Transport Policy 34 (2014) 85–101

Contents lists available at ScienceDirect

Transport Policy

journal homepage: www.elsevier.com/locate/tranpol

Estimation of the global impacts of aviation-related noise using an income-based approach

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ARTICLE INFO

Available online 21 March 2014

Keywords:
Aircraft noise
Hedonic pricing
Willingness to pay
Aviation noise impacts
Cost-benefit analysis

ABSTRACT

Current practices for assessing the monetary impacts of aviation noise typically use hedonic pricing methods that estimate noise-induced property value depreciation. However, this approach requires detailed knowledge of local housing markets, which is not readily available at a fine resolution for most airport regions around the world. This paper proposes a new noise monetization method based on city-level personal income, which is often more widely available. Underlying the approach is a meta-analysis of 63 hedonic pricing studies from eight countries, conducted between 1970 and 2010, which is used to derive a general relationship between average city-level personal income and the Willingness to Pay for noise abatement. Applying the new model to income, noise, and population data for 181 airports worldwide, the global capitalized monetary impacts of commercial aviation noise in 2005 are estimated to be \$23.8 billion, with a Net Present Value of \$36.5 billion between 2005 and 2035 when a 3.5% discount rate is applied. Comparison with previous results based on real estate data yields a difference of −34.2% worldwide and −9.8% for the 95 US airports in the analysis. The main advantages of the income-based model are fewer data limitations and the relative ease of implementation compared to the hedonic pricing methods, making it suitable for assessing the monetary impacts of aviation noise reduction policies on a global scale.

1. Introduction

The demand for commercial aviation is expected to rise steadily in the coming years, with annual growth estimated to be 5% over at least the next two decades (FAA, 2009b; Metz et al., 2007; Schäfer and Waitz, this volume). With this anticipated growth comes increasing concerns regarding the potential environmental impacts of aviation, which include aircraft noise, air quality degradation, and climate change. Of these issues, aircraft noise is of chief concern, as it has the most immediate and perceivable impact on surrounding communities (GAO, 2000; Schipper, 2004; Wolfe et al., this volume). These impacts can include annoyance, sleep disturbance, interference with school learning and work performance, and physical and mental health effects (McGuire, 2009; Swift, 2009). In addition to the physical effects, policy-makers, researchers, and aircraft manufacturers are also interested in the monetary impacts of aviation noise, such as housing value depreciation, rental loss, and the monetary value of lost work or school performance. The quantification of these monetary impacts provides tangible measures with which to conduct cost–benefit analyses of various policy options for aviation.

The objectives of this paper are two-fold. First, the paper introduces a method to assess the monetary impacts of aviation noise in order to evaluate policy alternatives and inform decision-making. The proposed method is termed the income-based noise monetization model, and estimates individuals' Willingness to Pay for noise abatement based on city-level personal income, which differs from conventional approaches that rely on detailed real estate data. The second objective of the paper is to describe how such a monetization model can be implemented within the framework of an aviation policy assessment tool, such as the United States Federal Aviation Administration's APMT-Impacts Noise Module, to estimate the worldwide economic impacts of aviation noise.[1]

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[1] The US Federal Aviation Administration (FAA) is developing a comprehensive suite of software tools that can characterize and quantify a wide spectrum of environmental implications and tradeoffs, including interdependencies among aviation-related noise and emissions, impacts on health and welfare, and industry and consumer costs under various scenarios (Mahashabde et al., 2011). This effort is

http://dx.doi.org/10.1016/j.tranpol.2014.02.020

The organization of the paper is as follows: Section 2 presents an overview of valuation methods used for aviation noise and motivates the need for a new monetization approach. Section 3 details the development of the income-based noise monetization model, with particular emphases on meta-analysis and econometric estimation. Section 4 frames the context for model application by presenting an overview of the APMT-Impacts Noise Module. Section 5 describes the use of the model to perform benefit transfer using a realistic aviation noise scenario; the results of this section not only demonstrate model applicability but also give a benchmark measure of convergent validity. Finally, Section 6 provides some concluding remarks.

2. Background and motivation

In environmental economics, quietness is viewed as an amenity that has an associated economic value. However, because there are no explicit transaction costs associated with this public good, it is necessary to employ non-market valuation methods in order to discern its value to the community (Hanley et al., 1997). The two general categories of non-market valuation methods are revealed preference and stated preference (EPA, 2000).

The most common approach for assessing the monetary impacts of aviation noise is hedonic pricing (HP), a revealed preference technique that uses statistical methods to identify differences in housing markets between noisy and quiet areas to determine the implicit value of quietness (or conversely, the cost of noise) (Wadud, 2009). Typical metrics used in HP are housing value depreciation and rental loss. These real estate-related damages are used as surrogate measures for the wider range of interdependent noise impacts that are difficult to assess separately, although it is recognized that such estimates may undervalue the full impacts of noise.

Hedonic pricing studies typically derive a Noise Depreciation Index (NDI) for one airport region, which represents the percentage decrease in property value corresponding to a one decibel (dB) increase in noise level in the area. Numerous such studies have been conducted for various airports in North America, Europe, and Australia, though few studies exist for other regions. Several meta-analyses have summarized the HP literature, showing that typical aviation NDI values for owner-occupied properties range between 0% and 2.3%, with median estimates between 0.60% and 0.70% (Nelson, 2004; Schipper et al., 1998; Wadud, 2009). Furthermore, NDI values tend to be similar across countries and stable over time (Nelson and Palmquist, 2008).[2]

In addition to quantitatively integrating literature pertaining to a specific topic, meta-analyses also enable researchers to identify trends and make inferences (Stanley and Jarrell, 1989; Rosenberger and Stanley, 2006). In the context of aviation noise, the goal of a meta-analysis is to derive a generally valid relationship between noise level and community impact in order to enable benefit transfer from one location to another. Such transfers are of critical importance to environmental policymaking; because of the broad (potentially global) scope of aviation policies and limited time and resources to perform new valuation studies, it is desirable and necessary to generalize the results from "study sites" to "policy sites" where limited or no data exist (Rosenberger and Loomis, 2000; Navrud, 2004). To date, there has been only one study which uses HP-derived NDI values to estimate the global economic impacts of aviation noise (Kish, 2008). The Kish (2008) study was conducted using a previous HP-based version of the APMT-Impacts Noise Module, which employed an NDI of 0.67% (derived by Nelson, 2004) to perform benefit transfer across 181 airports around the world. These 181 airports are part of the 185 Shell 1 airports in the FAA's Model for Assessing Global Exposure to the Noise of Transport Aircraft (MAGENTA), and comprise an estimated 91% of total global aviation noise exposure.[3] The study concluded that at 2005 noise levels, commercial aviation noise resulted in a total of $21.4 billion in capitalized housing value depreciation in year 2006 US Dollars (USD), and an additional $800 million per year in lost rent.[4] In terms of physical impacts, Kish (2008) estimated that there were over 14.2 million people exposed to at least 55 dB DNL of commercial aviation noise; of that group, 2.3 million were estimated to be highly annoyed based on surveys that related annoyance to noise level (Miedema and Oudshoorn, 2001).[5]

As the Kish (2008) study estimated monetary impacts in terms of depreciation in real estate value, it required detailed data for house prices and rental costs around all 181 airports. However, except for the United States and the United Kingdom, these data were generally not readily available at the required resolution. Instead, a statistical model was employed based on US data, which estimated house price as a function of distance from an airport, number of enplaned passengers at the airport, county-level population density, and state GDP per capita (ICF International, 2008). While this real estate model enabled the APMT-Impacts Noise Module to perform global estimates of aviation noise impacts, it had several limitations: it was derived solely from US property value data, verification tests for three UK airports revealed discrepancies of up to 70% between predicted and observed house prices, and additional estimation models were required to obtain all the necessary inputs (He, 2010). In order to be a practical and reliable tool to support policy analysis and decision-making, a new version of the APMT-Impacts Noise Module was desired, one which does not suffer from the same data constraints and delivers comparable or greater accuracy and robustness for global applications. The development of such a model is the subject of the following sections.

(*footnote continued*)
known as the Aviation Environmental Tools Suite, and was motivated by a report made to the US Congress on aviation and the environment that underscored the need to develop a set of tools and metrics that can be used to assess and communicate the environmental impacts of aviation, as well as inform policy-making decisions (Waitz et al., 2004). The Tools Suite consists of five main components, one of which is the Aviation environmental Portfolio Management Tool for Impacts (APMT-Impacts). The various modules within APMT-Impacts evaluate the physical and socio-economic impacts of policy alternatives as they relate to climate, air quality, and aircraft noise. This paper pertains to the APMT-Impacts Noise Module. For more information on the Aviation Environmental Tools Suite and APMT, see Mahashabde et al. (2011).

[2] An alternative to HP is contingent valuation (CV), a stated preference approach that uses survey methods to explicitly determine individuals' Willingness to Pay (WTP) for noise abatement, or alternatively, Willingness to Accept (WTA) compensation for noise increases. However, the accuracy of CV is often questioned (Diamond and Hausman, 1994), and CV-based studies of aviation noise impacts are very few and yield no consistent results (for example, Navrud (2002) summarizes a handful of such studies, which predict WTP values ranging between €8 per dB per household per year to almost €1000). For these reasons, CV studies for aviation noise will not be discussed further in this paper.

[3] MAGENTA is an FAA-developed model used to estimate the number of people exposed to aviation noise worldwide. The model's database includes 1700 world civil airports that handle jet traffic, which are divided into two sets: Shell 1 includes 185 airports, and Shell 2 the remainder (FAA, 2009a). The base year of the noise exposure estimates is 1998.

[4] An NDI of 0.67% was used to estimate both housing value depreciation and rental loss.

[5] The Day-Night average sound Level, or DNL, is the 24-h A-weighted equivalent noise level with a 10 dB penalty applied for nighttime hours. A similar measure, the Day-Evening-Night average sound Level (DENL), is commonly used in Europe; DENL is very similar to DNL, except that it applies a 5 dB penalty to noise events during evening hours.

3. Meta-analysis

Following Nelson and Palmquist (2008), the procedure for the development of the income-based noise monetization model is to start with a meta-analysis of existing HP studies, derive a relationship for the Willingness to Pay (WTP) for noise abatement with respect to income and other significant explanatory variables, and use the resulting function for global benefit transfer of monetized aviation noise impacts. The underlying assumption of this approach is that the WTP for noise abatement is correlated with regional income level.

3.1. Data set

The data set used in the meta-analysis is based on Wadud (2009), which compiled 65 HP studies for aviation noise from various airports in seven countries: the US, Canada, the UK, Australia, France, Switzerland, and the Netherlands.[6] These studies were conducted between 1970 and 2007, and each determined an NDI for its respective airport region. Two more recent HP studies were added to the data set, which were conducted in Amsterdam, the Netherlands, and Bangkok, Thailand (Dekkers and van der Straaten, 2009; Chalermpong, 2010). The mean and median NDI of all 67 studies are 0.83% and 0.70%, respectively, which are higher than the unweighted mean and median values reported by Nelson (2004) (0.75% and 0.67%, respectively). For each study, the author, year, airport location, NDI, information about whether the functional form of the NDI regression model was linear, and whether benefits related to airport access were considered are listed in Appendix A. Where available, the study sample size and average property value in the airport region are also presented.

