Development of an Income-Based Hedonic Monetization Model for the Assessment of Aviation-Related Noise Impacts

by

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Abstract

Aviation is an industry that has seen tremendous growth in the last several decades. With demand for aviation projected to rise at an annual rate of 5% over the next 20 to 25 years, it is important to consider technological, operational, and policy changes that can help accommodate the forecasted growth while minimizing detrimental effects to the environment, which include aircraft noise, air quality degradation, and climate change. This thesis presents a new method to quantify the monetary impacts of aviation-related noise, which are of particular interest to policymakers and other aviation stakeholders for the evaluation of policy options and tradeoffs.

Previous studies on the monetization of aviation noise impacts typically used the hedonic pricing method to estimate noise-induced property value depreciation. However, this approach requires detailed data on local real estate markets, which are not readily available at a fine resolution for many airports regions around the world. The new monetization model developed in this thesis is based on city-level personal income, which is often more widely available than real estate data. At the core of the approach is a meta-analysis of 60 hedonic pricing noise studies from North America, Europe, and Australia, which was used to derive a general relationship between average personal income and the Willingness to Pay (WTP) for noise abatement by means of a multivariate regression analysis. Several explanatory variables were introduced, and a backward selection procedure was used so that the final regression contained only parameters that have a significant effect on WTP. The resulting model expressed WTP for noise abatement as a function of the city-level average personal income and an interaction term, which is the product of the income and a dummy variable for non-US airports. Applying the new model to income data, noise contours, and population data for 178 airports worldwide, the global capitalized monetary impacts of commercial aviation noise in 2005 were estimated to be $25.0 billion, with a standard deviation of $2.2 billion. Comparison with previous results yielded a difference of less than 17%, demonstrating convergent validity of the new model.

Uncertainty assessment of the income-based model was conducted in order to understand the sources of uncertainty and how they may limit the model's functionality and applicability. Monte Carlo Simulations were used to explicitly quantify the propagation of uncertainties. Local, global, and distributional sensitivity analyses were also performed to investigate how each model input contributes to output variability, and to prioritize the inputs on which future research should be directed. The results suggested that further research should be conducted to expand the meta-analysis data set, with a particular emphasis on low-income nations where few noise studies currently exist. A more comprehensive meta-analysis data set would elucidate the relationship between income and WTP for noise abatement, thereby reduce epistemic uncertainty and broaden model applicability.

Thesis Supervisor: Ian A. Waitz
Title: Department Head and Jerome C. Hunsaker Professor of Aeronautics and Astronautics

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List of Acronyms

AAS	Average Adjusted main-effect Sensitivity index
adjS	Adjusted main-effect Sensitivity index
AEDT	Aviation Environmental Design Tool
AEE	Office of Environment and Energy (part of the Federal Aviation Administration)
APMT	Aviation environmental Portfolio Management Tool
BEA	Bureau of Economic Analysis
BNL	Background Noise Level
CAEP	Committee on Aviation Environmental Protection (part of the International Civil Aviation Organization)
CFR	Code of Federal Regulations
CPI	Consumer Price Index
CRF	Capital Recovery Factor
CU	Contour Uncertainty
CV	Contingent Valuation
dB	Decibel
dBA	A-weighted Decibel
ΔdB	Noise level above the background
DENL	Day-Evening-Night average sound Level
DNL	Day-Night average sound Level
DSA	Distributional Sensitivity Analysis
EDS	Environmental Design Space
EEA	European Environmental Agency
EKC	Environmental Kuznets Curve
EPA	Environmental Protection Agency
EPNL	Effective Perceived Noise Level
FAA	Federal Aviation Administration
FESG	Forecast and Economic Sub-Group
GDP	Gross Domestic Product
GNI	Gross National Income

GRUMP	Gridded Rural-Urban Mapping Project
GSA	Global Sensitivity Analysis
%HA	Percent of people Highly Annoyed by aircraft noise
HP	Hedonic Pricing
ICAO	International Civil Aviation Organization
INM	Integrated Noise Model
L_{eq}	Equivalent Noise Level
L_{max}	Maximum Sound Exposure Level
LSA	Local Sensitivity Analysis
MAGENTA	Model for Assessing Global Exposure to the Noise of Transport Aircraft
MCS	Monte Carlo Simulation
MSA	Metropolitan Statistical Area
MSI	Main-effect Sensitivity Index
NASA	National Aeronautics and Space Administration
NDI	Noise Depreciation Index
NPV	Net Present Value
OLS	Ordinary Least-Squares
PARTNER	Partnership for AiR Transport Noise and Emissions Reduction
PPP	Purchasing Power Parity
RP	Revealed Preference
SD	Standard Deviation
SEL	Sound Exposure Level
SP	Stated Preference
SPL	Sound Pressure Level
TSI	Total-effect Sensitivity Index
USD	United States Dollar
UTM	Universal Transverse Mercator
WLS	Weighted Least-Squares
WTA	Willingness to Accept
WTP	Willingness to Pay

1 Introduction

The advent of human flight over 100 years ago was one of the most defining scientific achievements of the modern age. Aviation is an industry that has vitalized national economies, enabled the mobility of millions of people, and helped to establish a global society that is unprecedented in its interconnectivity. The growth of aviation over the last several decades has been unmatched by any other major form of transportation, and is expected to continue at a rate of about 5% per year for the next 20 to 25 years [Society of British Aerospace Companies, Metz et al. (2007)]. However, with this progress comes a price, as the environmental impacts of aviation have become increasingly important in the last 50 years. A 2000 survey by the United States General Accounting Office revealed that 72% of delayed work and 25% of cancelations in US airport expansion projects have been due to environmental issues [GAO (2000)].

Environmental concerns associated with aviation include aircraft noise, air quality degradation, water pollution, and climate change. Of these issues, aircraft noise is the one with the most immediate and perceivable community impact, and was thus the first to be regulated when negative public reactions surged in the 1960's due to the proliferation of commercial jet aircraft. In 1969, the United States Federal Aviation Administration (FAA) adopted Part 36 of Title 14 of the Code of Federal Regulations (CFR), which set forth noise certification standards for commercial aircraft [FAA (2004b)]. In 1971, the International Civil Aviation Organization (ICAO) published Annex 16: Environmental Protection, Volume I: International Noise Standards, which has subsequently been updated for newer aircraft technologies [ICAO (2005)]. In 1979, the US Congress enacted the Aviation Safety and Noise Abatement Act, which led to the establishment of 14 CFR Part 150 and guidelines for compatible land use surrounding airport regions [FAA (2004a)]. Similar aviation noise directives have also been enacted in other parts of the world, for example in the European Union [European Parliament (2002)], Australia [Commonwealth of Australia Law (2010)], and Japan [Ministry of the Environment (2000)].

As a result of legislations and technological improvements, significant progress has been made to mitigate aviation-related noise over the last few decades. In the US, the number of people impacted by aircraft noise has dramatically decreased over the past 35 years, despite a six-fold increase in mobility during that period [Waitz et al. (2004)]. However, the aviation noise problem is far from eradicated. Worldwide, there are still more than 14 million people exposed to at least 55 dB of commercial aviation noise, incurring an equivalent of $1.1 billion per year in housing value depreciation, and an additional $800 million per year in rental value loss [Kish (2008)]. About 42% of those monetary noise impacts are in the US. A survey of the 50 busiest airports in the US revealed that noise is the most serious environmental issue in aviation [GAO (2000)]. Similarly in Europe, noise is also cited as the dominant concern, comprising a large share of the total monetary environmental impacts [Schipper (2004)]. Given that long-term growth in aviation is anticipated despite the recent global economic downturn, it is expected that environmental issues will continue to increase in prominence and urgency [FAA (2009b)]. Therefore, when assessing the potential of future technological, operational, or policy options, it is crucial to consider these matters so as to make decisions that are both economically feasible and environmentally responsible. Balancing competing environmental and economic interests presents a challenge for policymakers, aircraft designers, aircraft manufacturers, and other aviation stakeholders. Adding to the complexity is that there exist numerous interdependencies among aircraft noise emissions, air quality, and climate impacts, such that any mitigation efforts must consider the full spectrum of environmental implications and tradeoffs. It is a difficult problem influenced by politics, budget constraints, and uncertainties in forecasting future events.

1.1 Project Scope

In order to address some of various environmental challenges facing the future of aviation, the FAA, along with the National Aeronautics and Space Administration (NASA) and Transport Canada, established the Partnership for AiR Transportation Noise and Emissions Reduction (PARTNER), a Center of Excellence and academic research consortium. It comprises of nine universities and approximately 50 advisory board members from industry, academia, and government working together to address the myriad environmental challenges of aviation, which affect aircraft design, performance, emissions, efficiency, operations, economics, and alternative fuels [PARTNER (2010)]. The work of this thesis falls within the scope of PARTNER Project 3: Valuation and Trade-offs of Policy Options.

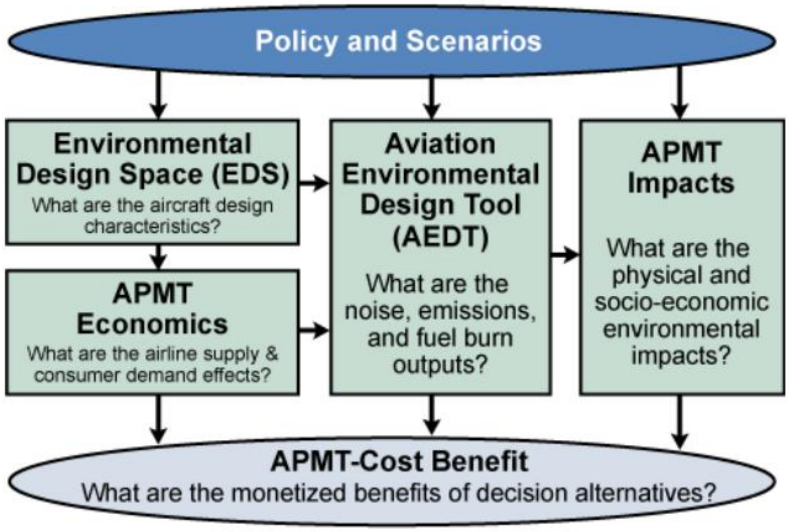


Figure 1: Aviation Environmental Tools Suite [PARTNER (2010)]

Project 3, under the auspices of the FAA's Office of Environment and Energy (AEE), has as its goal to contribute to the development of a comprehensive set of tools, known as the Aviation Environmental Tools Suite (Figure 1), and to more thoroughly assess the environmental impacts of aviation activity. The inputs to the tools suite are aviation policies or scenarios of interest, which may pertain to regulations (e.g. noise and emissions stringencies, changes to aircraft operations and procedures), finances (e.g. fees or taxes), or anticipated technological improvements. These inputs are processed through several modules to produce a cost-benefit analysis that explicitly details the monetized benefits of the policy with respect to a well-defined baseline [Waitz et al. (2006)].

The modules within the tools suite framework include the Environmental Design Space (EDS), the Aviation Environmental Design Tool (AEDT), and the Aviation environmental Portfolio Management Tool (APMT). An in-depth discussion of each of these modules may be found in Mahashabde (2009). The EDS estimates the source noise, emissions, performance, and vehicle cost characteristics associated with particular aircraft and engine designs, or with proposed technologies. The AEDT receives aircraft design characteristics from EDS and computes the corresponding noise and emissions footprints. Within the realm of APMT, there are the Economics and Impacts modules. The APMT-Economics module receives information regarding vehicle cost and performance from EDS, and models the air transportation supply and demand responses necessary to meet future demands for aviation.

The APMT-Impacts module aims to provide policymakers and stakeholders with the capability to evaluate the physical and socio-economic impacts of environmental policy alternatives, which are presented as public and private mitigation costs and public environmental benefits [Waitz et al. (2006)]. It consists of three areas of focus: climate impacts, air quality impacts, and noise impacts (Table 1). The APMT-Impacts Climate Module estimates the globally-averaged impact of aircraft emissions on surface temperature and the monetary value of the resulting effects on health, well-being, and ecology. The Air Quality Module estimates incidences of mortality and morbidity from primary and secondary particulate matter, as well as their associated monetary value. More details regarding the development and application of the Climate and Air Quality Modules may be found in [Brunelle-Yeung (2009), Fan (2010), Mahashabde (2009), and Marais et al. (2008)].

Table 1: Overview of environmental impacts modeled in APMT

Impact Type	Effects Modeled	Primary Metrics	
		Physical	Monetary
Climate	• CO_2 • Non-CO_2: NO_x-O_3, cirrus, sulfates, soot, H_2O, contrails, NO_x-CH_4, NO_x-O_3 long	• Globally-averaged surface temperature change	• Annual impacts • Net present value
Air Quality	• Primary particulate matter (PM) • Secondary PM by NO_x and SO_x	• Incidences of mortality and morbidity	• Annual impacts • Net present value
Noise	• Property value depreciation (owner-occupied and rental properties)	• Population exposed to noise • Noise exposure area	• Capitalized impacts • Annual impacts • Net present value

The work of this thesis focuses on the development of a new noise monetization model for use in the APMT-Impacts Noise Module. The motivation behind the project is to create a model that has fewer data limitations than the previous approach employed by Kish (2008), and is more widely applicable for estimating global noise impacts. The main deliverable is a fully-functioning model within the larger Aviation Environmental Tools Suite that may be used to estimate the physical and monetary noise impacts associated with aviation environmental policies. The overarching goal of the model is to support cost-benefit analyses that may help inform policy assessment and decision-making.

1.2 Thesis Organization

This thesis is composed of eight chapters. The structure and content of the remaining chapters are briefly described below.

Chapter 2 provides an overview of aviation noise impacts, including how they are measured and methods used for their assessment. It also presents previous work pertaining to the APMT-Impacts Noise Module, and the motivation for the current thesis.

Chapter 3 introduces the connection between the current project and the field of environmental economics, and presents a literature review of various valuation methods used for environmental goods, with a particular focus on aviation noise. It also discusses the role of meta-analysis in environmental economics, as well as how benefit transfer may be employed to apply the findings from one study to estimate impacts in other locales.

Chapter 4 presents a detailed discussion of the development process for the new income-based hedonic noise monetization model to be integrated into the APMT-Impacts Noise Module. It describes the adapted meta-analysis of existing aircraft noise studies, the data search to supplement primary study findings, statistical methods used for multivariate regression, and finally, the derivation of a relationship between income and Willingness to Pay for noise abatement, which can be used for global benefit transfer of monetary aviation noise impacts.

Chapter 5 details how the income-based hedonic noise monetization model can be applied for environmental policy analysis. It describes the various inputs of the model and their associated assumptions, as well as how they fit together in the algorithm to produce the desired outputs. Chapter 5 also introduces the *lens* concept for selecting a particular combination of model parameters to assess proposed policy measures. This chapter concludes with a discussion of some of the key limitations of the model and their implications for model applicability and validity.

Chapter 6 describes the uncertainty assessment of the income-based hedonic noise monetization model. Some key steps include classification of uncertainty sources, quantification of uncertainty propagation using Monte Carlo Simulation, and conducting local, global, and distributional sensitivity analyses to characterize the contribution of each model input to output variability.

Chapter 7 describes the use of the new income-based hedonic noise monetization model to solve a sample problem on global aviation noise impacts. The results of this exercise are compared to previous findings from the APMT-Impacts Noise Module, hence providing a benchmark measure of model validity.

Chapter 8 summarizes the findings and conclusions of this thesis and highlights areas of the project that may benefit from additional research.

1.3 Thesis Contributions

The objectives of this thesis center on the development of a new noise monetization model for integration into the APMT-Impacts Module, and the Aviation Environmental Tools Suite as a whole. Some key contributions include:

1. Conducted a comprehensive meta-analysis of hedonic pricing studies for aviation-related noise to understand trends in the literature which may enable benefit transfer of aircraft noise impacts on an international scale.

2. Developed a globally-applicable regression model relating the Willingness to Pay for aviation noise abatement to city-level income.

3. Applied the new model to analyze policy measures relevant to environmental issues in aviation.

4. Performed an uncertainty assessment of the model to understand limitations in functionality and identify sources of uncertainty which may be reduced through further research.

2 Background and Motivation

This chapter provides the motivation for the thesis by presenting an overview of the issues relevant to the assessment of aviation-related noise impacts and describing some previous work on the subject. First, a brief summary is provided of several measures commonly used to quantify aircraft noise. Section 2.2 outlines some of the known effects of aviation-related noise and describes methods for their evaluation. Specifically, the estimation of the monetary impacts of noise through hedonic pricing with real estate values is addressed, for which further elaboration will be provided in Chapter 3. The last two sections of this chapter discuss the use of the hedonic pricing method in the previous work in the APMT-Impacts Noise Module and identify the limitations of the approach, which segues into a statement of the need to develop a new method to monetize aviation-related noise impacts.

2.1 Noise Metrics

Before delving into a discussion about noise impacts, it is first necessary to introduce the nomenclature of the field – namely, some metrics that are used to quantify sound, and more specifically, noise from aircraft. The measures described below are by no means a comprehensive list of relevant noise metrics, but are terms that will be used repeatedly in subsequent sections of this thesis.

The most basic measure of sound is the Sound Pressure Level (SPL), which is expressed as the logarithm of the ratio of a measured pressure to a reference pressure. The unit of SPL is the decibel (dB). One of the major challenges in applied acoustics is to relate physical measures of sound, such as dB, intensity, or frequency, with the subjective perception of sound by human listeners, which is often qualified by psychophysiological terms such as loudness or pitch [Kryter (1960)]. Furthermore, the source of the sound, as well as the duration, also affects how it is perceived. For example, aircraft noise is perceived to be more annoying to the surrounding community than road and rail traffic noise, even when the measured noise levels are equivalent [Miedema and Oudshoorn (2001)]. Explanations for this observation include acoustic factors, such as the presence of discrete tones in aircraft engine noise, as well as non-acoustic factors, such as the fear of an aircraft crashing [Fields (1992)].

Because of difficulties in selecting a single metric to convey the relationship between sound level and human response, many measures have been proposed to attempt to quantify aviation-related noise. They are typically sorted into two groups: those that describe noise from a single event, and those that refer to the time-averaged sound over multiple events. For single-event noise, a common metric to use is the Sound Exposure Level (SEL), which is the total energy produced from the noise event, expressed in dB. For describing the short-term effects of noise, such as sleep awakenings, a metric such as L_{max}, the maximum A-weighted[1] SEL of the event, may be appropriate. Another common metric is the Effective Perceived Noise Level (EPNL or EPNdB), which accounts for the duration of the sound and the presence of discrete tones, and is used by the FAA as the standard for aircraft noise certification under 14 CFR Part 36. For longer-term effects, such as annoyance or housing value depreciation, a time-averaged measure, such as the Equivalent Noise Level (L_{eq}), is more suitable. The L_{eq} corresponds to a particular time period, and represents the constant A-weighted noise level that carries the same amount of energy in that duration as the actual, time-varying sounds that occur in the time period. The most commonly chosen length of time is 24 hours, and the 24-hour A-weighted L_{eq}, with a 10 dB penalty applied for night time hours,[2] is known as the Day-Night average sound Level (DNL). In the US, the FAA has established DNL as the primary metric for measuring aircraft noise exposure and establishing regulations. For example, under 14 CFR Part 150, the FAA sets 65 dB DNL to be the threshold below which all forms of land use are deemed compatible. In Europe, the Day-Evening-Night average sound Level (DENL) is used instead; DENL is very similar to DNL, except that it also applies a 5 dB penalty to noise events during evening hours. Both DNL and DENL are expressed in dB.

2.2 Effects of Aviation-Related Noise

Noise emission from aviation is an example of an environmental externality, which is defined as "a by-product of consumption activities that adversely affects third parties not directly involved

[1] The A-weighted filter adjusts the dB level of noise according to the frequency-dependent response of the human hearing mechanism. For example, it discriminates against low-frequency (below 1 kHz) and very high-frequency (above 5 kHz) noises because the human ear is less sensitive to sounds at those frequencies. Many metrics used for quantifying aircraft noise employ the A-weighted filter on dB measurements; the weighted results have units of dBA. See Cunniff (1977) for more details about various weighting networks used in acoustics.

[2] In the formulation of DNL, nighttime hours are between 10:00pm and 7:00am. For DENL, evening hours are 7:00pm to 11:00pm, and nighttime hours are 11:00pm to 7:00am.

in the associated market transactions" [Nelson (2008)]. In this case, the third party in question is the people residing near airports, who experience the positive and negative effects of aviation in their daily lives. These effects may be broadly categorized as physical and monetary.

2.2.1 Physical Effects

The physical effects of aviation noise include annoyance, sleep disturbance, interference with school learning and work performance, and physical and mental health effects.

2.2.1.1 Annoyance

Annoyance is one of the readily apparent effects of aviation-related noise, and has been the focus of many research studies over the last several decades. It is the broad term given to the general adverse reaction of people to living in noisy environments, and may encompass effects such as speech interference, sleep disturbance, conflict with the desire for a tranquil environment, and the inability to use the telephone, radio or television satisfactorily [FICON (1992)]. A noise is said to be annoying if an individual or a group of individuals would actively try to reduce the noise, or avoid or leave the noisy area if possible [Molino (1979)]. Factors that influence an individual's annoyance may be acoustic (e.g. sound level, frequency, duration) or non-acoustic (e.g. physiological responses, adaptation and past experience, personality, fear of the noise source) [Molino (1979), Passchier-Vermeer and Passchier (2000)].

Noise level increase is closely related to annoyance and adverse reactions from the affected community (Table 2). Because of this, it is often desirable to estimate the number of people near an airport who may be highly annoyed by aircraft noise. While this number can be explicitly determined through community surveys, it is usually predicted by applying an exposure-response function to relate DNL and the percentage of the population highly annoyed. Many such relationships have been proposed for aviation as well as other transportation noise sources, for example: Schultz (1978), Fidell et al. (1991), FICON (1992), Miedema and Vos (1998), and Miedema and Oudshoorn (2001). A review of the literature on community annoyance due to aircraft noise may be found in Kish (2008) and Miller et al. (2008). Kish (2008) also summarizes the relationship between various exposure-response functions and the social survey annoyance data provided in Fidell and Silvati (2004) (Figure 2).

Table 2: Effects of noise on people (residential land uses only) [FICON (1992)]

Effects	Hearing Loss	Annoyance	Average Community Reaction	General Community Attitude Towards Area
DNL (dB)	**Qualitative Description**	**% of Population Highly Annoyed**		
75 and above	May begin to occur	37%	Very severe	Noise is likely to be the most important of all adverse aspects of the community environment
70	Will not likely	22%	Severe	Noise is one of the most important adverse aspects of the community environment
65	Will not occur	12%	Significant	Noise is one of the important adverse aspects of the community environment
60	Will not occur	7%	Moderate to Slight	Noise may be considered an adverse aspects of the community environment
55 and below	Will not occur	3%	Moderate to Slight	Noise considered no more important than various other environmental factors

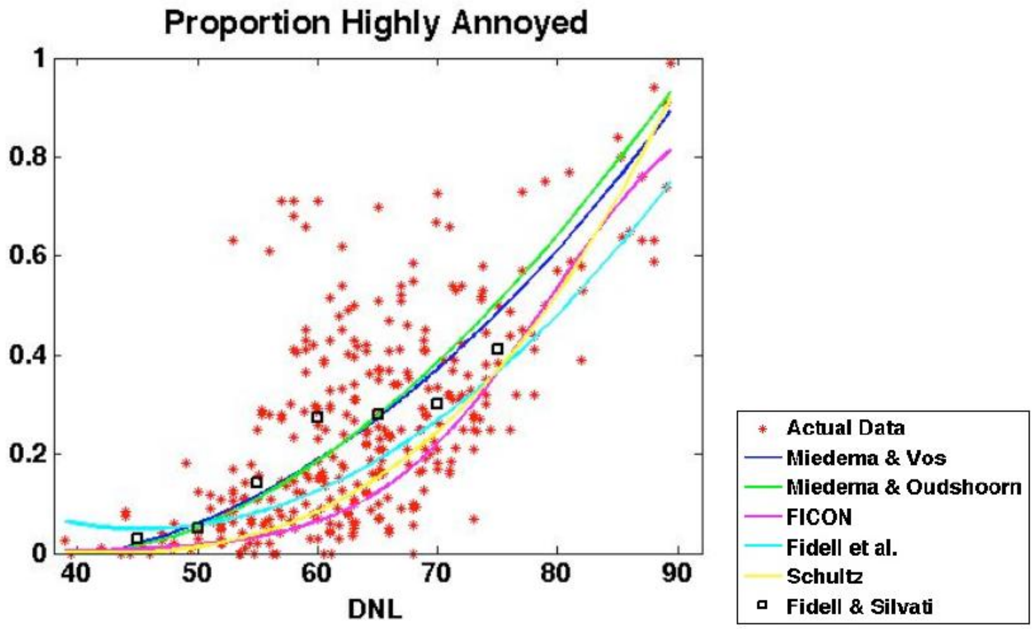


Figure 2: Exposure-response functions for annoyance [Kish (2008)]

Prior to this thesis project, the APMT-Impacts Noise Module calculated the percentage of people highly annoyed (%HA) as one of the physical impacts of aviation-related noise. It employed the annoyance exposure-response function proposed by Miedema and Oudshoorn (2001), which estimated %HA as a function of DNL:

$$\%\mathrm{HA} = -1.395 \times 10^{-4}(\mathrm{DNL} - 42)^3 + 4.081 \times 10^{-2}(\mathrm{DNL} - 42)^2 + 0.342(\mathrm{DNL} - 42) \quad (1)$$

2.2.1.2 Sleep Disturbance and Health Effects

Sleep disturbance and health effects are other examples of physical impacts related to aviation noise. Extensive literature reviews on these subjects may be found in McGuire (2009) and Swift (2009), respectively. Some of the key issues identified in the two reports are paraphrased below.

Nighttime noise from aviation is connected with a number of physiological responses, including a higher number of awakenings, changes in the sleep structure, increased heart rate and blood pressure, and other potential short-term and long-term health effects. Griefahn et al. (2008) summarized the ways in which nighttime noise can alter sleep patterns, citing increased time to fall asleep, prolonged time to reach deeper stages of sleep, less time spent in these deeper stages, and a larger number of awakenings lasting longer than three minutes, which constitute conscious awakenings. Potential short-term effects associated with sleep disturbance include next-day sleepiness, tiredness, increased annoyance, and poor work performance. There are also several pathways by which aviation noise may lead to long-term health effects; these are mostly cardiovascular and metabolic in nature, and include elevation of heart rate and blood pressure, changes in hormone regulation that can lead to obesity, and potentially higher chances of developing ischemic heart disease and Type 2 diabetes.

A challenge with using sleep disturbance and health effects to quantify aviation noise impacts is that they are difficult to measure in a consistent manner. In order to characterize nighttime awakenings, for example, several types of experiments may be used. Social surveys can be administered to individuals to elicit subjective evaluations of sleep quality. Motility measurements may be made by asking subjects wear accelerometer devices or by placing force sensors under bed posts, but their accuracy is debatable. Polysomnography is another option, which involves using several instruments to simultaneously measure electrical activity in the brain and heart, as well as eye and muscle movements. This approach provides the most detailed information about an individual's sleep patterns, but is highly intrusive and expensive to implement. Sleep awakenings can also be measured by asking subjects to press a button when they are awakened at night. While this method is less intrusive than polysomnography, it is also less sensitive, and prone to individuals' habituation over the length of the study. In addition to myriad options in experimental design, there is also evidence to suggest that sleep disturbance measurements can differ significantly depending on whether the study was conducted in the laboratory or in the field [Pearsons et al. (1995)]. Other confounding factors include the noise metric chosen, the source and duration of the noise, the presence of sound insulation materials, the time of night, and the sleep stage of the individual exposed to the noise. Despite these difficulties, however, researchers have nevertheless created models to quantify noise-induced sleep disturbance; for example, similar to annoyance, several exposure-response relationships have been developed to estimate the percent of people awakened by noise as a function of the indoor SEL [FICON (1992), FICAN (1997), Passchier-Vermeer (2003)].

To date, the APMT-Impacts Noise Module has not modeled sleep disturbance or health effects associated with aviation-related noise. From August 2009 to March 2010, the FAA held a series three workshops entitled Aircraft Noise Impacts Research Roadmap, which drew the participation of expert noise researchers from around the world. The objectives of the workshops were to better understand the key questions regarding the impact of aircraft noise on sleep and annoyance, and to prioritize research efforts for the future. As the findings from these workshops are released and the recommended research efforts come to fruition, it would be desirable to broaden the scope of the APMT-Impacts Noise Module to account for annoyance, sleep disturbance, and health effects due to aviation-related noise.

2.2.2 Monetary Effects

While the physical effects of aviation noise are important, policymakers and other aviation stakeholders are also interested in understanding the monetary impacts of noise in order to assess the inflicted damage and evaluate the benefits and tradeoffs of various policy options [Schipper et al. (1998)].

The monetary effects of aviation noise include housing value depreciation, rental loss, and the monetary value of lost work or school performance. Many studies that investigate the monetary impacts of aviation noise quantify housing value depreciation and rental loss through the hedonic pricing method,[3] which uses observed differences in housing markets between noisy and quiet areas to determine the implicit value of quietness (or conversely, the cost of noise) [Wadud (2009)]. These hedonic pricing studies usually focus on deriving a Noise Depreciation Index (NDI) for one airport, which represents the percentage decrease in property value corresponding to one decibel increase in the noise level in the region. Typical NDI values for aviation noise found in the literature range from 0% to 2.3% per dB for owner-occupied properties [Wadud (2009)], and tend to be similar across countries and stable over time [Nelson and Palmquist (2008)]. There is limited literature on the NDI for rental properties; seven studies summarized by Nelson and Palmquist (2008) reported estimates between 0.21% and 0.90% per dB, with a mean of 0.64% per dB. The NDI derived from a hedonic pricing study in one area can also be applied to property value and noise exposure data from other airport regions to estimate the monetary impacts in various locations.[4]

While the monetary effects of noise are usually communicated independently of the physical impacts, the two categories are not necessarily separate – that is, monetary effects may serve as a surrogate for the aggregate environmental impacts of aviation noise. To illustrate this concept, consider the explanation put forth by Kish (2008):

> *[The] monetary value of noise is not a separate effect that occurs in addition to the physical impacts. Instead, it is a different way to account for them. Existing residents who experience a drop in their house price due to an increase in the noise level experience the effect of lost wealth, but the total value of the effects of the noise is not the lost housing value plus the value of the annoyance and health effects. It is only the lost housing value… because with that money the person can move to an equivalent house in a quieter area and return to his or her original level of well-being.*

[3] See Chapter 3 for a more in-depth discussion of hedonic pricing as it relates to valuation methods used for environmental goods.
[4] This approach is known as benefit transfer, and is described in detail in Section 3.3.

