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Article

Meta-analysis of contingent valuation studies on air pollution-related morbidity risks

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Abstract Benefits of reduced morbidity are important information for cost-benefit analyses of air pollution control policies. With an increasing number of morbidity valuation studies, policymakers are facing some difficulty handling the accumulated information. This article uses a meta-analysis to attain insights from the literature on economic valuation of short-term health effects due to air pollution. Sixteen available contingent valuation studies on morbidity risk valuation were pooled to identify the relations between willingness-to-pay (WTP) estimates and possible influential factors. The results indicate that health risk characteristics expressed in terms of severity and duration of illness, population characteristics (e.g., income and education), and study features affect individuals' WTP to reduce or avoid a given morbidity. By controlling for these factors, a meta-regression-based function can be used to predict WTP values for use in benefit analyses of policy evaluation.

Key words Air pollution · Contingent valuation · Meta-analysis · Short-term morbidity valuation

1 Introduction

Achieving the air pollution control objectives established by the government requires massive expenditure on the part of both the public and private sectors. The question arises whether we are getting the most improvement possible in environmental quality for the money spent. To design efficient environmental

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policies, economists propose using cost-benefit analysis as a tool for decision-making.[1]

Improvements in human health are regarded as the most important benefits of air quality regulations (Cropper 2000). When evaluating health effects, economists merge the results from the epidemiological literature, which links air pollution to illness, with the results from the economic literature that places a value on illness. A number of health effects are under valuation: acute morbidity, chronic morbidity, and mortality. Even though mortality risk reduction dominates the health benefits, a significant part of the health effects are due to morbidity. The morbidity effects calculated from dose-response functions are dominated by reduced well-being due to acute respiratory symptoms such as coughing, sinus congestion, and wheezing, as well as measures such as symptomatic days and restricted activity days. More serious respiratory illness measures such as asthma symptoms, emergency room visits, and respiratory hospital admission are also important.

Economists have developed methods for estimating the monetary values of changes in human health associated with environmental changes. The monetary values are expressed in terms of individual preferences, called willingness to pay (WTP). In the area of morbidity valuation, the main source of estimates of the WTP value of reduced morbidity for cost-benefit analyses has been contingent valuation (CV) studies. The CV technique requires that researchers directly ask people of their WTP for a given change in their health effects. Most commonly referred to studies are five CV surveys conducted in the United States (see Appendix 1): Loehman et al. (1979), Tolley et al. (1986), Dickie et al. (1987, 1988), Rowe and Chestnut (1985), and Chestnut et al. (1988). Each study estimated values for various symptoms. Four of these studies elicited respondents' WTP to reduce or avoid common health effects associated with air pollution, such as cough, wheezing, asthma attacks, headaches, and chest discomfort. In addition, Tolley et al. (1986) and Chestnut et al. (1988) elicited WTP to avoid angina attacks. All five studies were conducted during the late 1970s and 1980s, the early period of the development of CV methodology. Because of several shortcomings found in these pioneering CV studies,[2] the WTP estimates from these studies are seen as uncertain and often unreliable.

Several authors have qualitatively reviewed the literature and used their knowledge to make judgments about which estimates are more reasonable. Some researchers have even agreed with the conclusion that the imprecision of the available estimates of morbidity benefits preclude a definitive point-estimate of the benefit. This has become common practice in benefit studies on air quality improvements in that the authors select a "best study" qualitatively or use a wide range of values from the literature with some probability weights for all health effects.[3]

In contrast to adhoc adjustments or selections of the existing studies, the present study uses meta-analysis to assess the morbidity valuation literature quantitatively. The results from the existing studies are pooled to identify systematic relations between individuals' WTP for reducing short-term health effects and various underlying factors that possibly affect WTP.

This study is an extension of a prior meta-analysis performed by Johnson et al. (1997), a pioneering group who combined a health-state index and morbidity valuation studies. Using this method, the various health conditions valued in the five U.S. studies referred to above could be pooled. However, this meta-analysis is limited in the number of studies included and explanatory variables. That is, only two attributes of health conditions, duration of illness and degree of severity, are controlled in the panel models.