In order to relate income with the WTP for noise abatement, a search was conducted to obtain a complete set of property value, household size, and income data for all 67 studies. For 54 of the studies, the average property value in the airport region during the year of the study was available from Wadud (2009). For the remaining 13 studies, the average value of owner-occupied properties in the city during the year of the noise study was obtained from national statistical agencies, including the US Census Bureau, the UK Office for National Statistics, the Australian Bureau of Statistics, and Statistics Netherlands. Similarly, the household size in each city during the year of the noise study was also obtained from these agencies.

For income, the selected indicator was the average per capita personal income for each city derived from household surveys; alternatively, the city-level average household income was also used where available, as dividing by the city-level household size results in the average per capita personal income. This metric was chosen because it is directly reflective of the economic status of the local population. Other common economic indicators, such as the per capita Gross Domestic Product (GDP) or Gross National Income (GNI), do not properly account for social and environmental costs and benefits, and therefore may not be suitable proxies for the standard of living in a region (Goossens et al., 2007). For the US cities, income data were obtained from the US Bureau of Economic Analysis, which provides per capita personal income for each year and metropolitan statistical area (MSA) dating back to 1969 (US BEA). For non-US cities, historical income data were obtained from various national statistical agencies. In the few cases where city-level income data were not available, county-level or region-level income data were used. Though most studies were conducted in high-income regions, a large income range is represented – from $2630 (Bangkok, Thailand) to $36,019 (Reno-Sparks, NV, USA). The mean income in the meta-analysis was $21,786, the median $21,923, and the standard deviation $7378 (all in year 2000 USD-PPP).

In order to ensure consistent comparison across all studies, the year 2000 was selected as the reference time point, the US Dollar as the reference currency, and the Purchasing Power Parity (PPP) as the metric for currency conversion.[7] If the income or property value for the year of the study was not available, the value for a nearby year was selected and adjusted to the year of interest using the national growth rate in income or real estate value, respectively (He, 2010). Further time adjustments were made using the national inflation rate between the study year and 2000. Upon the completion of the data search, four of the 67 studies were excluded because city-level property value or income data could not be obtained.[8]

Following Nelson and Palmquist (2008), the NDI, mean property value, and mean household size were used to estimate a per capita WTP for noise abatement. This relationship is given by

$$\mathrm{WTP} = \frac{\mathrm{NDI} \times \mathrm{Property\ value}}{\mathrm{Household\ size}} \tag{1}$$

The product of the NDI derived in each study and the corresponding average property value can be interpreted as the WTP for one decibel less noise per household. Dividing this value by the average household size gives the WTP per person. It is important to note that the result is a capitalized value that encompasses not only the property value depreciation due to the current noise level, but also the future noise damages anticipated by the house buyers.[9] Fig. 1 shows the per capita income and WTP for the 63 studies in the meta-analysis, separated by US and non-US airports.

Several statistical tests were performed on the data set. The Cook's Distance Test was used to identify five outliers; ordered by significance, they are: New York – John F. Kennedy (1994); London – Gatwick (1996); Los Angeles (1994), Geneva (2005), and London – Heathrow (1996) (Fig. 1). Another typical concern in meta-analyses is the presence of heteroscedasticity (Stanley and Jarrell, 1989; Nelson and Kennedy, 2009).[10] The Breusch–Pagan/Cook–Weisberg Test was used to conclude that heteroscedasticity is not present in the data set, as the null hypothesis of homoscedasticity could not be rejected for a p-value of 0.24.

3.2. Econometric estimation

A meta-regression analysis was performed to derive a general relationship between average personal income and the WTP for noise abatement (Stanley and Jarrell, 1989; Stanley, 2001). First, it was necessary to specify the functional form of the regression.

[6] Twenty-one of the 65 studies compiled in Wadud (2009) were previously included in other meta-analyses by Walters (1975), Pearce and Markandya (1989), Barde and Pearce (1991), Bateman et al. (2001), Nelson (2004), and Envalue (2007).

[7] The PPP is used in lieu of the market exchange rate because it accounts for the relative cost of living in different countries. This choice is consistent with the meta-analysis of Wadud (2009). The PPP is appropriate for global comparisons because it does not systematically understate the purchasing power of low-income nations (Schäfer and Victor, 2000).

[8] These four studies are: Sydney 1971, Englewood 1972, Bodo 1984, and Basel 1988 (see Appendix A).

[9] In hedonic pricing, the monetary impacts of aviation noise (or conversely, the implicit value of quietness) are captured by the observed difference in the price between a house in a noisy area and an otherwise identical house in a quiet area. However, the monetary loss due to noise is a one-time occurrence, which is only realized when the owner sells the house. When applying the income-based noise monetization model, the capitalized noise impacts (estimated using the capitalized WTP) can also be transformed into annual impacts and Net Present Value. These conversions are discussed in more detail in Section 4.

[10] Heteroscedasticity means that the individual observations in the data set were drawn from samples with disparate variances, which would violate the homoscedasticity assumption of ordinary least-squares regression (Kennedy, 2003; Schipper et al., 1998).

Several options were considered, including linear, quadratic, cubic, logarithmic, exponential, and power regressions. However, none of the more complex functional forms was a particularly good fit for the data, and a simple linear function was selected. This specification choice confers the most tractable model given in the scattered data set, and is also consistent with several previous studies that examined the income elasticity of WTP for various environmental goods (Hökby and Söderqvist, 2001; Kriström and Riera, 1996).

An initial regression model was constructed that relates income and WTP (Model 0). Using ordinary least-squares (OLS) regression, coefficients α and β corresponding to the intercept and income were computed to be 302.72 ($p=0.19$) and 0.0107 ($p=0.29$), respectively. The mean-square-error (MSE) of the regression was 3.32e5, and the R^2 and adjusted R^2 values were 0.02 and 0.003, respectively. These statistics, especially the low R^2 and adjusted R^2 values, indicate that income alone does not adequately capture the observed trends in WTP, and additional explanatory variables must be considered.

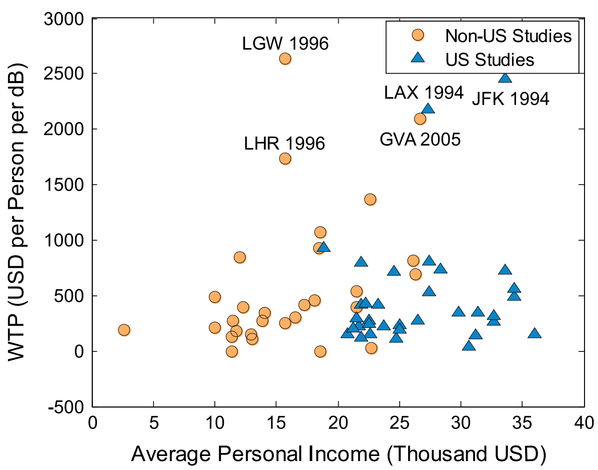

Fig. 1. WTP versus income in year 2000 USD-PPP.

$$\text{Model 0}: \ \text{WTP} = \alpha + \beta \times \text{income}$$

Fig. 1 illustrates that the US studies show a consistently lower WTP relative to income than the non-US studies. To capture this trend, two new regression models were considered. In Model 1, a dummy variable was included, which equals zero for US studies and one for non-US studies. Since most of the non-US studies were carried out in Europe, where airport-related noise is a major concern and has led to many delays in airport expansion projects, a positive correlation is expected for this variable and WTP. However, the use of a non-US dummy variable assumes that the slope of the relationship between WTP and income remains identical between the US and non-US studies, with the only difference being the intercept. To permit the slope to vary, Model 2 introduced an interaction term between income and the non-US dummy variable. This variable effectively acts as a Boolean switch that selects between two different regression relationships – one for US studies, and one for non-US studies. These two regression models are shown below, where α, β, and γ denote the coefficients of the intercept, income, and the selected non-US variable, respectively.

$$\text{Model 1}: \ \text{WTP} = \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy}$$

$$\text{Model 2}: \ \text{WTP} = \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy} \times \text{income}$$

Performing F-tests between Models 0 and 1, and between Models 0 and 2 give $F(1, 60)=5.15$ ($p=0.03$) and $F(1, 60)=5.91$ ($p=0.02$), respectively, indicating that there is enough evidence to conclude that Models 1 and 2 outperform Model 0 in explaining the 63 observations. Therefore, US versus non-US differences in the WTP for noise abatement must be accounted for. Using OLS linear regression, the regression statistics for Models 1 and 2 are shown in the left side of Table 1.

In addition to income and the interaction term, several other control variables were introduced in the meta-regression analysis so as to assess their potential effect on the WTP for aviation noise

Table 1
Comparison of regression coefficients, standard errors (in parentheses), and statistics.

Reg. scheme	**OLS**			**WLS-Sample Size**			**WLS-Robust**		
Model	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Intercept	−383.75	−93.26	−125.67	−723.17	75.80	11.43	−26.75	45.68	40.58
	(374.44)	(273.40)	(288.68)	(518.59)	(356.96)	(360.09)	(217.78)	(156.10)	(230.21)
Income	0.0326**	0.0216**	0.0217*	0.0357*	0.0101	0.0103	0.0141*	0.0109*	0.0109
	(0.0136)	(0.0106)	(0.0128)	(0.0189)	(0.0138)	(0.0159)	(0.0079)	(0.0060)	(0.0102)
Non-US dummy	454.03**			863.89***			168.91		
	(200.02)			(280.97)			(116.33)		
Non-US × income		0.0211**	0.0162		0.0300**	0.0203		0.0093*	0.0116
		(0.0087)	(0.0108)		(0.0114)	(0.0136)		(0.0050)	(0.0086)
Func. form dummy			−159.94			−120.08			−106.60
			(248.66)			(329.52)			(198.29)
Airport acc. dummy			315.03			−82.52			−16.17
			(192.80)			(248.06)			(153.74)
1980s Dummy			24.36			179.14			−27.39
			(227.97)			(283.67)			(181.79)
1990s Dummy			318.23			174.52			182.64
			(198.21)			(248.50)			(158.06)
2000s Dummy			−125.76			−92.80			1.65
			(161.10)			(202.15)			(128.47)
MSE	3.12e5	3.08e5	2.82e5	2.87e5	2.58e5	2.66e5	3.56e5	3.54e5	3.54e5
R^2	0.10	0.11	0.25						
Adj. R^2	0.07	0.08	0.16						
# Observ.	63	63	63	60	60	60	63	63	63