While generally agreeing with Kish (2008)'s statement, Nelson and Palmquist (2008) also point out that the monetary value of noise does not necessarily encompass the cost of potential long-term health effects, though additional research is needed to conclusively link such effects to aircraft noise.

Furthermore, the assessment of monetary impacts through hedonic pricing is a way to quantify individuals' defensive behaviors in response to a perceived risk. In order for this method to capture the full effects of an environmental change, therefore, it is required that the affected individual is able to recognize the differences in property value, health, quality of life, etc. associated with the change [EPA (2000)]. Specifically for aircraft noise, though the noise itself may be readily perceived, it is uncertain that all the potential detrimental effects of noise are fully comprehended by the impacted individuals.[5] If the physical effects of aviation noise are not perceived by the population examined in a hedonic pricing study, then the measured monetary impacts cannot be used as a surrogate for the physical effects.

Unfortunately, few studies exist that explicitly address the issue of interactions between the physical and monetary impacts of aviation noise. An example is a study conducted by Jacobs Consultancy (2008) in the vicinity of Bob Hope Airport in Burbank, CA, which found that the equivalent NDI computed from survey data on annoyance is similar to the NDI estimates from previous hedonic pricing models.[6] Interpreting the results of that study, Nelson and Palmquist (2008) concluded that housing value depreciation around the airport is reflective of the annoyance costs of aircraft noise, and because of this, and advised against assessing physical and monetary impacts separately and then adding them together to represent cumulative impacts, as that may lead to an overstatement of the total cost.

[5] Section 3.1.2 provides a further discussion on the assumptions used in hedonic pricing studies. In particular, the notion of asymmetric information is addressed, which refers to individual differences in the perception and understanding of the detrimental effects of aviation noise.

[6] The Jacobs Consultancy (2008) study first used a contingent valuation survey (see Section 3.1.1) to collect information on the number of people highly annoyed by aircraft noise. Various exposure-response functions for annoyance were used [Finegold et al. (1994), Miedema and Oudshoorn (2001), and Fidell and Silvati (2004)] to express noise level as a function of the empirical %HA results, which were then used in a traditional hedonic pricing regression analysis to estimate an equivalent NDI.

2.3 Previous Work

Hedonic pricing studies for aviation noise typically assess the localized impacts around one airport or a few airports; to date, there has been only one study which estimates the worldwide economic impacts of aviation-related noise [Kish (2008)], which was conducted using the APMT-Impacts Noise Module. Previously, the Noise Module employed an NDI of 0.67%, which is the weighted-effect size of 33 NDI estimates computed in a meta-analysis of aviation noise studies [Nelson (2004)]. Kish (2008) used the Nelson (2004) NDI to estimate the monetary impacts of noise around 181 airports, and found that at 2005 levels, commercial aviation noise resulted in a total of $21 billion in capitalized housing value depreciation in year 2006 US Dollars (USD), and an additional $800 million per year in lost rent.[7] In terms of physical impacts, Kish (2008) estimated that there were over 14 million people exposed to at least 55 dB DNL of commercial aviation noise; of that group, 2.3 million were highly annoyed.

2.3.1 Data Availability

In order to achieve the Kish (2008) results, comprehensive data on population, housing value, and rent prices were required for each of the 181 airports. While population data were available globally (see Section 4.2), detailed housing value data were available only for the United States and the United Kingdom, and detailed rent price data were even more scarce. For the US, the aggregate value of owner-occupied properties and the aggregate rent paid for renter-occupied dwellings were obtained from the 2000 Census on the census block group-level.[8] In order to adjust the property values to year 2006 USD (see Section 4.3), the distribution of housing price growth rates from the Office of Federal Housing Enterprise Oversight was used; it was assumed that both housing and rental prices increased at the same annual rate. For the UK, the housing price data were obtained for postcode sectors in 2001 from the UK Land Registry, and adjusted to year 2006 prices using the appropriate house price indices.

[7] An NDI of 0.67% was used to estimate both housing value depreciation and rental loss, since the existing literature suggests that NDI values for owner-occupied properties and rental properties are similar.

[8] The US Census Bureau defines a census block group (BG) as “a cluster of census blocks having the same first digit of their four-digit identifying numbers within a census tract… BGs generally contain between 600 and 3,000 people, with an optimum size of 1,500 people” [US Census Bureau (2005)].

2.3.2 House Price Model

Outside of the US and the UK, Kish (2008) used a model developed by ICF International to estimate housing and rental values around each airport. The model estimates the house price as a function of several variables, including distance away from an airport, and subsequently approximates the rent price at a given distance based on the house price at that location [ICF International (2008)]. The ICF International model was developed based on census block group-level housing value data for 227 US airports that had commercial operations in 2000; the geographical extent of the data was a 25-mile radius around each airport. The resulting model estimates the house price, P, based on a regression equation of the form:

$$\begin{aligned}\ln(P) = \text{Intercept} + c_1 \times \text{Distance} + c_2 \times \text{Distance}^2 + c_3 \times \text{Pop density} + c_4 \times \\ \text{GDP per cap} + c_5 \times \text{Enplaned pax} + c_6 \times \text{Dummy}_1 + \cdots + c_{n+5} \times \text{Dummy}_n\end{aligned} \quad (2)$$

where: P = Estimated house price in USD

Intercept = Regression intercept

Distance = Distance between the house location and the airport in miles

Pop density = County-level population density per square mile of land area

GDP per cap = State-level GDP per capita in thousands of USD

Enplaned pax = Number of enplaned passengers in 2000 in thousands

Dummy_j = Dummy variable for airport j

c_i = Regression coefficient

In addition to distance away from the airport, Equation 2 above also controls for several other explanatory variables, such as the population density of the region, the Gross Domestic Product (GDP) per capita, the number of enplaned passengers, a regression intercept, and a dummy variable for each airport.

Table 3: Regression results of ICF International house price model [ICF International (2008)]

Variable	Coefficient	t-statistic	95% Confidence Interval
Intercept	11.4817000	791.56	[11.45327, 11.51013]
Distance	0.0265700	28.73	[0.02476, 0.02839]
Distance^2	-0.0006708	-19.88	[-0.00073691, -0.00060466]
Pop density	0.0000037	22.53	[0.00000338, 0.00000403]
GDP per cap	0.0005854	2.26	[0.00007877, 0.00109]
Enplaned pax	0.0000101	27.65	[0.00000938, 0.00001082]
No. of observations	170,020		
R^2	0.4177		
Adjusted R^2	0.4169		

Table 3 shows the coefficients of the regression model derived from 170,020 observations in the US. All non-dummy regression variables, with the exception of GDP per capita, were statistically significant at the 1% level. The coefficient of the distance variable was positive, suggesting that the presence of an airport nearby has a detrimental effect on property value. The distance squared variable was introduced to address the hypothesis that the unfavorable consequences of airports on house prices will likely taper off after a certain distance. That a negative and statistically significant coefficient was observed for this variable lends credence to the hypothesis. The population density variable was introduced to attempt to capture the local real estate situation; for example, one might expect that, all else being equal, a high population density would exert upward pressure on housing values, making for a positive coefficient [ICF International (2008)]. The GDP per capita was included as a proxy for the standard of living in the airport region; therefore, a positive coefficient was reasonable for this variable. The enplaned passengers variable was expected to capture any positive (e.g. employment opportunities) or negative effects (road congestion, aircraft noise) due to the size of the airport. The value of the regression intercept depends on the average house price in the airport region. For US airports, this value is 11.48, as derived from the regression; for foreign airports, the intercept must be computed by solving Equation 2 with *P* set to the city-level average house price and distance set to 20.3 miles, which is the average distance for which the average house price was obtained with the regression equation for several US cities. Finally, a dummy variable was included for each of the airports in the regression analysis to address any local eccentricities not accounted for by the other variables.

Similar to the house price model, ICF International also developed a model to estimate rent prices as a function of distance away from an airport, which requires housing values computed from the house price model as one of the inputs. As it bears many similarities to the house price model, the details of the rent price model will not be discussed in this thesis; the interested reader is referred to ICF International (2008) and Kish (2008).

2.3.3 Limitations

While the ICF International house price model facilitated the APMT-Impacts Noise Module to perform global estimates of aviation noise impacts, and was indispensable to the Kish (2008) analysis, it nevertheless has several limitations that must be noted. Primary among the concerns is that the model was derived solely from US data but applied worldwide, and therefore assumes that the property value – airport distance relationship observed in the US real estate market is transferable to foreign markets. Whether this use of benefit transfer (see Section 3.3) is valid is difficult to judge due to the challenges in obtaining property value data for locations outside of the US and the UK. Kish (2008) tested the results of the house price model with real estate data within 25 miles of UK's Heathrow, Gatwick, and Manchester airports (Figure 3). The ICF International model predicted house prices to within 47% of the actual 0.5 mile or 0.75 mile band-averaged prices around Heathrow and Gatwick; for Manchester, the discrepancy was up to 70% [Kish (2008)]. While these errors are not unreasonable given the underlying variability of the data, they do raise doubts about the validity of the model for airports in foreign nations, especially those with economic situations very dissimilar to the US.

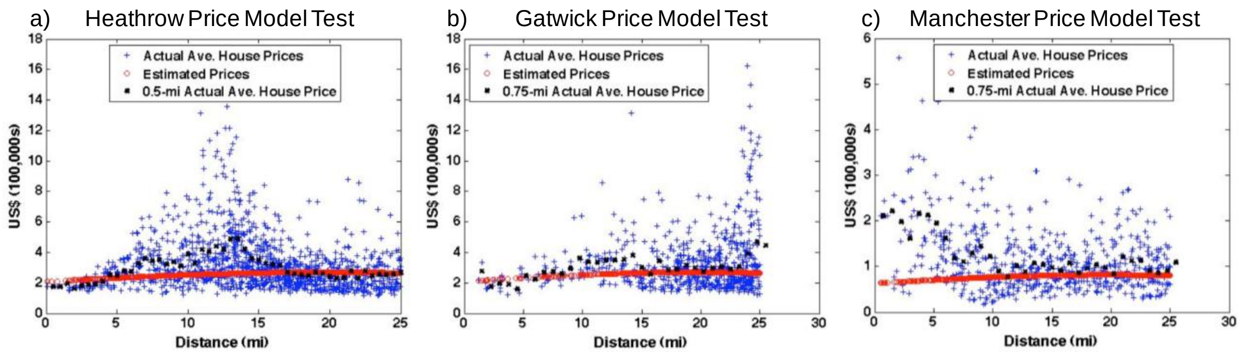


Figure 3: Comparison of the ICF International house price model and actual house prices around a) London-Heathrow Airport b) London-Gatwick Airport and c) Manchester Airport [Kish (2008)]

Another limitation of the ICF International model is that one must first adjust the intercept term for each foreign airport based on prior knowledge about the average house price in the region. For many parts of the world, however, even the city-level average house price is not readily available. To overcome this problem, Kish (2008) developed a model to first estimate the average rent price in each city based on the GDP per capita, average income, and lodging per diem provided by the US Department of State to civilian employees traveling abroad. Next, another model was used to approximate the average house price based on the previously estimated average rent price. While the scarcity of foreign property value data necessitates the use of such models in order to apply the ICF International house price and rent price models, these additional tiers of estimation further complicate and obscure the data collection procedure. In terms of the APMT-Impacts Noise Module as whole, the numerous assumptions and uncertainties present in the inputs will propagate downstream, contribute to output variability, and potentially detract from the validity of the module results.

2.4 Motivation

The use of a hedonic pricing method to monetize aviation noise impact requires detailed property value data for each airport region in a policy analysis. While this approach may be suitable for US-based analyses, where such data are available from the decennial census, for global calculations the search for foreign property value data is extraordinarily difficult and must be supplemented with price estimation models. The ICF International model discussed in the previous section is very useful in filling in data gaps, but introduces numerous assumptions and uncertainties and requires time and effort to apply for all foreign airports of interest.

This thesis was mainly motivated by the limitations of the previous APMT-Impacts Noise Module. The objective was to update the module with a new noise monetization model that circumvents some of the previous data constraints, and has greater accuracy and robustness for global applications.

3 Literature Review

A key starting point for this thesis was an expert review of the APMT-Impacts Noise Module by Nelson and Palmquist (2008), which proposed several suggestions to modify and improve the methodology used for noise impacts valuation. Some recommendations from this report were a more thorough look into different valuation techniques and accounting for potential variations in the perception of noise due to income disparities between locations.

In order to explore these ideas, it is first necessary to establish the context of the project. This chapter examines the problem in the framework of environmental economics, and presents a literature review of several topics relevant to the Nelson and Palmquist (2008) review, as well as to the goals of the APMT-Impacts module as a whole. Section 3.1 identifies some commonly-used methods for the valuation of environmental goods, with an emphasis on pointing out the strengths and weaknesses of each approach. Also presented in this section is a review of the literature examining the effect of income on individuals' valuation of environmental amenities. Section 3.2 discusses the concept of meta-analysis, a technique for synthesizing large amounts of data in order to derive new information. Finally, Section 3.3 provides a literature review of benefit transfer, a valuable method in environmental policy assessment which makes possible the estimation of global impacts using limited data. The advantages and deficiencies of the procedure are also addressed – a discussion that sets a cautious tone for the subsequent chapters of this thesis that describe model development, applicability, limitations, and uncertainties.

3.1 Valuation of Environmental Goods

The monetization of aviation-related noise impacts falls within the field of environmental economics, which is a branch of economics that views the natural environment as an asset with an associated economic value [Tietenberg (2003)]. Central to this subject is the idea that environmental goods, like water quality, clean air, and forestation, are public goods that are available to everyone without restriction, such that the consumption of the good by one individual does not reduce it for another, and the improvement of the good as a whole benefits each member of the society [Samuelson (1955)]. Because public goods lack transaction costs, it is necessary to employ non-market valuation methods in order to measure the economic value of an environmental amenity [Hanley et al. (1997)]. These methods are sorted into two general categories: stated preference and revealed preference. A comprehensive reference on guidelines for practicing various economic analysis methods is provided by the US Environmental Protection Agency (EPA) [EPA (2000)]; some of the key ideas will be discussed in the following sections.

3.1.1 Stated Preference

Stated preference (SP) methods directly measure people's response to changes in a particular good. The two main examples are choice experiments and contingent valuation (CV) surveys; of the two, the latter is much more widely-used for the valuation of environmental qualities [Boxall et al. (1996)]. In CV, respondents are asked to state their Willingness to Pay (WTP) for an environmental improvement, or alternatively, their Willingness to Accept (WTA) compensation for an environmental degradation. Willingness to Pay is more commonly used in environmental economics than WTA because surveyed households tend to have greater familiarity with purchasing decisions, and would therefore provide more valid answers to WTP questions [Feitelson et al. (1996)].[9] Though the format of CV surveys may differ greatly depending on the research questions posed, there are seven key commonalities present in most CV studies, which are described in Carson et al. (2001).

Contingent valuation surveys have been used to assess the value of a variety of environmental goods: for example, the natural resource damages due the Exxon Valdez oil spill in Alaska [Carson et al. (2003)], the public's WTP for clean water in the US [Carson and Mitchell (1993)], the economic value of urban wooded recreation areas in Finland [Tyrväinen and Väänänen (1995)], and tourists' WTP for wildlife viewing and conservation in Namibia [Barnes et al. (1997)]. Despite their broad applicability, however, there is much controversy surrounding the use of CV in environmental economics. First, stated preference measures such as CV capture intended behavior, not actual behavior [Huang et al. (1997)]. Therefore, they will be inaccurate if the risks perceived by the affected population do not match actual risks associated with the environmental detriment [EPA (2000)]. For example, Neill et al. (1994) found that WTP values stated in a hypothetical survey are consistently and significantly higher than revealed WTP values that reflect real economic commitments. Another major criticism is that the findings of

[9] Carson et al. (2001) provides a more in-depth discussion on why WTP and WTA estimates are consistently and substantially different.

CV studies are highly dependent on the credibility, reliability, and precision of the survey responses [Diamond and Hausman (1994)]. Credibility refers to whether the respondents are answering the exact question that the interviewer intended to ask, reliability refers to the size and direction of any biases that may be present in the responses, and precision refers to the variability in the answers. Another cause for concern is the presence of embedding effects, which describes the phenomenon that WTP estimates can differ significantly depending on whether the environmental good is evaluated on its own or "embedded" as part of a more inclusive package [Kahneman and Knetsch (1992)]. For example, Tolley et al. (1983) found that the WTP to prevent visibility decline at the Grand Canyon was five times greater when measured independently than when listed third in a sequence of choices. Furthermore, issues in survey design and administration may also influence validity; these include the scope of the study, the sample size, the survey method, and sequence and context effects [Carson et al. (2001)].

In light of these concerns, some critics have panned CV as a "deeply flawed methodology" that "[does] not have much information to contribute to informed policy-making" [Diamond and Hausman (1994)]. On the other hand, a panel convened by the National Oceanic and Atmospheric Administration to review the use of CV in environmental economics, chaired by Nobel laureates Kenneth Arrow and Robert Solow, concluded that when used properly, "CV studies can produce estimates reliable enough to be the starting point of a judicial process of damage assessment," and provided guidelines for conducting rigorous and meaningful CV surveys [Arrow et al. (1993)].

In the context of aviation-related noise, the environmental quality of interest is quietness. Therefore, the two possible types of CV measures are WTP for noise abatement and WTA for increased noise exposure. While about a dozen CV studies have been conducted to estimate the WTP for road noise reduction (summarized in Navrud (2002), Table 1), there have been only a handful of CV studies conducted specifically for aircraft noise (summarized in Navrud (2002), Table 2). In the latter case, the WTP estimates vary greatly (between €8 per dB per household per year to almost €1,000), and Navrud (2002) concluded that more CV studies on this topic are required before a consistent range of WTP values can be established.

For the valuation of aviation-related noise, CV methods are used far less often than hedonic pricing methods [Schipper (2004)]. A potential explanation for this trend is the concern over credibility, as it can be very difficult to elicit individuals' opinions regarding noise. For example, two types of questions that may be asked in a CV survey are: "How much would you be willing to pay in higher apartment rents (or higher taxes) if a noise mitigation program could reduce your noise exposure by 50%?" [Pommerehne (1988), Soguel (1996)], and "How much would you be willing to pay for daytime noise to be reduced from workday levels to that of a Sunday morning?" [Barreiro et al. (2000)]. While the second question may elicit more consistent interpretations than the first, both are problematic for survey purposes [Miller et al. (2008)]. In the second question, "Sunday morning" noise level will have a different meaning for each individual, whereas in the first, it is not clear whether "reduce your noise exposure by 50%" refers to a sound that is half as loud (a 10 dB reduction in SPL), or to half as many noise events, or to half as much total sound energy (50% drop in SEL). Therefore, in order to adopt CV as the method for valuating aviation-related noise impacts, care must be taken to ensure that the survey is constructed for consistent interpretation, and avoids the common pitfalls that may detract from its validity.

3.1.2 Revealed Preference

The second category of valuation methods used for environmental goods is revealed preference (RP), which measures the implicit value of an attribute. A commonly-used approach in this category is hedonic pricing (HP), which is "a technique that derives value for non-market goods such as environmental quality based on the value of market goods, such as residential property" [Schipper et al. (1998)]. For aviation noise, the idea is that the market for residential housing is complementary to that for noise avoidance; therefore, the variation in property values with noise level naturally sorts buyers and sellers according to their Willingness to Pay for quietness [Nelson (2008)].

The basic concept of HP is that, everything else being the same, a property in a noisier area will fetch a lower selling price than one in a quieter area. The disparity in the price can be tied to the difference in the noise level at the two properties, allowing for the calculation of an NDI, which represents the percentage decrease in monetary value per dB increase in noise. In order to draw valid conclusions from an HP study, however, the "everything else being the same" clause must be respected – that is, the study must account for all other factors that may influence property value, such that the only remaining explanatory variable is the level of noise exposure. These potential explanatory factors can be classified into several groups: structural, accessibility, neighborhood, and environmental [Bateman et al. (2001)]. Structural variables include property type, year of construction, floor area, the number and size of rooms, the number of bathrooms, presence of a garage, etc. Accessibility variables include the distance to downtown, shopping centers, public parks, or transportation infrastructure, such as highways and airports. Neighborhood variables define the quality of a property's surroundings; some examples include the crime rate, quality of schools, and age distribution. In addition to noise level, other potential environmental variables include air pollution level and quality of the views from the property. A complete hedonic pricing study must control for all relevant explanatory variables to ensure that any observed trends between property value and noise level may indeed be attributable to aircraft noise.

The theoretical foundations of hedonic pricing were laid by Lancaster (1966) and Rosen (1974), and the use of HP to assess the economic impacts of aviation noise is well-established. In the US, the first applications of HP for this purpose were in 1970's, with examinations into property values in the vicinity of airports in Minneapolis [Emerson (1972)], Dallas, Los Angeles, New York City [Paik (1972)], San Francisco, St. Louis, Cleveland, New Orleans, San Diego, and Buffalo [Nelson (1979)]. Since then, the HP method has been used to estimate the noise impacts around numerous airports in the US, Canada, Europe, and Australia; many of these studies are summarized in Nelson (1980), Schipper et al. (1998), Nelson (2004), and Wadud (2009). The NDI estimates derived from these studies are typically positive, indicating that aviation noise is viewed as a detrimental environmental externality. Wadud (2009) found that raw NDI estimates range between 0% and 2.3% per dB, whereas Nelson (2004) used a variety of meta-analytical techniques to narrow that range to between 0.50% and 0.70% per dB, with a weighted-effect size of 0.67% per dB. Other HP studies have found, however, that the advantages of close proximity to an airport outweigh the negative effects associated with higher noise levels [Tomkins et al. (1998), Lipscomb (2003)]. One hypothesis for explaining this observation is that the presence of the airport increases the ease of travel and the number of employment opportunities in the region.

While most HP studies focus on single-family detached homes, there have also been efforts to examine the impact of aviation noise on rental properties. Seven studies of aircraft noise-induced rental loss reported NDI values ranging from 0.21% to 0.90% per dB, with an average of

0.64% per dB [Nelson and Palmquist (2008)].[10] The similarity of owner-occupied and rental property NDI estimates was the basis for the selection of one common NDI value to estimate both housing value depreciation and rental loss in the Kish (2008) analysis. Some studies have also investigated the impact of aviation noise on multi-unit residential condominiums and vacant land; Uyeno et al. (1993) found that the NDI for multi-unit condominiums around Vancouver International Airport was higher than that for detached homes (0.90% per dB versus 0.65% per dB), and that the NDI for vacant land was much higher than those of the two other property types.

Despite the extensive use of HP in valuating aviation noise impacts, the approach is not without weaknesses. The drawbacks of HP mainly revolve around the assumptions that must be made in order to use the method. Chief among those assumptions is that the housing market under consideration is in perfect equilibrium, such that individuals are perfectly sorted in their residences according to their personal appraisal of quietness. In reality, this is likely not the case, as there may be external constraints on the housing market (e.g. price caps, scarcity of housing), and nonzero transaction costs associated with selling one property and purchasing another.[11] Adding to the complexity is that there may be inherent differences in housing markets between various airports, or even within the same city, such that despite best efforts to account for discrepancies using regression variables, some variations remain unexplained. These effects are not always well-understood, and Nelson and Palmquist (2008) concluded that there is not sufficient evidence to suggest that housing market imperfections systematically bias HP results in one direction or another. Hedonic pricing also does not control for individual differences in the perception of and response to noise, nor does it consider the possibility that certain properties may have sound insulation, which would alter the residents' discernment of noise. Furthermore, it can be impeded by issues such as inadequate control of explanatory variables, regression misspecification, unrepresentative sample size, and limitations in the availability of real estate data.

[10] One of the seven studies, Feitelson et al. (1996), used CV instead of HP to estimate the NDI for rental properties around Dallas-Fort Worth airport.

[11] In HP, it is assumed that there are no transaction costs; that is, if a resident desired to sell a house in a noisy area and purchase one in a quiet area, he or she would be able to do so immediately and effortlessly.

Another major concern is that in order for HP results to be meaningful, the homeowners must have been aware of the presence of aviation noise, and have taken that factor into account when purchasing their property. Only in this case does the comparatively lower house price reveal the implicit cost of noise. This illustrates the concept of asymmetric information, which was shown by Pope (2007) to be a significant issue in HP. Pope (2007) examined 16,900 single-family housing transactions between 1992 and 2000 near Raleigh-Durham International Airport. During this period, the state of North Carolina passed a statute mandating the disclosure of aviation noise to potential homebuyers in impacted areas, which went into effect in 1996. Pope (2007) found that after the enactment of the disclosure, house prices decreased by as much as 2.9% in the noisiest regions, corresponding to a 37% increase in NDI. This suggests that prior to the disclosure, homebuyers may not have been fully informed of aviation noise, or else did not adequately consider it as a factor when purchasing their house. The Pope (2007) analysis demonstrates that the assumption of full information in HP studies is not always met, and therefore the reported monetary impact of aviation noise may not reflect the full environmental cost.

3.1.3 Comparing Stated Preference and Revealed Preference Methods

In theory, stated preference and revealed preference methods are two ways to account for the same environmental costs. Therefore, it has been a topic of interest to compare findings from the two types of studies to see whether they present the same information.[12] For example, Carson et al. (1996) analyzed 83 studies and made 616 comparisons of CV and revealed preference estimates for a variety of quasi-public goods (not limited to aviation noise), and found that CV results were generally smaller than RP results, but not grossly so. The ratio of CV/RP estimates had a mean of 0.89, with a 95% confidence interval of [0.81, 0.96]. Specifically for aircraft noise, Pommerehne (1988)'s study in Basel, Switzerland found that the mean WTP per dB of noise reduction per household per month derived using HP was 22 CHF (Swiss francs, where 1 euro = 1.47 CHF), whereas the equivalent value from CV was 32 CHF [Navrud (2002)]. Another way to compare the two methods is in terms of the equivalent NDI values. Feitelson et al. (1996) used CV telephone surveys to estimate the noise costs of airport expansion, finding

[12] This is the idea of testing for convergent validity. Convergent validity tests are useful when "two or more measurement techniques are potentially capable of measuring the desired quantity, but both do so with error" [Carson et al. (1996)].

equivalent NDI values between 2.4% and 4.1% per dB, which are significantly higher than typical NDI values reported by HP studies. Kish (2008) collected a series of 13 NDI and 15 WTP values from transportation noise studies in Europe and Japan. Using reasonable assumptions for discount rate, time span, and household size, Kish (2008) converted the NDI of 0.67% used in the APMT-Impacts Noise Module into an equivalent WTP. This test for convergent validity revealed that the 0.67% NDI falls well within the range of 13 international NDI values (mean = 0.59% per dB), and that the equivalent WTP of €76 per dB per household per year computed from this NDI was comparable to the 15 international WTP values (mean = €56 per dB per household per year) (Figure 4). These examples all seem to suggest that there is no consistent trend as to which of the HP or CV method estimates higher premiums for aircraft noise, a sentiment echoed by Nelson (2008) and Nelson and Palmquist (2008).

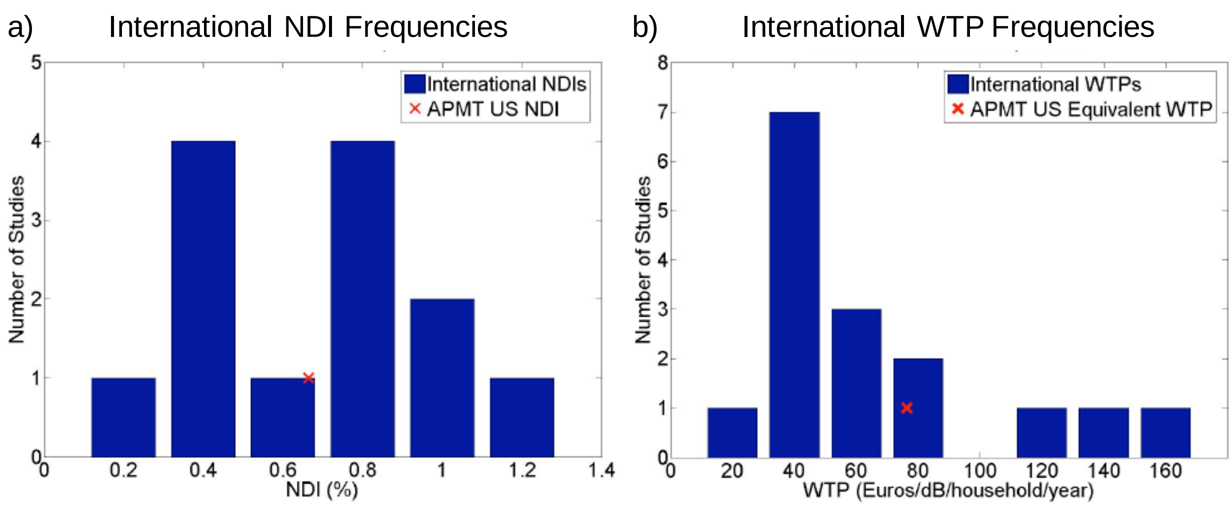


Figure 4: International and US equivalent values for a) NDI and b) WTP [Kish (2008)]

3.1.4 Variation with Income

Another topic of much discussion in environmental economics is the whether the public's valuation of environmental goods varies with income. Aside from a matter of academic interest, this issue also has important policy implications – for example, if distributional effects exist, environmental policies may be regressive and thus disproportionately favor wealthy individuals [Flores and Carson (1997)]. A term that is commonly used when describing this issue is *income elasticity*, which is a measure of the responsiveness of an economic quantity to changes in income. Contingent valuation studies often discuss the income elasticity of WTP, which is the ratio of the percent change in WTP for a particular good to the percent change in income. When that ratio is negative, the good being considered is inferior; when it is between zero and one, the good is considered necessary; when it is greater than one, the good is considered a luxury. Some economists have argued that environmental goods are luxuries, and that concern for these goods is a pursuit of the wealthy, which in poor families would be displaced by the basic needs for food and shelter [McFadden (1994)]. There is some empirical support for this claim: Borcherding and Deacon (1972) found that the income elasticity for the "parks-recreation" public good was greater than one for three of the four examined groups,[13] and Walters (1975) reported that the ratio of the average valuation of noise to permanent income is between 1.7 and 2.0. However, other economists assert that the evidence is weak [Carson et al. (2001)]; in fact, Kriström and Riera (1996) dismisses the suggestion that environmental improvements are luxury goods as economic "folklore."

