposure and are generally determined using Hedonic Price (HP) techniques, which utilizes the trade-off between varying property prices and associated noise levels (and other factors that affect the price of properties) in the real estate market. There are now a number of NDI estimates from the HP studies, which enables us to understand the underlying factors affecting the estimates or cause differences among the estimates and provide a measure of confidence. We investigate 65 such NDI estimates from different parts of the world, with a view to determining a transfer function for NDI's for regions where no direct NDI estimate is available. We are also interested in investigating the contradictory finding by two earlier summary studies by Nelson (2004) and Schipper *et al.* (1998) on the effect of property prices on NDI. Effect of property prices or income on NDI estimates, which proxies for the effect of wealth on willingness to pay to avoid airport noise, is an important parameter for transferring NDI estimates to other locations. Cost or benefit estimates could be different if NDI estimates are constant rather than if they vary with wealth or income in different regions of the world.

Section 2 of this paper briefly describes the HP method for estimating NDI, followed by a short summary of two previous reviews of NDI estimates in section 3. Section 4 describes why the estimates could be different in different studies to set up our statistical model to understand the differences. Section 5 presents the meta analysis process in this paper, followed by results in section 6. Section 7 draws conclusions.

2. HEDONIC PRICE NDI ESTIMATES

The hypothesis in the HP method for NDI calculations is that a property in a noisy area will fetch a lower selling price or a lower rent than a similar house in a quiet area, while the effects of other factors are controlled for. The difference in the prices of properties thus reveals the value of quiet. Since it is almost impossible to find properties that are otherwise identical but for their noise exposure, econometric models are employed to extract the impact of different attributes that may affect the price of properties. The attributes that directly affect the price or rent of a property can be classified into four groups (Bateman *et al.* 2001):

1. Structural attributes: Number and size of rooms, number of bathrooms, presence of garage, gardens, heating, window glazing, etc.
2. Accessibility attributes: Distance to bus stop, train stations, town centre, shopping centre, highway, airport etc.
3. Neighborhood quality: Crime rate, quality of schools, age and race distribution etc., and
4. Environmental quality: Noise level, air pollution, quality of view, etc.

The hedonic price of a property therefore can be generally expressed in an econometric model as:

$$Price = \beta \times Noise\ Level + \boldsymbol{X\lambda} \qquad (1)$$

where, $\boldsymbol{X}$ is a vector of other attributes mentioned above with associated parameter vector $\boldsymbol{\lambda}$, and β is the parameter associated with noise level. Eq. (1) can be estimated using information on property prices and various attributes of the properties for a large number or properties. Various functional specifications (linear, log-linear, log-log, etc.) are possible within this framework. The marginal price with respect to any of the attributes is an estimate of the marginal willingness to pay for that attribute, *i.e.* the *value* of that attribute (*e.g.* the value of quiet is $\partial Price/\partial Noise$). NDI, however, is defined as the percent change in property prices due to a unit increase in noise and therefore defined as:

$$NDI = \partial ln(Price)/\partial Noise \qquad (2)$$

3. PREVIOUS SUMMARIES OF NDI'S

There are now a significant number of published studies on NDI estimates from different parts of the world, with majority from the USA and Canada (Nelson 2007). Two well cited studies summarize the NDI estimates from aviation noise through meta-analyses. Meta regression analysis is a statistical technique to quantitatively investigate empirical research where the dependent variable is a summary statistic from each study and the explanatory variables include the characteristics of each sample, analytical method or experiment design (Stanley 2001). The meta-analysis allows us to understand the causes of differences in empirical results in the literature. Schipper *et al.* (1998) and Nelson (2004) followed this approach to summarize the available NDI estimates from the literature. Results of these two analyses are presented in Table 1.

The first of these studies, by Schipper *et al.* (1998), contains 30 estimates from 19 studies, but not the same airports from the same studies. Majority (21) of their sample contained estimates from the USA, and the rest from Canada, UK and Australia. Schipper *et al.* (1998) conjectured that the NDI estimates may increase with wealth, which is in line with the hypothesis that environmental goods, *i.e.* peace and quiet, are luxury goods. They found that NDI was positively correlated with relative property prices (average house price/average per capita income). Schipper *et al.* (1998) concluded that NDI would be between 0.9% (for a non-linear specification) and 1.3% (for a linear specification) at the mean relative house price of their sample. One significant limitation of Schipper *et al.* (1998) is that they did not control for the differences in underlying noise measurement units in different studies. For example, Pennington *et al.* (1990) NDI estimate of 0.15 as presented in Schipper *et al.* (1998) is for NNI, and will be different (0.34) when converted to NEF or DNL. While this may not result in differences in NDI measures based on NEF and DNL, since roughly *DNL=35+NEF*, and there is an approximate one to one correspondence between one unit *change* in NEF and one unit *change* in DNL or L_{dn}, it is not the same with unit *changes* in CNR, NNI or NEF. Therefore, some of their NDI estimates in previous meta analyses are not in the same unit as the rest and the results could thus be unreliable.