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

abatement (Stanley and Jarrell, 1989; Stanley, 2001). These variables include dummies for the NDI functional form, airport accessibility, and each of the decades represented in the data set, and are consistent with the control variables employed by Nelson (2004) and Wadud (2009). A full linear regression model including all control variables is shown in Model 3; the respective coefficients are denoted by α, β, γ, and δ_1 through δ_5.

$$\begin{aligned}\text{Model 3}: \ \text{WTP} &= \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy} \times \text{income} \\ &+ \delta_1 \times \text{func. form dummy} \\ &+ \delta_2 \times \text{airport access dummy} \\ &+ \delta_3 \times \text{1980s dummy} + \delta_4 \times \text{1990s dummy} \\ &+ \delta_5 \times \text{2000s dummy}\end{aligned}$$

The functional form dummy variable refers to whether the primary study derived the NDI based on a linear or a semi-logarithmic regression specification; this choice has been shown to significantly affect the NDI result (Schipper et al., 1998). A linear model generally tends to overestimate noise impacts, and thus a positive sign is expected for this variable (Wadud, 2009). The airport accessibility dummy variable refers to whether or not the primary study considered the benefits of having an airport nearby in addition to the drawbacks. Such benefits can include, for example, the ease of travel and employment opportunities. The expected sign for this variable is therefore negative, because the property value depreciation (and the corresponding WTP) should be less when also considering positive externalities of an airport. Three decade dummy variables are also introduced, one each for studies conducted in the 1980s, 1990s, and 2000s (with the 1970s decade as the default). These are used to capture any time-specific trends relating to having a set of studies that spans almost 40 years. The regression statistics for Model 3 using OLS regression are also shown in Table 1.

Due to the large variability in the data set, weighted least-squares (WLS) regression was also considered in order to lessen the susceptibility of the meta-regression model to outliers. Common WLS strategies include weighting each observation by the primary study sample size or by the reciprocal of the sample variance, such that observations derived from studies with larger sample sizes or smaller sample variances are considered to be more reliable (Nelson and Kennedy, 2009). Sample variances were not readily available for a number of the 63 hedonic noise studies, though primary study sample size was known for 60 of the 63. The middle set of columns in Table 1 shows regression statistics for Models 1–3 using WLS regression with sample size weights (also known as WLS-Sample Size for short).

In addition to the WLS-Sample Size regression scheme, another WLS strategy was also considered, which uses a robust bisquare estimator (abbreviated as WLS-Robust). This approach iteratively reweights the 63 observations in order to minimize the sum of the absolute error.[11] The resulting scheme underweighs outlying observations such that the regression model follows the bulk of the data; other outcomes include smaller standard errors and lower sensitivity to outliers. For these reasons the WLS-Robust regression may be well-suited to handle the scattered data set; regression statistics for Models 1–3 using this approach are shown in the last set of columns in Table 1.[12]

3.3. Selecting a noise monetization model

Appendix B provides a discussion of various possible interpretations of the meta-regression results, which suggest that of the nine regression relationships listed in Table 1, there does not appear to be one that clearly dominates the rest in terms of statistical significance and aptness in fitting the observed data set. However, in adopting a model to evaluate global monetary noise impacts, several factors can be considered to guide a sensible choice. First, the selected model should suitably fit the underlying data, and contain significant explanatory variables for WTP. Second, the model should be widely applicable; that is to say, it should provide reasonably accurate WTP estimates over a large income range, for both US and non-US airport regions. Finally, the desired model should be as parsimonious as possible for easy applicability. This means that when using the model to perform global benefit transfer, there would be fewer data limitations than in the previous HP approach. In the first and third points, Models 1 and 2 in any of the three regression schemes would suffice, as they contain significant regression variables and require obtaining only city-level income for each airport region in order to carry out a policy analysis.[13] The second point, however, is especially relevant to the WLS-Robust regression scheme, which suitably predicts WTP while downplaying the influence of outlying observations.

Taking these considerations into account, one approach that fits all the criteria is WLS-Robust regression with Model 2. The remainder of this paper proceeds with this selected model, and demonstrates its applicability in the APMT-Impacts Noise Module. However, it is recognized that this choice is but one interpretation of the meta-regression results; as discussed in Appendix B, other model selections are possible and may also be appropriate. Finally, as additional hedonic noise studies are performed, more observations can be included in the meta-analysis, and it is expected that the relationship between income and WTP for noise abatement will be further elucidated.

For the selected model, the income variable, interaction term, and intercept (henceforth collectively referred to as the regression parameters) are related to the WTP for noise abatement according to the following equation:

$$\begin{aligned}\text{WTP} = \ & 0.0109 \times \text{income} + 0.0093 \times \text{income} \\ & \times \text{non-US dummy} + 45.68\end{aligned} \tag{2}$$

Fig. 2(a) shows Eq. (2) superimposed on the meta-analysis data set. The solid and dashed lines represent the different relationships between WTP and income for the non-US and US studies, respectively. Fig. 2(b) gives a visual representation of the weighting scheme used in the robust linear regression. The markers indicating the individual observations are sized in proportion to their weights; observations near the regression lines have a weight close to one, whereas those farther away have a weight closer to zero. The five outliers identified through Cook's Distance Test are given a weight of zero, and therefore effectively excluded from the data set.

4. Model application

4.1. Inputs and data sources

The APMT-Impacts Noise Module uses the derived relationship between income and WTP for noise abatement to assess the global monetary impacts of aviation-related noise. In order to confirm

[11] The robust bisquare estimator assigns each observation a weight of w, based on the residual r and tuning constant k, according to the equation $w = \begin{cases} \left|\frac{r}{k}\right| \left[1 - \left(\frac{r}{k}\right)^2\right]^2, & \left|\frac{r}{k}\right| \le 1 \\ 0, & \text{otherwise} \end{cases}$ The default tuning constant of $k = 4.685$ is used.

[12] R^2 and adjusted R^2 values are omitted for the two WLS regression schemes because they are meaningful only for OLS regression with a linear model (Kennedy, 2003).

[13] If Model 3 were selected, it is not apparent how the additional dummy variables, such as NDI functional form or airport accessibility, might be accounted for when evaluating monetary impacts for various airport regions based on proposed aviation policy scenarios.

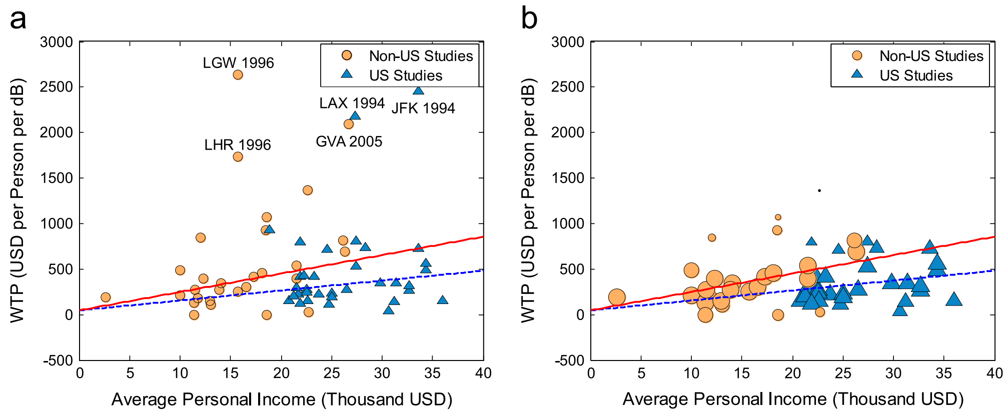

Fig. 2. Results of robust linear meta-regression: (a) with all 63 observations and (b) with observations sized to reflect the robust weighting scheme.

model applicability and test for convergent validity with previous results, the new model is used to assess the monetary noise impacts of a realistic aviation noise scenario. For this, several inputs are required, which include external inputs corresponding to the scenario considered for analysis (noise contours, population data, and city-level average personal income), as well as parameters intrinsic to the model itself, which are user-specified and independent of the scenario of interest (discount rate, income growth rate, significance level, background noise level, noise contour uncertainty, and regression parameters).

The noise contours and population data used in this analysis are identical to those from Kish (2008). Noise contours represent the Day-Night average sound Level (DNL) of aircraft noise at a particular location, and are computed as yearly averages around each airport. For a policy analysis, usually two sets of contours are needed: baseline and policy. The baseline noise contours for the reference year are constructed according to actual aircraft movement data for a representative day of operations. The baseline or consensus forecast for future years represents an estimate of the most likely future noise scenario while maintaining the status quo for technology, fleet mix, and aviation demand. The policy forecast reflects the expected future noise levels after the implementation of a particular aviation policy. Typically, when using the income-based noise monetization model for policy assessment, the relevant result is the difference in the noise impacts as a result of policy implementation (termed the "policy minus baseline" scenario). However, for consistency with Kish (2008), only the baseline scenario is considered in the present analysis. The reference year of the noise contours is 2005, and the forecasted future year is 2035. The contours were created using MAGENTA based on operations conducted on October 18, 2005, which comprised a total of 65,235 flights. The analysis includes 181 Shell 1 airports located in 38 countries plus Taiwan; 95 of the airports are located in the US and Puerto Rico (Appendix C).

Since the new model assesses monetary impacts using a per person WTP value, detailed population data are required to estimate the number of people residing in the region surrounding each airport. They are presented as discretized grids of population density (number of persons per square meter) in the Universal Transverse Mercator (UTM) coordinate system, and were gathered from several sources: for US regions, block group-level 2000 census data were used; for European regions, the European Environmental Agency's (EEA) population maps were used; for most of the rest of the world, population data were obtained from the Gridded Rural-Urban Mapping Project (GRUMP). At present, all population data correspond to 2000 (US Census and GRUMP data) or 2001 values (EEA data), and any population changes since that time are not accounted for.

Income data were gathered from numerous sources, which are summarized in Appendix C. For the 95 US airports, MSA-level income data were obtained for 2005 from the US Bureau of Economic Analysis (US BEA). For 53 of the 86 non-US airports, city- or region-level income data were available from various national statistical agencies, which were adjusted to year 2005 USD using the appropriate income growth rate and PPP. Of the remaining airports, country-level income data were available for 26, and neither city-level nor country-level data were available for the last seven. For those airports, income was estimated at the national level based on GNI per capita for 2005 in USD-PPP.[14]

The model parameters can be either deterministic or distributional. Deterministic parameters are used when the exact value of the parameter is known, or can be selected based on guidelines or on previous knowledge about a particular situation. The values used for the model parameters in this paper are consistent with the definition of the midrange lens in the APMT-Impacts Noise Module (He, 2010; Mahashabde et al., 2011).[15]

Of the six model parameters, the discount rate, income growth rate, and significance level are set to be deterministic values, as they represent value judgments rather than parameters rooted in scientific knowledge. The discount rate captures the depreciation in the value of money over time, and is expressed as an annual rate. It is closely related to the time span of the analyzed policy, which is based on the typical economic life of a building and the duration of future noise impacts that is considered by the house buyers. In this analysis, the policy time span is 30 years (2005–2035). The nominal discount rate is selected to be 3.5%, which is consistent with previous work in APMT-Impacts (Kish, 2008; Mahashabde, 2009); however, because discount rates can vary greatly from country to country, Section 5 also presents a sensitivity analysis of the monetized noise impacts with various discount rate assumptions.