Several studies have suggested that environmental goods are in fact necessary goods. A meta-analysis of CV studies for various environmental services in Sweden revealed that income has a positive and significant effect on WTP, but that the income elasticity of WTP was less than one [Hökby and Söderqvist (2001)]. These findings are consistent with the results reported by Kriström and Riera (1996) for CV studies in other parts of Europe. That the income elasticity for environmental goods is between zero and one means that as income rises, individuals' valuation of the environment increases at a decreasing rate. In the policy context, this implies that environmental improvements are more beneficial to low-income groups, and conversely, that environmental costs are also borne disproportionately by the poor.

The trend of diminishing returns with increasing income brings up another much-discussed topic in environmental economics – the Environmental Kuznets Curve. The Environmental Kuznets Curve (EKC) is an inverted-U-shaped curve that describes the relationship between income and environmental qualities (Figure 5). It conjectures that as the per capita income of a society increases, environmental deterioration rises, reaches a turning point, then decreases. The EKC is

[13] However, Borcherding and Deacon (1972) found income elasticities between 0.2 and 1.0 for many of the other public goods examined in the study, such as local education and hospitals.

adapted from Simon Kuznets' eponymous observation that the economic inequality in a country follows an inverted-U function with respect to income level [Kuznets (1955)].

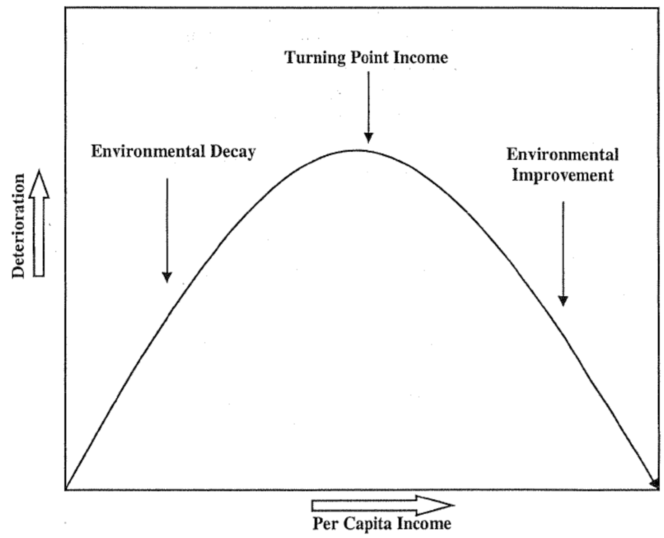


Figure 5: Environmental Kuznets Curve [Yandle et al. (2004)]

The intuition behind the shape of the EKC is thus [Arrow et al. (1995)]:

> *[People] in poor countries cannot afford to emphasize amenities over material well-being. Consequently, in the earlier stages of economic development, increased pollution is regarded as an acceptable side effect of economic growth. However, when a country has attained a sufficiently high standard of living, people give greater attention to environmental amenities. This leads to environmental legislation, new institutions for the protection of the environment, and so forth.*

Given this description, it is not difficult to see why the EKC is often closely tied to discussions about whether environmental goods are necessary or luxury goods. One of the first uses of the EKC was to address the environmental implications of a North American Free Trade Agreement (NAFTA), in particular with respect to air pollution [Grossman and Krueger (1992)]. That study concluded that the liberalization of world trade may promote both economic and environmental goals; the explanation adopted by the authors for the downward turn of the EKC is that as countries increase in wealth, they also tend to employ cleaner technologies in their industrial operations. Since the Grossman and Krueger (1992) report, over 100 studies have been published about the EKC; a detailed literature review and a survey of issues relating to the subject may be found in Yandle et al. (2004) and Dinda (2004), respectively.

The use of the EKC to describe the valuation of environmental goods is a contentious topic. First, the applicability of the EKC is very limited: only some air quality indicators, such as local pollutants, exhibit evidence of the EKC, and there is also no agreement in the literature about the income level of the turning point [Dinda (2004)]. Many critics also challenge the rigor and robustness of the econometrics used in the EKC literature. Stern (2004) calls the EKC a "stylized fact" which arose because of insufficient attention paid to diagnostic statistics. When the appropriate statistical tests are performed, Stern (2004) suggests that there is no evidence that an EKC exists; instead, the reduction of environmental impacts with higher income is due to time-related effects previously unaccounted for. Similarly, Deacon and Norman (2006) reports that an examination of air pollution data with robust empirical methods suggests that the correlation between income and pollution level does not agree with the EKC any more than what would be dictated by chance. Finally, Arrow et al. (1995) stresses that the EKC is but an empirical relationship, and criticizes those who use it to conclude that promoting a nation's economic growth will in turn induce environmental improvement. Instead, the downward turn in the EKC at high income levels is not a self-fulfilling prophecy, but rather the result of legislations and policies enacted for environmental protection. In light of the debate surrounding the issue, perhaps the only sure conclusion to be drawn is that the EKC underscores the importance of policies and technological improvements aimed at mitigating environmental degradation.

3.2 Meta-Analysis

One of the major difficulties with research in environmental economics is that large-scale CV and HP studies require the collection and synthesis of copious amounts of data, which can be prohibitively expensive and time-consuming. For this reason, *meta-studies* (which carry out *meta-analyses*) are often used to summarize and integrate the findings from individual primary studies in order to derive generalized relationships. The meta-analysis concept was first proposed by Glass (1976) for use in the field of education, which, like environmental economics, relies more heavily on applied research and outcome evaluation than on basic research and controlled experiments. Glass (1976) points out many advantages to performing meta-analysis, which include making sense of large amounts of information, decreasing the dependence on original data, deriving untapped knowledge from existing studies, and discerning overarching, systems-level trends. Meta-analysis has been used extensively in the medical sciences and psychology, and since the 1990's, in environmental economics as well [Schipper et al. (1998)]. In fact, many of the studies cited in this chapter are meta-studies rather than primary studies – for example, Hökby and Söderqvist (2001), Kriström and Riera (1996), and Carson et al. (1996). Meta-studies pertaining to the monetary impacts of aviation noise, and therefore of particular relevance for the current thesis project, include Nelson (1980), Schipper et al. (1998), Nelson (2004), and Wadud (2009).

The use of meta-analysis in environmental economics raises a new set of concerns. For example, Schipper et al. (1998) points out that economics is only a "quasi-experimental science," wherein study circumstances are difficult to control. The lack of a consistent set of controls among the primary studies subsequently leads to a lack of comparability in the meta-study, because individual results were obtained for local sets of conditions rather than with the intention of cross-study comparisons. Nelson and Kennedy (2009) examined 140 meta-analyses spanning 17 categories within environmental and natural resource economics and described some commonly-observed problems. These issues include sample heterogeneity, heteroscedasticity, correlation within or between primary studies, and publication bias. Sample heterogeneity refers to the aforementioned concern of Schipper et al. (1998), where differences in empirical results may be due to potential disparities in the scope, design, and methodology of the various studies. Heteroscedasticity is the notion that the primary study observations may have non-homogeneous variances, a problem with implications for data reliability and regression model specification (see Section 4.5.2). Correlation effects are important when meta-studies extract multiple estimates from the same primary study, or from a group of studies of similar design, which can lead to the non-independence of meta-analysis samples. Publication bias refers to a form of selection bias wherein primary studies with statistically weak, insignificant, unusual, or otherwise "undesirable" results are less likely to be submitted or selected for publication. Many of these problems may be avoided by using stringent selection criteria for primary study inclusion, employing various meta-regression techniques, and adopting the meta-analysis "best-practices" outlined in Nelson and Kennedy (2009). A high-quality meta-study must test and account for these issues before attempting to derive new information from the primary study data set.

3.3 Benefit Transfer

Closely tied to the meta-analysis technique is the idea of benefit transfer, which is the application of the findings from an empirical study in one location to estimate the effect in another location [Schipper et al. (1998)]. Benefit transfer is of critical importance to environmental policymaking: because of limited time and money to perform new valuation studies, it is often desirable and necessary to generalize the results from "study sites" to "policy sites" [Navrud (2004)]. Its use dates back to the US water resource development era of the 1960's: Krutilla and Fisher (1975) reports on the application of technique to estimate the lost recreational value resulting from the Hells Canyon hydroelectric project. Benefit transfer is sometimes also given the broader term of "value transfer" in order to reflect both the positive and negative connotations of measured quantities in environmental economics. The history, methods, and technical literature of benefit transfer are discussed in great detail in Navrud (2004) and Navrud and Ready (2007). The following paragraphs summarize some of the key points from those texts.

There are two main categories of benefit transfer, unit value transfer and function transfer. Within unit value transfer, there can be simple unit transfer, or unit transfer with income adjustments. Simple unit transfer is the most straightforward approach, involving the application of an estimate (e.g. WTP per household per year for some environmental attribute) derived from one site to another site. An example in the assessment of aviation noise impacts is the use of an NDI calculated from an HP study in one airport region to estimate the housing value depreciation around a different airport. This approach involves making the assumption that the residents of the two locations have the same implicit valuation of aircraft noise. When the regions have very different income levels and costs of living, however, simple unit transfers should not be used, and instead the parameter being transferred should be scaled by the ratio of the income levels as well as by the income elasticity of demand for the environmental good in question.

The second category of benefit transfer also contains two related approaches: benefit function transfer and meta-analysis. The first refers to the use of a benefit function derived from empirical results in one location to estimate the benefits at the policy site. For a CV study pertaining to the WTP for a particular environmental good, the function may have the following form [Navrud (2004)]:

$$\mathrm{WTP}_{ij} = b_0 + b_1 G_j + b_2 H_{ij} + e \tag{3}$$

where: WTP_{ij} = Willingness to pay of household *i* at site *j*

G_j = Set of characteristics associated with the environmental good at site *j*

H_{ij} = Set of characteristics associated with household *i* at site *j*

b_0, b_1, b_2 = Regression coefficients

e = Random error

The valuation of environmental goods is typically a complex function of many variables, including site characteristics, individual preferences, and income levels [Loomis (1992)]. As such, benefit function transfers are generally more reliable than unit value transfer because they allow for these explanatory variables to be taken into account [Kirchhoff et al. (1997)].

The final subcategory of benefit transfer is meta-analysis, discussed in the previous section, which differs from benefit function transfer in that instead of deriving the transfer function from one valuation study, multiple primary studies are used. One particularly relevant example of this approach is found in Kish (2008), which used the NDI derived from the Nelson (2004) meta-study of 0.67% per dB to estimate the total aviation noise impacts around 181 airport regions worldwide. The use of meta-analysis results to perform benefit transfer illustrates the hierarchical nature of research in environmental economics.

While benefit transfer offers an appealing alternative to conducting full-fledged environmental valuation studies, its accuracy has long been questioned. Like the other topics addressed in this chapter, the validity of benefit transfer applications is highly dependent on the quality and consistency of the available data, and the scope and design of the experiment. Several studies have examined this issue by testing for convergent validity of transfer estimates. Downing and Ozuna (1995) performed benefit function transfer using eight CV studies for recreational fishing along the Texas Gulf Coast over three distinct time periods, and concluded that the method tends to overestimate the value of the environmental good. Loomis (1992) took the same approach for recreational fishing sites in several US states, and concluded that such transfers are likely to be inaccurate (errors range from 5% to 40%). Similarly, Kirchhoff et al. (1997) found that 16 of 24 intrastate and interstate benefit transfers involving WTP for recreational activities had errors of less than 50%, although the largest reported error was in excess of 200%. The last two studies included many site-specific regression variables in the benefit function, including average income, population characteristics, and attributes of the environmental good. On the international scale, Ready et al. (2004) examined the benefit transfer of WTP for the avoidance of specific health impacts related to air and water quality in five European countries, finding that the average error of international unit value transfers was 38%. Perhaps more interestingly, however, Ready et al. (2004) found that the use of benefit function transfers in lieu of unit value transfers did not improve the result, which contrasts with the findings of Kirchhoff et al. (1997). Rozan (2004) conducted CV studies to measure the WTP for air quality in two cities, one in France and one in Germany, and compared the directly estimated benefits with the transferred benefits in each city. While the two chosen sites had the similar income levels and demographic distributions, the WTP for air quality differed significantly – 282 FF (French francs) in the French city versus 466 FF in the German city, leading the author to conclude that benefit transfer was not generally valid.

Despite these lackluster results, however, the authors of the above studies also concede that benefit transfer can be a useful tool for policymaking, and that its accuracy is open to interpretation. For example, while it may not be a suitable method for determining compensation schemes for individuals subject to environmental harms [Downing and Ozuna (1995)], benefit transfer may be appropriate for conducting cost-benefit analyses so that policymakers can use approximate values to make an acceptable decision [Rozan (2004)]. Furthermore, the reliability of the method may be improved through the meticulous accounting of potential explanatory variables. In attempting to make a benefit transfer between two locations, one must be aware that the approach may be limited by inherent differences between the sites, the environmental resources, the populations (e.g. income, demographics, nationality, customs), and the time periods [Rozan (2004), Downing and Ozuna (1995), Navurd (2004)]. Because of these spatial and temporal uncertainties, it is difficult to define a threshold of satisfactory validity for benefit transfer; Navrud (2004) concludes that for environmental policymaking, the level of acceptable accuracy is subjective and depends on the context of the proposed policy.

This thesis project touches on all of the topics discussed in this chapter. The model development process described in Chapter 4 addresses objectives 1 and 2 listed in Section 1.3, and involves extensive use of the concepts of HP, WTP, income elasticity, and meta-analysis. Once development was complete, Chapter 5 discusses how the model may be used to estimate the global physical and monetary impacts of aviation-related noise, thereby performing benefit transfer and fulfilling thesis objective 3. Chapter 6 describes the characterization of model uncertainties (thesis objective 4), and Chapter 7 presents a sample problem to demonstrate the convergent validity of using the new model to perform benefit transfer on an international scale.

4 Model Development

The core of the thesis project is the development of a new monetization model for use in the APMT-Impacts Noise Module. The approach was to start with a meta-analysis of existing HP noise studies, and based on the recommendations of Nelson and Palmquist (2008), derive a function for WTP for noise abatement with respect to income and other significant explanatory variables for use in global benefit transfer of monetized noise impacts.

4.1 Noise Meta-Study

The data set used to derive a relationship between income and WTP for noise abatement was based on a meta-study by Wadud (2009). The Wadud (2009) study expanded upon several previous meta-analyses [Walters (1975), Nelson (2004), Envalue (2007), Bateman et al. (2001)], and compiled the results of 65 hedonic pricing noise studies from various airports in seven countries: the United States, Canada, the United Kingdom, Australia, France, Switzerland, and the Netherlands. These studies were conducted between 1970 and 2008, and all had the goal of determining a NDI for a particular airport region. For each study, the author, year, airport name, location, and NDI result were listed. Where available, the sample size, property value in the airport region, and standard error associated with the derived NDI were also presented. The full list of noise studies is provided in Appendix A.

4.2 Data Search

In order to adapt the Wadud (2009) meta-study for the current work, a data search was first carried out to obtain a complete set of property value, household size, and income data for each of the 65 noise studies.

For 54 of the 65 studies, the average property value in the airport region during the year of the study was available; this value was presented in year 2000 USD. For each of the remaining 11 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.

The income indicator that was used was the average per capita personal income for each city derived from household surveys; alternatively, the city-level average household income was also acceptable, as dividing by the city-level household size resulted 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 studies, income data on the Metropolitan Statistical Area (MSA) level for each year dating back to 1969 were available from the US Bureau of Economic Analysis [US BEA]. For the other six countries, income data were obtained from national statistical agencies. In the few cases where city-level income data were not available, county-level or region-level income data were used.

At the completion of the search, five studies were excluded from further consideration due to the lack of available city-level property value or income data.[14] Therefore, 60 studies were used to derive a relationship between income and WTP for noise abatement.

4.3 Monetary Adjustments

In order to make comparable monetary values from different time periods and countries, it was necessary to establish a consistent method for making adjustments to income and property value data. The year 2000 was selected as the reference time point, and the US Dollar (USD) was selected as the reference currency. Foreign currencies were converted to USD through the Purchasing Power Parity (PPP). The PPP is the ratio of the cost of an identical basket of goods in two separate economies, and represents a way to compare the purchasing power of different currencies. It is more appropriate for use in the current work than the market exchange rate because it accounts for the relative cost of living in different countries, hence allowing for global

[14] This was the case for 4 of the 5 studies (Sydney 1971, Englewood 1972, Bodo 1984, and Basel 1988). The Toronto 1990 study was excluded because the negative NDI would have resulted in an implausible negative WTP.

comparisons without systematically understating the purchasing power of low-income nations [Schafer and Victor (2000)]. The PPP uses the US as a reference economy, and has the unit of International Dollar, where one International Dollar has the same purchasing power as one US Dollar in same time period. The year 2000 PPP values were obtained from the Organisation for Economic Co-operation and Development [OECD (2000)].

The income values associated with the 60 studies were adjusted to year 2000 USD using the procedure shown in Figure 6. First, the income in the year in which the study was conducted was obtained from the appropriate national statistical agency; this value was specified in the national currency associated with the airport region. If income data could not be obtained for the year of the study, then the income value for a nearby year was used, and adjusted to the year of the study by applying the nationwide growth rate in the per capita GNI (Step 1) [IMF]. The assumption in this step is that the income growth in the airport region during those years is consistent with the growth in the GNI per capita in the same period. It was important to determine the income in the year of the primary study so as to provide a common point of reference between the income and the noise study findings. In Step 2, the nationwide growth in the Consumer Price Index (CPI) between the year of the study and 2000 was applied to inflate or deflate the income value to the year 2000 level. Finally, the PPP in 2000 was applied to convert the foreign income value to USD (Step 3). For the US studies, the income adjustment process was much simpler. Historical income data from the BEA were adjusted to year 2000 USD using an inflation calculator from the US Bureau of Labor Statistics (Step 2) [BLS (2010)]; no PPP adjustment was necessary.

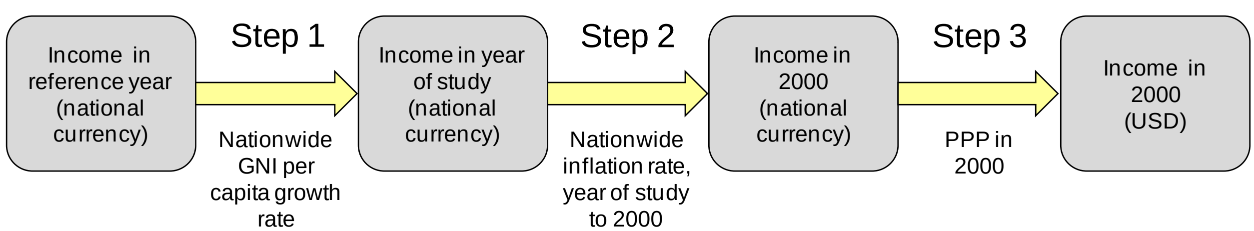


Figure 6: Procedure for adjusting foreign income

For the non-US studies where property values were provided in Wadud (2009), the conversion to year 2000 USD had been performed with the currency exchange rate in 2000 instead of the PPP. Therefore, for the sake of consistent comparison, it was necessary to readjust the property values for those studies by first reverting back to the foreign currency using the year 2000 market exchange rate, then converting to USD using the PPP. For the US studies, no further adjustments on property value were necessary.

For those studies where property value data were obtained from national statistical agencies, the monetary adjustment process was similar to that for income, and is shown in Figure 7. The key difference is that in Step 1, the nationwide housing price growth rate is used instead of the growth rate in the GNI per capita to adjust a monetary value to the year of the primary study.

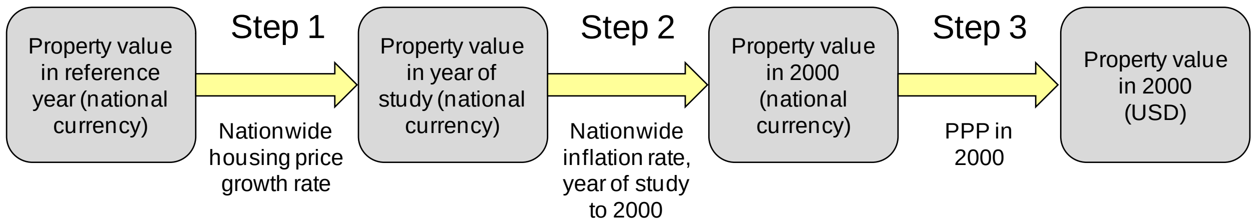


Figure 7: Procedure for adjusting foreign property value

4.4 Relating Willingness to Pay and Income

In the 60 hedonic pricing noise studies, the derived NDI ranged from 0% to 2.3% per dB and followed a scattered distribution, as shown in Figure 8a. The mean and median NDI were 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). The property values in year 2000 USD ranged from $64,422 (Atlanta 1985) to $502,775 (New York – John F. Kennedy 1994), with a mean of $154,950 and a median of $125,332 (Figure 8b).

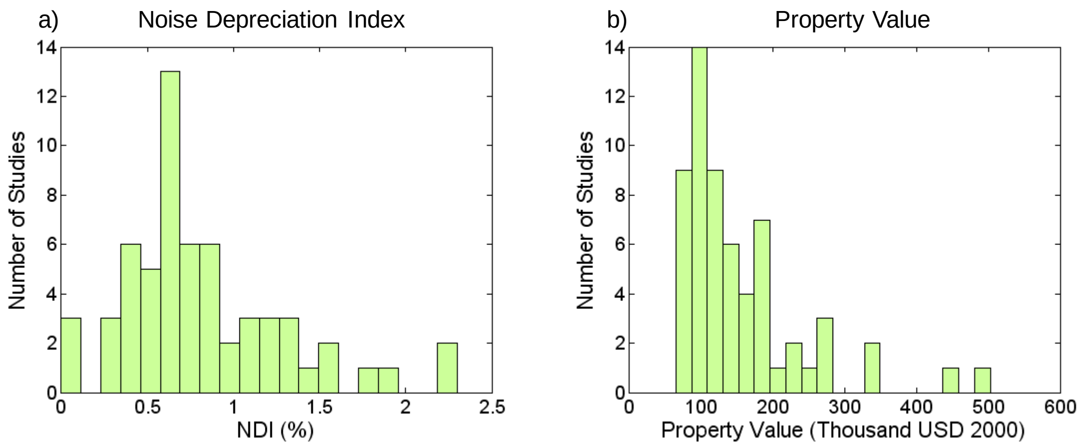


Figure 8: Distribution of a) NDI and b) property values in the meta-study

The WTP for noise abatement was derived using the NDI, property value, and household size corresponding to each study and its airport region. The steps for calculating WTP are described in Nelson and Palmquist (2008) and paraphrased below:

1. Adopt an average NDI for housing values, and assume that this value is stable over time and across developed countries.

2. Convert the NDI into a marginal WTP measure by using an average housing value. Multiplying the house value by the NDI produces a WTP value per dB per household.

3. Divide the WTP per dB per household value by the number of people per household or dwelling to yield a capitalized value per person per dB.

For each airport region, the WTP per person per dB of noise reduction is simply given by:

$$\text{WTP} = \frac{\text{NDI} \times \text{Property Value}}{\text{Household Size}} \tag{4}$$

Because WTP is calculated directly from the mean property value in each region, the resulting quantity represents the *capitalized* monetary value, which means that it embodies all future noise impacts. The procedure for transforming capitalized noise impacts into annual impacts will be discussed in Section 5.3.2.2.

It is also important to note that while Equation 4 relates the WTP as a function of the average house value in each airport region, the average rent price could also have been used. Nelson and

Palmquist (2008) states that in areas where both house price and rent data are available, such as the US, the conversion between the two data sets should be straightforward. Therefore, Equation 4 could have also used the average rental value in each airport region to estimate the WTP for noise abatement; in theory the two results should be interchangeable, assuming that the relationship between rent and house prices is known and stable. In this thesis, however, the approach of using rent prices will not be considered, due to the inconsistent availability of rental value data globally.

Figure 9 shows the resulting WTP for the 60 studies plotted versus the per capita income, separated by US and non-US studies. The US studies tend to be clustered in the bottom right corner, suggesting a lower WTP for noise abatement with respect to income around US airport regions.

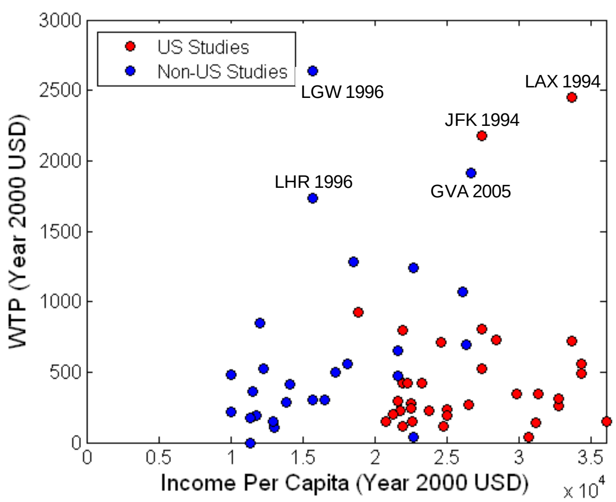


Figure 9: WTP versus income for meta-study data

4.5 Statistical Considerations

4.5.1 Outlier Identification

The observations in Figure 9 appear scattered, suggesting the presence of significant outliers. Using a Cook's Distance Test,[15] five outliers were identified in the 60-observation data set. These studies were: Los Angeles 1994, New York – John F. Kennedy 1994, London – Gatwick 1996, London – Heathrow 1996, and Geneva 2005. These studies correspond to the five points in Figure 9 with the highest WTP.

4.5.2 Heteroscedasticity

One problem that is often present in meta-studies is heteroscedasticity, which implies that the individual observations in the data set were drawn from distributions with disparate variances [Nelson and Kennedy (2009)]. If heteroscedasticity were observed, the assumption of homoscedasticity in ordinary least-squares (OLS) regression would be violated [Schipper et al. (1998)]. There are several ways to identify heteroscedasticity. First, one can visually inspect a plot of the residuals versus the predicted values: if such a plot "fans out," then heteroscedasticity may be present. Second, the Breusch-Pagan/Cook-Weisberg Test checks for heteroscedasticity by performing hypothesis testing with a χ^2 distribution, with the null hypothesis of equal variance on all observations in the data set [Breusch and Pagan (1979)]. Third, the White Test, which is a special case of the Breusch-Pagan/Cook-Weisberg Test, may be used in cases where heteroscedasticity takes on a non-linear form [Kennedy (2008)].

In this thesis, the first two methods were used to check for heteroscedasticity. A plot of the residuals on WTP versus the predicted values does appear to "fan out" to both sides of the dashed line representing zero residual, suggesting that heteroscedasticity may be present (Figure 10). Furthermore, the result of a Breusch-Pagan/Cook-Weisberg Test was $\chi^2(1) = 6.52$, with a p-value of 0.0107, which suggested that there is enough evidence to accept the alternative hypothesis of heteroscedasticity at $\alpha = 0.05$.

[15] A Cook's Distance Test measures the influence of a particular observation. It determines the effect on the residuals for all other observations in the data set when one observation is deleted. Observations with a larger Cook's Distance than the rest of the data are those which have unusually high influence and may be identified as outliers [Garson (2010)].

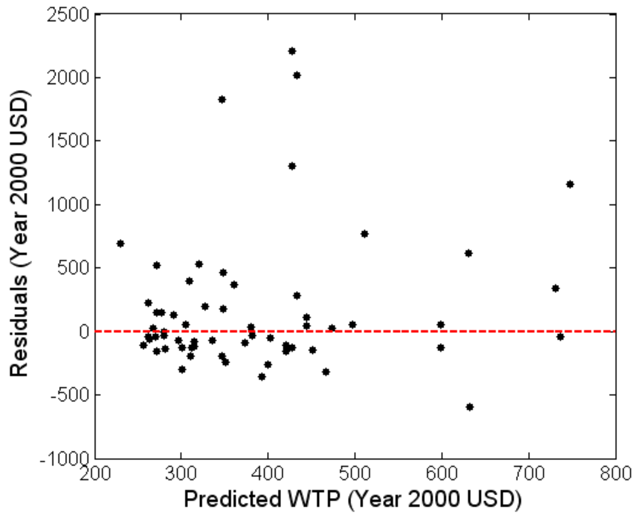


Figure 10: Residuals versus predicted values for WTP

Because heteroscedasticity was observed, OLS regression was no longer appropriate, as the resulting parameters would not be the best linear unbiased estimators (BLUE). This is because OLS regression gives equal weight to all observations when, in fact, observations with larger variance contain less information than observations with smaller disturbance variance [Kennedy (2008)]. When this is the case, alternative regression models, such as weighted least-squares (WLS), are typically used (see Section 4.6.1).