In the current meta-analysis, 11 new studies were added to the five U.S. studies used in the Johnson et al. study. The sufficient number of WTP estimates across countries enables incorporation of national demographic characteristics in the analysis (referred to as "population characteristics"). In addition, study features such as different elicitation formats and survey methods (referred to as "study design characteristics") are included in this meta-analysis to assess the contingent valuation technique development in the area of morbidity valuations.

The remainder of this article is organized as follows. Section 2 reviews the morbidity valuation studies and the discussions of their techniques. Section 3 presents the analytical tool of meta-analysis, including the meta-regression model. Section 4 describes the characteristics of the data set and the approach linking WTP to the health-state index. Section 5 contains the meta-regression analysis. The results are reported in Section 6. Conclusions are drawn in Section 7.

2 Morbidity valuation studies

This study focuses on an economic valuation of air pollution-related morbidity risk reduction, particularly for the short term.[4] Freeman (1993) defined morbidity as a departure from a state of physical or mental well-being, resulting from

[1] The role of cost-benefit analysis took a major leap in the United States with President Reagan's Executive Order 12291, issued in 1981, requiring that all new major regulations be subject to a cost-benefit test. The U.S. Environmental Protection Agency (U.S. EPA) has issued the Benefit-cost Analysis of Clean Air Act 1970 to 1990 and the Benefit-cost Analysis of Clean Air Act 1990 to 2010. The Organization for Economic Cooperation and Development (OECD) and the United Nations have also developed guidelines for evaluating projects in developing countries. The World Bank has used cost-benefit analysis to evaluate its projects (Desvousges et al. 1998).

[2] For example, Rowe et al. (1995) commented that most of the WTP studies completed to date have limitations due to small sample sizes and limited variation in the health effect studied, and few of these studies have been replicated.

[3] Examples of previous benefits studies using this approach are those of Krupnick and Portney (1991), Hall et al. (1992), Rowe et al. (1995), Small and Kazimi (1995), Pearce and Crowards (1996), Ostro and Chestnut (1998), and McCubbin and Delucchi (1999).

[4] Although the benefit estimate from reduced mortality risks dominates the total health benefits, estimating the short-term morbidity benefit is also important, as a large number of people exposed to air pollution experience a wide range of short-term illnesses.

disease or injury, of which the affected individual is aware. Morbidity can be classified in a variety of ways, among them the duration of the condition (chronic and acute), the degree of activity impairment, and the type of symptoms. This study included only acute morbidity, which is defined as an ill condition that lasts only a matter of days and would have a well-defined beginning and end (Cropper and Freeman 1991).

Economists have developed many environmental valuation methods. Three methods are used most often to value environmental morbidity: (1) cost of illness; (2) averting behavior; and (3) contingent valuation (Cropper and Freeman 1991; U.S. EPA 2000b).[5] The first is the cost-of-illness (COI) method, which measures the costs incurred as a result of illness such as medical expenses and foregone earnings. This method directly measures values using observed behavior and is most prevalent in the medical economics literature. The COI method does not measure WTP for reduced morbidity. Two other methods are more prevalent in the environmental economics literature. The averting behavior method (a revealed preference method) estimates WTP from observed behavioral responses to real situations. This method infers WTP from the cost and effectiveness of actions taken to defend against illness. The contingent valuation (CV) method, the most commonly used stated preference method, measures respondent's WTP for hypothetical health improvements.

Each of these three methods has its strengths and weaknesses. The COI method is the most straightforward, but it does not measure WTP and neglects the value of avoided pain and suffering. The averting behavior method is the only one among the three that provides WTP estimates based on actual behavior, but it is difficult to measure the costs and health benefits of averting action.[6] The CV method, regarded as the most flexible method in principle, could be designed to value any illnesses. The method also appears to be the only way to measure dollar values for altruism toward people outside the immediate household. The hypothetical nature of contingent valuation, however, makes it controversial and subject to potential inaccuracy and imprecision.

Although the CV method has some limitations, it has become widely accepted in recent years. In the area of acute or short-term morbidity, CV studies have been used as a main source of estimates of most cost-benefit studies on pollution control. Most referred studies are from the United States: Loehman et al. (1979), Tolley et al. (1986), Dickie et al. (1987), Rowe and Chestnut (1985), and Chestnut et al. (1988). New CV studies conducted in many countries include those of Alberini et al. (1997) in Taiwan, Navrud (1998) in Norway, and Ready et al. (2001) in five European countries.