The income growth rate represents the annual rate of change in the city-level average personal income. It is universally applied to

[14] A regression relationship was developed between GNI per capita and country-level income for the 79 airports where income data were available (World Bank, 2010). Each country represents one observation in the regression data set; for countries with multiple airports in the analysis, the mean income over the various airport regions was used. Using linear OLS regression, the relationship is: income per capita $=0.6939\times$ GNI per capita ($R^2=0.82$).

[15] Lenses are pre-defined combinations of inputs and assumptions that are used to evaluate decision alternatives in APMT-Impacts. They can be used to assess a given policy from a particular perspective: for example, the midrange lens describes the most likely to occur scenario, whereas the low-impacts lens adopts an optimistic (or best-case) outlook in which the environmental impacts are minimum, and the high-impacts lens represents a pessimistic (or worst-case) view where the environmental impacts are maximum.

the income levels of all airports in the analysis when calculating the WTP for noise abatement. While this parameter may be user-selected to be any reasonable value (even negative growth rates), in this analysis it is set to zero so as to ensure consistent comparison with the Kish (2008) results, and consider noise impacts solely due to the growth of aviation, rather than due to changes in economic activity.

The significance level is the threshold DNL above which aircraft noise is considered to have "significant impact" on the surrounding community. It does not affect the value of the computed monetary noise impacts, but rather designates impacts as significant or insignificant, and thereby includes or excludes them from the reported results. In this analysis, the significance level is set to equal the background noise level, such that any aviation noise above the ambient noise level in the community is perceived as having a significant impact. However, other levels of significance may also be chosen; for example, 65 dB DNL is the level defined by the FAA as the threshold below which all types of land used are deemed compatible (FAA, 2006).

4.2. Uncertainty analysis

The distributional parameters of the model are the background noise level, noise contour uncertainty, and the regression parameters. These inputs have uncertainties that arise from limitations in knowledge, a lack of predictability, or modeling difficulties, which propagate through the model to yield uncertainties in the output. In the income-based noise monetization model, Monte Carlo (MC) simulations are used to capture this uncertainty by specifying each parameter as a probabilistic distribution, and computing an output for each input sample. Previous work has shown that 2000 MC samples are sufficient for convergence in the APMT-Impacts Noise Module (He, 2010).

The economic impacts of aviation noise should only be evaluated when aircraft noise exceeds the ambient noise level. This threshold is termed the background noise level (BNL). The BNL can vary from region to region, but for urban areas, it is typically about 50–60 dB in the daytime and 40 dB at night (Nelson, 2004). Navrud (2002) cites numerous studies in Europe that use a BNL of either 50 or 55 dB, and recommends using 55 dB DENL for aircraft noise. In the US, under the 1972 Noise Control Act, the EPA recommends 55 dB DNL as the "level requisite to protect health and welfare with an adequate margin of safety" (EPA, 1974). The BNL imparts uncertainty in estimated noise impacts on two fronts. First, the level of aircraft noise exceeding the assumed BNL directly affects the computed monetary damages (Eqs. (3)–(5)). Second, many of the primary noise studies in the meta-analysis estimated NDI based on an assumed BNL for the airport region; these assumptions are not consistent across studies. Inaccurate BNL assumptions in the primary studies can impact the validity of the derived NDI, and thereby influence the WTP estimate associated with the study. For example, a too-low BNL assumption correlates a higher level of aircraft noise exposure with the observed property value depreciation, resulting in an underestimate of the airport region NDI. This leads to smaller values for WTP in Eq. (1), and affects the regression models in Section 3 that relate WTP, income, and other control variables. While it may be difficult to capture the effect of BNL uncertainty in primary study NDI estimation, an attempt is made to account for BNL uncertainty in computing the level of noise exposure by specifying the parameter as a triangular distribution between 50 and 55 dB DNL, with a mode of 52.5 dB DNL.

Currently, the noise contours generated by MAGENTA are fixed values. However, any uncertainty in the area of the contours may disproportionately affect the estimated monetary noise impacts (Tam et al., 2007). This noise contour uncertainty is modeled as a triangular distribution between -2 and 2 dB DNL, with a mode of zero.

To express the three regression parameters from Section 3.3 as probabilistic input distributions, bootstrapping is performed with the 63 meta-analysis observations in order to generate alternative data sets and construct multiple estimates of the coefficients. In the bootstrapping procedure, 63 samples are randomly drawn with replacement from the original data set, and a WLS-Robust regression with Model 2 is used to compute the coefficients for income, the income $\times$ non-US dummy interaction term, and intercept. This process is repeated 2000 times for each of the 181 airports in the analysis, for a total of 362,000 estimates of each regression parameter. Fig. 3 shows the bell-shaped distributions obtained from bootstrapping, as well as the associated mean and standard deviation (SD). Note that the mean value of each distribution is slightly different from the corresponding coefficient in Eq. (2) due to random sampling.

Finally, it should be noted that when assessing the monetary impacts model of a proposed aviation policy, the pertinent result is typically the difference between the policy and baseline noise scenarios. In that regard, while the modeling uncertainties discussed in this section produce first-order effects on the baseline or policy scenario outcomes individually, the effects become second-order when considering a policy minus baseline scenario.

4.3. Algorithm and outputs

The income-based noise monetization model is a suite of scripts and functions implemented in the MATLAB® (R2009a, The MathWorks, Natick, MA) numerical computing environment. The algorithm is shown schematically in Fig. 4 and summarized below.

For each airport, the city-level average per capita personal income is combined with the income growth rate and the coefficients of the regression parameters to calculate a WTP per

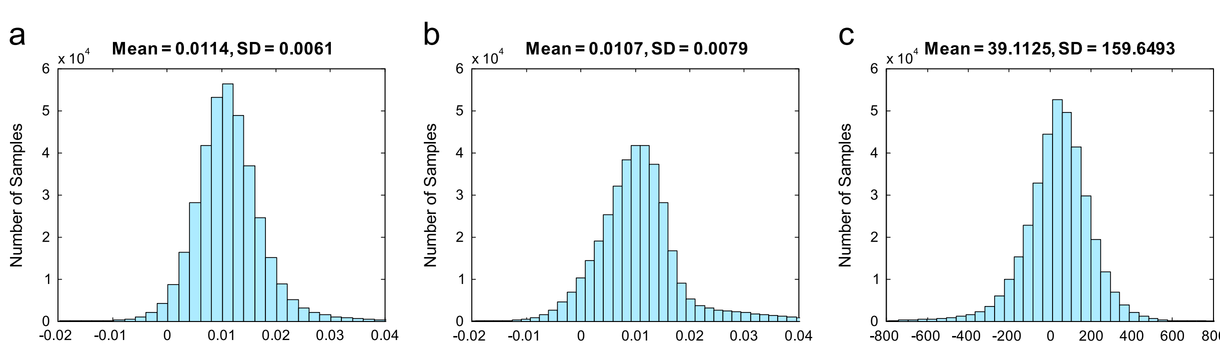

Fig. 3. Bootstrapping distributions for: (a) income coefficient, (b) interaction term, and (c) intercept.

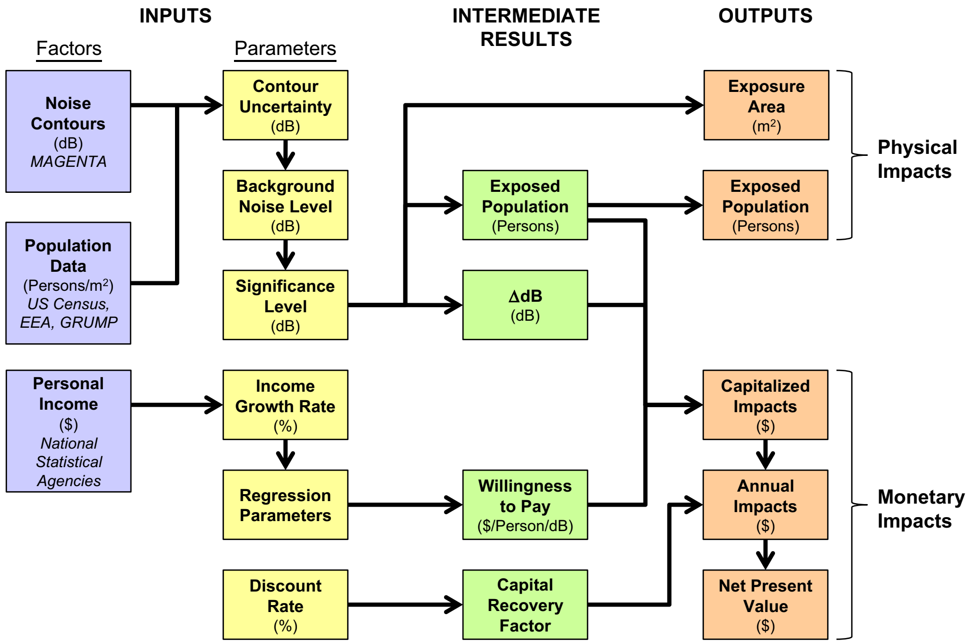

Fig. 4. Schematic of income-based noise monetization model.

person per dB of noise abatement for the airport region. The population density grid and noise contour are spatially aligned according to their UTM coordinates, and superimposed to calculate the number of people around each grid point exposed to the DNL represented in the noise contour.

Taking into account uncertainty in the background noise level and the MAGENTA noise contours, the noise level (in year t) used in the calculation of monetary impacts (termed $\Delta\text{dB}(t)$) is given by

$$\Delta\text{dB}(t) = \text{noise contour level}(t) + \text{contour uncertainty} - \text{BNL} \tag{3}$$

For each grid point p, the monetized value of noise in year t, $V_p(t)$, is given by

$$V_p(t) = \text{WTP} \times \Delta\text{dB}(t) \times \text{number of persons} \tag{4}$$

The units of $V_p(t)$ are USD in the reference year of the noise contours. In order to compute $V(t)$, the total noise impacts associated with year t, $V_p(t)$ is summed over all grid points within each noise contour band (e.g., 55–60 dB DNL, 60–65 dB DNL), across all noise contour bands for each airport, and finally across all airports in the analysis

$$V(t) = \sum_{\textit{Airports}} \sum_{\textit{Noise Contour Bands}} \sum_{\textit{Grid Points}} V_p(t) \tag{5}$$

In this analysis, there are two sets of noise contours, corresponding to baseline aviation noise levels in 2005 and the forecasted level for 2035. Therefore, only $V(0)$ (for the reference year) and $V(30)$ (for the final policy year) are explicitly computed, and intermediate values of $V(t)$ are obtained through linear interpolation.