4.5.3 Multicollinearity

Because WTP was calculated as the product of property value and NDI divided by household size in Equation 4, one concern was that any observed relationship between income and WTP may in fact be due to the correlation between income and property value. This is the issue of multicollinearity, which occurs when two or more explanatory variables in a multiple regression model are highly correlated, and may lead to unreliable regression estimates [Verbeek (2008)]. To check for multicollinearity, a matrix may be constructed that lists the correlation coefficient between each of the explanatory variables. In econometrics, multicollinearity is usually indicated by an entry in the correlation matrix greater than 0.80 [Kennedy (2008)]. Table 4 shows the symmetric correlation matrix for WTP, property value, NDI, and income; the correlation coefficient between income and property value was 0.22, implying that multicollinearity was not observed.

Table 4: Correlation matrix between WTP, property value, NDI, and income

	WTP	Property Value	NDI	Income
WTP	1.00	0.84	0.69	0.10
Property Value	0.84	1.00	0.28	0.22
NDI	0.69	0.28	1.00	-0.09
Income	0.10	0.22	-0.09	1.00

4.6 Multivariate Regression

As suggested in Figure 9, there appears to be a different relationship between income and WTP for the US studies and the non-US studies. To capture this trend, an interaction term was introduced, which was defined as the product of income and a dummy variable that equals zero for US studies, and one for non-US studies. Such an interaction term effectively acts as a Boolean switch that selects between two different regression relationships – one for US studies, and one for non-US studies.[16]

4.6.1 Regression Form Specification

Prior to performing a regression analysis, it was necessary to first specify the functional form of the regression. Because the relationship under consideration was between an environmental amenity and income, the Environmental Kuznets Curve was an appealing choice. However, it was not chosen due to concerns regarding the EKC identified in Section 3.1.4, and because the data in Figure 9 did not seem to suggest an inverted-U relationship. Several other options were also considered, including linear, quadratic, cubic, logarithmic, exponential, and power regressions. However, none of these functional forms was a particularly good fit for the data – similarly low R^2 values were observed for the simplest form (linear) and the more complex functions.[17] Concerns also arose as to the validity of more complex functional forms in light of a

[16] An alternative to the interaction term was to use only a non-US dummy variable. However, that approach assumes that the slope of the relationship between WTP and income remained constant between the US and non-US studies, with the only difference being in the intercept. The interaction term was chosen over the non-US dummy variable because of the added flexibility to vary the slope of a regression relationship between WTP and income.

[17] While R^2, the coefficient of determination, was considered in the regression form selection process, it was used only to conclude that the various functional forms were equally inadequate in fitting the data set, which motivated the selection of the simplest (linear) regression form. It was not used as a parameter for choosing among different functional forms, or between OLS and WLS regression. Kennedy (2008) cautions against the

heteroscedastic data set with significant outliers. Therefore, a simple linear function was selected as the form of the regression. This specification choice is consistent with numerous previous studies in Europe that examined the income elasticity of WTP for various environmental goods [Hökby and Söderqvist (2001), Kriström and Riera (1996)].

An ordinary least-squares linear regression is the simplest model to use, but is not appropriate in this case due to the presence of heteroscedasticity. A weighted least-squares regression should be used instead, as the assumption of homoscedasticity was violated [Garson (2010)]. Common WLS strategies include weighting each observation by the sample size of the primary study 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)]. However, as sample size[18] and sample variance were not consistently available for all 60 studies, another weighting scheme must be considered.

Another option is to use robust estimators, which are "insensitive to violations of any of the assumptions made about the way in which the data are generated," and commonly used in lieu of OLS regression estimators when there are concerns regarding outliers, heteroscedasticity, multicollinearity, and errors in variables [Kennedy (2008)]. The robust estimator used in this case is a bisquare estimator, which assigns each observation a weight of *w*, based on the residual *r* and tuning constant *k*, according to the following equation:

$$w = \begin{cases} \left|\frac{r}{k}\right| \left[1 - \left(\frac{r}{k}\right)^2\right]^2, & \left|\frac{r}{k}\right| \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The robust regression with a bisquare weighting function iteratively reweighted the 60 observations to minimize the sum of the absolute error. Using the default tuning constant of 4.685, a visual representation of the bisquare weighting scheme is shown in Figure 11.

applicability of the R^2 parameter in econometrics, citing that the R^2 parameter is only meaningful in OLS regression, that it is very sensitive to the range of the independent and dependent variables, and that it is generally very low for cross-sectional econometric data.

[18] Of the 60 studies, 57 reported the primary study sample size. For those 57, a weighted least-squares linear regression was implemented where each observation was weighted by its primary study sample size. This weighting scheme generated regression parameters that were very similar to those from a robust regression with a bisquare weighting function; the latter method was ultimately chosen.

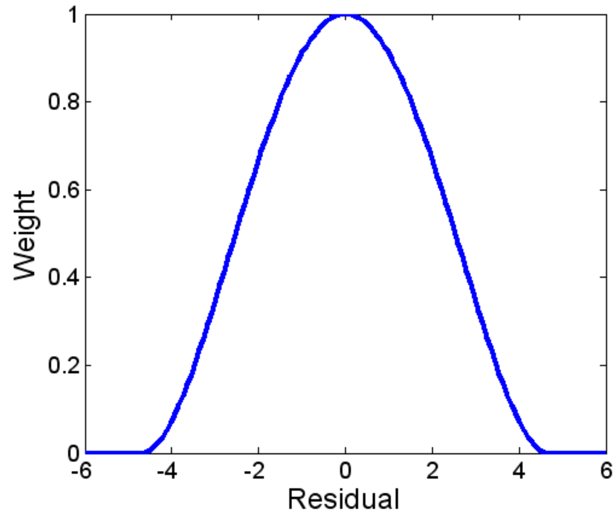


Figure 11: Weighting scheme of robust regression with bisquare estimator

The weight *w* is approximately equal to one for observations with small residuals, decreases to zero as the absolute value of the residual increases from zero to 4.685, and equals zero for observations with an absolute residual value of greater than 4.685. The underlying assumption for using this robust WLS regression is that the residual of each observation can be used to proxy the sample variance, and thereby correct for heteroscedasticity. An added benefit is that five outliers identified with the Cook's Distance Test all had residuals with an absolute value greater than 4.685, and were therefore given a weight of zero. In this way, the robust WLS regression result follows the bulk of the observations, and simultaneously accounts for both heteroscedasticity and outliers in the data set.

4.6.2 Backward Selection

When deriving a relationship between income and WTP for noise abatement, control variables must be introduced so as to account for any correlations between those parameters that may not be due to aviation noise. The inclusion of these variables was also an attempt to address any sample heterogeneity in the data set as well as to adhere to meta-analysis best-practices set forth in Nelson and Kennedy (2009). The control variables included in the meta-analysis are very similar to those employed by Nelson (2004) and Wadud (2009); they include the sample size of the primary study, a functional form dummy variable, an airport accessibility dummy variable, and dummy variables for each of the decades represented in the data set.

The functional form dummy variable refers to whether the primary study derived the NDI based on a linear or a semilogarithmic regression specification; this choice has been shown to significantly affect the NDI result [Schipper et al. (1998)]. In a linear model, property value is assumed to be a linear function of the explanatory variables, whereas in a semilogarithmic model, the logarithm of property value is assumed to be a linear function of the other variables. As a linear model generally tends to overestimate noise damages, a positive sign was expected for the functional form dummy 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 terms of ease of travel, employment opportunities, etc.) in addition to the drawbacks. The expected sign for this variable was therefore negative, because the housing value depreciation (and the corresponding WTP) should be less when also considering the positive externalities of the airport.

Because the meta-study used a data set that spans almost 40 years, it was also necessary to control for possible changes in the perception of noise over time. To this end, three decade dummy variables were introduced, one each for studies conducted in the 1980's, 1990's, and 2000's (with the 1970's decade as the default). Taking all of the above variables into account, a multivariate robust linear regression was carried out with the 60 observations in order to identify the significant variables through backward selection. Backward selection is an iterative procedure in which the least significant parameter (based on p-value) at each step is discarded, and the process is repeated until all remaining parameters are significant at the 10% level. The step-by-step results of the backward selection are shown in Table 5, listing the insignificant parameter at each iteration.

Table 5: Backward selection – insignificant parameters

Iteration	Least Significant Parameter	p-value
1	1990's decade dummy variable	0.9334
2	Airport accessibility dummy variable	0.8598
3	Sample size	0.6788
4	1980's decade dummy variable	0.4895
5	2000's decade dummy variable	0.3613
6	Functional form dummy variable	0.1729

Table 6 shows the outcome of the backward selection procedure. The interaction term was the most significant parameter, with a p-value of 0.0052 and a coefficient of 0.0154. The income parameter was also significant, with a p-value of 0.0424 and a coefficient of 0.0138. The sign of both the income and interaction term coefficients represent a positive relationship between income and WTP for noise abatement. These results are also in line with the observation that the US airport regions in the meta-study tend to exhibit a lower WTP for noise abatement with respect to income than the non-US airports.

Table 6: Backward selection – significant parameters

Parameter	Coefficient	p-value
Income	0.0138	0.0424
Interaction term	0.0154	0.0052

The intercept of the linear regression model was -30.3440 (p-value = 0.8620). The intercept was not considered an explanatory variable eligible for exclusion through backward selection, and was therefore included in the final regression result despite its large p-value. The income coefficient, interaction term, and intercept will henceforth be collectively referred to as the regression parameters. The equation specifying the relationship between WTP for noise abatement and the regression parameters is given by:

$$\text{WTP} = 0.0138 \times \text{Income} + 0.0154 \times \text{Income} \times \text{Non-US Dummy} - 30.3440 \tag{6}$$

Since the effect of the interaction term is that the coefficient on the income variable is increased for studies conducted around non-US airports, Equation 6 may also be rewritten as:

$$\text{WTP} = \begin{cases} 0.0138 \times \text{Income} - 30.3440, & \text{US airports} \\ 0.0292 \times \text{Income} - 30.3440, & \text{Non-US airports} \end{cases} \tag{7}$$

The above equations match the form of the relationship proposed by Navrud (2004) to perform benefit function transfer of WTP for environmental goods (Equation 3). Figure 12a shows Equations 6 and 7 superimposed on the meta-analysis data set. The two black lines represent the different relationships between WTP and income for the US and non-US studies. Figure 12b gives a visual representation of the weighting scheme used in the robust linear regression. The circles indicating the individual observations are sized in proportion to the weighting scheme of the robust regression; 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 in Section 4.5.1 were given a weight of zero, and were therefore effectively excluded from the data set.

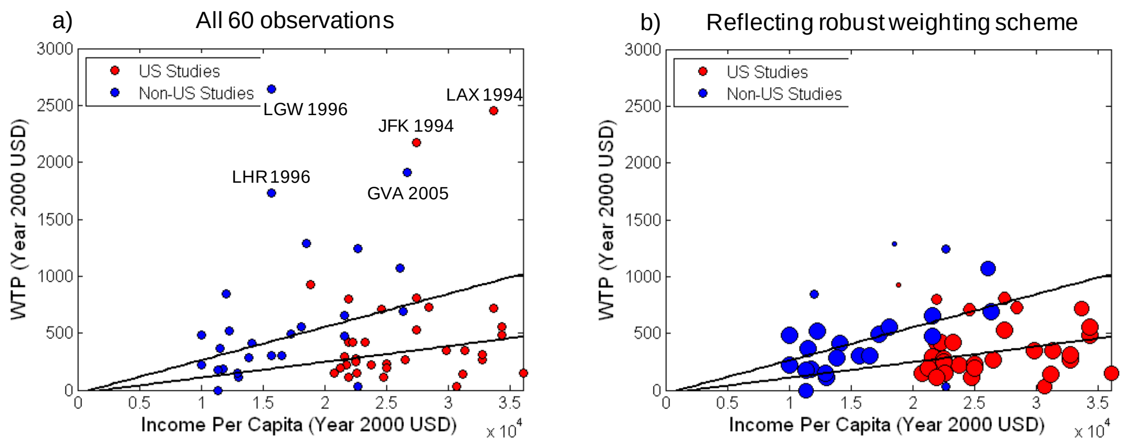


Figure 12: Result of robust linear regression: a) with all 60 observations and b) observations sized to reflect robust weighting scheme

5 Model Application

This chapter defines and explains the three main aspects of the new income-based hedonic noise monetization model: inputs, algorithm, and outputs. The goal of the chapter is to inform would-be users of the model on how the various pieces fit and work together to produce the desired results.

5.1 Inputs

To avoid confusion between the terms *input*, *factor,* and *parameter,* it is necessary to first establish the terminology in the context of the income-based hedonic noise monetization model. The definitions provided below are consistent with those set forth in Allaire (2009) for describing models with application to aviation environmental systems.

Model inputs are the set of all factors and parameters that must be specified in order to enable model operation. Model factors are external inputs to the model that correspond to the scenario considered for analysis; specifically, they include the noise contours, the population density grids, and the city-level average per capita personal income. Model parameters are quantities that determine the characteristics of the model, and are independent of the scenario of interest. They include the regression parameters, income growth rate, noise contour uncertainty, background noise level, significance level, and discount rate. The model factors and parameters are described in detail in the following sections.

5.1.1 Model Factors

5.1.1.1 Noise Contours

Noise contours represent the Day-Night Level of aircraft noise at a particular location, and are computed as yearly averages around each airport. They are created using the Model for Assessing Global Exposure to the Noise of Transport Aircraft (MAGENTA), which is an FAA batch processing tool for the Integrated Noise Model (INM). The INM computes the noise level for a single aircraft event at distinct grid points around the runway given the aircraft's engine type, airframe characteristics, thrust setting, and flight trajectory. These calculations are based on noise-power-distance curves derived from empirical data and industry standards for various aircraft and engine types. To characterize the full set of operations at an airport, MAGENTA requires airport-specific data (e.g. airport location and runway configuration), weather conditions, as well as the arrival and departure trajectories for each aircraft operating through the airport. The single aircraft events are summed to obtain the cumulative noise level, which is temporally-averaged over a 24-hour period, consistent with the DNL metric.

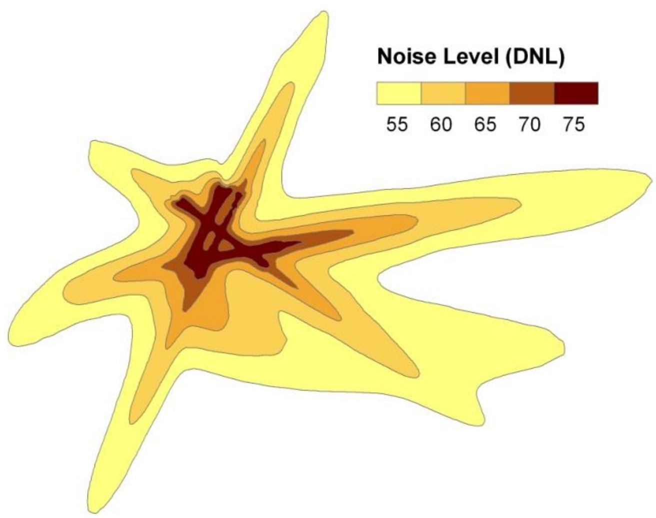


Figure 13: Sample INM noise contour output. Note: This contour is for demonstrative purposes only.

The output noise contour of INM is a geographically-referenced (in latitude/longitude) contour map with bands demarcating regions of a particular DNL of noise exposure, as shown in Figure 13. In order to be compatible for use with the income-based noise model, the noise contours must be referenced in the Universal Transverse Mercator (UTM) coordinate system. The UTM is an example of a projected coordinate system, which is preferable to the conventional latitude/longitude specification because it allows locations to be referenced on a regularly-spaced grid.[19] Each noise contour is transformed from a latitude/longitude coordinate system to a UTM coordinate system using the appropriate reference system and zone map for the airport's location: for US airports, the 1983 North American Datum (NAD83) geodetic reference system

[19] The use of a regularly-spaced grid is particularly important for performing global analyses of aviation noise impacts. The degree-minute-second convention of latitude/longitude references corresponds to different physical distances depending on the location of the airport. To batch-process many airports for a policy analysis, it is necessary to employ a system where the relationship between the coordinate values and physical distances is consistent across the globe. The UTM system divides the portion of the Earth between 80°S and 84°N latitude into 60 zones, each of which is mapped onto a two-dimensional surface using the Transverse Mercator projection. The distortion introduced in the projection is minimized when using the reference projection map for the appropriate UTM zone.

is used; for non-US airports, the 1984 World Geodetic System (WGS84) reference system is used.

To perform a policy analysis, usually two sets of noise contours are needed: baseline and policy. The baseline noise contours for the reference year (also known as the 0^{th} year) are constructed based on 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. Forecasting of future noise scenarios is conducted by the Forecast and Economic Sub-Group (FESG) within the ICAO Committee on Aviation Environmental Protection (CAEP). To evaluate the economic implications for noise associated with a particular aviation policy, the difference between the policy and the baseline scenarios (henceforth referred to as a “policy minus baseline” scenario) is considered.

5.1.1.2 Population Data

Population data are required to estimate the number of people residing in the region surrounding each airport. They are presented as grids of population density (number of persons per square meter) in UTM coordinates. As the population density grid must be overlaid with the noise contour for each airport in order to compute the monetary noise impacts, the geographical extent of the grid must completely contain the noise contour so that the entirety of the noise-impacted area may be considered in the analysis. Population data are obtained from several sources: for US regions, block group-level 2000 Census data are used; for European regions, the European Environmental Agency’s (EEA) population maps are used; for most of the rest of the world, population data are obtained from the Gridded Rural-Urban Mapping Project (GRUMP). For some countries, more detailed data from local statistical agencies are available, which are used in lieu of the EEA or GRUMP data. This is the case for the UK, South Africa, Canada, and Australia. Currently, 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.

5.1.1.3 Income Data

The city-level average personal income must be acquired for each airport in the analysis. These data may be obtained from a variety of sources, most notably from national statistical agencies (see Section 4.2). Many such agencies are listed in Appendix C for the sample problem presented in Section 7.1. The income data search should be conducted for the baseline reference year, and adjusted to reference year USD using the procedure outlined in Figure 6. In cases where the city-level income cannot be found, it may be estimated based on the relationship between income and GNI per capita observed for other airport regions in the study (see Section 7.1.2).

5.1.2 Model Parameters

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. Of the six model parameters, the discount rate, significance level, and income growth rate are set to be deterministic values, as they represent value judgments rather than parameters rooted in scientific knowledge.

Some model parameters have uncertainties that arise from limitations in scientific knowledge, a lack of predictability, or modeling difficulties. Such parameters include the background noise level, contour uncertainty, and the regression parameters. The uncertainty in these parameters will propagate through the model calculations and create uncertainty in the output. In order to capture this propagation of uncertainty, Monte Carlo Simulations (MCS) are conducted, which entail specifying each input parameter as a probabilistic distribution, and calculating an output for each input sample. In this way, numerous runs are performed, resulting in a distribution of output values. For the uncertainty assessment and sample problem presented in this thesis (Chapters 6 and 7, respectively), the number of Monte Carlo runs was set to 2000. Uncertainty analysis using MCS will be further discussed in Section 6.3.

5.1.2.1 Discount Rate

The discount rate is a parameter that captures the depreciation in the value of money over time, and is expressed as an annual rate. It is an important consideration in the monetization of aviation noise impacts because aviation policies usually have a time span on the order of several decades. Though the discount rate may be chosen to be any reasonable value, in this thesis rates of 1%, 3.5%, and 5% will be considered (corresponding to high, nominal, and low monetized noise impacts, respectively), consistent with previous work in APMT-Impacts [Kish (2008), Mahashabde (2009)].

5.1.2.2 Significance Level

The significance level is the threshold DNL above which aircraft noise is considered to have "significant impact" on the surrounding community. It is unique as a model parameter in that it does not affect the value of the computed monetary noise impacts. Instead, its only function is to designate noise impacts as significant or insignificant, and thereby include them in or exclude them from the reported results.

The nominal value of the significance level is equal to the background noise level, such that any aviation noise above the ambient noise level in the community is regarded as having a significant impact (see Section 5.1.2.4 for discussion about background noise level). However, other levels of significance may also be chosen. According to 14 CFR Part 150, the FAA defines the level of significant noise exposure to be 65 dB DNL, below which all types of land use are deemed compatible [FAA (2006a)].

5.1.2.3 Income Growth Rate

The income growth rate represents the annual rate of change in the city-level average personal income. It is universally applied to the income levels of all airports in the analysis when calculating the WTP for noise abatement. The appropriate value to use for the income growth rate will vary from country to country, but may be estimated from the yearly growth in the GNI per capita for various nations included in the analysis. It is important to note that the value of interest is the *real* income growth rate, independent of inflation – thus, when considering the nominal growth in GNI per capita, the annual inflation rate must be deducted.[20]

For many developed nations, an annual growth rate between 2 to 3% may be a reasonable assumption; however, for parts of the developing world the value may be more extreme, or may fluctuate greatly from year to year [World Bank (2010)]. The nominal value of the income

[20] Alternatively, inflation may be accounted for by first adjusting the GNI per capita values from different years to the currency of a common reference year using an inflation calculator, then computing the percent change in GNI per capita.

growth rate is zero so as to allow for the quantification of the monetary impacts of noise solely due to the growth of aviation, rather than due to growth in economic activity (this is particularly useful when considering a policy minus baseline scenario).

5.1.2.4 Background Noise Level

The economic impacts of aviation-related noise should only be evaluated when aircraft noise exceeds the ambient noise level in the airport region. This threshold is termed the background noise level (BNL), and is implemented as 2000 random samples for each airport, drawn from a triangular distribution between 50 dB and 55 dB, with a mode of 52.5 dB. In the previous version of the APMT-Impacts Noise Module, the background noise level was known as the quiet level. The BNL may vary from region to region, but for urban areas, it is typically about 50 to 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 DENL 55 for aircraft noise. In the US, under the 1972 Noise Control Act, the EPA recommended 55 dB DNL as the "level requisite to protect health and welfare with an adequate margin of safety" [EPA (1974)]. Further discussion of the choice of the BNL distribution can be found in Kish (2008).

5.1.2.5 Contour Uncertainty

Currently, the noise contours from MAGENTA are fixed values. In order to account for uncertainty in those contours, it is assumed that the contour noise levels have a triangular uncertainty distribution with minimum, maximum, and mode at -2 dB, 2 dB, and 0 dB, respectively. This contour uncertainty (CU) distribution represents an engineering estimate, and should be updated as a greater understanding is gained of the uncertainties in the INM output. Another limitation of the triangular distribution is that it only captures uncertainties in the noise level, not uncertainties in the area of the contour, which may disproportionately affect the estimated monetary noise impacts [Tam et al. (2007)]. Future work in the AEDT assessment effort should include quantifying the uncertainty in the noise levels calculated by the INM, as well as implementing the capability to scale the area of the noise contours.

5.1.2.6 Regression Parameters

In order to obtain probabilistic distributions for the three regression parameters, bootstrapping was performed with the 60 meta-analysis observations in order to generate alternative data sets and construct multiple estimates of the regression parameter coefficients. In the bootstrapping procedure, 60 samples are randomly drawn with replacement from the original data set, and a bisquare robust regression is performed in order to compute the income coefficient, interaction term, and intercept. This process was repeated 2000 times for each airport included in the analysis.[21]

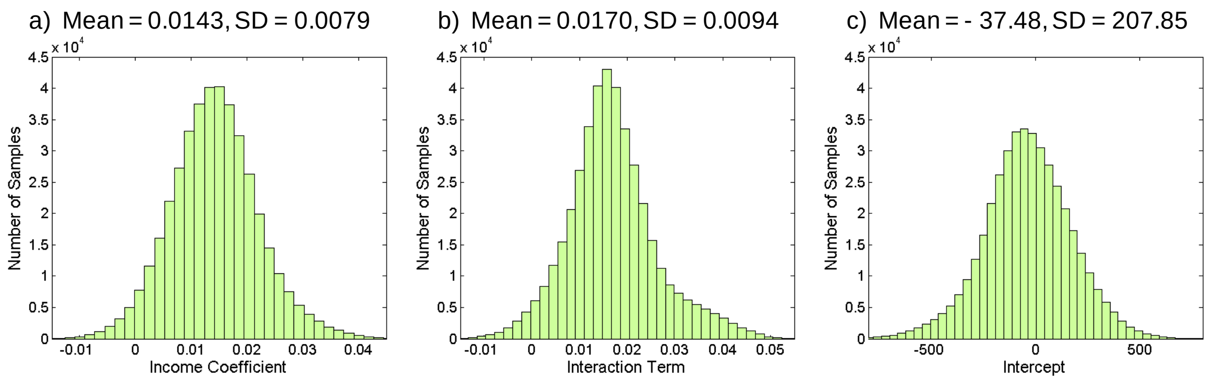


Figure 14: Bootstrapping distributions for: a) income coefficient, b) interaction term, and c) intercept

Figure 14 shows the approximately Gaussian probabilistic distributions for the three regression parameters obtained from bootstrapping, as well as the mean and standard deviation (SD) of each distribution. The histograms represent 2000 bootstrap samples for each of 207 airports, for a total of 414,000 discrete points.[22] Notice that the mean of each distribution is slightly different from the coefficients in Equation 6 due to the random sampling in the bootstrapping procedure.

5.1.3 Lenses

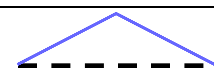
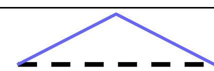
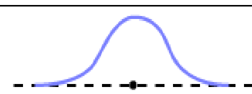
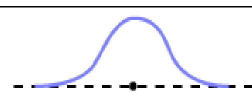
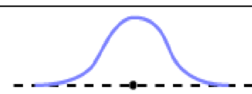
For the ease of policy analysis, lenses were created as ready-made sets of inputs that can be used to evaluate decision alternatives. Each of the three lenses – midrange, low-impacts, and high-impacts – is a group of model parameter values that can be applied to any set of model factors to evaluate the outcome given a particular perspective or outlook. The midrange lens represents a most likely scenario, where all model parameters are set to their nominal value or distribution (as

[21] In order to check whether 2000 iterations were enough for convergence, the running mean and variance were plotted versus the iteration number for each regression parameter. After 2000 iterations, fluctuations in the running mean of the income coefficient and the interaction term were on the order of 0.1%, and those in the running mean of the intercept were on the order of 1%. After 2000 iterations, fluctuations in the running variance of all three parameters were on the order of 1%.

[22] Bootstrapping was performed for 207 airports, corresponding to the number of airports in the ICAO-CAEP/8 Goals Forecast. However, when using these bootstrapping results as part of the noise lenses to perform uncertainty assessment, only 172 of the 207 sets of 2000 samples were used (see Section 6.1).

described in Section 5.1.2). The low-impacts lens represents an optimistic outlook, or the best-case scenario, in which the impacts of aviation noise are minimum. The high-impacts lens, on the other hand, represents a pessimistic or worst-case scenario, wherein the impacts of aviation noise are maximum. Table 7 summarizes the parameters for each of the three lenses. The midrange lens is the only one that employs MCS, and therefore produces a distribution of outputs. The low-impacts and high-impacts lenses are purely deterministic, in which the model parameters are set to the bounds of their respective distributions. Because there are no clear lower and upper bounds in the regression parameter distributions, the income coefficient is instead set to the 10^{th} and 90^{th} percentile value of the nominal distribution for the low-impacts and high-impacts lenses, respectively. The interaction term and intercept are set to their nominal values (from Equation 6) in the two deterministic lenses. The discount rate is not explicitly included in any of the input lenses because its effect is solely in the post-processing of the model outputs. That is, any discount rate may be applied to the results from any of the lenses to reflect different economic scenarios.

Table 7: Noise lenses

Model Parameter	Low-Impacts Lens	Midrange Lens	High-Impacts Lens
Significance Level	65 dB	Background Noise Level	50 dB
Income Growth Rate	0%	0%	0%
Background Noise Level	55 dB	 50 dB 52.5 dB 55 dB	50 dB
Contour Uncertainty	-2 dB	 -2 dB 0 dB 2 dB	2 dB
Income Coefficient	0.0046 (10^{th} percentile value)	 Mean = 0.0143 SD = 0.0079	0.0241 (90^{th} percentile value)
Interaction Term	0.0154	 Mean = 0.0170 SD = 0.0094	0.0154
Intercept	-30.3440	 Mean = -37.48 SD = 207.85	-30.3440

5.2 Algorithm

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 of the model is shown schematically in Figure 15.