[5] Several other methods have been used less frequently to value environmental morbidity, including hedonic methods and other methods that, similar to the COI method, do not measure WTP: risk-risk tradeoffs and health-state indexes (U.S. EPA 2000b).

[6] For more discussion on the averting-behavior approach, see Cropper (1981), Gerking and Stanley (1986), and Dickie and Gerking (1991).

These studies provide estimates for a wide range of common, often overlapping, minor symptoms, such as coughs and headaches or acute illnesses such as acute bronchitis and asthma attacks. For the estimates, which can be compared, WTP values for each short-term health effect are different across studies, as shown in Table 1. The diversity of health effect and WTP estimates reported in individual studies raises some difficulties in the use of the accumulated information for policy evaluations.

In addition, for the more serious health effects for which WTP estimates are not available, including restricted activity day, emergency room visits, and respiratory hospital admissions, previous health benefit studies on air quality improvements have used COI values with some adjustment factors.[7] However, WTP estimates for these health effects are available now in the literature (Chestnut et al. 1998; Dubourg 1998; Ready et al. 2001), and it is possible to replace the previously used COI values with the available WTP estimates.

Meta-analysis is used to explore ways in which greater insight may be gained by reviewing the findings of previous studies. This article reports the results of a meta-regression of 125 WTP estimates from 16 studies. The characteristics of the data set are presented later in Section 4.

3 Meta-analysis

Meta-analysis is the statistical analysis of the summary findings of prior empirical studies. The overall goal of meta-analysis is to combine the results of previous studies to arrive at summary conclusions about a body of research (Pettiti 1994). Meta-analysis has been developed over the last 30 years and has most commonly been applied in the fields of experimental medical treatment, psychotherapy, learning, and education.

Meta-analysis offers a number of possible advantages over conventional procedures, which follow a narrative style for bringing together information from previous case studies. In particular, the standard approach when reviewing previous work, and in making use of the selected results, suffers from several limitations, some of which can be circumvented, minimized, or at least made transparent by an appropriate meta-analysis (van den Berg et al. 1997). Although relatively little used for environmental research to date, meta-analysis does have the potential to offer new insights into a number of important areas (Button 1995). It can extract additional information from work that has already been done. It allows useful consideration of the pool of existing studies constructed on environmental issues and allows us to draw from this pool common threads, outliers, and linkages.

[7] Ostro and Chestnut (1998) used COI values adjusted upward because they claimed that COI does not normally reflect the full value of avoiding a health effect. Based on a previous review of three studies that estimated both WTP and COI for the same health effects, the WTP/COI ratios ranged from 1.3 to 2.4.

Table 1. Summary of previous WTP to avoid/reduce health effects from air pollution (1995 US$)

Health effect	Developed countries						Developing countries		
	Loehman et al. (1979)	Rowe & Chestnut (1985)	Tolley et al. (1986)	Dickie et al. (1987)	Navrud (1998)	Barton (1999)	Dubourg (1998)	Meegan (1998)	Barton (1999)
Cough	$12.3	—	$33.5	$15.2	$15	$71	$18.1	$2.4	$40
Eye irritation	—	—	$36.9	—	$19.8	$86	$26.7	$5.6	$43
Headache	$20.2	—	$53.4	$25	$6.3	—	—	$11.4	—
Throat irritation	—	—	$38.6	$22.1	$15	—	—	$7.2	—
Shortness of breath	$35.3	—	—	$9.2	$40.3	—	—	$7.7	—
Sinus congestion	—	—	$46.7	$17.5	$29.5	—	—	—	—
Chest congestion	—	—	—	$26.1	—	—	—	$10.9	—
Asthma attacks	—	$60.1	—	—	$84.6	—	—	$14.2	—

Source: See references in Appendix 1
WTP, willingness to pay
All estimates are for WTP to avoid/reduce 1-day of illness only