Because the income-based noise monetization model is developed from 63 hedonic pricing studies, the WTP for noise abatement is explicitly a function of capitalized attributes such as NDI and property value (Eq. (1)), making it also a capitalized value. Therefore, the quantity $V(t)$ also encapsulates the anticipated noise impacts in future years. In addition to capitalized monetary impacts, annual impacts are also useful as they capture changes in aviation noise over the time span of an environmental policy. Annual impacts may be computed by multiplying $V(0)$ by a Capital Recovery Factor (CRF), then adding the marginal increase in monetized noise impacts between adjacent years. Finally, the Net Present Value (NPV) of the impacts can be computed by summing the discounted annual noise impacts over the duration of the policy period, excluding the annuity in the reference year.

5. Results and discussion

The income-based noise monetization model estimates that the number of people exposed to at least 55 dB DNL of aviation-related noise around 181 airports was 14.2 million in 2005, and could rise to 24.0 million in 2035. As expected, these values match the figures reported by Kish (2008). Fig. 5 shows the worldwide distribution of the affected population in 2005. Approximately one-third of the 14.2 million people reside in North America, followed by 21% in Asia, 16% in the Middle East, 11% in Europe, and less than 10% in each of Eurasia, Central America, Africa, and Oceania.[16] Over the 30-year analysis span, we project a 69% increase in the exposed population solely due to the forecasted growth in aviation, since population growth is not accounted for in the model.

The distribution of the total capitalized monetary impacts has a mean of \$23.8 billion and a standard deviation \$1.7 billion (in year 2005 USD). Of the mean value, the 95 US airports account for \$9.8 billion, or some 41% of the global sum. Fig. 6 shows the relative magnitude of capitalized impacts around each of the 181 airport regions at 2005 noise levels. Approximately 44% of the global monetary impacts occur in North America, followed by 18% in Asia, 15% in Europe, 12% in the Middle East, 5% in Eurasia, 3% in Central America, and very low contributions from Africa and Oceania. Regions such as North America and Europe have a larger share of the global monetary noise impacts relative to exposed population because of the higher incomes in those areas, which result in a larger per capita WTP for noise abatement.

Of the 14.2 million people exposed to at least 55 dB DNL of aviation noise, Fig. 7(a) shows that about half live in developed

[16] Classification of continents and regions is based on the guidelines set by the United Nations Statistics Division (United Nations, 2010).

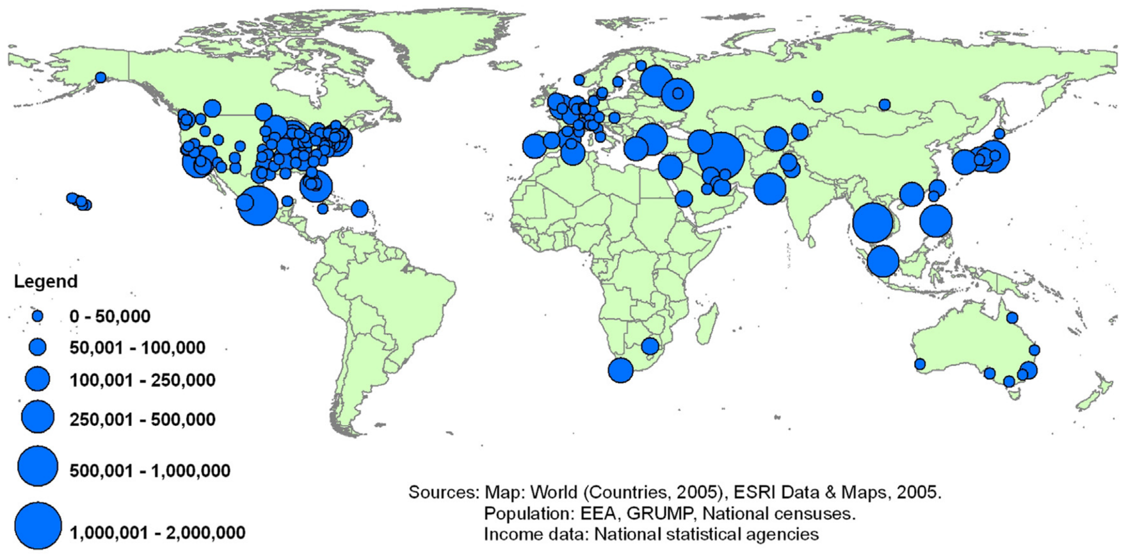

Fig. 5. Number of people exposed to at least 55 dB DNL of aviation noise in 2005.

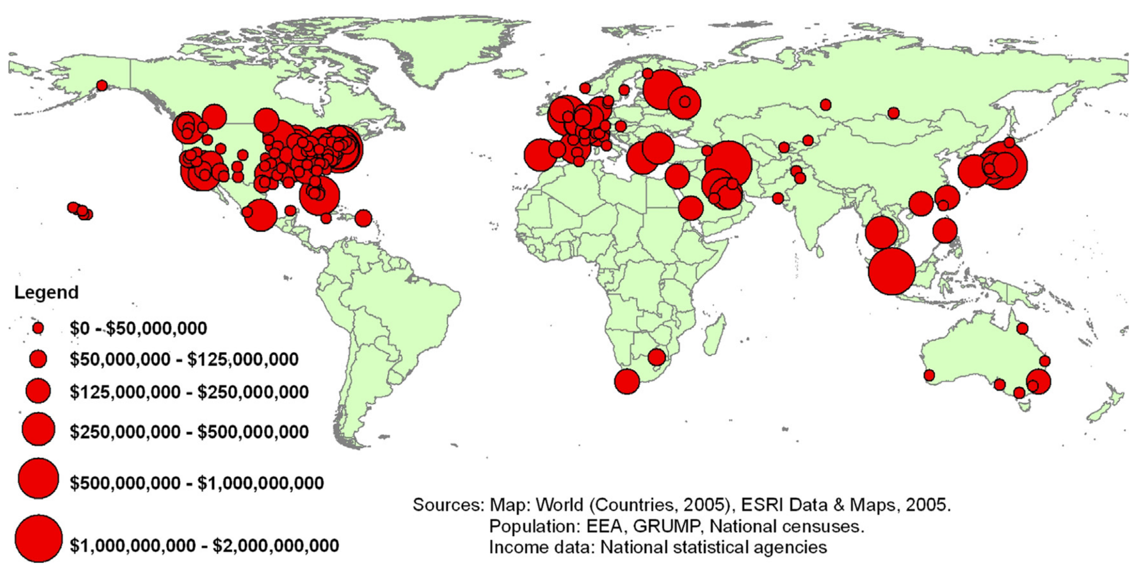

Fig. 6. Geographic distribution of capitalized noise impacts around 181 airports in 2005.

countries, 42% in developing countries, and 9% in transition countries.[17] Fig. 7(b) shows the total monetary impacts separated by economic development status. The developed countries account for more than two-thirds of the total monetary impacts, the developing countries 26%, and the transition countries 5%. The developed nations account for a significantly larger share of the monetary impacts relative to their population, and vice-versa for the developing nations. This trend is due to both the increased level of air transportation and the higher per capita income in developed nations. Another interesting metric that corroborates this trend is the relative burden of the impacts, defined as the capitalized monetary impacts for each airport normalized by the income level and exposed population in the airport region. Fig. 7 (c) shows the mean relative burden across all airports within each development category. Across a wide income spectrum, the relative burden is highest for developing nations, and lowest for developed nations.

[17] Classification of developed, developing, and transition countries is based on guidelines set by the United Nations Statistics Division (United Nations, 2010).

Using a CRF corresponding to a 3.5% discount rate and a 30-year period, the capitalized noise impacts are converted into annual impacts that total $1.3 billion in 2005. The NPV of the aviation noise impacts is also computed, and the mean and standard deviation of the MC estimates are $36.5 billion and $2.4 billion (in year 2005 USD), respectively (Fig. 8).[18]

Kish (2008) reported the monetary impacts of aviation noise in terms of both capitalized impacts ($21.4 billion in housing value depreciation at 2005 noise levels) and annual impacts ($800 million in rental loss per year). In order to ensure consistent comparison with the income-based model, the NPV of the Kish (2008) results is also computed, which accounts for both contributing sources of noise impacts. Fig. 9(a) shows the variation in the mean NPV for the two models for discount rates between 1% and 10%. At a discount rate of

[18] The NPV includes the anticipated increase in air traffic between 2005 and 2035, but does not account for any growth in population or income during that period. Furthermore, since the 181 airports in the analysis include few or no airports in Asia, Africa, and South America – regions with high expected rates of aviation growth, the analysis results do not capture the full extent of future aviation-related noise impacts.

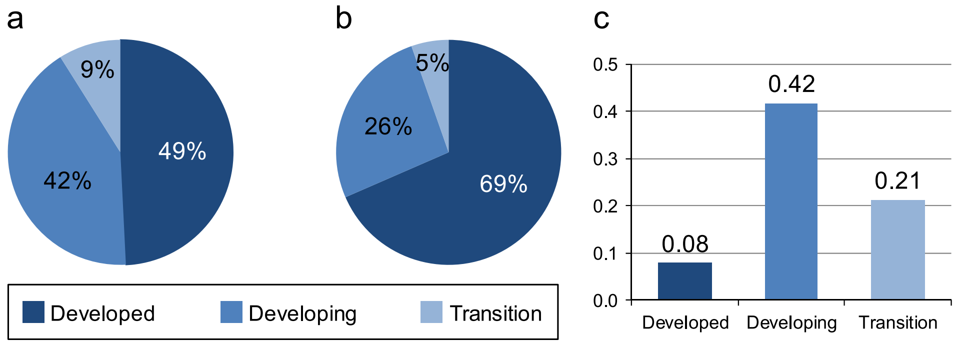

Fig. 7. Distribution of: (a) exposed population, (b) capitalized monetary impacts and (c) relative burden by development status.

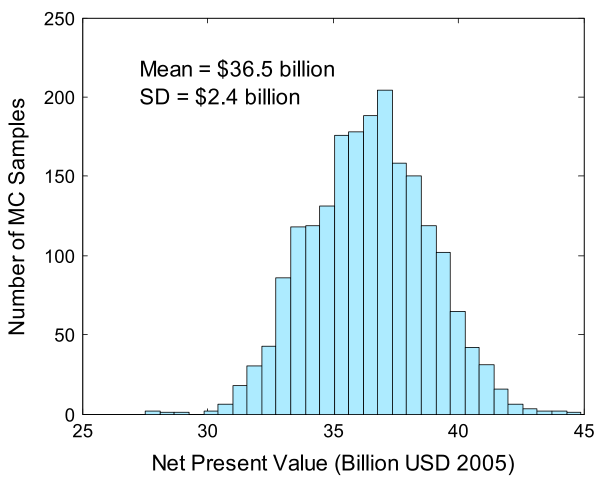

Fig. 8. Distribution of NPV with a 3.5% discount rate.