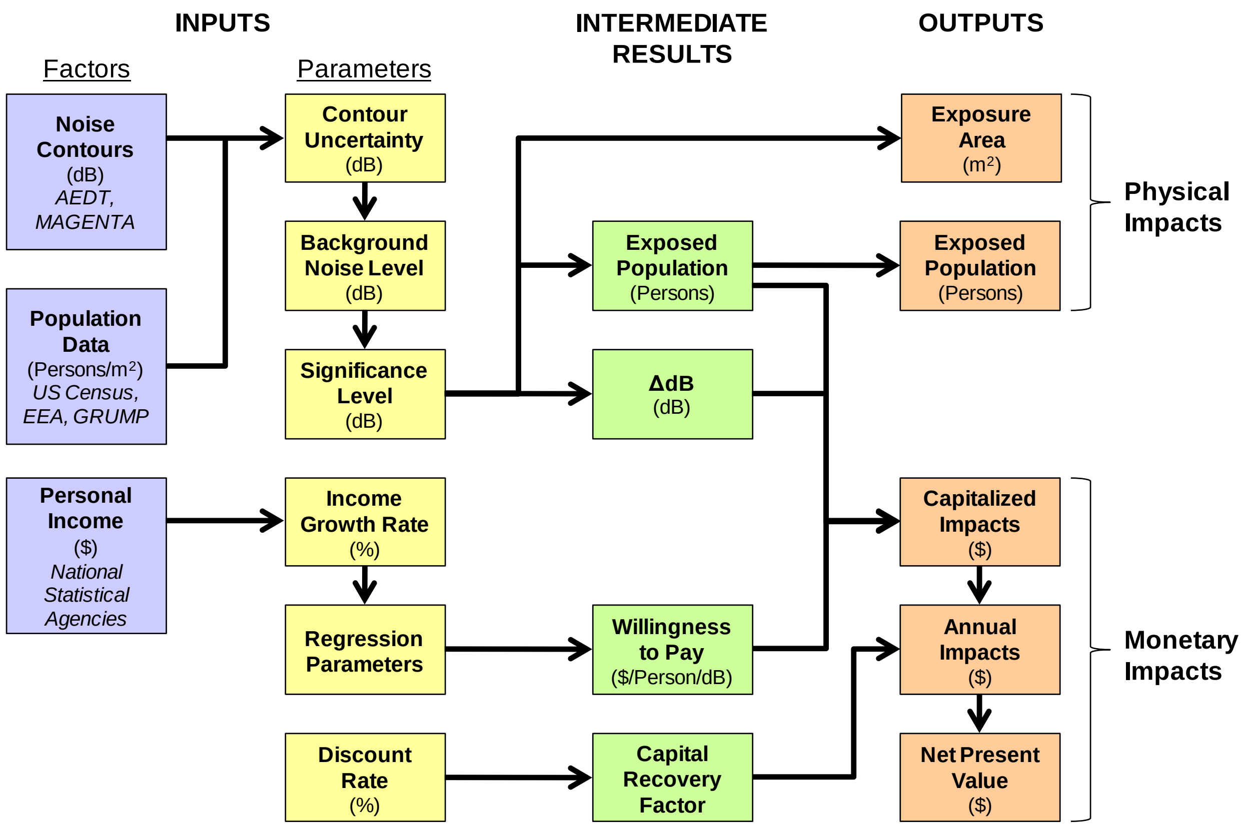


Figure 15: Schematic of income-based hedonic monetization model

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 derived in Section 4.6.2 to calculate a WTP per 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 at each grid point exposed to the DNL represented in the noise contour. Figure 16 shows an example of a rasterized noise contour overlaid on a population density grid. The white spaces in the map represent areas with no population according to census data (e.g. water, nature reserves, non-residential areas, etc.).

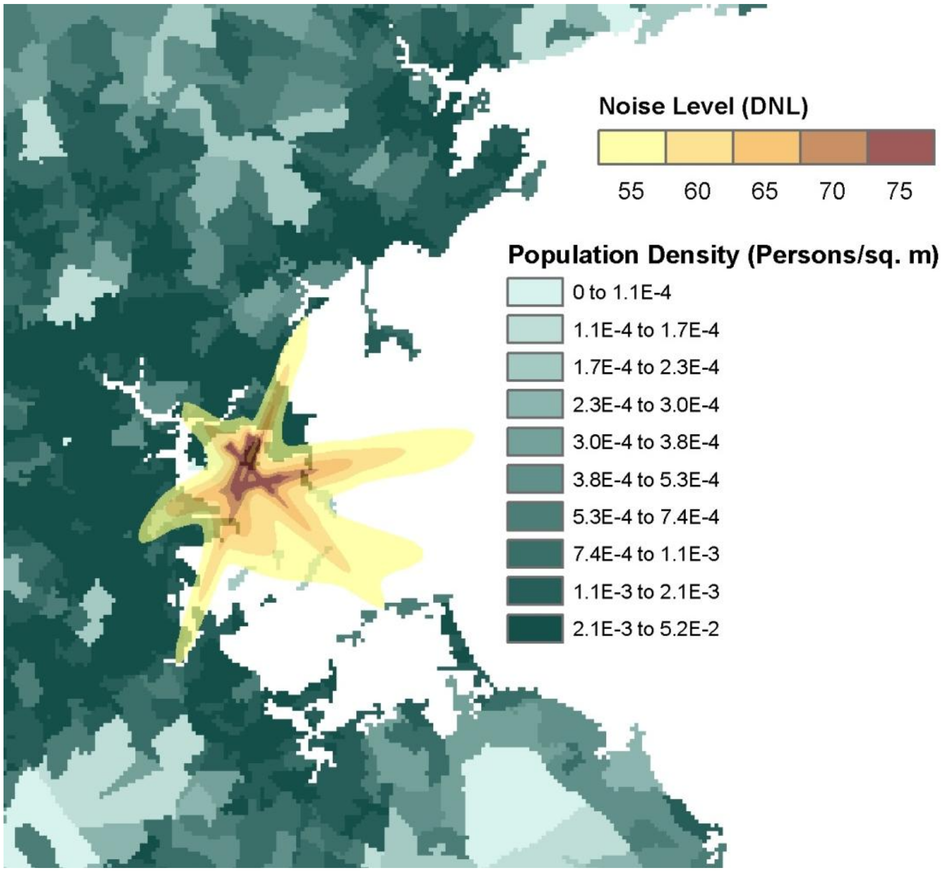


Figure 16: Superposition of noise contour and population density grid.[23] Note: This figure is for demonstrative purposes only.

Because it is assumed that the MAGENTA noise contours have some level of uncertainty, and that aviation noise impacts the surrounding community only if it is above the background noise level of the region, the expression for the noise level used in the calculation of monetary impacts (termed ΔdB) is given by:

$$\Delta\text{dB} = \text{Noise Contour Level} + \text{Contour Uncertainty} - \text{Background Noise Level} \tag{8}$$

For each grid point p, the monetized value of noise, V_p, is given by:

$$V_p = \text{WTP} \times \Delta\text{dB} \times \text{Number of Persons} \tag{9}$$

[23] The noise contour is shown as semi-transparent in order visualize the underlying population density. Slight distortions in the noise contour (compared to Figure 13) are due to the projection from latitude/longitude coordinates to UTM coordinates. The pixilation in the population density map is due to the resolution limit of the regularly-spaced grid. The scale bar is set to represent deciles in the population density.

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

$$V_t = \sum_{\text{Airports}} \sum_{\text{Noise Level Bands}} \sum_{\text{Grid Points}} V_p \qquad (10)$$

5.3 Outputs

There are two main classes of outputs for the income-based hedonic noise monetization model, physical impacts and monetary impacts. The physical impacts include the noise exposure area and the exposed population, whereas the monetary impacts include the capitalized noise impacts, annual noise impacts, and Net Present Value (NPV). The algorithm for computing these outputs is shown in Figure 15, and will be described in the following sections.

Because baseline and policy scenarios are usually provided for only a subset of the years in the policy period (e.g. at 10-year intervals), to report year-by-year impacts the results (both physical and monetary impacts) are linearly interpolated between fixed contour years.

5.3.1 Physical Impacts

For a particular set of noise contours, the physical impacts associated with each noise level band may be computed for all individual airports. The noise exposure area is the size (in m^2) of the geographical region that is subject to a particular level of noise. The exposed population is the number of people residing in the noise exposure area. The yearly physical impacts associated with both the baseline and policy scenarios may be obtained using interpolation. However, it must be noted that since there is no forecasted population growth in the income-based noise monetization model, the physical impacts of noise for future years should be interpreted in the context of changes in the policy scenario relative to the baseline, rather than as absolute numbers.

Unlike the monetary impacts of noise, physical impacts are reported as the number of people or the size of the geographical area exposed to at least 55 dB of aviation-related noise, rather than as impacts relative to the background noise level.[24] This is because in the scenarios considered in this thesis, the lowest noise level in any of the contours was 55 dB. Therefore, neither the contour uncertainty nor the background noise level triangular distributions affect the total estimated physical impacts.

5.3.2 Monetary Impacts

5.3.2.1 Capitalized Noise Impacts

The total monetary impact estimated from one set of noise contours is a capitalized value, which means that it embodies all future impacts associated with the given noise scenario. A more intuitive approach for understanding capitalized impacts may be to revisit the hedonic pricing method used in Kish (2008), which attempted to quantify noise-induced housing value depreciation.

In an area exposed to significant aviation-related noise, homeowners will generally pay less for a house because of the detrimental effects of noise. Therefore, the monetary impact of noise (or conversely, the implicit value of quietness) is captured in the difference in 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. Therefore, the total monetary impact computed from the noise contours of one year also encapsulates the housing value depreciation due to all future noise anticipated by the homeowners.

Because the income-based noise monetization model was derived from 60 hedonic pricing studies, the WTP for noise abatement is explicitly a function of capitalized attributes such as NDI and property value (Equation 4), making it also a capitalized value. Therefore, the economic damages computed from the noise contours of one particular year represent the capitalized noise impacts associated with that year. It is therefore not valid to sum the

[24] Monetary impacts of noise are calculated with respect to ΔdB away from the background noise level, which has an upper limit of 55 dB DNL in the current definition (Section 5.1.2.4). For example, for a noise contour level of 55 dB and ΔdB = 0 (e.g. contour uncertainty = 0 and background noise level = 55 dB), the estimated monetary impacts for that grid point would be zero, whereas the physical impacts would be non-zero, assuming the population density at that point is non-zero.

interpolated yearly capitalized noise impacts to compute a total amount for a specific scenario, as doing so would introduce double-counting.

A key difference between the income-based hedonic noise monetization model and the previous APMT-Impacts Noise Module is that rather than separating the monetary impacts of aviation noise into housing value depreciation and rental loss, the results of the income-based model in theory capture both effects. The explanation is thus: in the former hedonic pricing model, the people who reside within the area of the noise contour are sorted into homeowners and renters. The housing value depreciation and rental value loss experienced by residents, therefore, correspond to different portions of the total population exposed to aviation noise. However, in the income-based hedonic monetization model, the WTP for noise abatement is expressed as a *per person* monetary value, and is applied to all individuals residing within the noise contour area, with no distinction between homeowners and renters. The capitalized monetary impacts estimated using the income-based model, therefore, represent the cumulative effect of housing value depreciation and rental loss associated with of aviation noise. In this way, the income-based model exhibits an important advantage over the previous Noise Module, in that no knowledge is required about the split between owner-occupied and rental properties in each airport region.

5.3.2.2 Annual Noise Impacts

Because capitalized noise impacts do not capture changes in aviation noise over the time span of an environmental policy, it is often of interest to policymakers to consider annual noise impacts. To transform a capitalized value into an annual value, it is first necessary to assume a discount rate, R, and policy time span of N years. These values are then used to calculate the Capital Recovery Factor (CRF)[25]:

$$\mathrm{CRF} = \frac{\mathrm{R}(1+\mathrm{R})^{\mathrm{N}}}{(1+\mathrm{R})^{\mathrm{N}}-1} \tag{11}$$

The CRF converts a capitalized value into an annuity, which is a constant payment in each year over a period of N years. The capitalized noise impacts in the reference year, V_0 (see Equation

[25] The usage of CRF to denote the Capital Recovery Factor in the APMT-Impacts Noise Module should not be confused with Concentration Response Functions used in the APMT-Impacts Air Quality Module, which represent exposure-response relationships for estimating changes in health incidences.

10), can then be equally distributed over all subsequent years (1 through N) by multiplying by the CRF; the product is the annuity, B_0, or the base amount in each year independent of future changes in aviation noise.

$$\mathrm{B}_0 = \mathrm{V}_0 \times \mathrm{CRF} \tag{12}$$

The second contribution to annual noise impacts is the additional damages incurred each year due to the forecasted growth of aviation. This amount, termed the marginal impact, is simply the difference in the capitalized impacts between each year and the previous year. For year *t*, the marginal impact, M_t, is given by:

$$\mathrm{M}_t = \mathrm{V}_t - \mathrm{V}_{t-1} \tag{13}$$

Since yearly capitalized impacts are linearly interpolated between fixed noise contour years, M_t is constant within each interpolation set. There is no marginal impact associated with the reference year. The annual noise impact is the sum of the annuity and the marginal impact, which must then be discounted into the reference year dollar amount. The total annual noise impact for year *t* post-discount is given by:

$$\mathrm{A}_t = \frac{\mathrm{B}_0 + \mathrm{M}_t}{(1+\mathrm{R})^t} \tag{14}$$

Equation 14 can be rewritten in terms of only the capitalized noise impacts for each year, discount rate, and policy time span.

$$\mathrm{A}_t = \left[\frac{\mathrm{V}_0\mathrm{R}(1+\mathrm{R})^{\mathrm{N}}}{(1+\mathrm{R})^{\mathrm{N}}-1} + \mathrm{V}_t - \mathrm{V}_{t-1}\right]\frac{1}{(1+\mathrm{R})^t} \tag{15}$$

5.3.2.3 Net Present Value

The Net Present Value is a measure of the total monetary impacts of aviation noise over the time span of an environmental policy, expressed as a dollar amount in the reference year currency. It is the most convenient metric for comparing the noise impacts of different aviation policies, or for comparing the different categories of environmental impact (e.g. climate, air quality, and noise) associated with one particular policy. For this reason, NPV is usually the metric adopted for considering environmental impact tradeoffs in APMT-Impacts.

The NPV is calculated by summing the discounted annual noise impacts (Equation 15) over the duration of the policy period. The annuity in the reference year is not included in the summation.

$$\mathrm{NPV} = \sum_{t=1}^{\mathrm{N}} \left[\frac{\mathrm{V_0 R(1+R)^N}}{\mathrm{(1+R)^N - 1}} + \mathrm{V}_t - \mathrm{V}_{t-1} \right] \frac{1}{(1+\mathrm{R})^t} \tag{16}$$

An alternate way of thinking about the NPV is that it is the capitalized impact in the reference year plus the sum of the discounted marginal impact in all subsequent years. This approach bypasses the transformation from capitalized impacts to annual impacts, and is given in Equation 17. It can be shown that with algebraic manipulation, Equation 16 reduces to Equation 17; hence, the two approaches are equivalent.

$$\mathrm{NPV} = \mathrm{V_0} + \sum_{t=1}^{\mathrm{N}} \frac{\mathrm{V}_t - \mathrm{V}_{t-1}}{(1+\mathrm{R})^t} \tag{17}$$

5.4 Limitations

There are several limitations to the income-based hedonic noise monetization model. The most critical is that the model was developed based on 60 hedonic studies from North America, Europe, and Australia, which are all developed regions of the world with relatively high income. However, the regression relationship between WTP and income derived from these studies is then applied globally, for both low-income and high-income regions. It is not inconceivable that low-income regions may have an entirely different income elasticity of WTP for noise abatement, one that does not fit in with the linear relationship predicted by the robust multivariate regression. However, until more studies are available that address the economic impacts of noise in low-income regions, it is uncertain how this shortcoming affects the results of any analyses conducted using the income-based hedonic noise monetization model.

The limitations of meta-study data do not only affect the low-income regions. It is possible that the 60-observation data set does not accurately reflect the reality of the noise problem (for example, perhaps the studies were only conducted in areas where the local reaction to aviation noise was unusually strong), and thus the derived regression relationship does not precisely capture the monetary impacts of aviation-related noise. Similarly, it is also possible that the observed trend between income and WTP for noise abatement may be due to factors unrelated to aviation noise – while the backward selection procedure presented in Section 4.6.2 aimed to consider as many explanatory variables as possible, it is likely that the list was incomplete. Future work should focus on expanding the meta-analysis data set and introducing more explanatory variables into the regression model.

Another potential limitation of the income-based noise model is that it can only be used for airport regions where accurate and detailed population data are available. Though not a shortcoming of the model development process itself, this constraint does affect the applicability of the model and the accuracy of its results. While the US Census, EEA, and GRUMP population data provide extensive global coverage, these data sources are updated infrequently (the population data used in this thesis date from 2000 and 2001) and do not necessarily give an accurate portrayal of the population distribution in the reference year of the noise contours. Furthermore, the income-based noise model currently does not account for population growth, so there are no forecasted population grids to align with the projected future noise contours. However, while these limitations may affect the baseline or policy scenario results to the first order, when considering a policy minus baseline scenario, the effects become second-order. In this way, the limitation on detailed population data does not detract from the model's ability to discriminate the costs or benefits of a particular aviation policy scenario relative to the baseline.

6 Uncertainty Assessment

The income-based hedonic noise monetization model developed in this thesis is intended to be used as part of the Aviation Environmental Tools Suite to analyze proposed policies and inform decision-making. However, the use of an empirical model to predict probable outcomes necessitates questions such as: “What confidence can one have in the model results?” and “What can be done to improve this confidence?” [Allaire (2009)]. To answer these questions, it is important to understand how uncertainties evolve from the inputs and assumptions of the model and propagate to the outputs.

Uncertainty assessment refers to a rigorous procedure to represent, characterize, and analyze the uncertainties in a model [Allaire (2009)]. It is of critical importance to APMT-Impacts because it presents a way to quantify the uncertainties associated with each module, as well as those related to the system as a whole. Furthermore, because model outputs are driven by assumptions in the inputs, it is important to understand those causal relationships so as to provide the proper context for interpreting any conclusions drawn from the results. In this way, uncertainty assessment also plays an essential role in facilitating the transfer of policy-relevant information from the model developers to the policymakers and other stakeholders [Mahashabde (2009)].

Results of previous assessment efforts for the APMT-Impacts Climate, Air Quality, and Noise Modules can be found in Mahashabde (2009), Brunelle-Yeung (2009), and Kish (2008), respectively. System-level assessment of APMT-Impacts as well as of the Aviation Environmental Tools Suite as a whole is an area of ongoing research in PARTNER.

6.1 Objectives and Methodology

There are several objectives in conducting uncertainty assessment for the income-based hedonic noise monetization model. These include:

- Understand how uncertainties in each model input contributes to the variability in model outputs
- Rank model inputs based on their contribution to output variability
- Identify limitations in model functionality that may hinder the model’s applicability

- Identify sources of uncertainty which may be reduced through further research and validation

The noise contours used in the uncertainty assessment were obtained from the ICAO-CAEP/8 Goals Forecast, which included 207 airports worldwide. Of these 207, 172 airports were included the assessment effort, as population data were not readily available for the remaining 35. The baseline contours used in the analysis corresponded to the ICAO-CAEP/8 Goals Technology Freeze scenario, whereas the policy contours corresponded to the Advanced Technology scenario. The noise reference year was 2006, and the forecasted future noise contours corresponded to 2016, 2026, and 2036. Therefore, the policy of interest has a lifespan of 30 years.

Population data were obtained from the 2000 US Census, the EEA, and GRUMP, as described in Section 5.1.1.2. Income data were obtained from the US Bureau of Economic Analysis in 2006 for the 92 US airports, and from various national statistical agencies in 2005 for the 80 non-US airports.[26] The model parameters considered in the uncertainty assessment include those that are part of the noise lenses (Table 7), as well as the discount rate. The nominal case refers to the midrange noise lens and a discount rate of 3.5%, consistent with the definitions in Chapter 5.

The NPV was used as the output of comparison because it is the only metric that makes use of all model parameters, as well as considers the entire time span of the policy. Physical impacts were not considered because they do not incorporate many of the model parameters, such as discount rate, income growth rate, and regression parameters.

A comprehensive procedure for conducting uncertainty assessment using a probabilistic approach is described in detail in Allaire (2009), and the steps are list below:

1. Establish the desired outcomes of the uncertainty assessment
2. Document the assumptions and limitations of the model
3. Document factors and outputs of the model
4. Classify and characterize uncertainty

[26] 2005 income data were used for non-US airports because they were already available from the sample case discussed in Section 7.1 without requiring a new data search. Because the purpose of model assessment was to characterize the sensitivities of the various model parameters, not quantify the absolute value of the NPV, the one year income discrepancy should have no effect on the assessment results.

5. Conduct uncertainty analysis
6. Conduct sensitivity analysis
7. Communicate results

The current assessment effort followed the above guidelines. Steps 2 and 3 have already been discussed in previous sections of this thesis; the remainder of this chapter will focus on Steps 4 through 7 of the list.

6.2 Uncertainty Classification

Uncertainty in scientific models may be broadly categorized as *epistemic* or *aleatory*. Epistemic uncertainty arises due to limitations in scientific knowledge, and may be reduced with further research and improved understanding, whereas aleatory uncertainty arises from natural randomness and is therefore irreducible [Allaire (2009)].

The inputs to the income-based hedonic noise monetization model contain both epistemic and aleatory uncertainty. For example, the MAGENTA noise contours, population data, and income data are constrained by data availability and quality, which may be categorized as epistemic. Similarly, the model parameters, such as the discount rate, income growth rate, significance level, and regression parameters exhibit epistemic uncertainty as they are limited by insufficient knowledge about physical reality. The selection of the background noise level contains both epistemic and aleatory uncertainties: aleatory, due to natural variations in the ambient noise level in different communities; epistemic, due to inadequacies in the proposed triangular distribution for capturing these ambient noise levels, which arise due to limited knowledge.

In addition to the epistemic versus aleatory classification, within the context of evaluating aviation environmental policies in APMT-Impacts, uncertainty may also be categorized in the following groups according to the input type [Mahashabde (2009)]:

- **Valuation:** The valuation category refers to monetization methods used to quantify environmental impacts, and depends on the selection of parameters such as the discount rate and level of significant impact.

- **Scenario:** The scenario category includes alternative forecasts of future activities or situations, such as aviation demand growth, population estimates, and income growth.

- **Scientific and Modeling:** Scientific and modeling uncertainties are epistemic in nature and arise from limitations in scientific knowledge or modeling approaches.

Of the model parameters discussed in Section 5.1.2, the discount rate and the significance level contribute to valuation uncertainty. The income growth rate is an example of scenario uncertainty. The background noise level, contour uncertainty, and regression parameters contain scientific and modeling uncertainty, which are epistemic in nature. Of the three model factors identified in Section 5.1.1, the uncertainty in the MAGENTA noise contours is a type of scientific and modeling uncertainty, which is captured by the contour uncertainty model parameter. To date, no work has been done to characterize the uncertainty in the population data and the city-level income data, though these could be potential areas to focus future research efforts.

6.3 Uncertainty Analysis

The two main components of uncertainty assessment are uncertainty analysis and sensitivity analysis. Uncertainty analysis refers to the process of characterizing and analyzing the effects of uncertainty in model inputs, with the goal of identifying how these uncertainties propagate to the model outputs [Allaire (2009)]. In APMT-Impacts, the fundamental tool for conducting uncertainty analysis is Monte Carlo Simulations. In MCS, uncertainty characterization is achieved by defining model parameters as random variables with probability distributions when possible. Performing MCS requires iterating the model algorithm thousands of times, and computing an output for each set of parameters sampled from their probabilistic distributions. The goal of the analysis is to construct a histogram of the model output, estimate its mean and variance, and use that information to make quantitative comparisons of various policy scenarios or to evaluate the performance of the model relative to fidelity requirements [Allaire (2009)].

In the income-based hedonic noise monetization model, the probability distributions employed to characterize input uncertainty are triangular distributions for the background noise level and contour uncertainty, and approximately Gaussian distributions for the three regression parameters (see Section 5.1.2). Because of these selections, the model output is expected to have a unimodal (and approximately Gaussian) distribution with an unambiguous mean and variance. For the baseline scenario, the NPV distribution of the nominal case over 2000 MC runs had a mean of $44.4 billion (in year 2006 USD), and a standard deviation of $3.2 billion (Figure 17a). The 10th and 90th percentile NPV values were $40.4 billion and $48.3 billion, respectively.

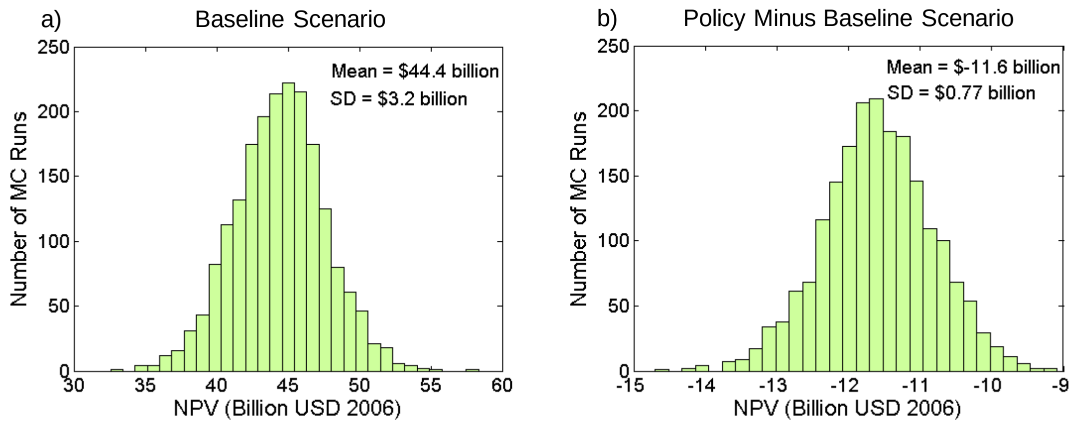


Figure 17: NPV distribution with all parameters set to nominal values for the a) baseline scenario and b) policy minus baseline scenario

As discussed previously, in order to evaluate the economic implications associated with a particular aviation policy, it is desirable to consider not just the results relating to the baseline or policy scenario alone, but rather the difference between the two. In order to conduct MCS for a policy minus baseline scenario, the choice exists to use either a paired sampling approach or an unpaired sampling approach for the model parameters. In a paired sampling approach, the same random draws for model parameters are applied to both the baseline and the policy scenarios, whereas in an unpaired approach, different random draws are used. Unpaired sampling in MCS has been shown to contribute to a larger output variance than paired sampling, resulting in double-counting of uncertainties [Mahashabde (2009)]. In the context of evaluating aviation-related noise impacts, many modeling uncertainties are common to both the baseline and policy scenarios, such that the only difference between the two should be changes in the noise contours as a result of policy implementation. Therefore, a paired sampling approach for MCS was employed for the policy minus baseline scenario in order to more accurately estimate output uncertainties.

Because the aviation policy considered in the uncertainty assessment represents the implementation of advanced technologies designed to reduce aircraft noise, it resulted in lower monetary noise impacts than the baseline scenario; hence, the NPV calculated in the policy minus baseline scenario were negative. For the policy minus baseline scenario, the NPV distribution of the nominal case had a mean of \$-11.6 billion and a standard deviation of \$0.77 billion (Figure 17b). The 10th and 90th percentile NPV values were \$-12.6 billion and \$-10.6 billion, respectively.

6.4 Sensitivity Analysis

The second component of uncertainty assessment is sensitivity analysis, which aims to investigate how each model input contributes to variability in the outputs. It can also be used to identify the inputs on which future research should be directed so as to reduce input uncertainty and thereby output variability. The reader is referred to Allaire (2009) for an overview of sensitivity analysis methods, as well as for detailed descriptions (including mathematical derivations) of the approaches outlined below.

In the current uncertainty assessment effort, three sensitivity analyses were performed: local sensitivity analysis (LSA), global sensitivity analysis (GSA), and distributional sensitivity analysis (DSA). As in the case of uncertainty analysis, the scope of the sensitivity analysis included the model parameters, but not the external model factors.

6.4.1 Local Sensitivity Analysis

Local sensitivity analysis assesses the output variability due to particular realizations of epistemic uncertainties in the model parameters; that is, it examines how the perturbation of each model parameter from its nominal selection changes the output [Mahashabde (2009)]. Local sensitivity analysis may be performed for both deterministic as well as distributional inputs; in latter case, since distributional inputs lead to a distribution of outputs, the mean of the distribution may be used to describe the result. The spread in the output between the low and high realizations of each input (with respect to the nominal case) may be compared so as to rank the inputs according to their sensitivity.

Table 8: Deterministic and distributional model parameters used in LSA

Deterministic Parameters	Distributional Parameters
Discount Rate 1% High NPV; 3.5% Nominal; 5% Low NPV	Background Noise Level 50 dB High NPV; 52.5 dB Nominal; 55 dB Low NPV
Significance Level Background Noise Level Nominal; 65 dB Low NPV	Contour Uncertainty -2 dB Low NPV; 0 dB Nominal; 2 dB High NPV
Income Growth Rate 0% Nominal; 3% High NPV	Income Coefficient 0.0046 Low NPV; Mean = 0.0143 SD = 0.0079 Nominal; 0.0241 High NPV

Table 8 shows the model parameters used in the LSA; note that these values were based on the noise lenses defined in Table 7, but with a few exceptions, which are discussed below. When conducting LSA, the first step was to run the nominal case, where all model parameters were set to their nominal values or distributions, as described in Section 5.1.2 and highlighted in blue in Table 8. The mean NPV over the 2000 MC runs for the nominal case was calculated, against which all other NPV results in the LSA were benchmarked. Next, the model parameters were varied one at a time across the full range of their values (corresponding to the low- and high-NPV cases in Table 8) while fixing all other parameters at their nominal selections. Of the three regression parameters, only the income coefficient was varied in the LSA to its 10th and 90th percentile values; the interaction term and intercept were held fixed at their nominal distributions for all cases, as their definitions in the noise lenses do not entail evaluation at more extreme values. For income growth rate, the nominal value was 0%, and a rate of 3% was selected as the high-impacts realization. No low-impacts case was selected because a negative income growth rate was judged to be non-realistic. The significance level was equal to the background noise level in the nominal case, and 65 dB DNL in the low-NPV case, as is consistent with the midrange and low-impacts lenses, respectively. However, the 50 dB DNL significance level corresponding to the high-impact lens was not implemented, because the lowest noise level in the contours used for uncertainty assessment was 55 dB.