Table 2. Advantages and disadvantages of meta-analysis

Advantages
Improves literature review and avoids the subjective nature of conventional reviews
Generates strong, reliable conclusions by using statistical analysis
Provides insights into new directions for research and finding relations either too subtle to see or that cannot be hypothesized and tested in individual studies
Disadvantages
Aggregate studies that have different methodologies and variables measured
Includes results from "poorly" designed studies with results from "good" studies, leading to uninterpretable results
Includes only studies reporting significant results, leading to study selection bias
Uses multiple results from the same studies, causing unreliable results

Source: Brouwer et al. (1997), Van den Bergh et al. (1997), and Wolf (1986)

Although the meta-analysis has many advantages over traditional reviewing procedures, it has some limitations when we employ it for economic research. Meta-analysis can reduce subjectivity when assessing several evaluation studies and seeking relevant common lines, but it cannot remove it. This is so because the technique brings together a number of studies, and the analyst is obviously instrumental in their selection. The subjectivity is inherent; but, equally, the use of statistical analysis would mean that the conclusions drawn from any given set of studies could be subjected to analysis that is more rigorous. Another problem is the possible bias that results from the nature of the studies: which are included or excluded.

Table 2 summarizes the merits and criticisms of meta-analysis often mentioned in the literature. Van den Berg et al. (1997) suggested the potential of meta-analysis in environmental economics for (1) developing a consensus on point estimates during economic valuation of environmental degradation or improvement and (2) exploring factors that have influenced variations in point estimates (WTP estimates) among individual studies.

Recently, the meta-analysis has started to play a role in environmental economics research, particularly in the field of environmental valuation (Smith and Kaoru 1990; Walsh 1992; Bateman et al. 1995a; Smith and Huang 1995; Carson et al. 1996).[8] Brouwer et al. (1997) pointed out several reasons for the increasing use of meta-analysis. First, there is an increase in the available number of environmental valuation studies. Second, the seemingly large differences in valuation outcomes are due to the use of different research designs. Finally, carrying out environmental valuation studies is costly, which tends to increase policymaker demand for transferable valuation results.

In the area of health benefit valuation, many meta-analyses have been carried out to evaluate value of statistical life (VSL) estimates for mortality risk reduc-

[8] Smith and Pattanayak (2002) reviewed most meta-analyses involving benefit estimates for changes in environmental resources.

tion (Van den Berg et al. 1997; Desvousges et al. 1998; Bowland and Beghin 1999; Day 1999; Blaeij et al. 2000; Miller 2000; Mrozek and Taylor 2002). By contrast, to our knowledge, only one full meta-analysis exists (Johnson et al. 1997) for morbidity valuation studies. Our meta-analysis thus contributes to the dearth of meta-analysis literature in the field of morbidity valuation studies.

Most of the meta-analyses in economics are based on the so-called meta-regression technique. A meta-regression is usually based on least-square estimation in which a specific effect measure observed in a series of studies is taken as the dependent variable. The set of independent variables frequently includes specific underlying causes for the phenomenon under consideration, and moderator variables representing, for example, differences among research designs, time periods, and locations covered in the original studies (Stanley and Jarrell 1989).

In this study, a meta-regression analysis has been adopted to examine the relation of WTP values and a number of potential independent variables as follows

$$\mathrm{WTP}_s = a + bX_j + cY_s + Z_s + u_{sj} \quad (1)$$

where WTP_s is the mean willingness to pay from study s; a, b, c are parameters; X_j is health risk characteristics (j); Y_s is the sample population characteristics of study s; Z_s is study design characteristics of study s; and u_{sj} is random error. The number of observations is equal to the number of the mean WTP estimates taken from each study.

4 Data set for meta-regression

Before we describe the data set, it is important to note here that because this study combines CV studies with different currencies at different times, the gross domestic product (GDP) deflator of each country of study is adopted to deflate all money values to 1995 prices (IMF 2001). The deflated values then are converted to the U.S. dollar at the national market exchange rate for the U.S. dollar in 1995.[9]

4.1 Characteristics of data set

Prior to data set-making, it is necessary to define the characteristics of the studies to be pooled that have a similar basis. Several fundamental characteristics of individual studies included in the meta-analysis are as follows.[10]

[9] The GDP deflator for Taiwan was not available in the International Financial Statistics Yearbook (IMF 2001). We found the index on the Internet (http://www.asianinsider.com/Economic/history_taiwan.asp).