Table 1. Schipper and Nelson's meta analysis (dependent variable NDI, t-stat in parenthesis)

Explanatory factors	Nelson (2004)	Schipper *et al.* (1998)
Intercept	0.5332 (2.82)**	-1.54 (-2.57)**
Mean property price × 0.001	-0.0001 (-0.08)	
Relative property price	-	0.30 (12.04)**
Accessibility dummy	0.0196 (0.22)	-
Log (Sample size)	-0.0186 (-0.54)	-
Linear model dummy	0.3320 (2.10)**	-
Log-linear/semilog dummy	-	-0.40 (-2.39)**
Canada dummy	0.3389 (4.06)**	-
1960 data dummy	-	2.01 (3.88)**
Year of publication (last 2 digits)	-	0.01 (1.83)*
R^2	0.77	0.94
Number of observations	29	30
Weight used	Inverse variance	Inverse variance
Countries	USA (24), Canada (5)	USA (21), Canada (5), UK (2), Australia (2)

** Statistically significant at 95% confidence level, * Statistically significant at 90% confidence level

Nelson (2004) argued that Schipper et al.'s (1998) constructed measure of relative property price were misspecified and reasoned that the average property prices in the sample alone can capture the effect of wealth of people. In addition Nelson (2004) also questioned Schipper *et al.*'s (1998) results because of the negative intercept term in their meta-regression, which he reasoned should be positive. Nelson (2004) conducted a meta-analysis on 29 NDI estimates from the USA (24) and Canada (5) and found that differences in property values (as proxy for wealth) in different studies had no statistically significant impact on NDI estimates. This contradicts Schipper *et al.* (1998) and suggests that people of different wealth are willing to pay the same proportion of their property prices to avoid aviation noise. Nelson (2004) concluded that the NDI estimates in the USA lie between 0.5% and 0.6%, and in Canada it is around 0.9%.

Although the NDI estimates between Schipper *et al.* (1998) and Nelson (2004) are almost identical, the effect of wealth or relative wealth is contradictory. This contradiction needs to be resolved since the effect of wealth, relative wealth or income on NDI can be important to the policy makers. It is also important in the context of transferring the NDI values to other countries, especially to the developing countries, where people can be less wealthy, and therefore potentially can have lower NDI. Both of these studies are also limited by a rather small sample size of 30 and contain results from only those studies that report a statistically significant NDI estimate. We seek to better explain the differences between NDI estimates by enhancing the sample size to 65, of which 53 could be used for a meta regression. We also include in our meta-regression the studies that report statistically insignificant NDI estimates, although the number of such studies is small.

4. POSSIBLE CAUSES OF DIFFERENCES IN NDI ESTIMATES

We collect 65 NDI estimates primarily by conducting a search on the internet such as google scholar, science direct and the Envalue database by the Department of Environment and Climate Change, New South Wales (Envalue 2007). Wadud (2009) contain the detailed list of the studies. Majority (35) of the estimates are from the USA, with the rest from Canada (8), Australia (8), the UK (8), the Netherlands (1), France (1), Switzerland (3) and Norway (1). For a few estimates, which could not be obtained first hand, we use Nelson's (2004) summary table. The range of estimates varies from no effects to 2.3% reduction in property prices per dB of noise. First we seek to understand the underlying factors that could generate different NDI estimates in these studies so that it can guide our meta-regression modeling:

Noise measurement: Several measurement metrics have been used to measure noise exposure in different studies. These include Noise Exposure Forecast (NEF), Noise Number Index (NNI), Australian Noise Exposure Forecast (ANEF), Composite Noise Rating (CNR), Day-Night sound Level (L_{eq}, DNL, or L_{dn}), Kosten Unit (KU) etc. All of these measures are not only objective measurement of noise, but also intends to capture the *perceived* annoyance of the people. For example, NEF and DNL both carry a penalty for night time noise generation. Although Levesque (1994) questions the effectiveness of these measures to capture the annoyance, Baranzini *et al.* (2006) reports that these metrics capture the perception of noise annoyance reasonably well in the HP studies. The choice of noise metric also has some implicit assumption about the importance of different elements. For example, NNI gives more weight to the number of flights, where as L_{eq} gives more weight to the individual aircraft's sound level. This is especially important in the context of policies to reduce noise exposure. An NNI based metric would encourage policies that reduce the number of flights, whereas an L_{eq} based metric would support policies that reduce noisiness of individual aircrafts.

The NDI estimates in this study have all been normalized to per dB change in NEF. There are some uncertainties during this process, since the appropriate conversion factors are airport specific and not unique. In the absence of the required extensive data to generate airport specific conversion factors, we utilize the factors from Walters (1975).

In addition to noise measurement units, noise level also can have important impact on the NDI estimates. Salvi (2003) uses a non-parametric approach to understand the impact of noise level on NDI. Although there were some evidence that NDI estimates may vary with noise level, the variation was applicable only to high and low levels of noise and, at the middle of the noise range, non-parametric results were similar to semi-log model results.

Regional Differences: The housing markets in different countries, even in different cities within a country, could be different. The background noise, and the perception of noise could also be different. There could also be regional differences in the wealth of people (section 3). All these differences could result in different NDI estimates. Nelson (2004) reports that NDI's in Canada are larger than in the USA. Fig. 1 presents the estimates from different regions in a box plot, where the ends of the boxes represent the 1st and the 3rd quartiles, the line within the box represents the median and the ends of the whiskers present the smaller of the 95% intervals or the non-outlier maximum and minimum. Although it appears that the median NDI estimates do not vary much from each other, the plot should be interpreted carefully since other explanatory factors have not been controlled for. We specify three dummy variables to control for the regional variations, one each for Canada, Australia and Europe in our meta-regression model.