Figure 18 shows the LSA results for the baseline scenario, benchmarked against the mean NPV for the nominal case of $44.4 billion (in year 2006 USD). Of the six model parameters, the income growth rate showed the largest spread between its low- and high-NPV realizations. The ranking of the model parameters with respect to contribution to output variability, from greatest to least, is: 1) income growth rate, 2) income coefficient, 3) background noise level, 4) significance level, 5) contour uncertainty, and 6) discount rate.

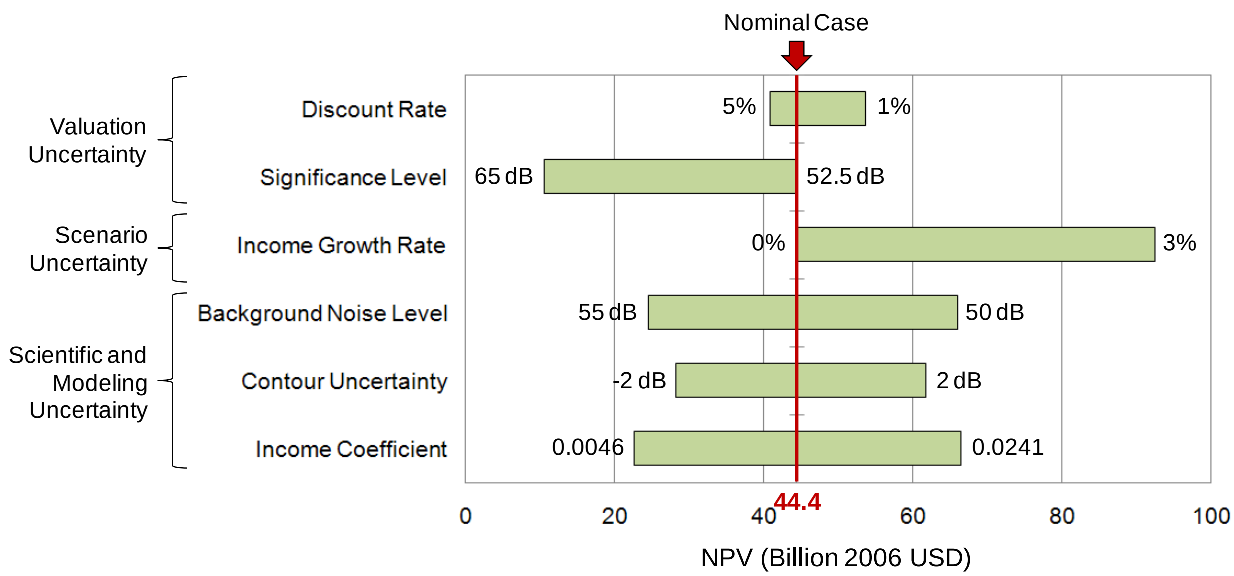


Figure 18: Local sensitivity analysis results – baseline scenario

Figure 19 shows the LSA results for the policy minus baseline scenario, where the mean NPV of the nominal case was $-11.6 billion. The ranking of the model parameters with respect to contribution to output variability, from greatest to least, is: 1) income growth rate, 2) income coefficient, 3) discount rate, 4) background noise level, 5) significance level, and 6) contour uncertainty.

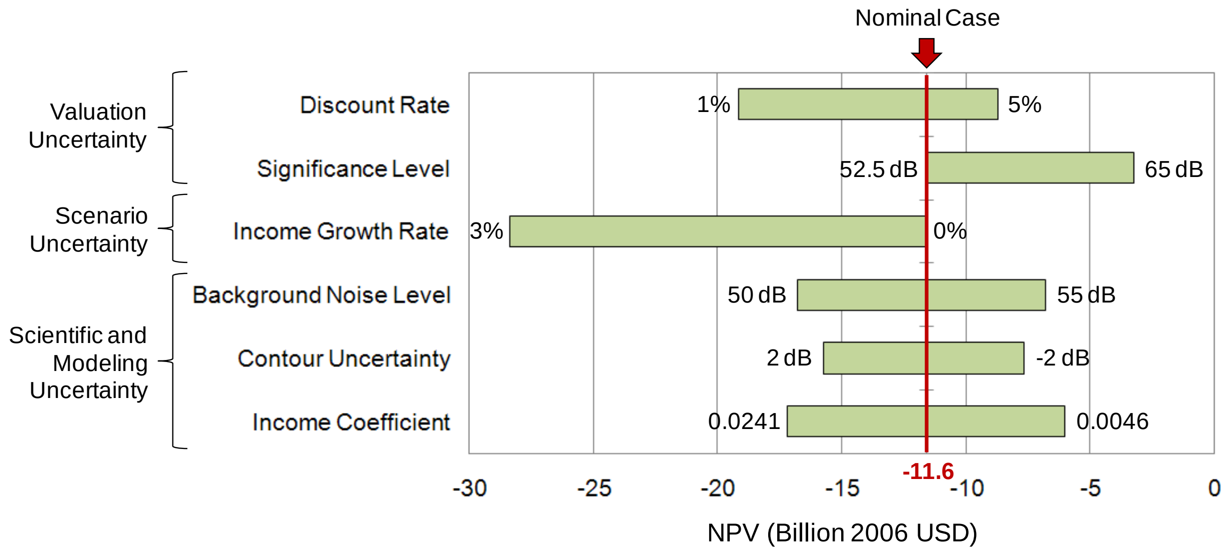


Figure 19: Local sensitivity analysis results – policy minus baseline scenario

6.4.2 Global Sensitivity Analysis

Global sensitivity analysis is a method of decomposing output variance into contributions from the individual model parameters and the interactions between parameters. Unlike LSA, it is conducted only for those inputs that can be expressed as probabilistic distributions. The process of variance apportionment in GSA is carried out with the Sobol' method, which uses MCS to calculate the Main-effect Sensitivity Index (MSI) and the Total-effect Sensitivity Index (TSI) for each parameter [Homma and Saltelli (1996), Sobol' (2003)]. The MSI of a parameter signifies the contribution to output variance due to that parameter alone, whereas the TSI denotes the contribution to output variance due to that parameter and its interactions with other model parameters. The TSI calculations are performed using the mean-subtracted alternative GSA approach, which enhances computational stability [Sobol' (2001)]. The MSI and TSI values can be used to rank the model inputs based on their contribution to output variability. The sum of all MSI for the model should be roughly equal to one, whereas the sum of the TSI should be greater than or equal to one, depending on the magnitude of the interaction effects. The Sobol' method has been employed extensively for GSA of various modules within APMT-Impacts [Mahashabde (2009), Brunelle-Yeung (2009), Kish (2008), Jun (2007)].

Global sensitivity analysis was conducted only for the distributional model parameters – namely, the background noise level, contour uncertainty, and the three regression parameters. Since GSA inputs must be independent distributions, the three regression parameters were considered collectively, as together they represent one independent regression distribution obtained from the bootstrapping procedure described in Section 5.1.2.6. Therefore, a total of three inputs were examined, and for each parameter a MCS with 2000 runs was performed where the distribution of the given parameter was fixed at its base sample values, while all other parameters were resampled from their respective distributions. A total of five runs were required for each GSA scenario – one resampled case for each of the three model parameters, one base case without resampling, and one case where all parameters were resampled. The MSI and TSI for the model parameters were calculated based on the NPV distributions obtained from the five evaluations.

For the deterministic parameters, an inner loop/outer loop procedure may be employed in order to investigate what interaction effects, if any, they have on the MSI and TSI of the distributional parameters. In the outer loop, a deterministic input, such as income growth rate, is set to its extreme value (as defined in the LSA) while holding all other parameters at their nominal values. The inner loop consists of conducting the GSA for the distributional inputs at their nominal values, as described above. In this thesis, three outer loop settings were considered, corresponding to the nominal case for all model parameters, a significance level of 65 dB DNL, and an income growth rate of 3%. The discount rate was not varied from 3.5% in the inner loop/outer loop procedure because it solely affects the post-processing of the NPV results, and therefore has no impact on the MSI and TSI of the other inputs.

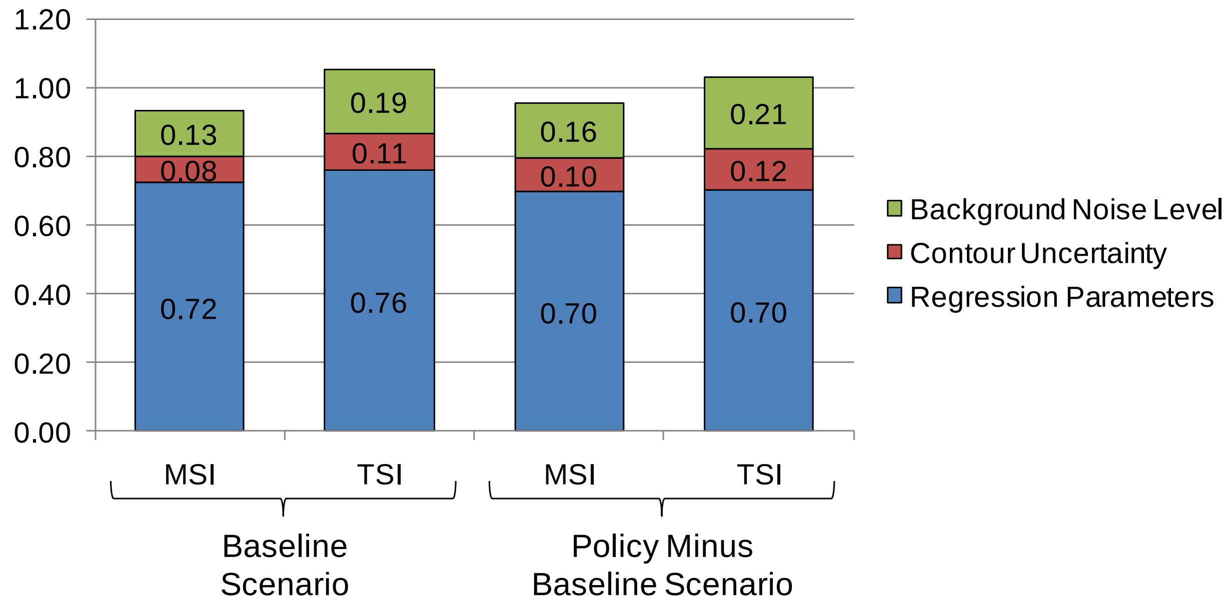


Figure 20: Global sensitivity indices – outer loop: nominal case

Figure 20 shows the MSI and TSI for the nominal baseline and policy minus baseline scenarios. In both scenarios, the regression parameters had by far the largest MSI and TSI, followed by the background noise level, with the contour uncertainty having the smallest indices. This suggests that the majority of the output variability is attributable to scientific and modeling uncertainties associated with the WTP versus income regression relationship implemented in the model.

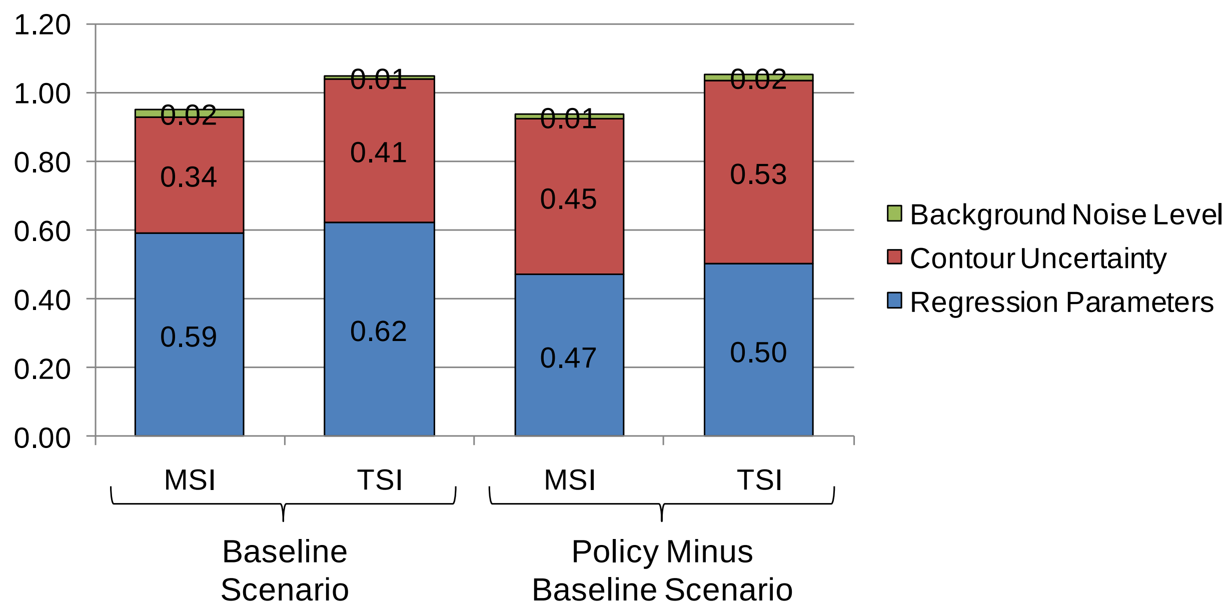


Figure 21: Global sensitivity indices – outer loop: significance level = 65 dB

Figure 21 shows the GSA results for the outer loop setting where the significance level is set to 65 dB. With this change, the background noise level becomes a negligible contributor to output variability because no longer is each grid point in the noise contours considered to have significant monetary impact. Therefore, only a subset of the noise grid points – those exceeding 65 dB DNL – are included in the NPV calculation; those points all have a ΔdB of at least 10 dB, hence reducing the relative influence of the variability in the background noise level in the monetary impact calculation. Correspondingly, the contour uncertainty has a larger relative contribution to output variability, as it plays a key role in determining whether or not certain grid points are included in the impact calculation.[27] The decrease in the MSI and TSI for the regression parameters is also explained by the larger ΔdB values in this particular outer loop setting, which downplays the relative influence of the WTP (and therefore the regression parameters) in the computation of monetary noise impacts.

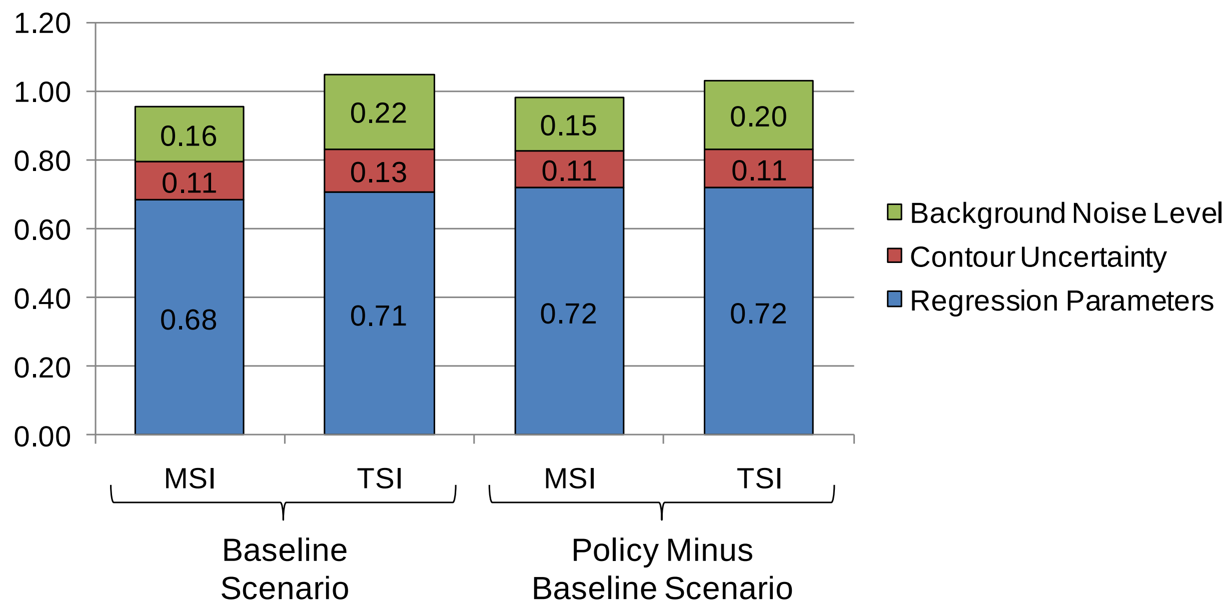


Figure 22: Global sensitivity indices – outer loop: income growth rate = 3%

Figure 22 shows the GSA results for the outer loop setting where the income growth rate is set to 3% per year. There are only minor changes in the MSI and TSI between Figure 20 and Figure 22, and no shifts in relative ranking of the three inputs the based on their indices. This result is

[27] For example, if the noise contour level at a grid point is 65 dB DNL, it will be judged to have significance noise impact if the contour uncertainty associated with that point is greater than or equal to zero. Otherwise, if the contour uncertainty is negative, the noise level at that point will not meet the 65 dB significance threshold, and is therefore excluded from the monetary impact calculation.

not surprising, given that the income growth rate should have no effect on the noise level (ΔdB), but rather scale the WTP by a constant value for each airport in each year. For this setting, the magnitude of the NPV is much larger than for the nominal case, but the breakdown of model parameters by contribution to output variability remains relatively unchanged.

6.4.3 Distributional Sensitivity Analysis

For parameters whose uncertainty is epistemic, distributional sensitivity analysis may be conducted to investigate how choices regarding the input distribution can affect the output variability. The DSA procedure was developed by Allaire (2009) and is summarized below.

Distributional sensitivity analysis builds upon the GSA concept, and attempts to account for one of its inherent limitations. In GSA, it is assumed that all epistemic uncertainty associated with a particular input may be reduced to zero through further research and improved knowledge – an optimistic assumption that can lead to inappropriate allocation of resources. Distributional sensitivity analysis, on the other hand, avoids this generalization by treating the portion of an input's variance that can be reduced as a random variable. For this reason, it may be more appropriate than GSA for the prioritization of efforts aimed at uncertainty reduction, as it could convey for which input(s) directed research will yield the greatest return.

One key parameter in DSA is δ, defined as the ratio of the variance of a particular input that cannot be reduced and the total variance of the original distribution for that input. An output of interest in GSA is the MSI of each input; the analogous quantity in DSA is the $\mathrm{adjS}_i(\delta)$, or the adjusted main-effect sensitivity index of input *i* given that it is known that only $100(1-\delta)\%$ of its variance can be reduced. Additionally, the AAS_i, or average adjusted main-effect sensitivity index of input *i*, is the expected value of adjS_i over all δ on the interval [0, 1].

One advantage of the DSA methodology is that it is performed directly on the outputs generated from GSA, thus the computational cost remains at five runs for each outer loop setting. The technique that permits the reuse of GSA results is acceptance/rejection sampling. For the income-based hedonic noise monetization model, two forms of acceptance/rejection sampling are employed: a triangular distribution scheme for the background noise level and contour uncertainty, and a multivariate normal distribution routine to accommodate the three correlated regression parameters.[28]

Before presenting DSA results, it is first necessary to note a few inherent differences between the structure of the income-based hedonic noise monetization model and the DSA methodology. In order to successfully employ acceptance/rejection sampling, it is crucial to achieve exact correspondence between the input and output distributions. That is to say, for each GSA run, the variability in the 2000 NPV outputs computed via MCS must be attributable to corresponding variations in the 2000 input samples. Otherwise, non-realistic negative indices may result. As described in Sections 5.1.2.4 through 5.1.2.6, however, the background noise level, contour uncertainty, and regression parameters inputs were created by drawing 2000 samples from the appropriate distribution *for each airport*; for the 172 airports included in the uncertainty assessment, this represented a total of 344,000 samples for each input. The NPV, on the other hand, was calculated based on the total monetary noise impacts over all 172 airports, resulting in a total of only 2000 output samples. This disconnect in the number of samples violates the input-output correspondence required for acceptance/rejection sampling. In order to reconcile this discrepancy, the NPV was computed for each airport individually, resulting 172 sets of 2000 output samples. For each airport *j*, its 2000 NPV samples, denoted by NPV_j, could then be exactly matched to the three corresponding sets of 2000 input samples. Fortunately, since NPV is additive, the linearity of the problem allows for the decoupling of the outputs in this way.

Taking the above approach, an adjusted main-effect sensitivity index may be computed for each of the three distributional inputs (vary *i*) for each airport (vary *j*) for each choice of irreducible variance ratio (vary δ) – the three degrees of freedom can be expressed by writing $adjS_{ij}(\delta)$. In order to synthesize these values into representative results for the sake of comparison, it is

[28] Allaire (2009) outlines the acceptance/rejection sampling procedure for input distributions that are triangular, uniform, or Gaussian. For a Gaussian distribution with one independent variable, the mean is held constant while the variance is scaled by δ in order to generate new Gaussian input distributions on which to perform acceptance/rejection sampling. For a multivariate normal distribution, the analogous quantities are the vector of means and the covariance matrix. The vector of means is held constant while the entries of the covariance matrix are scaled by δ in order to generate new distributions with pre-determined variance characteristics. Rather than one-dimensional Gaussian distributions described with bell-shaped curves, the new multivariate normal distributions generated for acceptance/rejection sampling are represented by ellipsoids in three-dimensional space. The volume of each ellipsoid corresponds to the determinant of the original covariance matrix scaled by δ^D, where D is the dimensionality of the multivariate normal distribution. In order for this procedure to be valid, the original covariance matrix must be positive-definite.

necessary to adopt an approach to that converts $adjS_{ij}(\delta)$ into an overall $adjS_i(\delta)$ for each input i by accounting for the individual contributions of all 172 airports. This may be done by computing a weighted sum along the j index, where each $adjS_{ij}(\delta)$ is scaled by the ratio of the variance of NPV_j to the variance of the total NPV. The details of this procedure are provided in Appendix B. The result is $adjS_i(\delta)$, the desired DSA output, which can in turn be used to compute AAS_i.

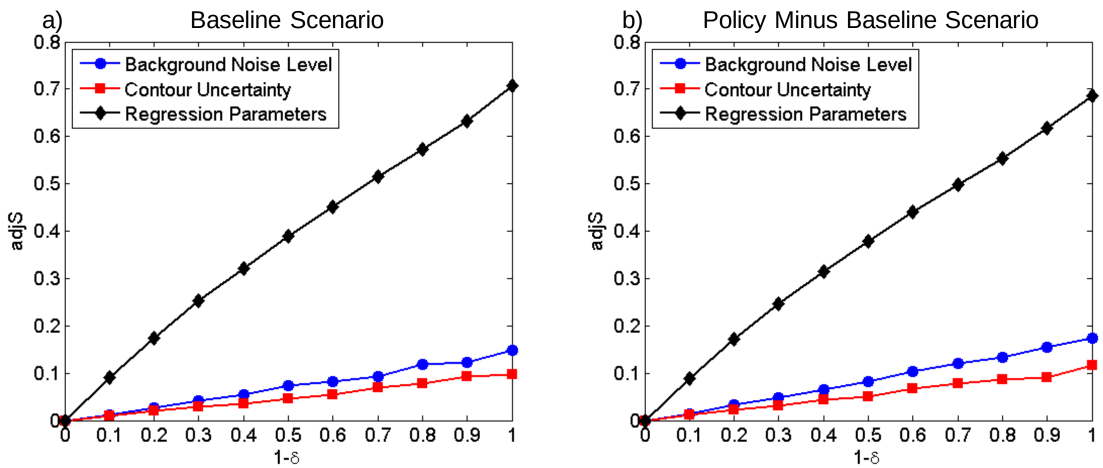


Figure 23: Adjusted main-effect sensitivity indices as a function of percent reducible input variance for the a) baseline scenario and b) policy minus baseline scenario

Figure 23 plots the $adjS_i$ for each of the three distributional parameters as a function of $1-\delta$, the percent of the input variance that is assumed to be reducible through further research and improved knowledge. The baseline and policy minus baseline scenarios exhibit very similar trends. These results were obtained by performing acceptance/rejection sampling on the GSA outputs corresponding to the nominal case outer loop setting.

As expected, $adjS_i$ grows with increasing $1-\delta$, exhibiting an approximately linear relationship for all three parameters. One way to interpret this result is that each parameter's contribution to total output variability can be decreased in proportion to reductions in its epistemic uncertainty. In theory, when $\delta = 0$ (or $1-\delta = 1$), the $adjS_i$ for each input (rightmost points in Figure 23a and Figure 23b) should match the MSI computed in GSA. Indeed, Table 9 shows that for $1-\delta = 1$, the $adjS_i$ for all three parameters closely match the MSI results from GSA, with discrepancies no larger than 0.02.

Table 9: Adjusted main-effect sensitivity indices for various choices of 1– δ

1-δ	Baseline Scenario			Policy Minus Baseline Scenario		
	BNL	**CU**	**Reg. Param.**	**BNL**	**CU**	**Reg. Param.**
0.1	0.01	0.01	0.09	0.01	0.01	0.09
0.2	0.03	0.02	0.17	0.03	0.02	0.17
0.3	0.04	0.03	0.25	0.05	0.03	0.25
0.4	0.05	0.04	0.32	0.06	0.04	0.32
0.5	0.07	0.05	0.39	0.08	0.05	0.38
0.6	0.08	0.06	0.45	0.10	0.07	0.44
0.7	0.09	0.07	0.52	0.12	0.08	0.50
0.8	0.12	0.08	0.57	0.13	0.09	0.55
0.9	0.12	0.09	0.63	0.15	0.09	0.62
1.0	0.15	0.10	0.71	0.17	0.12	0.69
MSI	0.13	0.08	0.72	0.16	0.10	0.70
AAS	0.07	0.05	0.37	0.08	0.05	0.36

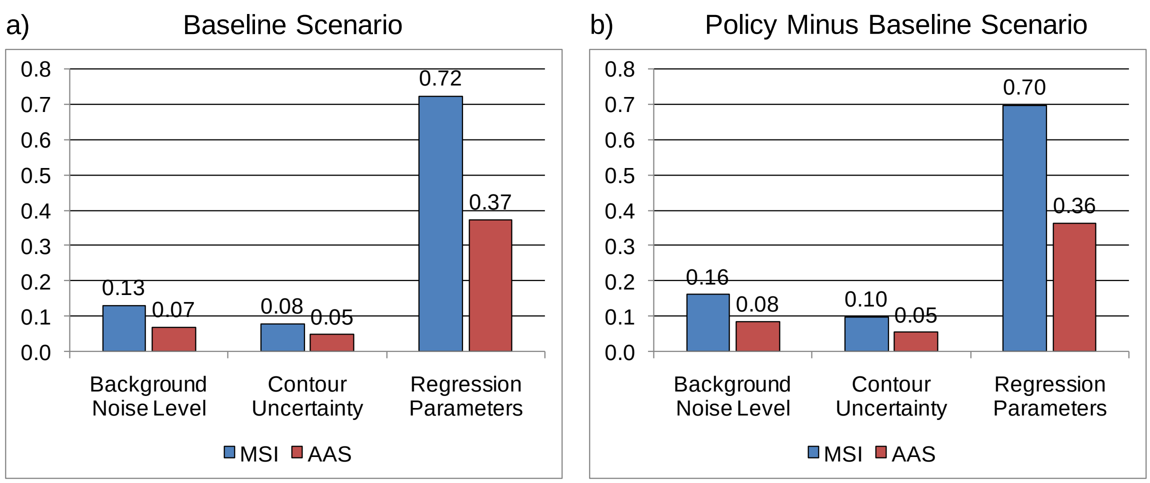


Figure 24: Comparison of MSI and AAS for the a) baseline scenario and b) policy minus baseline scenario

Figure 24 shows a comparison of the AAS and MSI for the three parameters. The MSI results from GSA suggested that the prioritization of inputs for further research should be the regression parameters first, followed by the background noise level, and the contour uncertainty last. This ranking order is corroborated by the AAS values from DSA, which indicates that the greatest reduction in model uncertainty can be achieved by improving the regression relationship shown in Equations 6 and 7. One way to achieve this reduction is to supplement the meta-analysis data set with additional aviation noise studies, especially from airport regions with low average personal income. Doing so would shed light on the relationship between income and WTP for noise abatement in the portion of the income spectrum where such information is currently lacking. This issue will be discussed in more detail in Section 8.2. While the DSA results suggest that the data set used in the model development process may benefit from the inclusion of additional noise studies, it must be cautioned that they do not imply that further research will necessarily lead to a decrease in the regression parameters' epistemic uncertainty or contribution to output variability. Furthermore, the DSA results should not be interpreted to indicate that the uncertainties associated with one input are easier to reduce than those of another.

7 Noise Impacts Calculations

When developing a new method to monetize global aviation-related noise impacts, it is important benchmark the new model against results from previous work in order to check for convergent validity, or the achievement of similar outcomes using different noise monetization methods [Nelson and Palmquist (2008)]. This chapter describes this verification process through a sample problem. The various model factors, parameters, and assumptions used in the sample problem are consistent with the Kish (2008) study, thereby allowing for a direct comparison with the results obtained previously using the APMT-Impacts Noise Module. The chapter concludes with a discussion of the sample problem findings and their implications for the model development effort.

7.1 Sample Problem

7.1.1 Model Factors

The sample problem used the same set of population density and noise contour inputs as Kish (2008). The noise contour reference year was 2005, and the forecasted future year was 2035. The noise contours were created using MAGENTA based on operations conducted on October 18, 2005, which comprised a total of 65,235 flights. There were 181 airports in the analysis, which are located in 38 countries plus Taiwan, with 95 of the airports located in the US (see Appendix C). These 181 airports are part of MAGENTA's database of 185 Shell 1 airports, which account for an estimated 91 percent of total global noise exposure [FAA (2009a)]. For the sake of consistency with the Kish (2008) result, only the baseline scenario was considered.

Population data were obtained from the 2000 US Census, the EEA, and GRUMP, as described in Section 5.1.1. Both the noise and population inputs were already available from the Kish (2008) analysis; therefore, the collection of new data for these factors was not necessary.