[10] Other selection criteria may be the reliability and validity of studies (e.g., discarding studies having a small sample size). Although realizing the need for these criteria, because of the small number of available studies on morbidity valuation we stand on the "collect as many as possible" principle. This principle was adopted in a meta-analysis of the value of statistical life in road safety (Blaeij et al. 2000).

First, the studies all use CV methods. Studies that use other valuation approaches, such cost of illness and averting behavior, are not included because COI studies do not measure WTP. Averting-behavior studies are impaired by the problem of joint products and require information about the efficacy of goods in producing health information that may be limited. Moreover, given the many criticisms of the CV design effects on WTP estimates, it is interesting to investigate whether different CV designs have a strong effect on varying WTP estimates. Results from other CV-based meta-analyses suggest that differences in CV designs play an important role in explaining the variation among valuation outcomes (Bateman et al. 1995a; Brouwer et al. 1997).

Second, the studies value short-term morbidity associated with air pollution. WTP studies of chronic morbidity are omitted. Initially, chronic morbidity valuation studies were examined to see the possibility of combining both valuation studies; however, most of the chronic morbidity studies value WTP in terms of WTP per case, not WTP per duration of being reduced or avoided. Given the different units of value and the scarcity of research studies on chronic morbidity, this meta-analysis includes only short-term morbidity studies valuing relatively similar durations. Finally, the studies specify the exact number of days being reduced or avoided. To control for temporal differences among studies, we must know the number of days being reduced or avoided.

Because of a growing concern over the reliability of CV methods in non-use valuations, a panel group under the National Oceanic and Atmospheric Administration (NOAA) has provided a guideline for obtaining reliable, valid WTP results. One of the principal criteria in the guideline is that WTP estimates that are "adequately" responsive to the scope of the environmental insult (Arrow et al. 1993). This requires a test of CV estimates to determine if CV estimates of WTP are responsive to the amount, or scope, of the environmental goods being offered; this is called the scope test. In the case of environmental health valuation, the meta-analysis can be used to examine whether the WTP to reduce or avoid 10 days of having a given symptom is greater than the WTP to reduce one symptom day.[11]

The initial reference of CV studies on short-term health effects is taken from the meta-analysis of Johnson et al. (1997). New studies were traced from the World Wide Web search engines and relevant journals. Consequently, our data set covers studies from various developed and developing countries. In addition to articles published in journals, unpublished papers, or "gray literature" such as dissertations, conference papers, and preprints of articles, have been retrieved to minimize publication bias, which is a criticism against the meta-analysis. Consequently, 11 new studies have been added to the previous 5 studies in the Johnson

[11] The scope test was used in Smith and Osborne's (1996) meta-analysis of five CV studies that estimated WTP for visibility improvements. The authors found a positive, statistically significant relation between the WTP estimates and the percentage improvement in the visible range.

et al. study, resulting in 16 studies with 125 observations in our database (Table 3).[12] Some studies are responsible for multiple observations because they value several short-term health effects. This can be differentiated by use of the quality of well-being (QWB) score (explained in the next section).

It is worthy of note that our research tries to overcome the limitation of the meta-analysis that can utilize only the common features of the existing studies. An attempt was made to contact some of the authors of the existing studies to obtain important information about the socioeconomic background of the respondents. As a result, this study has been able to collect demographic data of respondents and include them as explanatory variables in meta-regressions. All of the studies, except that by Loehman et al. (1979), reported the average household incomes of the respondents.[13] Data, however, are still missing in some studies for which we were unable to contact the authors. For example, two studies (Loehman et al. 1979; Yee 1998) did not report data for average age and percentage of male respondents, and Liu et al. (2000) did not give any information on the average age of the respondents. Information on the respondents' education attainment level was not reported in two studies (Rowe and Chestnut 1985; Kartman et al. 1996). Ibanez and McConnell (2001) lacked data on education attainment and percentage of male respondents.

Substantial useful information would be lost if all observations that had some missing data were deleted. Therefore, the missing data were filled in by external data available at official government websites and in international statistics yearbooks such as the World Bank's world development indicators for the year of the study (or the closest year).