Functional Specification: The functional specification defining the relationship between property price and its explanatory variables can be a major source of difference between the NDI estimates. The functional forms also impart a built-in assumption as to whether the NDI

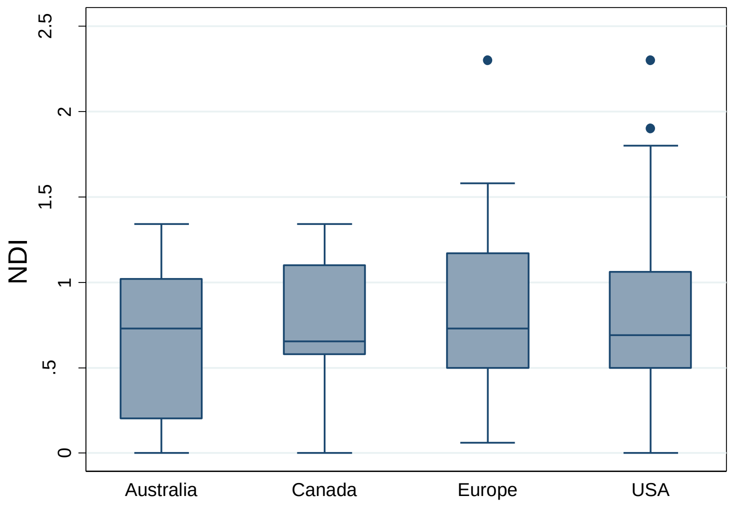

Fig. 1 Box plot for NDI (% change per unit change in NEF) for different regions

estimates are constant or variable across noise levels. For example, a semilog model with continuous noise variable implies a constant NDI, whereas a linear model implies that NDI varies with noise levels. In fact, given the definition of NDI (Eq. 2), any functional form other than the semilog price on level, continuous noise variable would make the NDI dependent on noise level.

Table 2 presents 12 NDI estimates from 7 studies that test the linear and semilog specification with the same explanatory variables.[1] It is evident that a linear functional specification consistently results in higher estimates of NDI, a finding that is supported by a paired-t test for statistical significance of the mean differences between each pairs. Semilog models, however, are more prevalent in the estimation of HP relationships because of its implications of a constant NDI, which has practical advantages in application of the NDIs for policy analysis.

Number of Covariates: Different types and number of variables can explain the variation of property prices. Omission of one or some of these variables may result in an omitted variable bias, if the excluded variable was correlated with noise. Thus, the NDI estimates could be sensitive to the number and types of covariates in the study. The direction of the bias would be study specific and therefore, there may not be any systematic difference between studies. There could be a bias in the meta-analysis as well, if many of the studies have failed to incorporate the same variable that should have been in the model and that variable is correlated to noise.

Table 2. Observations used to compare semilog and linear specifications

Study	NDI estimate	
	semilog	Linear
Mieszkwoski and Saper (1978)-1	0.914	1.133
Mieszkwoski and Saper (1978)-2	0.383	0.522
Mieszkwoski and Saper (1978)-3	0.458	0.64
Espey and Lopez (2000)	0.257	0.3
Cohen and Coughlin (2007)-1	0.42	0.769
Cohen and Coughlin (2007)-2	0.51	1.09
Rossini *et al.* (2002)-1	1.627	1.917
Rossini *et al.* (2002)-2	0.635	0.691
Rossini *et al.* (2002)-3	0.978	1.298
Abelson (1979)	0.4	0.352
Mark (1980)-1	0.42	0.505
Mark (1980)-2	0.47	0.521
Mean of the differences (t-stat)	0.189 (3.75)***	

*** statistically significant at 99% level

Access to the airport, however, is one variable for which the direction of bias can be hypothesized a priori. Proximity to the airport has both positive benefits (since airports offer employment opportunities) and negative impacts (noise). Thus, if only noise is in the HP model and not distance from airport, then the parameter for noise picks up the joint effects of noise (negative) and accessibility to airport (positive), biasing the NDI downward. Tomkins *et al.* (1998) find that both noise and proximity are statistically insignificant when they enter the HP model independently, but both become statistically significant, with expected signs, when entered jointly. McMillen (2004) and Cohen and Coughlin (2007) also report that proximity to airport has a positive impact on property prices. Therefore, NDI estimates could be smaller in the studies where airport access has not been controlled for.

Spatial Autocorrelation: The HP models generally use the Ordinary Least Squares (OLS) methods to estimate the model parameters. However, the errors in observations can be correlated with each other, giving rise to spatial autocorrelation. OLS estimations in these cases may be biased. Salvi (2003), however, did not find much evidence of such bias. Cohen and Coughlin (2007) corrected their NDI estimates for spatial autocorrelation, although their modification is not appropriate and the uncorrected results are used in meta-regression here.[2]

Other Statistical Modeling Issues: The data used in generating the HP equations can be of different types. Most recent models use information on individual households whereas earlier studies in the USA generally utilized information on an aggregate level of census tracts or census blocks, resulting in aggregation errors. Thus the use of different data types can result in differences in NDI estimates.

Statistical estimation of the parameters also can be affected by the sample size, degrees of residual freedom and statistical power of the sample. Generally large sample or large residual degrees of freedom affords more variation in the dataset and could result in more precise estimates (*i.e.* smaller standard errors). However it is possible that a model estimated on large dataset, thus with small standard error for NDI, is misspecified. This particular model would report a precise, but biased estimate.