7.1.2 Income Data and Income Estimation

For the airports included in the sample problem, income data were obtained from numerous sources, which are summarized in Appendix C, Table C1. For the 95 US airports, MSA-level income data were obtained for 2005 from the US Bureau of Economic Analysis (see Appendix

C, Table C2). For 53 of the 86 non-US airports, city- and region-level income data were available from various national statistical agencies, which were adjusted to year 2005 USD using the procedure described in Section 4.3. 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 these seven airports, it was necessary to estimate the income based on another economic indicator, such as GNI per capita. Using year 2005 PPP values, a regression relationship was developed between GNI per capita and country-level income for the 79 airports where income data had already been obtained [World Bank (2007)]. Each country represented 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. Equation 18 shows the result of the linear OLS regression, which had an R^2 value of 0.82.

$$\text{Income per capita} = 0.6939 \times \text{GNI per capita} \tag{18}$$

There were three Pakistani airports in the analysis that had an extremely low country-level income. When estimating the WTP for those regions, the combination of the low income and the negative intercept in Equation 6 resulted in a negative WTP for noise abatement, which was deemed non-realistic. Therefore, those three airports were excluded from the data set, and the analysis proceeded with only 178 airports. This illustrates one of the limitations of the income-based monetization model in that it lacks robustness for estimating noise impacts in very low-income areas.

7.1.3 Model Parameters

There are several model parameters that are common to both the previous hedonic pricing noise model used in APMT-Impacts and the current income-based model. These include the discount rate, significance level, background noise level (previously known as the quiet level), and the contour uncertainty. In the sample problem, these parameters were defined in the same way as in the Kish (2008) analysis; namely, they were set to the nominal values or distributions corresponding to the midrange lens (Table 7).

7.2 Results

7.2.1 Physical Impacts

Using the income-based hedonic noise monetization model, the number of people exposed to at least 55 dB DNL of aviation-related noise around 178 airports was 13.7 million in 2005, and 23.0 million in 2035 (Figure 25a). This represents a 67.9% increase over the 30-year time span, which is due solely to the change in the forecasted noise contours, since population growth was accounted for in the model. Kish (2008) reported a total of 14.2 million people exposed to at least 55 dB DNL in 2005 around 181 airports. The discrepancy between the two results is due to the exclusion of the three Pakistani airports. If those three airports were included in the analysis, then the global population exposed to at least 55 dB DNL in 2005 would be 14.2 million.

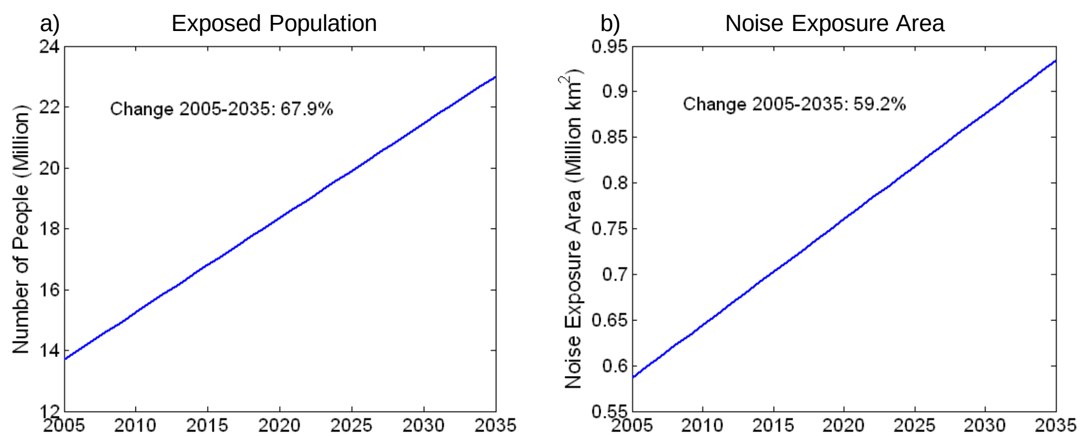


Figure 25: Change in physical impacts between 2005-2035: a) exposed population and b) noise exposure area

The total area around 178 airports subject to at least 55 dB DNL of noise exposure was 0.59 million km^2 in 2005, and 0.93 million km^2 in 2035, representing an increase of 59.2% over the 30-year time span. The physical impacts estimated by the income-based hedonic noise monetization model match those reported in Kish (2008); this is not surprising, as the algorithm for computing these impacts was not modified between the two different noise models used in APMT-Impacts.

7.2.2 Monetary Impacts

In terms of the monetary impacts of aviation noise, Kish (2008) reported a total of $21.4 billion in capitalized housing value loss in 2005 around 181 airports, and an additional $800 million per year in rental value loss. Figure 26 shows the distribution of the capitalized noise impacts in 2005 around 178 airports computed using the income-based hedonic noise monetization model. The output histogram had a mean of $25.0 billion (also designated as V_0 in Section 5.3.2), a standard deviation of $2.2 billion, and 10th and 90th percentile values of $22.3 billion and $27.9 billion, respectively. Comparing the mean result from the new income-based model with the Kish (2008) housing value depreciation estimate, the difference is 16.8%.[29] However, it should be noted that this comparison is only for the capitalized noise impacts – that is, the $800 million per year in rental value loss reported by Kish (2008) were not included, so the actual difference between the two models is even less than 16.8%. Section 7.3.2 will address the topic of comparing the results of the income-based model with both the housing value depreciation and rental loss reported by Kish (2008).

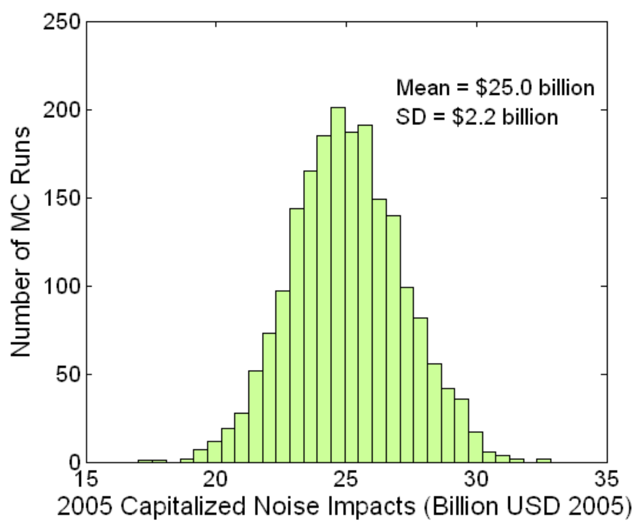


Figure 26: Distribution of capitalized noise impacts in 2005

The projected growth in aviation between 2005 and 2035 resulted in a 91.3% change in the undiscounted capitalized noise impacts over the 30-year period, or a 2.7% annual increase. This

[29] It should be noted that percent differences for all model comparisons in this chapter do not account for the exclusion of the three Pakistani airports. Therefore, the monetized impacts calculated with the income-based model would be larger if all 181 airports were included in the analysis.

trend is shown in Figure 27a, where the solid red line and the error bars denote the mean and standard deviation, respectively. However, when a 3.5% discount rate is applied to account for the depreciation in the value of money over time, the discount rate outpaces the annual increase in capitalized noise impacts, resulting in a decaying curve (Figure 27b).

Kish (2008) also reported that the equivalent worldwide annual noise impacts (also known as the annuity, or B_0 from Equation 12) was \$1.1 billion, assuming a 3% discount rate and a 30-year time span. Using a 3% discount rate, the annuity computed from the capitalized noise impacts with the new income-based model was \$1.3 billion, representing a difference of 18.2%.[30] As the nominal value of the discount rate was defined as 3.5% instead of 3% in this thesis, the annuity result with a 3% discount rate is only presented for the sake of comparison; the results communicated in the remainder of this chapter were calculated using a 3.5% discount rate.

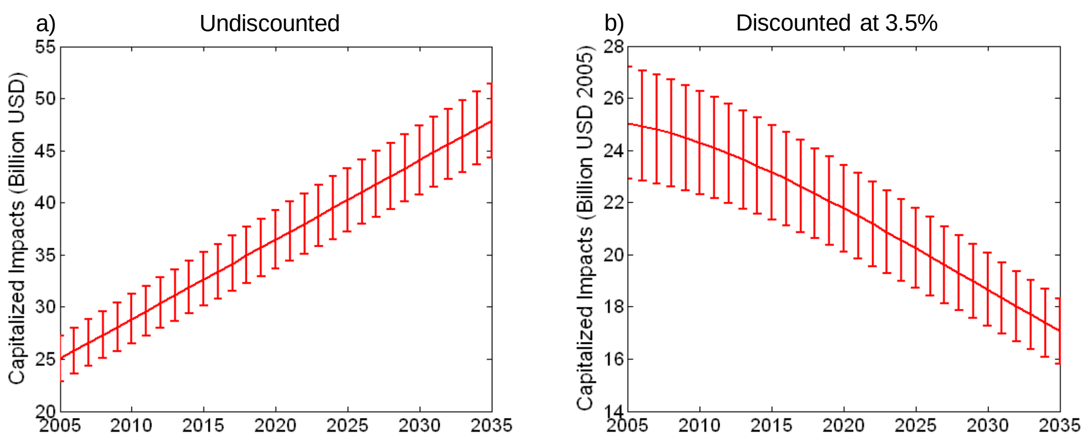


Figure 27: Change in capitalized noise impacts between 2005-2035 a) undiscounted and b) with a 3.5% discount rate

Figure 28 shows the NPV distribution computed in the sample problem. The mean NPV over the 2000 MC runs was \$39.1 billion in year 2005 USD, and the standard deviation was \$2.2 billion.

[30] As before, the additional \$800 million per year in rental loss was not considered in the comparison. This issue will be addressed in Section 7.3.2.

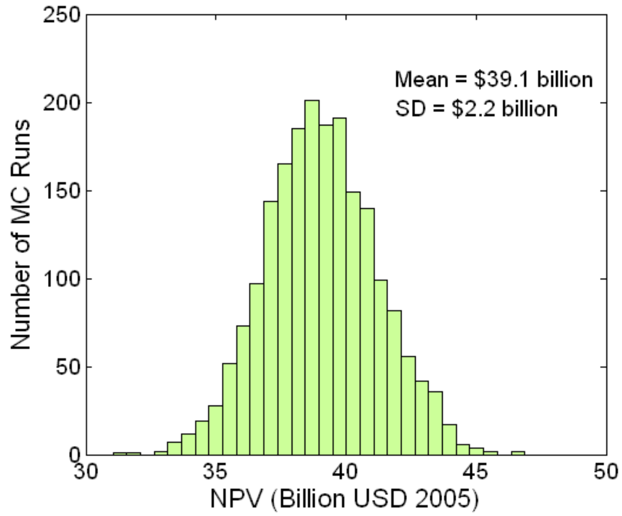


Figure 28: NPV distribution for midrange lens with 3.5% discount rate

7.3 Discussion

7.3.1 Spatial Distribution of Impacts

The results presented in the previous section signify the physical and monetary impacts of aviation noise worldwide. However, in addition to the global sum, it is also useful to understand where the estimated noise impacts occur. Figure 29 shows the location of the 178 airports in the sample problem, and the relative magnitude of the number of people exposed to at least 55 dB DNL of aviation noise in each airport region.

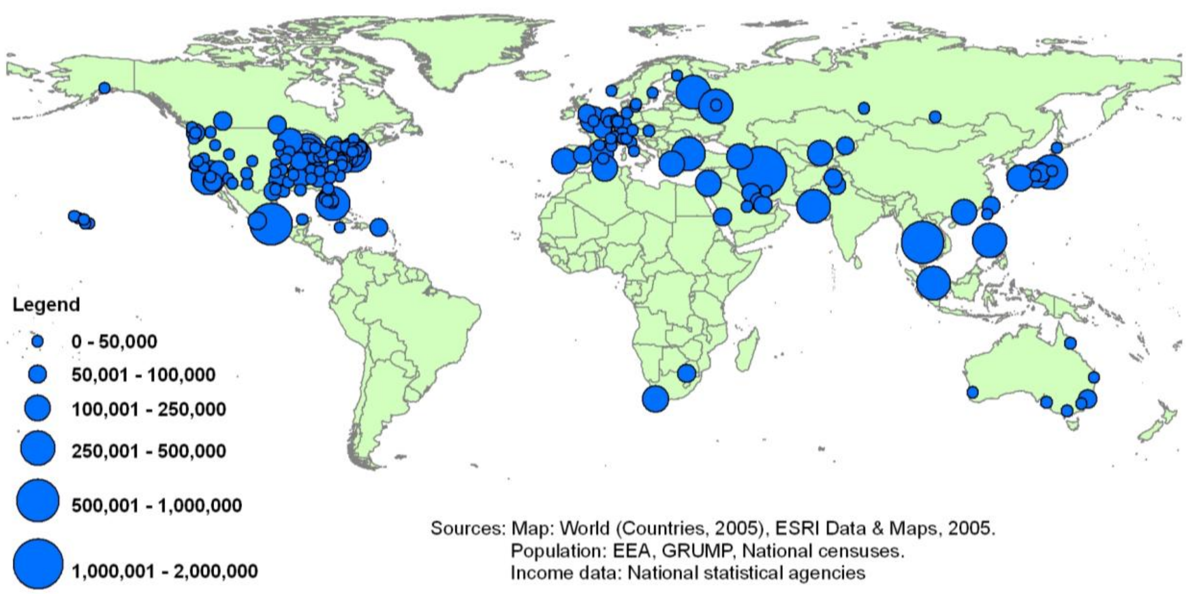


Figure 29: Number of people exposed to at least 55 dB DNL of aviation noise

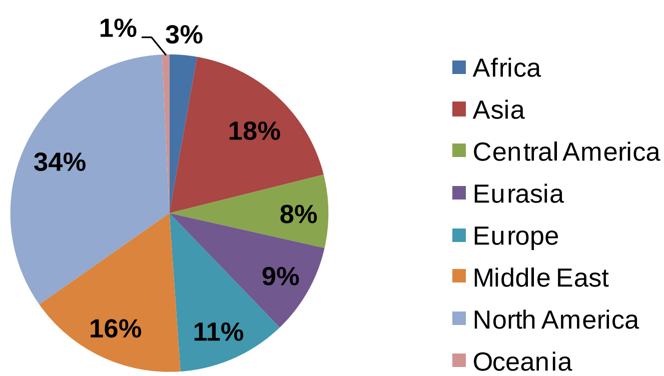


Figure 30: Number of people exposed to at least 55 dB DNL of aviation noise, percent by region

Figure 30 shows the breakdown of the exposed population into different geographical regions, as classified by the United Nations [United Nations (2010)]. North America has the highest total population exposed to aviation-related noise (about one-third), followed by Asia (18%), the Middle East (16%), Europe (11%), Eurasia (9%), and Central America (8%). Africa and Oceania had the lowest number of people exposed to at least 55 dB DNL of aviation noise.

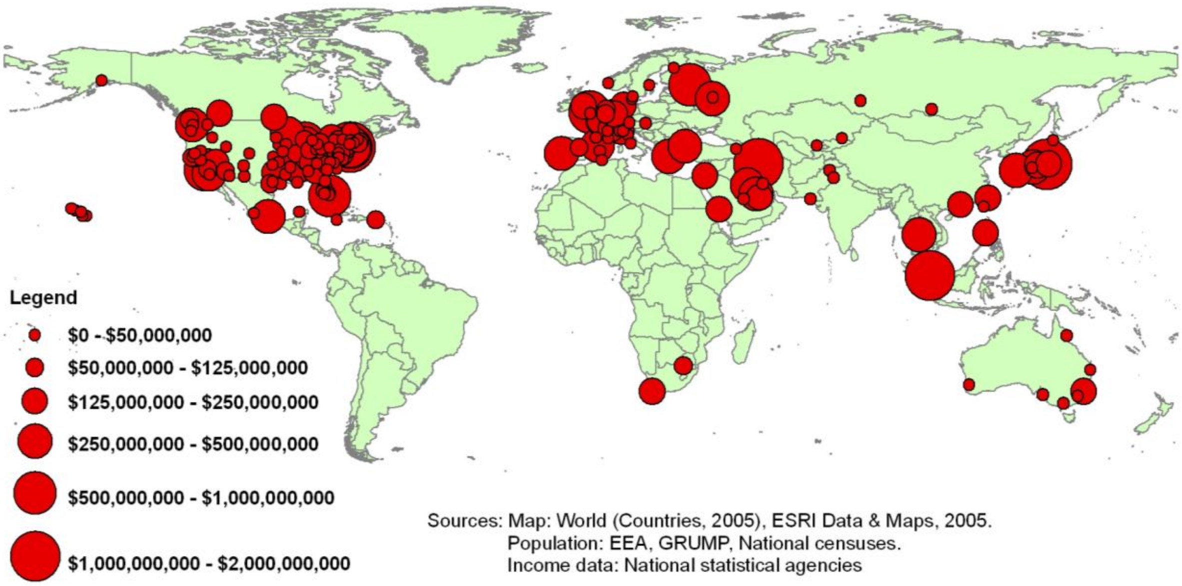


Figure 31: Mean capitalized noise impacts in 2005

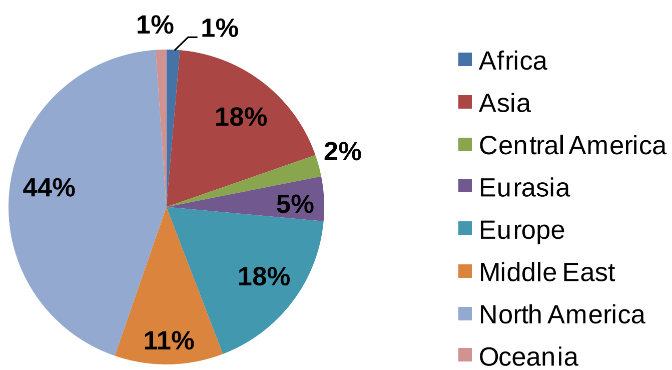


Figure 32: Mean capitalized noise impacts in 2005, percent by region[31]

Figure 31 shows relative magnitude of capitalized impacts around each of the 178 airport regions at 2005 noise levels. Approximately 44% the global monetary impacts of aviation noise occur in North America, followed by 18% each in Europe and Asia, 11% in the Middle East, 5% in Eurasia, 2% 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 than

[31] Figure 31 and Figure 32 were created based on the mean capitalized noise impacts in the 2005 reference year. Were similar figures to be made for the mean equivalent annual noise impacts, they would look practically identical, as conversion between the two types of monetary impacts is easily facilitated by multiplying by the appropriate CRF.

exposed population because of the higher income in those areas, which result in a relatively larger WTP for noise abatement. Conversely, regions such as Africa, Eurasia, Central America, and the Middle East have a smaller proportion of monetary impacts relative to exposed population due to the lower income in those areas, which lead to a smaller WTP per dB of noise reduction.

7.3.2 US Airports Comparison

The comparisons of monetary impacts between the sample problem and the Kish (2008) results presented in Section 7.2.2 only revealed the net difference in the mean aggregate capitalized noise impacts between the two models. Rental loss results from Kish (2008) were not included because of the inherent disconnect between capitalized noise impacts and annual noise impacts. This section presents an analysis that attempts to reconcile this discrepancy and compare the total monetary impacts estimated from the two models, using the results from the 95 US airports as the basis for comparison. These airports are listed in Appendix C, Table C2. Only the US airports were selected because they represent the subset of airports for which comprehensive data were available: that is, detailed data for population, housing value, rental value, and income. Therefore, a comparison of the monetary impacts for the US airports would demonstrate convergent validity between the two models, while minimizing uncertainties related to the quality and availability of input data or the applicability of the ICF International house price and rent price estimation methods. Such a comparison also eliminates any output discrepancies due to the exclusion of the three Pakistani airports in the sample problem.

Using the income-based hedonic monetization model, the capitalized aviation noise impacts in 2005 for the 95 US airports totaled $10.5 billion, representing 42.1% of the global sum. From the Kish (2008) study, the US airports comprised $5.9 billion in capitalized housing value depreciation and $291.7 million in yearly rental loss, representing 27.5% and 36.7% of the global totals for those quantities, respectively.

In order to add together housing value depreciation and rental loss in a meaningful way, two approaches may be adopted. The first is to convert both quantities into a common metric for comparison, either capitalized impacts or annual impacts. The second is to compare the NPV, which already incorporates such a conversion in its computation (Equations 16 and 17). Both methods require the assumption of a discount rate and a policy time period, and will be discussed below.

7.3.2.1 Capitalized Noise Impacts

The first method compares the capitalized monetary impacts at 2005 noise levels estimated using the previous and new versions of the APMT-Impacts Noise Module. The rental loss, an annual impact value, was converted into a capitalized value by dividing by the appropriate CRF (e.g. rearranging Equation 12 to solve for V_0), and added to the housing value depreciation to obtain a total capitalized noise impacts estimate associated with the Kish (2008) analysis. Assuming a 3.5% discount rate and a 30-year policy time period, this total was \$11.2 billion; compared with the \$10.5 billion result from the income-based model, the difference in the sum over the 95 US airports was -6.3%.

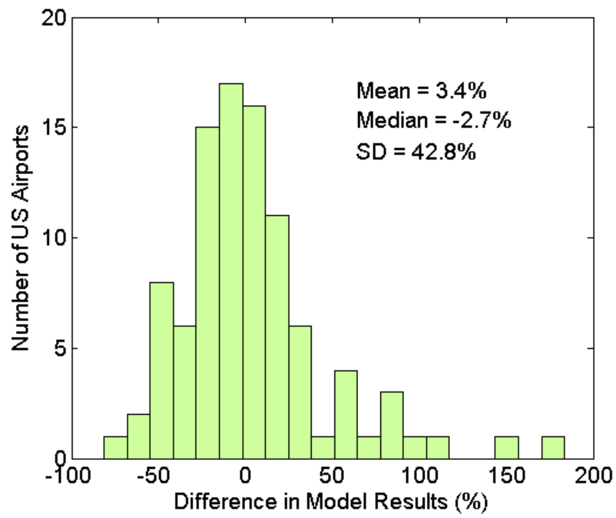


Figure 33: Percent difference in model estimates of capitalized noise impacts for 95 US airports, assuming a 30-year time period and a 3.5% discount rate

Figure 33 shows the distribution of the difference in capitalized noise impacts for each airport individually; the mean, median, and standard deviation of the histogram are 3.4%, -2.7%, and 42.8%, respectively. This airport-by-airport comparison demonstrates that the communication of aggregate results may belie model differences; that is, comparing the total capitalized noise impacts summed over all 95 airports revealed a difference of only -6.3% between the two models, whereas the large variance in the airport-by-airport comparison suggested that the local difference may be as high as 183%.

The difference in the estimated capitalized noise impacts between the two models was also plotted as a function of income and exposed population in order to investigate the effect of these factors on model comparability (see Figure 34). For example, if a positive and significant relationship existed between the model difference and the income, then that may suggest that the benefit function in Equation 6 overstates the relationship between WTP and income. However, no correlation was observed between the magnitude of the difference in the model estimates and either of these potential explanatory variables ($R^2 < 0.1$ in both cases). This suggests that the model differences must be attributed to other variables, or to inherent variability in the conversion between a hedonic pricing monetization method and one based on a per person WTP for noise abatement.

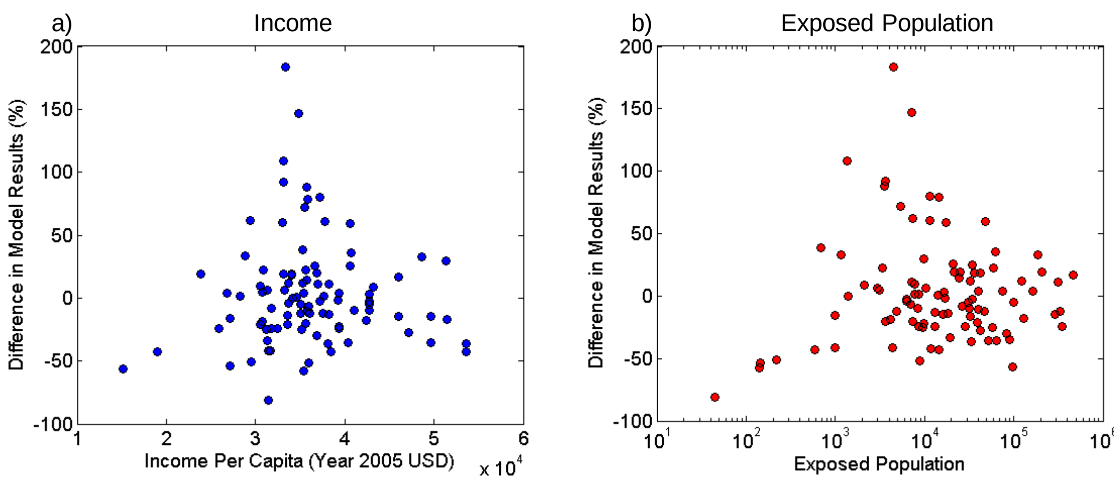


Figure 34: Percent difference in model estimates of capitalized noise impacts for 95 US airports as a function of a) city-level income and b) exposed population (note the semilogarithmic scale)

One important advantage of using capitalized noise impacts in 2005 to establish convergent validity is that assumptions for the annual housing growth rate used by Kish (2008) do not affect the comparison results. However, one major limitation is that the conversion of rental loss from an annual value to a capitalized value is highly dependent on the adopted discount rate and policy time period. Because these assumptions are applied only to the rental loss, not to the housing value depreciation or the results of the income-based model, they introduce potential sources of inconsistency. Figure 35 illustrates this issue: the percent difference in the model estimates for the total capitalized noise impacts summed over 95 airports is plotted versus the assumed policy time period for three commonly-used discount rates. It shows that for the previously stated set of assumptions, the difference is -6.3%. However, if the policy time period were shortened to 10 years while the discount rate is held constant at 3.5%, the difference between the two models would become 26.8%. Similarly, if the discount rate were decreased to 1% and the time period held constant at 30 years, the difference would become -21.4%. These examples point out that the results of the model comparison can vary greatly across multiple sets of valid assumptions. One way to mitigate the comparison uncertainties introduced by these assumptions is to consider the NPV estimates, because in order to calculate NPV, the discount rate and policy time period must be applied across the board – to housing value depreciation, rental loss, and the results of the income-based monetization model. This analysis is presented in the next section.

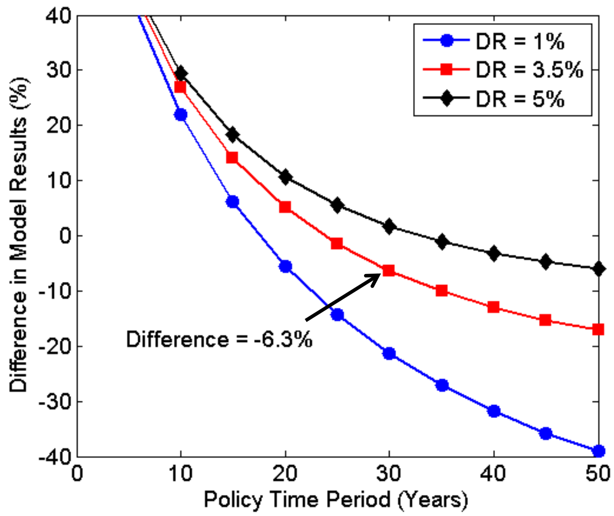


Figure 35: Percent difference in model estimates of capitalized noise impacts summed over 95 US airports as a function of policy time period and discount rate

7.3.2.2 Net Present Value

Since the noise contours used in the sample problem corresponded to 2005 and 2035, the natural choice for policy time period was 30 years. The discount rate was selected to be 3.5%, as consistent with the results from Section 7.2.2, though the effect of varying the discount rate will also be discussed. To convert the Kish (2008) housing value depreciation results into NPV estimates, the procedure is the same as for the capitalized noise impacts derived from the income-based monetization model, shown in Equations 16 and 17. The rental loss associated with year t, denoted Rent_t, is computed through linear interpolation between the 2005 and 2035 estimates. For a selected discount rate R, the NPV associated with rental loss is given by:

$$\text{NPV}_{\text{rent}} = \sum_{t=0}^{N} \frac{\text{Rent}_t}{(1+\text{R})^t} \tag{19}$$

The sum of the housing value depreciation and rental loss NPV estimates over the 95 US airports was $17.0 billion in year 2005 USD. The NPV calculated using the income-based hedonic monetization model was $16.2 billion, representing a -4.6% difference when compared with the Kish (2008) result. Figure 36 shows the distribution of the percent difference in NPV for each airport individually; the mean, median, and standard deviation of the histogram are 2.9%, -3.4%, and 39.8%, respectively. As in the case of capitalized noise impacts, local variations in the NPV estimates were often quite large, despite a mean difference of only 2.9% across the 95 airports.

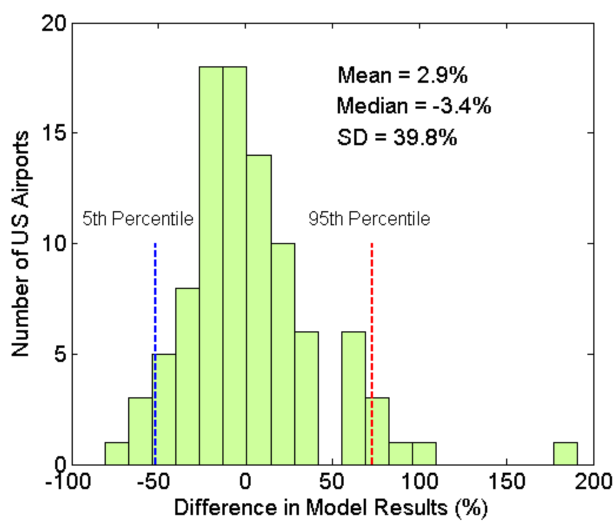


Figure 36: Percent difference in model estimates of NPV for 95 US airports, assuming a 30-year time period and a 3.5% discount rate

Figure 36 raises another question: if the monetary noise impacts predicted by the two models can differ by almost 200%, what confidence can one have in the results of either model? One way to answer this question is to investigate the outliers of the histogram to see if there is anything to be learned from the results of those airports. For example, do the outliers represent large airports with high traffic, or small airports with fewer operations? To what extent do the outliers influence the overall NPV estimate for all airports?