It is worthy of note here that some studies reported only median WTP estimates (Alberini et al. 1997; Liu et al. 2000). Notwithstanding differences between mean and median values, median estimates in both studies were assumed to be comparable to the mean WTP in other studies. Because these two studies accounted for only five observations, it is unlikely that these estimates biased the general results.

4.2 Linking WTP with QWB scores

In contrast to mortality, which presents a single, well-defined health outcome, morbidity can be assessed at various stages. This creates a difficult problem regarding the comparability of morbidity WTP values from different studies. Johnson et al. (1997) solved this problem by combining different WTP studies with a "health-state index." In the literature, the health-state index is based on the idea that both objective factors (e.g., behavior function) and subjective factors (e.g., people's ability to fulfill the roles they have set for themselves) affect

[12] In the earlier draft, we reported the results from 14 studies with 119 observations. The data set was updated during the revision process.

[13] Median income of Florida residents in 1975 was used (http://www.census.gov/hhes/income/4person.html).

Table 3. Studies included in meta-analysis

Study	Location	Type of publication	Health condition	No.[a]
Alberini et al. (1997)	Taiwan	Journal article	Respiratory illness (cold)	4
Chestnut et al. (1988)	U.S.	U.S. EPA report	Angina attack	2
Chestnut et al. (1998)	Thailand	Consultancy report	Respiratory symptom day, restricted activity day, work loss day	3
Barton (1999)	Costa Rica, Portugal	Doctoral dissertation	Coughing, eye irritation	4
Dickie et al. (1987)	U.S.	U.S. EPA report	Coughing, throat irritation, sinus congestion, wheezing, shortness of breath, pain on deep inspiration, chest tightness, cannot breath deeply, headache	9
Dubourg (1998)	Malaysia	Consultancy report	Respiratory hospital admission, ER visit, influenza bed day, coughing, eye irritation	5
Ibanez & McConnell (2001)	Colombia	Working paper	Respiratory illness (mild/severe)	2
Kartman et al. (1996)	Sweden	Journal article	Angina attack	2
Liu et al. (2000)	Taiwan	Journal article	Respiratory illness (cold)	1
Loehman et al. (1979)	U.S.	Journal article	Coughing (mild/severe), shortness of breath (mild/severe), head congestion (mild/severe)	18
Meegan (1998)	Iran	Government report (used in M.Sc. thesis)	Coughing, shortness of breath, eye irritation, sore throat, headache, chest pain, asthma attack	7
Navrud (1998)	Norway	Working paper	Coughing, sinus congestion, throat congestion, eyes itching, headache, shortness of breath, acute bronchitis, asthma attacks	18
Ready et al. (2001)	England, The Netherlands, Norway, Portugal, Spain	EU report	Respiratory hospital admission, ER visit, influenza bed day, coughing, eye irritation	25
Rowe & Chestnut (1985)	U.S.	U.S. EPA report	Asthma attack	1
Tolley et al. (1986)	U.S.	U.S. EPA report, book chapter	Coughing, sinus congestion, throat congestion, eyes itching, drowsiness, headache, nausea, angina (mild/severe)	20
Yee (1998)	Hong Kong	Consultancy report	Respiratory hospital admission, respiratory illness, cardiovascular hospital admission, cardiovascular disease	4

See the full data set in Appendix 2

[a] Number of observations reported from each study

EPA, Environmental Protection Agency; ER, emergency room

people's well-being. The indexes place the objective and subjective components of health along a range of functional health states, and then arrange them in a common scale that measures different levels of well-being. Specifically, they employ the quality of well-being (QWB) index of Kaplan et al. (1993), which rates health status on a scale from 0 to 1, where 0 represents death and 1 represents perfect health. With this index, they can assign an index score to each of the health effects valued in the CV studies.

In the current study, we investigated the possibility of using other health status indexes such as the Sickness Impact Profile (Bergner 1993), the 15D Index (Sintonen and Pekurinen 1993), and years lived with disability (YLDs) (Murray and Lopez 1996). However, these indexes do not measure the health conditions or symptoms specifically. For this reason, the QWB index was chosen as the most appropriate index for morbidity valuation studies in this meta-analysis.