This distinction is important in the context of meta-regression. Weighted least squares (WLS) methods are often employed for estimating a meta-model, where the weights are generally inverse of standard errors or variances of individual estimates (Koetse *et al.* 2007). This implies that the NDI estimate with the smallest standard error (which will most likely be from a larger sample) will get the largest weight, although this estimate could itself be biased due to inadequate specification. Since we are not employing any qualitative judgment to select only the 'best' studies, employing simple OLS (with heteroskedasticity correction) for meta-analysis can have some benefits.

5. META-ANALYSIS OF NDI ESTIMATES

5.1 Description of the Meta-Model

Fig. 2 summarizes the NDI estimates through a frequency distribution. We find that there is no publication bias in the estimates (See Appendix). Following Nelson (2004) and Schipper *et al.* (1998), we believe that these NDI estimates vary systematically among the studies. Our focus is to identify the systematic pattern underlying the differences.

We use both property prices and relative property prices alternately in our meta-model to understand the effect of wealth on NDI. Property prices are adjusted reflecting Purchasing

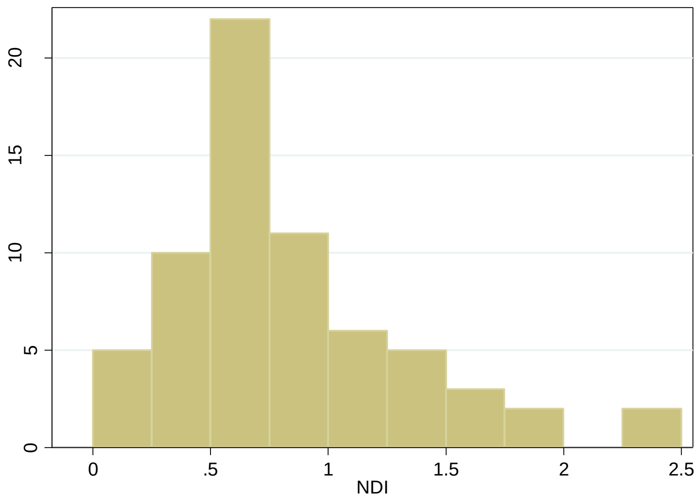

Fig. 2 Frequency distribution of NDI (% change per unit change in NEF): 65 studies

Power Parity (PPP) of different countries and chained to year 2000 USD using Consumer Price Indices (CPI). Relative wealth is constructed by dividing the PPP and adjusted *real* property prices by PPP adjusted real per capita GDP for the country (except in the USA, where state GDP is used). However, we also note that both property prices and relative property prices can be imperfect measures of wealth, since both these measures depend on the housing market structure. Therefore we also use real per capita GDP (PPP adjusted) as a (potentially better) explanatory factor in an alternate specification.

In our earlier discussion in section 4, we identified the factors that can result in differences in the NDI estimates among the various studies in our sample. We therefore want to control for the impact of these factors in our meta analysis model in order to decipher the true impact of income, as expressed above. This control is done via the introduction of dummy variables reflecting these factors in our meta analysis model. We control for a linear specification using a dummy variable (1 if linear). We expect this dummy variable to have a positive value from earlier discussions. We also use a dummy to indicate if airport accessibility has been included in the study (1 if accessibility is included). A priori, this dummy should have a positive sign. We also introduce a dummy to separate studies using individual data from those using census block or tract data. Three dummies for Canada, Australia and Europe attempt to capture the regional differences. Our last dummy variable separates the studies prior to 1965 since they have been reported to estimate larger NDIs (Schipper et al. 1998).

We were not able to collect all relevant information that we required to perform a meta-analysis with all 65 observations. For example, the standard error or variance of the NDI estimates was not reported for some studies. Similarly for some studies the mean sample household prices were unavailable. We could analyze our preferred specification on 53 observations. Clearly, there is a trade-off involved here. If we wanted to incorporate more explanatory factors (e.g. noise level), there were higher chances that we would lose more observations. This would reduce the residual degrees of freedom for estimation even further.

5.2 Specification Tests for Various Models

In meta-regression, the assumptions of OLS regression are often violated, especially the assumption of homoskedasticity or constant variance of the error terms (Stanley and Jarrell 1989). Thus, Weighted Least Squares (WLS) using inverse standard error or variance of each observation as the weights, are employed for estimation. It is assumed that the heteroskedasticity is caused by the differences in precision of the original NDI estimates. We note that statistical tests do not reject a homoskedastic error in our formulation, therefore OLS would not bias our estimates significantly. Also, we mentioned earlier (section 4) about our concern regarding weighting the estimates. However, we still make heteroskedasticity correction using White's heteroskedasticity consistent estimator to allow a more precise estimation of the parameters. We will also see later that WLS does not improve our model fit significantly.

Table 3 presents the model specification information for three variables representing income or wealth, using different functional specification of the variables. Specifications A, B and C use property prices, relative property prices and PPP corrected real GDP per capita respectively, with other variables remaining the same. Since this specification (C) has a statistically insignificant intercept, alternative D drops the constant in regression specification. The normality tests of the residuals also indicate that the errors are normally distributed.