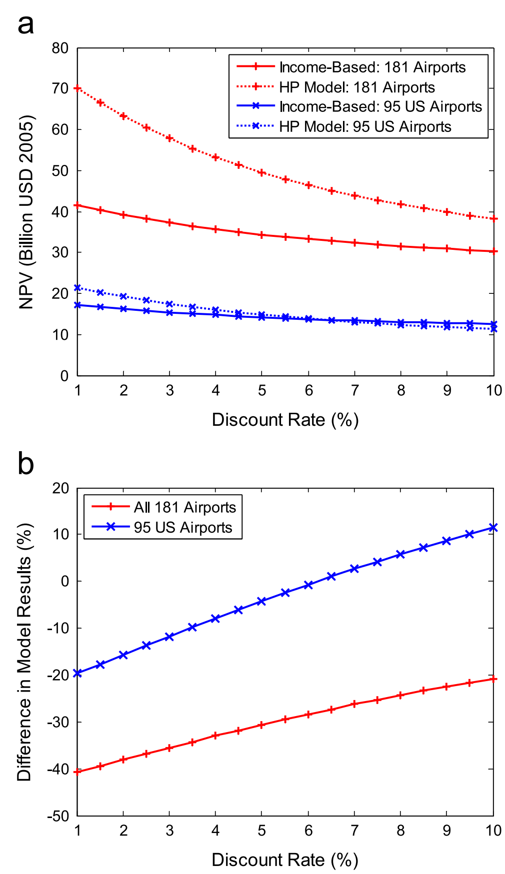

Fig. 9. Comparing the income-based model with the Kish (2008) HP results. (a) NPV as a function of discount rate and (b) difference in NPV between the two models as a function of discount rate.

3.5%, the NPV of the Kish (2008) analysis is $55.4 billion in year 2005 USD, corresponding to a −34.2% discrepancy between the two models. For most reasonable discount rate choices, the lower curve in Fig. 9(b) shows that the magnitude of the difference in the global NPV estimates between the income-based model and the HP model used by Kish (2008) is on the order of 30%.

For the 95 US airports in the analysis, comprehensive data are available for population, housing value, rental value, and income, and thus a more detailed comparison of the two monetization models is possible. Such a comparison minimizes uncertainties related to the quality and availability of real estate and income data, or to the applicability of various property value and rental price estimation methods. From the HP model, the mean NPV of aviation noise impacts for US airports total $16.7 billion, representing 30.2% of the global sum. Using the income-based model, the NPV for the US airports has a mean value of $15.1 billion, which differs from the HP model estimate by −9.8%. Fig. 9(a) shows that over a range of discount rates, the mean NPV computed from the two models for the 95 US airports is comparable; the upper curve in Fig. 9(b) reveals that the magnitude of the difference is on the order of 10%. Finally, it should be noted that the magnitude of the discrepancy is also influenced by the selection of the regression model in Section 3; for example, choosing a regression relationship that predicts higher WTP with respect to income (e.g., a model employing OLS regression) would increase the estimated noise impacts, and may produce a closer comparison with the Kish (2008) results.

This comparison illustrates that results for the 95 US airports from the two models are similar, despite the disparate noise valuation methods employed in the analyses. Convergent validity is achieved in that two different measurement techniques produced similar outcomes, although neither result can be assumed to be the true answer (Rosenberger and Loomis, 2000). Each model has its own set of assumptions, such that comparisons of the results may be influenced by model uncertainties as well as by the accuracy of the algorithms.

However, there are several important advantages of the income-based model. The main benefit is that it does not require detailed real estate data for each airport in the analysis, relying instead on city-level income data, which are much more readily available for most regions of the world. Another key difference between the two models is that rather than separating the monetary impacts of aviation noise into housing value depreciation and rental loss, as is the case in the HP approach, the results of the income-based model in theory capture both effects. This is because in the income-based model, the WTP for noise abatement is expressed as a *per person* monetary value, and is applied to all individuals residing within the noise

Table A1

Study #	Author	Year	City	Country	Sample size	Property value (USD-PPP 2000)[a]	NDI (% per dB)[b]	WTP per HH (USD-PPP 2000)	House-hold size[c]	WTP per person (USD-PPP 2000)	Income (USD-PPP 2000)	Airport acc.	Linear spec.
1	Paik[d]	1970	Dallas	USA	94	104,824	2.30	2411	2.60	927	18,853	N	N
2	Paik[d]	1971	Los Angeles	USA	92	115,073	1.80	2071	2.60	797	21,923	N	N
3	Paik[d]	1972	New York (JFK)	USA	106	96,938	1.90	1842	2.60	708	24,586	N	N
4	Roskill Commission[e]	1970	London (LHR)	UK	20	86,086	0.71	633	2.90	218	10,010	N	N
5	Roskill Commission[e]	1970	London (LGW)	UK	20	*86,086*	1.58	1409	2.90	486	10,010	N	N
6[f]	Mason[g]	1971	Sydney	Australia			0.00					N	N
7	Emerson	1972	Minneapolis	USA	222	101,564	0.59	599	2.68	224	21,747	N	N
8[f]	Coleman[e]	1972	Englewood	USA	21		1.58					N	N
9	Dygart[d]	1973	San Francisco	USA	82	122,544	0.50	613	2.27	270	26,536	Y	N
10	Dygart[d]	1973	San Jose	USA	98	93,240	0.70	653	2.92	224	23,732	Y	N
11	Price[d]	1974	Boston	USA	270	*128,120*	0.81	1038	2.48	419	21,900	N	Y
12	Gautrin	1975	London (LHR)	UK	67	82,011	0.62	527	2.80	188	11,759	Y	N
13	De Vany	1976	Dallas	USA	1270	97,680	0.80	781	2.67	293	21,563	N	Y
14	Maser et al.	1977	Rochester	USA	398	81,175	0.86	698	2.56	273	22,511	N	Y
15	Maser et al.	1977	Rochester	USA	990	92,650	0.68	630	2.56	247	22,511	N	N
16	Balylock[d]	1977	Dallas	USA	4264	111,000	0.99	1099	2.60	423	22,267	Y	Y
17	Mieszkowski & Saper	1978	Toronto	Canada	509	139,771	0.66	1111	2.70	411	14,082	N	N
18	Fromme[d]	1978	Washington Reagan	USA	28	133,502	1.49	1989	2.46	809	27,441	Y	N
19	Nelson[d]	1978	Washington Reagan	USA	52	121,900	1.06	1292	2.46	525	27,441	Y	N
20	Nelson	1979	San Francisco	USA	153	131,806	0.58	764	2.20	347	29,801	Y	N
21	Nelson	1979	St. Louis	USA	113	72,865	0.51	372	2.51	148	22,614	Y	N
22	Nelson	1979	Cleveland	USA	185	92,787	0.29	269	2.37	114	24,720	Y	N
23	Nelson	1979	New Orleans	USA	143	97,569	0.40	390	2.65	147	20,761	Y	N
24	Nelson	1979	San Diego	USA	125	143,150	0.74	1059	2.53	419	23,275	Y	N
25	Nelson	1979	Buffalo	USA	126	91,713	0.52	477	2.40	198	21,276	Y	N
26	Abelson	1979	Sydney	Australia	592	98,773	0.40	517	3.00	172	11,356	N	N
27	Abelson	1979	Sydney	Australia	822	112,883	0.00	0	3.00	0	11,356	N	N
28	McMillan et al.	1980	Toronto	Canada	352	133,817	0.51	822	2.70	304	15,708	N	N
29	Mark	1980	St. Louis	USA	6553	68,543	0.42	288	2.49	116	21,903	N	N
30[f]	Hoffman[h]	1984	Bodo	Norway			1.00					N	N
31	O'Byrne et al.	1985	Atlanta	USA	248	80,597	0.64	516	2.24	231	25,014	Y	N
32	O'Byrne et al.	1985	Atlanta	USA	96	64,422	0.67	432	2.24	193	25,014	N	N
33	Opschoor[i]	1986	Amsterdam	Netherlands		*82,732*	0.85	854	2.82	303	16,501	N	N
34[f]	Pommerehne[i]	1988	Basel	Switzerland			0.50					N	N
35	Burns et al.[g]	1989	Adelaide	Australia	100	92,482	0.78	943	2.60	363	11,504	N	N
36	Penington	1990	Manchester	UK	3472	78,357	0.34	276	2.50	110	13,058	N	N
37	Gillen & Levesque	1990	Toronto	Canada	1886	214,899	1.34	3468	2.70	1284	18,539	Y	N
38[f]	Gillen & Levesque	1990	Toronto	Canada	1347	135,472	−0.01	−14	2.70	−5	18,539	Y	N
39	BIS Shrapnel[g]	1990	Sydney	Australia	344	*170,836*	1.10	2457	2.90	847	12,035	N	N
40	Uyeno	1993	Vancouver	Canada	645	156,558	0.65	1226	2.60	471	21,557	N	N
41	Uyeno	1993	Vancouver	Canada	907	156,558	0.90	1697	2.60	653	21,557	Y	N
42	Tarassoff	1993	Montreal	Canada	427	151,859	0.65	1189	2.40	495	17,278	N	Y
43	Collins & Evans	1994	Manchester	UK	558	78,357	0.47	381	2.50	153	12,916	N	N
44	Levesque	1994	Winnipeg	Canada	1635	88,488	1.30	1385	2.50	554	18,078	N	N
45	BAH-FAA	1994	Baltimore	USA	30	163,281	1.07	1747	2.39	731	28,380	Y	Y
46	BAH-FAA	1994	Los Angeles	USA	24	442,338	1.26	5573	2.56	2175	27,370	Y	Y
47	BAH-FAA	1994	New York (JFK)	USA	30	502,775	1.20	6033	2.46	2451	33,625	Y	Y
48	BAH-FAA	1994	New York (LGA)	USA	30	264,815	0.67	1774	2.46	721	33,625	Y	Y
49	Mitchell McCotter[g]	1994	Sydney	Australia	750	170,836	0.68	1519	2.90	523	12,278	N	N
50	Yamaguchi[j]	1996	London (LGW)	UK		*264,782*	2.30	6308	2.39	2639	15,720	N	N

Table A1 (*continued*)