For the present analysis, the term "outlier" will be loosely applied to any airport whose percent difference in model estimates of NPV is less than -51.4% or greater than 72.9%; these values are the 5th and 95th percentiles of the histogram shown in Figure 36, and are marked by the blue and red dotted lines, respectively. There are a total of 10 outliers, 5 falling below the 5th percentile (KOA, LIH, OGG, SJU, and SMF), and 5 exceeding the 95th percentile (AUS, BHM, FSD, LIT, and OKC).[32]

A quick inspection of the list of outliers suggests that they tend to be smaller, regional airports rather than major air transportation hubs. In fact, none of the 10 are among the top 30 busiest airports in the US in 2005 by number of enplanements [FAA (2006b)]. Collectively, they make up only 1.6% of the overall US NPV estimated in the income-based hedonic monetization model. In fact, OKC (Will Rogers World Airport, Oklahoma City, OK), the strongest outlier at 191% difference between the two model NPV estimates, contributed only 0.05% of the total NPV.

Another useful way to compare the two models on an airport-by-airport basis is to examine the actual NPV estimates rather the percentage difference between the two results. Consider, for example, Figure 37, which plots the NPV calculated from the income-based model on the vertical axis, and that from the previous HP model on the horizontal axis. The blue and red lines denote the 5th and 95th percentiles of percentage difference between the two models, respectively, and correspond to the dotted lines on the histogram in Figure 36. The 10 outliers are marked with blue or red circles, and enlarged for emphasis. Figure 37a shows a scatter plot of the raw NPV data on a linear scale, which illustrates that the outliers are overwhelmingly clustered in the lower left corner, and therefore contribute only small fractions to the overall. Figure 37b shows the same set of data, but plotted on a log-log scale for improved legibility. These results demonstrate that though large percent differences between model predictions were observed locally, the extent to which the outliers influenced aggregate estimates of aviation noise impacts was very small.

[32] See Appendix C, Table C2, for a listing of the locations of these airports.

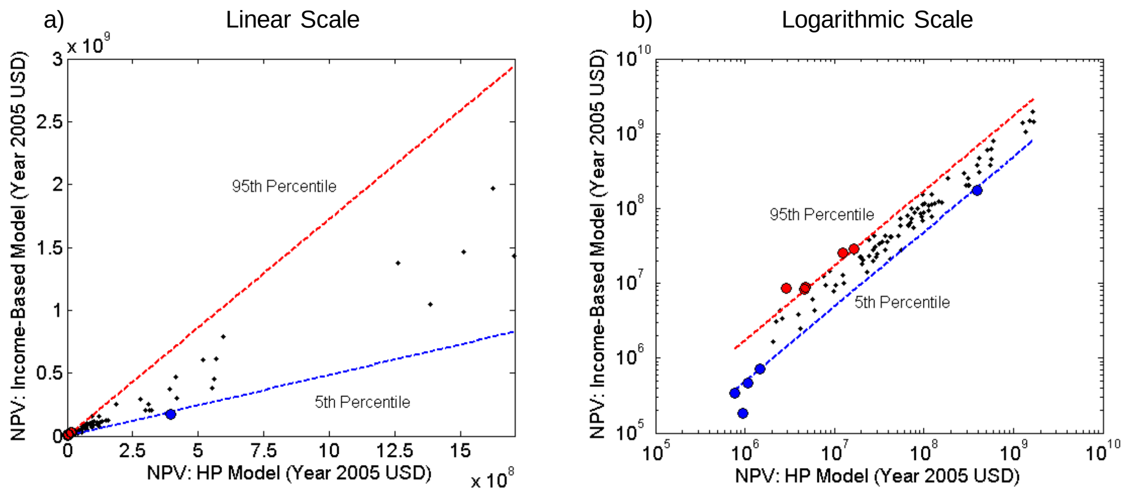


Figure 37: NPV estimates from income-based model versus previous hedonic pricing model: a) linear scale and b) log-log scale. Outliers are highlighted in blue or red and enlarged for emphasis.

Finally, even though the use of NPV as the metric for establishing convergent validity mitigates the inconsistencies and uncertainties discussed in Section 7.3.2.1, the choice of discount rate still has a great effect on the model comparison result. Figure 38 shows that the percent difference in the estimated NPV summed over the 95 US airports is smallest for a discount rate of around 4%. This example further highlights the importance of communicating not only the differences in the outputs when evaluating model performance, but also the assumptions that must be made in order to enable a valid comparison.

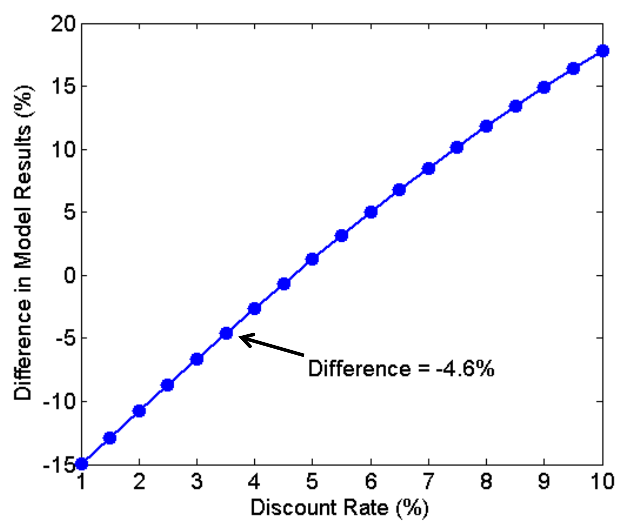


Figure 38: Difference in estimated NPV summed over the 95 US airports as a function of discount rate

The comparisons presented in Section 7.3.2 demonstrate that the income-based hedonic noise monetization model estimated similar capitalized noise impacts and NPV as the previous hedonic pricing model for the 95 US airports in the sample problem. Differences in the results of the two models were generally less than 10% in magnitude, though they were highly dependent on assumptions regarding discount rate and policy time period. It was also shown that those airports exhibiting the largest percent differences in model NPV estimates had only minor contributions to the overall monetary impacts of aviation noise. For the 178 airports around the world, the difference in the total noise impacts estimated by the two models was less than 17%. That the two different noise valuation approaches produced such consistent results is very encouraging for the development effort of the new income-based model. However, while the close comparisons are promising, it must be cautioned that as neither set of results is a gold standard, one model should not be used to validate the other. 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. In this way, the sample problem presented in this chapter has demonstrated the concept of convergent validity: two different measurement techniques produced similar outcomes, but neither result can be assumed to be the true answer. Furthermore, the sample problem showed that the new income-based model was much easier to utilize than the former hedonic pricing model. Therefore, the success of the model development effort is conveyed through the test of convergent validity, as well as through the new model's broad applicability and ease of implementation.

8 Conclusions and Future Work

8.1 Summary and Conclusions

As the global economy develops over the next several decades, it is expected that mobility will rise with income and motivate a shift toward faster modes of transportation [Schafer and Victor (2000)]. The growth of air transportation will also bring about the need to better understand and mitigate the environmental impacts of aviation, to which noise is a major contributor. There are both physical and monetary effects associated with aircraft noise, which include annoyance, sleep disturbance, and property value depreciation.

This thesis presented a new model to quantify the monetary impacts of aviation-related noise based on city-level income. The model development centered on a meta-analysis of 60 aviation noise studies from North America, Europe, and Australia. An extensive data search was performed in order to collect information on income, household size, average property value, income growth rate, inflation rate, and purchasing power parity for each airport region in the meta-study, which were used to derive a general relationship between average personal income and WTP for noise abatement. Various statistical and econometric methods were employed, including tests for outliers, heteroscedasticity, and multicollinearity, as well as weighted least-squares regression, inclusion of control variables, and identification of significant parameters through backward selection. Using a multivariate regression analysis, a model was developed that expressed WTP as a function of city-level personal income and an interaction term, which is the product of income and a non-US dummy variable. This relationship enables benefit transfer of aviation noise impacts on an international scale.

As part of the model development process, uncertainty assessment was conducted to identify sources of uncertainty and how they may limit the model's functionality and applicability. Both epistemic and aleatory uncertainties were identified in the input parameters. Monte Carlo Simulations were used to characterize the propagation of input uncertainties to the model outputs. Local, global, and distributional sensitivity analyses were also conducted. The results of the local sensitivity analysis revealed that the model outputs were particularly sensitive to the choice of income growth rate, as well as the income coefficient in the regression relationship.

From the global sensitivity analysis, it was shown that the three regression parameters – income, interaction term, and intercept – collectively had the greatest contribution to output variability. Finally, the distributional sensitivity analysis confirmed this result, suggesting that the regression parameters should be prioritized for further research, which could lead to refinements to the model that would reduce epistemic uncertainty and thereby enhance accuracy.

Applying the income-based hedonic monetization model to 178 airports worldwide, the global monetary impacts of aviation-related noise in 2005 were estimated. Using 2000 Monte Carlo trials, the mean capitalized impacts were computed to be $25.0 billion, with a standard deviation of $2.2 billion. About 42% of these monetary impacts were contributed by the 95 US airports in the analysis. Comparing the mean result from the new income-based model with the Kish (2008) result, the difference in the estimated capitalized noise impacts was less than 17%. Assuming a 3.5% discount rate and a 30-year policy time period, the Net Present Value of the monetary impacts was $39.1 billion in year 2005 USD.

The income-based hedonic noise monetization model can easily be integrated into the APMT-Impacts Module within the Aviation Environmental Tools Suite. It offers several key advantages over the previous hedonic pricing model used in APMT-Impacts. Chief among them is that it circumvents the need to collect detailed property value data for each airport in a policy analysis, which are often not readily available at a fine resolution outside of the US and the UK. Because property value data are not required, supplemental models to estimate house prices and rental values are also unnecessary, which reduces uncertainty in the model factors. The monetary impacts estimated by the income-based model represent both housing value depreciation and rental loss without the need to distinguish between homeowners and renters among the residents exposed aviation noise. Overall, the income-based hedonic noise monetization model is appealing for its relative ease of implementation, and 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.

8.2 Recommended Future Work

There are several areas of this project that may benefit from additional research efforts. One key issue is the accuracy of the population data used to estimate physical and monetary noise impacts. The US population data date from the 2000 Census, while the GRUMP and EEA data correspond to 2000 and 2001 population levels, respectively. As new data become available, it is important to update the model factors so as use the most accurate inputs possible. In addition to updating the population data, the model algorithm could also be expanded to apply an annual population growth rate, which would be useful for the estimation of future physical and monetary impacts.

Another area for potential future work is the enhancement of model factor data resolution. Currently, the resolution of the noise contour grids is 50m, and for the population density grids, it is 200m. In the future, it may be desirable to enhance this resolution, or employ alternative file formats that would obviate data rasterization and thus reduce information loss. However, in making these refinements, some tradeoffs may be required in order to reconcile the competing demands of data accuracy and computational time.

A third issue is that the current iteration of the APMT-Impacts Noise Module does not explicitly account for the physical impacts of aviation noise, such as annoyance, sleep disturbance, or health effects. Some techniques for assessing these impacts, such as exposure-response functions for estimating the number of people who experience annoyance or sleep disturbance, are already available and can be easily implemented within the algorithm of the existing model. It is expected that the FAA Aircraft Noise Impacts Research Roadmap workshops will stimulate new research in these areas, which will generate more information that can be incorporated into the APMT-Impacts Noise Module and be used to assess various physical impacts. These additional capabilities would enable a more comprehensive representation of the experiences of people affected by aviation noise, and also enhance the utility of the Noise Module for policy analysis and decision-making.

Finally, the area of this thesis project that would benefit the most from additional research is the expansion of meta-analysis data set. As the development of the income-based noise monetization model rested heavily on the collection of hedonic pricing noise studies from around the globe, the process was constrained by data availability, especially in parts of the developing world. As such, the income elasticity of WTP for low-income regions may differ from the linear relationship derived in the regression analysis, which could greatly affect estimates of monetary noise impacts. For example, a recent study of property values around Bangkok's Suvarnabhumi

International Airport between 2002 and 2008 computed an equivalent NDI of 2.14% for the region [Chalermpong (2010)]. When combined with the mean property value reported in the study and the average household size in Bangkok ($142,218 and 3.8 persons, respectively), the WTP per person for one decibel of noise abatement is estimated to be $801 (Equation 4) [National Statistical Office Thailand]. However, using an average national personal income of $3,566 in 2005, the WTP predicted by the regression model is $74 (Equation 6), which differs significantly from the previous result and illustrates the urgent need to increase knowledge of noise impacts around the globe. It is expected that additional studies conducted in parts of the developing world would help elucidate the relationship between income and WTP for noise abatement at the lower end of the income spectrum, which in turn would bolster the validity and broaden the applicability of the income-based hedonic noise monetization model.

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Appendix A: Aviation Noise Meta-Study

Study #	Author	Year	City	Country	Sample Size	Property Value (USD 2000)[1]	NDI (% per dB)	WTP per HH (USD-PPP 2000)[2]	House-hold size[3]	WTP per person (USD-PPP 2000)	Income (USD-PPP 2000)
1	Paik	1970	Dallas	USA	94	104,824	2.30	2,411	2.60	927	18,853
2	Paik	1971	Los Angeles	USA	92	115,073	1.80	2,071	2.60	797	21,923
3	Paik	1972	New York (JFK)	USA	106	96,938	1.90	1,842	2.60	708	24,586
4	Roskill Commission	1970	London (LHR)	UK	20	86086	0.71	633	2.90	218	10,010
5	Roskill Commission	1970	London (LGW)	UK	20	*86086*	1.58	1,409	2.90	486	10,010
6*	Mason	1971	Sydney	Australia			0.00				
7	Emerson	1972	Minneapolis	USA	222	101,564	0.59	599	2.68	224	21,747
8*	Coleman	1972	Englewood	USA	21		1.58				
9	Dygart	1973	San Francisco	USA	82	122,544	0.50	613	2.27	270	26,536
10	Dygart	1973	San Jose	USA	98	93,240	0.70	653	2.92	224	23,732
11	Price	1974	Boston	USA	270	*128,120*	0.81	1,038	2.48	419	21,900
12	Gautrin	1975	London (LHR)	UK	67	82,011	0.62	527	2.80	188	11,759
13	De Vany	1976	Dallas	USA	1,270	97,680	0.80	781	2.67	293	21,563
14	Maser et al.	1977	Rochester	USA	398	81,175	0.86	698	2.56	273	22,511
15	Maser et al.	1977	Rochester	USA	990	92,650	0.68	630	2.56	247	22,511
16	Balylock	1977	Dallas	USA	4,264	111,000	0.99	1,099	2.60	423	22,267
17	Mieszkowski & Saper	1978	Toronto	Canada	509	139,771	0.66	1,111	2.70	411	14,082
18	Fromme	1978	Washington Reagan	USA	28	133,502	1.49	1,989	2.46	809	27,441
19	Nelson	1978	Washington Reagan	USA	52	121,900	1.06	1,292	2.46	525	27,441
20	Nelson	1979	San Francisco	USA	153	131,806	0.58	764	2.20	347	29,801
21	Nelson	1979	St. Louis	USA	113	72,865	0.51	372	2.51	148	22,614
22	Nelson	1979	Cleveland	USA	185	92,787	0.29	269	2.37	114	24,720
23	Nelson	1979	New Orleans	USA	143	97,569	0.40	390	2.65	147	20,761
24	Nelson	1979	San Diego	USA	125	143,150	0.74	1,059	2.53	419	23,275

Study #	Author	Year	City	Country	Sample Size	Property Value (USD 2000)[1]	NDI (% per dB)	WTP per HH (USD-PPP 2000)[2]	House-hold size[3]	WTP per person (USD-PPP 2000)	Income (USD-PPP 2000)
25	Nelson	1979	Buffalo	USA	126	91,713	0.52	477	2.40	198	21,276
26	Abelson	1979	Sydney	Australia	592	98,773	0.40	517	3.00	172	11,356
27	Abelson	1979	Sydney	Australia	822	112,883	0.00	0	3.00	0	11,356
28	McMillan et al.	1980	Toronto	Canada	352	133,817	0.51	822	2.70	304	15,708
29	Mark	1980	St. Louis	USA	6,553	68,543	0.42	288	2.49	116	21,903
30*	Hoffman	1984	Bodo	Norway			1.00				
31	O'Byrne et al.	1985	Atlanta	USA	248	80,597	0.64	516	2.24	231	25,014
32	O'Byrne et al.	1985	Atlanta	USA	96	64,422	0.67	432	2.24	193	25,014
33	Opschoor	1986	Amsterdam	Netherlands		*82,732*	0.85	854	2.82	303	16,501
34*	Pommerehne	1988	Basel	Switzerland			0.50				
35	Burns et al.	1989	Adelaide	Australia	100	92,482	0.78	943	2.60	363	11,504
36	Penington	1990	Manchester	UK	3,472	78,357	0.34	276	2.50	110	13,058
37	Gillen & Levesque	1990	Toronto	Canada	1,886	214,899	1.34	3,468	2.70	1,284	18,539
38*	Gillen & Levesque	1990	Toronto	Canada	1347	135472	-0.01				
39	BIS Shrapnel	1990	Sydney	Australia	344	*170,836*	1.10	2,457	2.90	847	12,035
40	Uyeno	1993	Vancouver	Canada	645	156,558	0.65	1,226	2.60	471	21,557
41	Uyeno	1993	Vancouver	Canada	907	156,558	0.90	1,697	2.60	653	21,557
42	Tarassoff	1993	Montreal	Canada	427	151,859	0.65	1,189	2.40	495	17,278
43	Collins & Evans	1994	Manchester	UK	558	78,357	0.47	381	2.50	153	12,916
44	Levesque	1994	Winnipeg	Canada	1,635	88,488	1.30	1,385	2.50	554	18,078
45	BAH-FAA	1994	Baltimore	USA	30	163,281	1.07	1,747	2.39	731	28,380
46	BAH-FAA	1994	Los Angeles	USA	24	442,338	1.26	5,573	2.56	2,175	27,370
47	BAH-FAA	1994	New York (JFK)	USA	30	502,775	1.20	6,033	2.46	2,451	33,625
48	BAH-FAA	1994	New York LGA)	USA	30	264,815	0.67	1,774	2.46	721	33,625
49	Mitchell McCotter	1994	Sydney	Australia	750	170,836	0.68	1,519	2.90	523	12,278
50	Yamaguchi	1996	London (LGW)	UK		*264,782*	2.30	6,308	2.39	2,639	15,720
51	Yamaguchi	1996	London (LHR)	UK		*264,782*	1.51	4,141	2.39	1,733	15,720

Study #	Author	Year	City	Country	Sample Size	Property Value (USD 2000)[1]	NDI (% per dB)	WTP per HH (USD-PPP 2000)[2]	House-hold size[3]	WTP per person (USD-PPP 2000)	Income (USD-PPP 2000)
52	Myles	1997	Reno	USA	4,332	170,100	0.37	629	2.38	264	32,694
53	Tomkins et al.	1998	Manchester	UK	568	105,227	0.63	687	2.40	286	13,830
54	Espey & Lopez	2000	Reno-Sparks	USA	1,417	132,498	0.28	371	2.56	145	36,019
55	Burns et al.	2001	Adelaide	Australia	5,207	*135,353*	0.94	1,664	2.40	693	26,298
56	Rossini et al.	2002	Adelaide	Australia	4,139	146,181	1.34	2,561	2.40	1,067	26,105
57	Salvi	2003	Zurich	Switzerland	565	382,101	0.75	2,611	2.10	1,243	22,664
58	Lipscomb	2003	Atlanta	USA	105	105,766	0.08	85	2.40	35	30,625
59	McMillan	2004	Chicago	USA	4,012	183,727	0.81	1,488	3.06	486	34,347
60	Mc Millan	2004	Chicago	USA	22,541	193,917	0.88	1,706	3.06	558	34,347
61	Baranzini & Ramirez	2005	Geneve	Switzerland	1,847	376,673	1.17	4,015	2.10	1,912	26,650
62	Cohen & Coughlin	2006	Atlanta	USA	1,643	76,570	0.43	329	2.40	137	31,166
63	Cohen & Coughlin	2007	Atlanta	USA	508	120,696	0.69	833	2.40	347	31,347
64	Faburel & Mikiki	2007	Paris	France	688	123,895	0.06	86	2.40	36	22,698
65	Pope	2007	Raleigh	USA	16,900	212,005	0.36	763	2.46	310	32,700

Adapted from Wadud (2009), Table 4.2

* Study excluded from multivariate regression.

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[1] Property values from Wadud (2009) were given in USD 2000, and conversions were performed using the US-foreign currency exchange rate (later re-adjusted using the PPP). *Italicized values* are not given in Wadud (2009), but gathered from various national statistical agencies.

[2] Willingness to Pay per household was calculated as Property Value x NDI, where the property value from Wadud (2009) was adjusted to USD using the 2000 PPP [OECD (2000)].

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

Appendix B: Calculation of Adjusted Main-Effect Sensitivity Indices for DSA

Let NPV represent the Net Present Value of monetary noise impacts summed over all airports, which in the uncertainty assessment analysis of this thesis is an output vector computed over 2000 MC runs. Let NPV_j denote the contribution to the NPV by the j^{th} airport, which is also a 2000x1 vector. Taking advantage of the linearity of the problem, these contributions may summed according to:

$$\mathrm{NPV} = \sum_j \mathrm{NPV}_j \tag{B1}$$

Since the NPV_j distributions are independent (e.g. there are no interaction effects among airports), the variance may be decomposed in the following manner:

$$\mathrm{var}(\mathrm{NPV}) = \sum_j \mathrm{var}(\mathrm{NPV}_j) \tag{B2}$$

The variance of each NPV_j distribution may be apportioned to three different input parameters: background noise level, contour uncertainty, and regression parameters. This apportionment does not account for any interaction effects among the inputs. Let MSI_{ij} denote the main-effect sensitivity index of input *i* at airport *j*. Equation B2 may be rewritten as:

$$\mathrm{var}(\mathrm{NPV}) = \sum_j \sum_i \left[\mathrm{MSI}_{ij}\ \mathrm{var}(\mathrm{NPV}_j)\right] \tag{B3}$$

Rearranging Equation B3, the following relations may be used to explicitly express the MSI for each input *i*:

$$1 = \frac{1}{\mathrm{var}(\mathrm{NPV})} \sum_j \sum_i \left[\mathrm{MSI}_{ij}\ \mathrm{var}(\mathrm{NPV}_j)\right] \tag{B4}$$

$$\mathrm{MSI}_i = \frac{1}{\mathrm{var}(\mathrm{NPV})} \sum_j \left[\mathrm{MSI}_{ij}\ \mathrm{var}(\mathrm{NPV}_j)\right] \tag{B5}$$

The MSI_i represents the proportion of total output variance that may be attributed to input *i* alone when it is assumed that all epistemic uncertainty associated with input *i* may be reduced to zero through further research and improved knowledge. In DSA, however, it is desirable to understand how the sensitivity index changes with δ, the ratio of the variance of input *i* that cannot be reduced and the total variance of the original distribution for that input. The analogous quantity for MSI_i in DSA is $adjS_i(\delta)$, the adjusted main-effect sensitivity index of input *i* given that it is known that only 100(1– δ)% of its variance can be reduced. Similarly, the analogy for MSI_{ij} in DSA is $adjS_{ij}(\delta)$. Making the appropriate substitutions, Equation B5 may be rewritten to derive an expression for $adjS_i(\delta)$:

$$\mathrm{adjS}_i(\delta) = \frac{1}{\mathrm{var}(\mathrm{NPV})} \sum_j \left[\mathrm{adjS}_{ij}(\delta)\ \mathrm{var}\left(\mathrm{NPV}_j\right)\right] \tag{B6}$$

Appendix C: Airports and Sources of Income Data

Table C1: Non-US Shell 1 airports and income data sources

Airport	**City**	**Country**	**Data Resolution**	**Income Data Source**
ALG	Algiers	Algeria	Country	*Populstat*[1]
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*	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*	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*	Athens	Greece	Country (Estimated)	
SYZ	Shiraz	Iran	Country	*Central Bank of the Islamic Republic of Iran*
THR	Tehran			

Airport	**City**	**Country**	**Data Resolution**	**Income Data Source**
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*	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*	Kuwait	Kuwait	Country (Estimated)	
GDL	Guadalajara	Mexico	Country	*International Labour Organization*
MEX	Mexico City			
MID	Merida			
TIJ	Tijuana			
AMS	Amsterdam	Netherlands	City[2]	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*[3]
RUH	Riyadh			
SIN	Singapore	Singapore	City-state	Statistics Singapore

Airport	City	Country	Data Resolution	Income Data Source
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*	Istanbul	Turkey	Country (Estimated)	
LGW	London	United Kingdom	City	Office for National Statistics
LHR	London			
MAN	Manchester			
TAS*	Algiers	Uzbekistan	Country (Estimated)	

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

* Income was estimated for the airport region based on 2005 GNI per capita, PPP method [World Bank (2007)].

[1] Income was provided as a range between1600-2020 USD (unknown date); the midrange value was used. Source: Lahmeyer, J. (2004) [online]. *Algeria: General Data of the Country.* http://www.populstat.info/Africa/algeriag.htm. Accessed August 4, 2009.

[2] 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.

[3] Source: Japan International Cooperation Agency, Planning and Evaluation Department (2003). *Country Profile Study on Poverty: Saudi Arabia*, pp. 7.

Table C2: US Shell 1 airports and MSA-level income data obtained from the US BEA

Airport	City	State	2005 Income ($)
ABE	Allentown	PA	33,537
ABQ	Albuquerque	NM	30,880
ALB	Albany	NY	35,981
ANC	Anchorage	AK	39,379
ATL	Atlanta	GA	35,424
AUS	Austin	TX	34,863
BDL	Hartford	CT	42,797
BFI	Seattle	WA	42,804
BHM	Birmingham	AL	35,818
BNA	Nashville	TN	35,692
BOI	Boise	ID	32,444
BOS	Boston	MA	47,128
BUF	Buffalo	NY	31,832
BWI	Baltimore	MD	41,099
CAE	Columbia	SC	30,768
CLE	Cleveland	OH	35,322
CLT	Charlotte	NC	36,861
CMH	Columbus	OH	34,610
COS	Colorado Springs	CO	33,145
CVG	Cincinnati	OH	35,009
DAY	Dayton	OH	31,376
DCA	Washington, DC	DC	49,606
DFW	Dallas/Ft. Worth	TX	38,085
DSM	Des Moines	IA	37,634
DTW	Detroit	MI	36,692
ELP	El Paso	TX	23,875
EWR	Newark	NJ	48,675
FAT	Fresno	CA	25,950
FLL	Fort Lauderdale	FL	38,259
FSD	Sioux Falls	SD	35,754
GEG	Spokane	WA	28,802
GRR	Grand Rapids	MI	31,661
GSO	Greensboro	NC	31,391
HNL	Honolulu	HI	37,188
HOU	Houston	TX	40,565
IAD	Washington, DC	DC	49,606
IAH	Houston	TX	40,565
ICT	Wichita	KS	33,695
ILN	Wilmington	OH	28,237
IND	Indianapolis	IN	35,752
ITO	Hilo	HI	27,147
JAX	Jacksonville	FL	35,333

Airport	City	State	2005 Income ($)
JFK	New York	NY	46,026
KOA	Kailua-Kona	HI	27,147
LAS	Las Vegas	NV	36,869
LAX	Los Angeles	CA	37,543
LGA	New York	NY	46,026
LIH	Kauai Island/Lihue	HI	29,566
LIT	Little Rock	AR	33,184
MCI	Kansas City	MO	35,593
MCO	Orlando	FL	31,822
MDW	Chicago	IL	39,409
MEM	Memphis	TN	34,057
MHT	Manchester	NH	39,240
MIA	Miami	FL	38,259
MKE	Milwaukee	WI	37,193
MSP	Minneapolis	MN	42,377
MSY	New Orleans	LA	18,983
OAK	Oakland	CA	53,557
OGG	Kahului	HI	31,486
OKC	Oklahoma City	OK	33,387
OMA	Omaha	NE	37,816
ONT	Ontario	CA	26,789
ORD	Chicago	IL	39,409
ORF	Norfolk	VA	33,129
PBI	West Palm Beach	FL	51,374
PDX	Portland	OR	35,115
PHL	Philadelphia	PA	40,720
PHX	Phoenix	AZ	33,066
PIT	Pittsburgh	PA	36,097
PVD	Providence	RI	35,106
RDU	Raleigh/Durham	NC	36,001
RIC	Richmond	VA	36,995
RNO	Reno	NV	42,756
ROC	Rochester	NY	33,996
RSW	Fort Myers	FL	38,482
SAN	San Diego	CA	40,406
SAT	San Antonio	TX	31,168
SDF	Louisville	KY	33,751
SEA	Seattle	WA	42,804
SFO	San Francisco	CA	53,557
SHV	Shreveport	LA	30,574
SJC	San Jose	CA	51,418
SJU	San Juan	PR	15,182[1]
SLC	Salt Lake City	UT	33,287
SMF	Sacramento	CA	35,355

Airport	City	State	2005 Income ($)
SRQ	Sarasota	FL	43,206
STL	St. Louis	MO	35,653
SWF	Newburgh/Stewart Field	NY	34,105
SYR	Syracuse	NY	31,366
TOL	Toledo	OH	30,496
TPA	Tampa	FL	33,607
TUL	Tulsa	OK	35,483
TUS	Tucson	AZ	29,354
TYS	Knoxville	TN	30,720

[1] For San Juan, Puerto Rico, MSA-level income was not available from the US BEA; instead, city-level income from the 2000 US Census was used, and adjusted to year 2005 USD using the nationwide income growth rate.