Models A, B and C have similar explanatory powers, with Model C marginally better than A and B. Thus, GDP per capita is marginally better at explaining the variations in NDI than property prices or relative property prices. However, dropping the regression constant of Model C (as in Model D) makes it significantly better than the other specifications.

Table 3. Results from the meta regression of NDI with sample and study characteristics (dependent variable NDI, for parameters t-stat in parenthesis)

Model No		A	B	C	D	E
Description of explanatory factors in the model	Expected sign	Property price	Relative property price	GDP per capita, with constant	GDP per capita, without constant	GDP per capita, without constant, WLS
Constant	+/-	0.298 (2.66)**	0.318 (2.62)**	-0.158(-0.74)	-	-
Property price × 10^{-6}	+	1.490 (3.66)**	-	-	-	-
Relative property price	+	-	0.037 (2.09)**	-	-	-
GDP per capita × 10^{-5}	+	-	-	2.2 (3.24) **	1.76(5.37)**	1.69(5.03)**
Dummy for linear	+	0.196 (1.80)*	0.239 (2.39)**	0.337(3.23) **	0.321(3.27)**	0.317(3.03)**
Dummy for pre-1965 data	+	1.387 (6.94)**	1.367 (7.24)**	1.603(7.81) **	1.561(7.97)**	1.553(7.66)**
Dummy for Canada	+	0.183 (1.01)	0.088 (0.44)	0.404(1.98) **	0.336(1.96)**	0.397(1.87)*
Dummy for Australia	+/-	0.081 (0.24)	-0.009 (-0.03)	0.354(1.48)	0.285(1.26)	0.434(2.16)**
Dummy for Europe	+/-	-0.002 (-0.02)	-0.050 (-0.44)	0.251(1.54)	0.187(1.56)	0.200(1.43)
Dummy for census data	+/-	0.158 (1.29)	0.103 (0.86)	0.141(1.44)	0.108(1.29)	0.127(1.32)
Dummy for airport access	+	0.069 (0.58)	0.110 (0.91)	0.067(0.61)	0.066(0.61)	0.087(0.509)
R^2		0.591	0.563	0.604	0.891	0.868
Heterosked. Correc. Appl.		White Std. Err.	White Std. Err.	White Std. Err.	White Std. Err.	√Res Deg Freed WLS
Sample size		51	51	53	53	53

** statistically significant at 95% confidence level, * statistically significant at 90% confidence level

Specification D clearly has the largest R^2 of all models, indicating the best fit. Intutively, WTP for quiet and thus NDI should be negligible at zero income level and Model D captures this effect too. Model E is a WLS estimation of Model D, using square root of degrees of freedom of each study as corresponding weights. We use square root of residual degrees of freedom instead of inverse standard errors since standard errors for all the estimates were not available. However, the WLS model (Model E) is not an improvement over our OLS model (Model D).

5.3 Results

All five model specifications show that the variable wealth, whether it is defined by property prices (Model A), relative property prices (Model B), or GDP per capita (Models C, D and E) has a significant positive effect on the differences in NDI estimates between the studies. Our results thus support Schipper *et al.*'s (1998) finding. Using Stated Preference surveys, MVA Consultancy (2007) also reported that noise annoyance increases with increasing income. Linear models result in higher NDI estimates and is consistent with Nelson (2004) and Schipper *et al.* (1998) and the paired-t approach in section 4. Concentrating on our preferred model, Model D, we find that the studies that used data prior to 1965 also result in higher NDI estimates. The effect of regional differences is not statistically significant, other than for Canada. This, however, could be due to low statistical power of our sample. The parameter for Canada is positive in all specifications and statistically significant in our preferred model (Model D). This indicates that the NDI estimates in Canada are, in general, higher than those in the USA, a finding similar to Nelson (2004). On the other hand, the parameter estimates for Australia and Europe, change signs between different model specifications (and statistically insignificant in Model D), indicating that the parameters are not stable across specifications and that these NDI estimates are possibly not different from the US estimates.

The effect of using census block or census tract data is also statistically not different from zero. Studies that controlled for accessibility to the airport also do not report a statistically significant effect. However, the signs of the parameter are consistently positive across all five valid model specifications, indicating NDI estimates are possibly higher when access to the airport is controlled for in the study. The a priori theoretical expectation, combined with the consistency of the signs across studies, gives confidence that NDIs are underestimated in studies which did not control for proximity to the airports. We use this information later in our value transfer equation.

Table 4 reports the NDI estimates with associated t-statistics at different property price, relative property price or GDP per capita for five model specifications. We report the results for airport accessibility corrected estimates and estimates for Canada as well, since we believe that there is a consistent pattern coherent with a priori expectations for the effects of these variables. Our preferred meta regression model indicates that NDI at the sample mean GDP per capita is 0.5, with a range of 0.45 to 0.64 for other specifications (airport accessibility corrected). At a region with higher income per capita, the NDI estimate is around 0.68.