Study #	Author	Year	City	Country	Sample size	Property value (USD-PPP 2000)[a]	NDI (% per dB)[b]	WTP per HH (USD-PPP 2000)	House-hold size[c]	WTP per person (USD-PPP 2000)	Income (USD-PPP 2000)	Airport acc.	Linear spec.
51	Yamaguchi[j]	1996	London (LHR)	UK		*264,782*	1.51	4141	2.39	1733	15,720	N	N
52	Myles[d]	1997	Reno	USA	4332	170,100	0.37	629	2.38	264	32,694	N	N
53	Tomkins et al.	1998	Manchester	UK	568	105,227	0.63	687	2.40	286	13,830	Y	N
54	Espey & Lopez	2000	Reno-Sparks	USA	1417	132,498	0.28	371	2.56	145	36,019	Y	N
55	Burns et al.	2001	Adelaide	Australia	5207	*135,353*	0.94	1664	2.40	693	26,298	Y	N
56	Rossini et al.	2002	Adelaide	Australia	4139	146,181	1.34	2561	2.40	1067	26,105	Y	N
57	Salvi	2003	Zurich	Switzerland	565	382,101	0.75	2611	2.10	1243	22,664	N	N
58	Lipscomb	2003	Atlanta	USA	105	105,766	0.08	85	2.40	35	30,625	Y	N
59	McMillan	2004	Chicago	USA	4012	183,727	0.81	1488	3.06	486	34,347	Y	N
60	McMillan	2004	Chicago	USA	22,541	193,917	0.88	1706	3.06	558	34,347	Y	N
61	Baranzini & Ramirez	2005	Geneve	Switzerland	1847	376,673	1.17	4015	2.10	1912	26,650	N	N
62	Cohen & Coughlin	2006	Atlanta	USA	1643	76,570	0.43	329	2.40	137	31,166	Y	N
63	Cohen & Coughlin	2007	Atlanta	USA	508	120,696	0.69	833	2.40	347	31,347	Y	N
64	Faburel & Mikiki	2007	Paris	France	688	123,895	0.06	86	2.40	36	22,698	N	N
65	Pope	2007	Raleigh	USA	16,900	212,005	0.36	763	2.46	310	32,700	Y	N
66	Dekkers & van der Straaten	2009	Amsterdam	Netherlands	66,600	*252,539*	0.77	1945	2.10	926	18,435	N	Y
67	Chalermpong	2010	Bangkok	Thailand	37,591	*34,488*	2.14	738	3.80	194	2630	Y	N

Adapted from Wadud (2009), Table 4.2, except for studies 66 and 67.

[a] Property values from Wadud (2009) given in USD 2000, with conversions performed using the Purchasing Power Parity. Italicized values are not given in Wadud (2009), but gathered by the authors from various national statistical agencies.

[b] Wadud (2009) used conversion factors from Walters (1975) to make NDI values comparable.

[c] Household size data gathered from the US Census Bureau, or various national statistical agencies.

[d] From Nelson (2004).

[e] From Walters (1975).

[f] Study excluded from the meta-regression analysis.

[g] From Envalue (2007).

[h] From Barde and Pearce (1991).

[i] From Pearce and Markandya (1989).

[j] From Bateman et al. (2001).

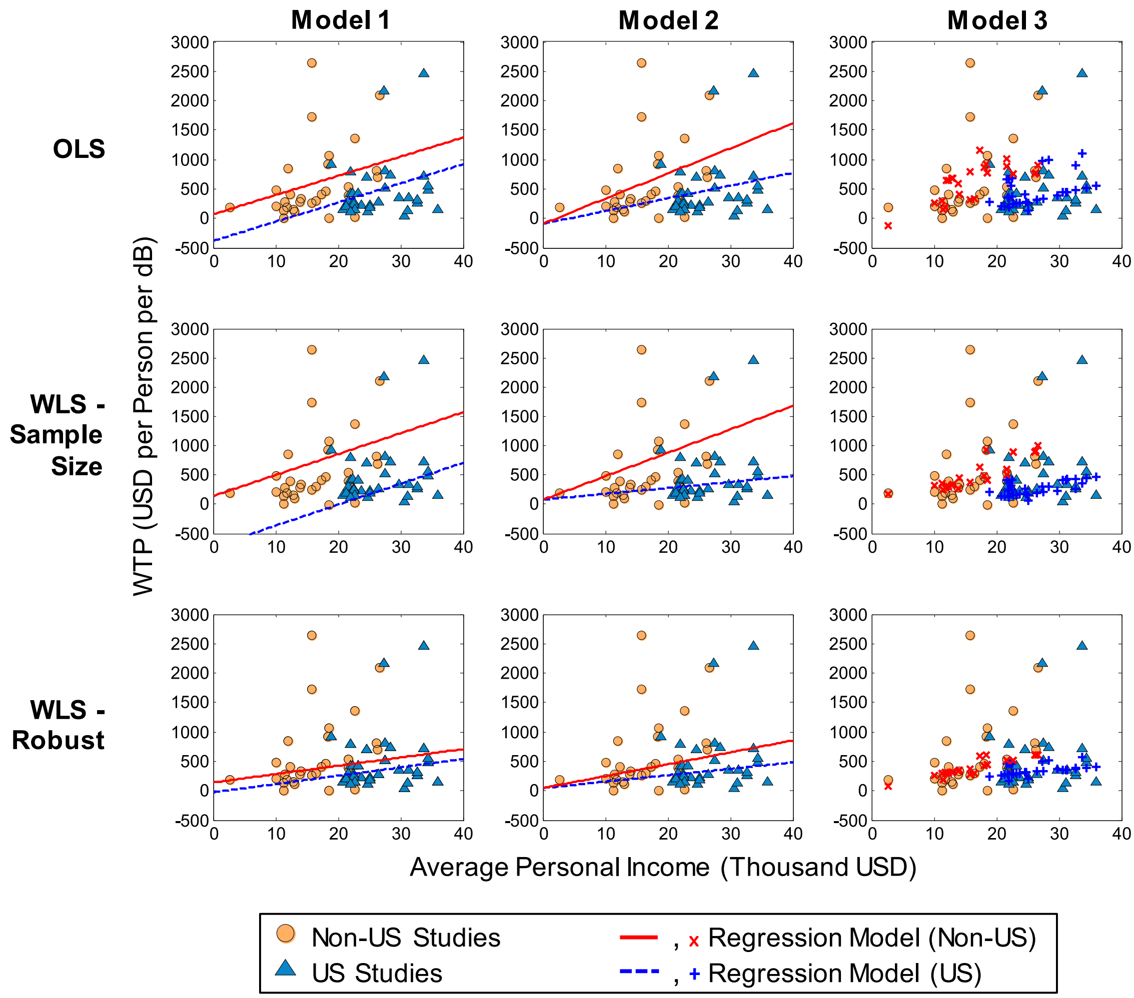

Fig. 10. Comparison of regression models and regression schemes.

contour area to estimate the cumulative effect of housing value depreciation and rental loss. In this way, the income-based model is advantageous for global-scale policy analysis, as no knowledge is required about the split between owner-occupied and rental properties in each airport region.

One limitation of the income-based noise monetization model is that it is sensitive to the availability, resolution, and accuracy of income data. While income data are available at the MSA- or city-level for many airports, this is not the case in general, and inconsistencies in data resolution can introduce uncertainties in impacts estimates. Furthermore, the mean per capita income for persons living in the noise exposure region surrounding each airport may be significantly different from the MSA or city average. A lower income level in the immediate airport region versus the city as a whole could result in underestimation of the monetary impacts, and vice-versa. This effect may more be pronounced in areas of large income disparity, or for airports that are located far from the cities they serve. This problem can be lessened by using airport region-level income data wherever possible.

Another limitation of the income-based noise monetization model (and of the Kish (2008) analysis) is that the meta-analysis is constrained by the availability of aviation noise studies. Most of the studies in the meta-analysis were conducted in high-income nations, but the relationship derived from them between income and WTP for noise abatement is applied globally in policy analyses. In fact, little is known about the applicability of the model in low-income regions, and thus the greatest uncertainty is expected for monetary impacts estimated for airports in those locations. This is an example of generalization error in benefit transfer, which is expected to vary inversely with the degree of similarity between the study site and the policy site (Rosenberger and Stanley, 2006). However, studies have found that generalization error tends to be mitigated when transferring the full demand function (e.g., WTP for aviation noise abatement as a function of income) instead of point values (e.g., individual NDI estimates) (Rosenberger and Stanley, 2006 and references therein). Furthermore, as these errors are common to the baseline and policy scenarios, their net effect is diminished when evaluating the change in aviation noise impacts as the result of policy implementation. Nevertheless, such uncertainties highlight the need to increase knowledge of aviation noise impacts around the globe, which would help elucidate the relationship between income and WTP for noise abatement at the lower end of the income spectrum and thereby enable a stronger assessment of the validity of results such as those shown in the present analysis.

6. Conclusions

Within this paper, a new model is presented that quantifies the monetary impacts of aviation-related noise based on city-level income. The model development centers on a meta-analysis of 63 aviation noise studies from eight countries, which is used to derive a relationship between the Willingness to Pay for noise abatement, city-level personal income, and an interaction term that captures US versus non-US differences. The resulting meta-regression model is statistically significant, easily applicable, and enables benefit transfer of aviation noise impacts on an international scale. This model was applied to assess the monetary impacts of aviation-related noise around 181 airports, estimating $23.8 billion in capitalized impacts in 2005, and $36.5 billion in Net Present Value between 2005 and 2035 when a 3.5% discount rate was assumed. These results compare closely with previous estimates from a hedonic pricing approach.

As a policy assessment tool for the FAA's APMT-Impacts Module, the income-based noise monetization model offers several advantages over previous hedonic pricing models, including fewer data constraints, reduced uncertainty in model inputs, and relative ease of implementation. It can be used by policymakers, aircraft manufacturers, and other stakeholders in the aviation industry to estimate the monetary impacts of technological improvements or policy measures related to aviation noise. Such analyses will enable comprehensive cost–benefit and tradeoff studies of various environmental impacts, which are crucial in making decisions to help ensure the sustainable growth of aviation in the future.

Acknowledgments

The authors would like to thank Professors Jon Nelson (Penn State) and Raymond Palmquist (North Carolina State) for their invaluable comments and advice throughout the duration of this project, and Professor Moshe Ben-Akiva (MIT) and Ronny Freier for insightful discussions relating to econometrics and statistical issues. They are also grateful for the helpful suggestions and constructive criticisms provided by the anonymous reviewers. They would also like to acknowledge the generous support of the Erich-Becker Foundation (Wollersheim) and the National Science Foundation Graduate Research Fellowship Program (He).

This work is funded by the US Federal Aviation Administration Office of Environment and Energy under FAA Contract no. DTFAWA-05-D-00012, Task Order nos. 0002, 0008, and 0009. The project is managed by Maryalice Locke of the FAA. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA.

Appendix A. Aviation noise studies

See Table A1.