Table 4. NDI estimates from different meta-regression models (t-stat in parenthesis)

Model	A	B	C	D	E
At sample mean property price, relative property price or GDP per capita	0.513 (5.15)**	0.532 (5.27)**	0.383 (3.60)**	0.432 (5.37)**	0.417 (5.18)**
Airport accessibility corrected	0.582 (6.57)**	0.642 (7.33)**	0.450 (4.37)**	0.499 (5.96)**	0.503 (7.29)**
Canada	0.697 (4.45)**	0.621 (3.69)**	0.787 (4.75)**	0.768 (4.85)**	0.812 (6.19)**
At property price USD 300,000	0.745 (6.12)**	-	-	-	-
At property price USD 300,000 with airport access	0.814 (8.54)**	-	-	-	-
At GDP per capita of USD 35,000	-	-	0.612 (5.23)**	0.615 (5.37)**	0.591 (5.18)**
At GDP per capita of USD 35,000 with airport access	-	-	0.680 (7.26)**	0.681 (7.26)**	0.679 (9.04)**

** statistically significant at 95% confidence level

5.4 Suggested NDI for Value Transfer

It is evident from the meta-analysis that the variations of NDI estimates between different studies can be attributed to differences in underlying sample property prices (absolute or relative), model specification (linear or not, airport accessibility controlled or not) or regional differences (*e.g.* Canada). For practical purposes, relative property prices (Model B) is not a good metric for transferring the NDI estimates to other countries: for some low to middle income countries, house price to income ratio is very high, *e.g.* Jakarta (Indonesia), 14.6; Dhaka (Bangladesh), 16.7; Sofia (Bulgaria) 13.2; compare that with London, 4.7 and our sample mean, 5.8 (data from UN-HABITA (2003). Property price data can also have difficulties. In many developing and emerging countries, the deed price can be much lower than the actual transaction price (*e.g.* in Bangladesh), thus making the property prices unreliable. A PPP adjusted GDP per capita is a more robust and widely available statistic for any country. Stated preference studies also reveal that the willingness to pay to avoid noise varies with income (INFRAS/IWW 2004). These practical advantages of GDP per capita along with the better fit of the model with GDP per capita encourage us to use Model D as the basis of our NDI transfer equation. Considering the potential effect of airport access on NDI (see discussion on previous section), this results in Eq. 3 below:

$$\underset{(0.109)}{NDI = 0.07} + \underset{(3.28\times10^{-6})}{1.76\times10^{-5}}\times PPP\ Adjusted\ GDP\ per\ capita \qquad (3)$$

The numbers in the parenthesis refer to the standard errors of the parameters, which can be used to derive the confidence interval of the calculated NDI. The GDP per capita needs to be converted to PPP and CPI adjusted USD in year 2000. Table 5 presents the NDI estimates for a sample of different locations using the suggested transfer equation. Note that city specific GDP data can fine tune the NDI even further.

5.5 Is ‘quiet’ a luxury good?

We have established that the NDI increases with increase in income. This in itself, does not guarantee that quiet is a luxury good. For ‘quiet’ to be a luxury good, the income elasticity of willingness to pay (WTP) to avoid noise should increase more than proportionally with income. Defining WTP as the product of NDI and property prices (PP), we find:

$$\eta_{WTP} = \eta_{NDI} + \eta_{PP} \qquad (4)$$

Table 5. Suggested NDI from the Meta-regression results

Country	GDP per capita in 2008 (local currency)	Real PPP adjusted GDP per capita (USD)	Suggested NDI	t-stat
Australia	54,035	31,107	0.613**	6.91
Bangladesh	34,815	1,889	0.100	0.95
Cambodia	2,669,970	3,317	0.125	1.22
China	21,262	9,019	0.225**	2.42
Hong Kong	239,991	31,579	0.621**	6.96
India	44,533	3,635	0.130	1.28
Indonesia	18,630,146	4,206	0.140	1.39
Iran	42,838,906	8,954	0.224**	2.41
Japan	4,100,071	27,042	0.542**	6.37
Jordan	2,104	5,020	0.155	1.55
Korea	19,296,537	19,979	0.418**	5.01
Malaysia	22,798	11,539	0.269**	3.01
New Zealand	43,087	23,124	0.473**	5.68
Pakistan	61,974	2,769	0.115	1.11
Saudi Arabia	61,227	21,085	0.437**	5.25
Singapore	54,693	30,675	0.606**	6.86
Sri Lanka	192,254	4,969	0.154	1.54
Taiwan	558,962	25,622	0.517**	6.14
Thailand[3]	128,892	8,292	0.212**	2.26

** statistically significant at 95% confidence level

Where η represents income elasticity. From Eq. 3, $\eta_{NDI} = 1 - \frac{0.07}{NDI}$. Income elasticity of NDI, η_{NDI}, is at least 0.67 (for the lowest statistically significant value of 0.21 for NDI in Table 5). On the other hand, income elasticity of housing price or expenditure (η_{PP}) lies between 0.7 and 2.8, with most values above 1.0 (Fernandez-Kranz and Hon 2006). This indicates that the income elasticity of WTP to avoid noise is above 1.0, making it a luxury good. Even at a low NDI of 0.1, it is highly likely that η_{WTP} will be larger than 1.0. We, however note that this is in contrast with most recent findings that environmental amenities, generally, are normal goods (Horowitz and McConnell 2003).

6. CONCLUSION

We conducted a meta-analysis of NDI estimates for aircraft noise around airports to understand the underlying factors that could result in the differences of NDI estimates which determines the costs attributable to aircraft noise around airports. We find that the model specification has a significant effect on NDI estimates, justifying earlier conclusions. Our NDI estimate is marginally lower than earlier meta-analyses in the literature and is around 0.5% per dB at the mean GDP per capita of the sample. The NDI is sensitive to property prices, relative property prices or income and increases with an increase in these parameters. This is plausible since environmental amenities (here, 'quiet') are often luxury goods. GDP per capita is the best indicator to explain the differences in NDI: For every thousand USD increase in PPP adjusted real per capita GDP, NDI increases by 0.017. After accounting for differences in NDI estimates due to income, we did not find specific regional influence on NDI estimates, although NDI estimates in Canada appear to be higher than the rest.

The dependence of NDI on income, or property prices can potentially allow the NDI estimates to be transferred to different locations, corrected by PPP adjusted real per capita GDP at the location. Given the difficulties and expenses involved in obtaining large datasets to derive specific NDI estimates for individual airports, the transferability of NDI could be an attractive way to determine first order estimates for airport related noise costs. This is especially true for developing or many Asian countries where information on all the variables is often unavailable or unreliable. The transferred NDI estimates can be useful for analyzing global or regional estimates of aviation related noise costs (e.g. Kish 2008). Also, until specific NDI estimates become available for specific airports in Asia, the these NDI's can be used as a first approximation to understand the economic losses due to aviation activities in Asian cities and for analyzing benefits due to changes in noise levels from policy interventions such as aircraft noise regulations, or noise permits trading. Since the NDI estimates increase with increasing per capita GDP, the economic costs of noise of an airport would be higher in a developed country than a similar airport in a country of lower per capita GDP.

The recommended NDI estimates through the meta-analysis can still be biased. Firstly, an individual's perception of noise has an important effect on noise costs. Recent estimates on compulsory disclosure of noise information by the seller have shown that noise discounts are higher (Pope 2007) in the presence of compulsory disclosure. This indicates that people may not have perceived the extent of noise before disclosure. Secondly, the hedonic price method rests on the assumptions of zero transaction costs of moving and perfect equilibrium in the housing market. However, transaction costs are never zero since moving involves opportunity costs for the households (van Leuvensteijn and van Ommeren 2003). Thirdly, households that are more sensitive to airport noise may have taken noise insulation measures, which are not accounted in the HP equation. And finally, housing markets in different countries are different and therefore the NDI themselves could be different in different countries or cities and there could be no unique NDI estimate.

Note that the first three of the factors mentioned above tend to bias the NDI estimates downwards, *i.e.* the true NDI could be higher than those estimated in the literature and reviewed here. This is also substantiated by the fact that Stated Preference studies generally report higher NDIs than the HP studies (Schipper *et al.* 1998, Feitelson *et al.* 1996). The noise cost estimates derived from property value depreciation alone, therefore, is possibly only the lower bound of the total social costs that can be attributed to aircraft generated noise. The uncertainty around the NDI estimates is also larger than those estimated by sampling standard errors alone. New hedonic studies on property price noise tradeoff therefore should address these sources of bias more carefully.

NOTES

1. For meta-analysis, we have picked one estimate for one location from one study. In Table 2, however, all the relevant estimates for one location are included to increase the sample size.
2. Cohen and Coughlin (2007) multiply their NDI estimate with a spatial multiplier to account for the effect that if property prices around a neighborhood increases, the prices of a specific property in that neighborhood will automatically increase. This results in an NDI of 7.2% per dB, which is significantly larger than other NDI estimates. Noise, however affects all properties in the neighborhood and since the effect is already captured in the HP estimates, the multiplier effect is not applicable. See Small and Steimitz (2006) for further discussion on this.
3. A recent paper (Chalermpong 2010) puts NDI at Bangkok's Suvarnabhumi Airport to be 2.12, a very high value as compared to the more recent estimates. The author offers no

explanation for the high NDI. Note that our estimate can also be biased downwards because of the use of Thailand specific GDP per capita rather than Bangkok specific GDP, which is possibly higher.

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SUPPORTING INFORMATION

A: LIST OF NDI'S INCLUDED

Table A. Summary of NDI estimates from different HP studies

Sl	Author	Year	Airport	Country	NDI (% per dB)
1	Paik[a]	1970	Dallas	USA	2.30
2	Paik[a]	1971	Los Angeles	USA	1.80
3	Paik[a]	1972	New York – JFK	USA	1.90
4	Roskill Commission [b]	1970	London – Heathrow	UK	0.71
5	Roskill Commission [b]	1970	London – Gatwick	UK	1.58
6	Mason [c]	1971	Sydney	Australia	0.00
7	Emerson	1972	Minneapolis	USA	0.59
8	Coleman[b]	1972	Englewood	USA	1.58
9	Dygert[a]	1973	San Francisco	USA	0.50
10	Dygert[a]	1973	San Jose	USA	0.70
11	Price[a]	1974	Boston	USA	0.81
12	Gautrin	1975	London-Heathrow	UK	0.62
13	De Vany	1976	Dallas	USA	0.80
14	Maser *et al.*	1977	Rochester	USA	0.86
15	Maser *et al.*	1977	Rochester	USA	0.68
16	Blaylock[a]	1977	Dallas	USA	0.99
17	Mieszkowski & Saper	1978	Toronto	Canada	0.66
18	Fromme[a]	1978	Washington Reagan	USA	1.49
19	Nelson[a]	1978	Washington Reagan	USA	1.06
20	Nelson	1979	San Francisco	USA	0.58
21	Nelson	1979	St. Louis	USA	0.51
22	Nelson	1979	Cleveland	USA	0.29
23	Nelson	1979	New Orleans	USA	0.40
24	Nelson	1979	San Diego	USA	0.74
25	Nelson	1979	Buffalo	USA	0.52
26	Abelson	1979	Sydney	Australia	0.40
27	Abelson	1979	Sydney	Australia	0.00
28	McMillan *et al.*	1980	Toronto	Canada	0.51
29	Mark	1980	St Louis	USA	0.42
30	Hoffman[d]	1984	Bodo	Norway	1.00
31	O'Byrne *et al.*	1985	Atlanta	USA	0.64
32	O'Byrne *et al.*	1985	Atlanta	USA	0.67
33	Opschoor[e]	1986	Amsterdam	Netherlands	0.85