Appendix B. Comparison of regression models and schemes

The section discusses some possible interpretations of the regression statistics in Table 1 of Section 3.2 in order to guide the selection of a particular monetization model for use in the APMT-Impacts Noise Module, and to enable benefit transfer of aviation noise impacts worldwide. Recall that nine different regression relationships were obtained by considering Models 1–3 below using the OLS, WLS-Sample Size, and WLS-Robust regression schemes.

$$\begin{aligned}
\text{Model 1:}\quad & \text{WTP} = \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy} \\
\text{Model 2:}\quad & \text{WTP} = \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy} \times \text{income} \\
\text{Model 3:}\quad & \text{WTP} = \alpha + \beta \times \text{income} + \gamma \times \text{non-US dummy} \\
& \times \text{income} + \delta_1 \times \text{func. form dummy} \\
& + \delta_2 \times \text{airport access dummy} \\
& + \delta_3 \times 1980s\ \text{dummy} + \delta_4 \times \text{1990s dummy} \\
& + \delta_5 \times \text{2000s dummy}
\end{aligned}$$

Graphical representations of the nine models are provided in Fig. 10, where separate US and non-US regressions are superimposed on the meta-analysis data set. All nine regression results predict a higher WTP for noise abatement with respect to income for non-US cities. Note that whereas the regressions are linear with income for Models 1 and 2, in Model 3 the predicted WTP estimates are represented as scatter plots for US and non-US cities. This is because the inclusion of additional dummy variables in Model 3 introduces discontinuities in the WTP function; Fig. 10 captures only the projection of the high-dimensional relationship between WTP and other explanatory variables along the income dimension.

Using OLS regression, income is statistically significant at the 10% level for all three models, and at the 5% level for Models 1 and 2. The non-US dummy variable and the interaction term are also significant at the 5% level in Models 1 and 2, respectively. The significance of the regression variables in Models 1 and 2 supports the hypothesis that WTP for noise abatement is related to average personal income, and that this relationship differs between US and non-US airport regions. In Model 3, the R^2 and adjusted R^2 values improve when more control variables are added. Performing F-tests between Models 1 and 3, and Models 2 and 3 give $F(5, 55)=2.28$ ($p=0.06$) and $F(5, 55)=2.13$ ($p=0.08$), respectively. This indicates that at the 10% level, Model 3 may be a better fit for the data than the simpler models.

Although OLS regression is the simplest to implement and maximizes R^2 and adjusted R^2, it may not be the best model for the data set. Fig. 11 shows box plots of the 63 WTP observations in the meta-analysis, as well as the predicted WTP computed using the nine regression results. In both the US and non-US groups, the three OLS models consistently overestimate WTP due to the presence of high-WTP outliers. In this respect, WLS regression may be advantageous if the weighting scheme decreases model susceptibility to outlying observations.

For the WLS-Sample Size regressions, Model 1 contains the most significant variables, with income at the 10% level and the non-US dummy variable at the 1% level. Although Model 2 only reveals the interaction term to be significant at the 5% level, it has

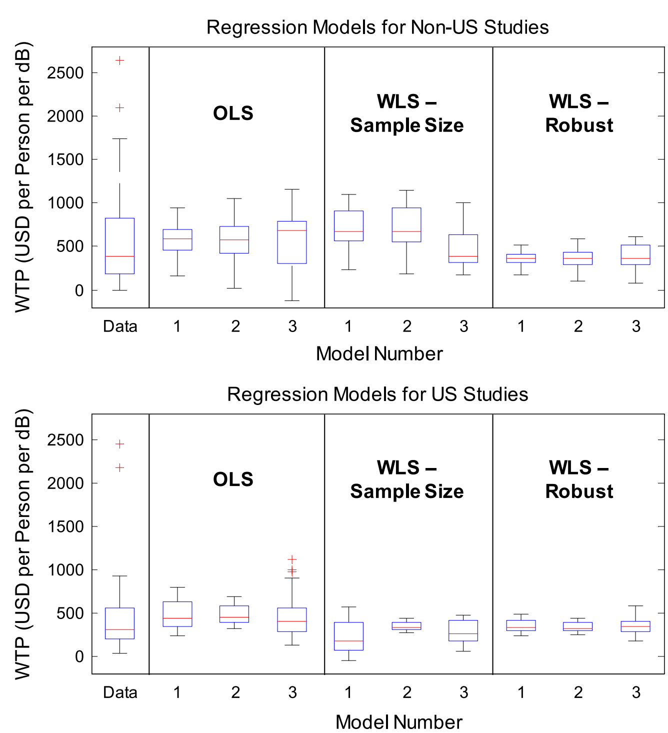

Fig. 11. Comparison of WTP estimates predicted using different regression models and regression schemes.

the smallest standard error on the income coefficient, and the lowest MSE (these trends are true across all three regression schemes). As for Model 3, there is no sufficient evidence to conclude that it better fits the data than Models 1 or 2, as *F*-tests give $F(5, 52)=1.91$ ($p=0.11$) between Models 1 and 3, and $F(5, 52)=0.67$ ($p=0.65$) between Models 2 and 3. However, there are several indications that using WLS-Sample Size regression may not be suitable for this meta-analysis. For example, primary study sample size is not known for all 63 studies, and in the 60 studies for which it was available, the sample size spans a large range between 20 and 66,000. Furthermore, Fig. 11 suggests that the WLS-Sample Size regression scheme does not necessarily reduce discrepancies in the predicted WTP over the OLS models.

In the case of the WLS-Robust regressions, income is significant at the 10% level for both Models 1 and 2, and the interaction term is also significant at the 10% level for Model 2. Because the robust bisquare estimator follows the bulk of the data, it has the smallest standard errors associated with its regression variables and low sensitivity to outliers. This trend is confirmed in Fig. 11 by the similarity between the median observed WTP and the median estimated WTP values, as well as by the narrow interquartile range associated with the three WLS-Robust regression models. Finally, *F*-tests between Models 1 and 3, and Models 2 and 3 give $F(5, 55)=1.07$ ($p=0.38$) and $F(5, 55)=0.99$ ($p=0.43$), respectively, which indicate that Model 3 does not better explain the meta-analysis observations than the more parsimonious Models 1 and 2.

Appendix C. Airports and sources of income data

See Table C1.

Table C1
Airports and sources of income data.

Airport	City	Country	Data resolution	Income data source
ALG	Algiers	Algeria	Country	*Populstat*[a]
EVN	Yerevan	Armenia	Country	National Statistical Service of the Republic of Armenia
ADL	Adelaide	Australia	City	Australian Bureau of Statistics
BNE	Brisbane			
CBR	Canberra			
CNS	Cairns			
MEL	Melbourne			
PER	Perth			
SYD	Sydney			
VIE	Vienna	Austria	City	Statistics Austria
BAH[b]	Bahrain	Bahrain	Country (estimated)	
BRU	Brussels	Belgium	Region	Statistics Belgium
YUL	Montreal	Canada	City	Statistics Canada
YVR	Vancouver			
YWG	Winnipeg			
YYC	Calgary			
YYZ	Toronto			
CAN[b]	Guangzhou	China	Country (estimated)	
CPH	Copenhagen	Denmark	City	Statistics Denmark
OUL	Oulu	Finland	City	Statistics Finland
CDG	Paris	France	City	National Institute of Statistics and Economic Studies (INSEE), Local Statistics
LYS	Lyon			
MRS	Marseille			
ORY	Paris			
TLS	Toulouse			
CGN	Cologne	Germany	County	Statistisches Bundesamt Deutschland
DUS	Dusseldorf			
FRA	Frankfurt			
HAM	Hamburg			
MUC	Munich			
ATH[b]	Athens	Greece	Country (estimated)	
SYZ	Shiraz	Iran	Country	*Central Bank of the Islamic Republic of Iran*
THR	Tehran			
TLV	Tel Aviv	Israel	Country	Israel Central Bureau of Statistics
BGY	Milan	Italy	Region	Italian National Institute of Statistics (Istat)
BLQ	Bologna			
FCO	Rome			
LIN	Milan			
MXP	Milan			
MBJ[b]	Montego Bay	Jamaica	Country (estimated)	
CTS	Sapporo	Japan	City	Ministry of Internal Affairs and Communications, Statistics Bureau, Consumer Statistics Division
FUK	Fukuoka			
HND	Tokyo			
ITM	Osaka			
KIX	Osaka			
NGO	Nagoya			
NRT	Tokyo			
ALA	Almaty	Kazakhstan	Country	Agency of the Republic of Kazakhstan on Statistics
KWI[b]	Kuwait	Kuwait	Country (estimated)	

Table C1 (*continued*)

Airport	City	Country	Data resolution	Income data source
GDL	Guadalajara	Mexico	Country	*International Labor Organization*
MEX	Mexico City			
MID	Merida			
TIJ	Tijuana			
AMS	Amsterdam	Netherlands	City[c]	Statistics Netherlands
BGO	Bergen	Norway	City	Statistics Norway
ISB	Islamabad	Pakistan	Country	Government of Pakistan, Statistics Division
KHI	Karachi			
LHE	Lahore			
MNL	Manila	Philippines	Country	National Statistics Office, Republic of the Philippines
LIS	Lisbon	Portugal	Country	*Institut de la Statistique Québec*
DOH	Doha	Qatar	Country	Qatar Statistics Authority
IKT	Irkutsk	Russia	Country	Federal State Statistics Office of Russia
LED	St. Petersburg			
OVB	Novosibirsk			
SVO	Moscow			
VKO	Moscow			
JED	Jeddah	Saudi Arabia	Country	*Japan International Cooperation Agency Planning and Evaluation Department* [d]
RUH	Riyadh			
SIN	Singapore	Singapore	City-state	Statistics Singapore
CPT	Cape Town	South Africa	Province	Statistics South Africa
JNB	Johannesburg			
BCN	Barcelona	Spain	Region	National Statistics Institute of Spain
MAD	Madrid			
PMI	Palma Mallorca			
AGH	Ängelholm/ Helsingborg	Sweden	City	Statistics Sweden
ARN	Stockholm			
GVA	Geneva	Switzerland	Region	Federal Statistical Office of Switzerland
ZRH	Zurich			
KHH	Kaohsiung	Taiwan	Country	National Statistics Republic of China (Taiwan)
TSA	Taipei	Taiwan	Country	
BKK	Bangkok	Thailand	Country	Thailand National Statistical Office
IST[b]	Istanbul	Turkey	Country (estimated)	
LGW	London	United Kingdom	City	Office for National Statistics
LHR	London			
MAN	Manchester			
TAS[b]	Algiers	Uzbekistan	Country (estimated)	

Italicized entries represent data sources that are not official national statistical agencies.

[a] Income was provided as a range between 1600 and 2020 USD (unknown date); the midrange value was used. Source: Lahmeyer (2004).

[b] Income was estimated for the airport region based on 2005 GNI per capita, PPP method (World Bank, 2010).

[c] Average personal income was only available at the country level, whereas disposable income was available at both the country-level and the city-level. The country-level average personal income was used, and adjusted to the city-level by the ratio of the city-level and country-level disposable income.

[d] Source: Japan International Cooperation Agency, Planning and Evaluation Department (2003).

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