[a] from Nelson (2004), [b] from Walters (1975), [c] from Envalue (2007), [d] from Barde and Pearce (1991),
[e] from Pearce and Markandya (1989)

Table A (contd.) Summary of NDI estimates from different HP studies

Sl	Author	Year	Airport	Country	NDI (% per dB)
34	Pommerehne[e]	1988	Basel	Switzerland	0.50
35	Burns *et al.*[c]	1989	Adelaide	Australia	0.78
36	Penington *et al.*	1990	Manchester	UK	0.34
37	Gillen & Levesque	1990	Toronto	Canada	1.34
38	Gillen & Levesque	1990	Toronto	Canada	-0.01
39	BIS Shrapnel[c]	1990	Sydney	Australia	1.10
40	Uyeno *et al.*	1993	Vancouver	Canada	0.65
41	Uyeno *et al.*	1993	Vancouver	Canada	0.90
42	Tarassoff[a]	1993	Montreal	Canada	0.65
43	Collins & Evans	1994	Manchester	UK	0.47
44	Levesque	1994	Winnipeg	Canada	1.30
45	BAH-FAA	1994	Baltimore	USA	1.07
46	BAH-FAA	1994	Los Angeles	USA	1.26
47	BAH-FAA	1994	New York – JFK	USA	1.20
48	BAH-FAA	1994	New York – LG	USA	0.67
49	Mitchell McCotter[c]	1994	Sydney	Australia	0.68
50	Yamaguchi	1996	London– Heathrow	UK	1.51
51	Yamaguchi	1996	London – Gatwick	UK	2.30
52	Myles[a]	1997	Reno	USA	0.37
53	Tomkins *et. al.*	1998	Manchester	UK	0.63
54	Espey & Lopez	2000	Reno-Sparks	USA	0.28
55	Burns *et. al.*	2001	Adelaide	Australia	0.94
56	Rossini *et. al.*	2002	Adelaide	Australia	1.34
57	Salvi	2003	Zurich	Switzerland	0.75
58	Lipscomb	2003	Atlanta	USA	0.08
59	McMillen	2004	Chicago	USA	0.81
60	McMillen	2004	Chicago	USA	0.88
61	Baranzini & Ramirez	2005	Geneve	Switzerland	1.17
62	Cohen & Coughlin	2006	Atlanta	USA	0.43
63	Cohen & Coughlin	2007	Atlnata	USA	0.69
64	Faburel & Mikiki	2007	Paris	France	0.06
65	Pope	2007	Raleigh	USA	0.36

[a] from Nelson (2004), [c] from Envalue (2007)

B: PUBLICATION BIAS

Publication bias occurs when there is a propensity to report and publish only those studies with statistically significant results in favor of a priori hypothesis or results consistent with a priori expectations for a specific sign. This implies that there could be a significant amount of unpublished evidence that may have contradicted the a priori hypothesis that property prices fall with exposure to noise. A meta-analysis of only the published literature therefore could present a biased view. It is therefore important to test if there is such a bias before analyzing the published NDI estimates.

The tests for publication bias draws on the statistical sampling theory that the observed effects (NDI estimates) among the different studies should vary independently of the standard errors of the effects. This can be incorporated in a statistical test to by observing the intercept (α_0) in the following equation:

$$t_i = \alpha_0 + \alpha_1 (sample\ size_i)^{1/2} + \varepsilon_i \tag{A1}$$

Stanley (2005) suggests that if α_0=0 through a conventional t-test then it is an evidence of no publication bias in the estimates. Stanley (2005) also recommends carrying out a meta-significance test (MST) to identify that there is genuine empirical effect present in the literature, and that the effect of interest is not an artifact of publication selection. The test is carried out by observing the parameter γ_1 in the estimating equation:

$$log(t_i) = \gamma_0 + \gamma_1 log\ (sample\ size_i) + \varepsilon_i \tag{A2}$$

There is a genuine empirical effect if γ_1 is positive (Stanley 2005). Equations B1 and B2, however, can only be estimated for those studies for which estimates of standard error or t-statistics are available. Of the 65 NDI estimates, we could collect t-statistics for 43 estimates. Tests on these 43 samples show that α_0 is statistically not different from zero and γ_1 is positive, suggesting that there is no serious evidence of publication bias and that the NDI estimates are genuine effects (Table A).

Table A. Tests for publication bias and meta significance, limited sample (n=43)

	parameter	t-stat
Publication bias test		
α_0	0.723	0.91
α_1	0.084	2.68
Meta significance test		
γ_0	-0.575	-1.23
γ_1	0.236	3.21

C: ADDITIONAL REERENCES

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