The QWB index measures health in four dimensions: three "function states"—mobility (MOB), physical activity (PHY), and social activity (SOC)—and the most severe symptom/problem complex (SYM) (for more details, see Kaplan et al. 1993). To calculate the QWB score, we assigned weights of these four dimensions and calculated the QWB scores using the following formula

$$W = 1 + (\mathrm{MOB}wt) + (\mathrm{PHY}wt) + (\mathrm{SOC}wt) + (\mathrm{SYM}wt) \quad (2)$$

where W is an individual's well-being score; *wt* is the preference-weighted measure for each factor (i.e., weighted measure for MOB mobility); PHY is physical activity; SOC is social activity; and SYM is the symptom/problem complex. When applying the QWB index to the health effects measured in the CV studies, we categorized each condition based on the descriptions in each CV study. It is noteworthy that the same condition may have several QWB scores. In cases where respondents received no description of the health condition, we assumed a moderate case; and in some cases we based it on scores estimated in the Johnson et al. (1997) study. Table 4 shows that the QWB score is calculated differently because of the different descriptions of the illness.

It should be noted that there are several studies with health effects not in the symptom/problem complex of the QWB index. For example, Alberini et al. (1997), Chestnut et al. (1998), Liu et al. (2000), and Yee (1998) asked about people's WTP to reduce a set of symptoms listed under (minor) respiratory illness. The QWB score would be incredibly low if we applied a QWB score of several symptoms to this kind of health outcome. Thus, we applied a weight for "common symptoms," which is the same weight as that for coughing.[14] For other illnesses (e.g., angina, asthma attacks, influenza, acute bronchitis) in some CV studies, the QWB score for each illness was assigned according to the major symptom of each illness defined in the study. Although there are some limitations

[14] Liu et al. (2000) used the QWB index in their analysis, so we can take the QWB score directly from that study (QWB = 0.656 for avoiding an episode of respiratory illness).

Table 4. QWB score calculation: comparison of three studies with different descriptions of coughing

Study	Description of coughing (1 day)	Calculating QWB score	QWB score
Navrud (1998)	Coughs 4–5 times per hour, and each cough lasts 5–20 s. Feels the cough in the chest, but it is not severe enough to make the patient red in the face. The coughing does not stop normal activities.	CPX no. 11 (cough, wheezing, or shortness of breath with or without fever, chills, or aching all over) with no limitation on daily functioning. W = 1 + (−0.257) + (−0.000) + (−0.000) + (−0.000)	0.743
Ready et al. (2001)	One minor restricted activity day: 1 day with persistent phlegmy cough, some tightness in the chest, and some breathing difficulties. Patient cannot engage in strenuous activity but can work and do ordinary daily activities.	CPX no.11 (cough, wheezing, or shortness of breath with or without fever, chills, or aching all over) with some limitations on daily functioning. W = 1 + (−0.257) + (−0.000) + (−0.000) + (−0.061)	0.682
Tolley et al. (1986)	No description provided.	Assume moderate case. CPX no. 11 (cough, wheezing, or shortness of breath, with or without fever, chills, or aching all over) with no limitation on daily functioning. W = 1 + (−0.257) + (−0.000) + (−0.000) + (−0.000)	0.743

QWB, quality of well-being

on the use of QWB indexes, this study demonstrates the usefulness of the QWB index for rating the short-term health effects in the meta-analysis.[15]

5 Meta-regression analysis

5.1 Variables included in meta-analysis

The dependent variable in the analysis is an estimate of the WTP for a given health effect reported in a particular study. The independent variables used to determine the source of variation in the WTP estimates are those that describe the factors assumed to influence the WTP estimate. We divided the factors into three subgroups. The first subgroup comprises the factors describing health risk characteristics, which are the duration and severity of health effects. The second subgroup of independent variables includes factors representing population

[15] As mentioned by Johnson et al. (1997), the use of a QWB score as an independent variable in a regression model may introduce an error into the analysis. The direction of this type of bias is indeterminate (Green 2000).

Table 5. Description of variables used in the meta-regression analysis

Variable	Mean	Expected sign	Definition of variable
WTP	138.2	+	Mean WTP to reduce/avoid illnesses
One-day WTP	35	+	Mean WTP for 1-day (WTP divided by number of ill days during each observation)
Health risk characteristics			
QWB	0.682	−	Perceived severity measured by quality of well-being (QWB) score
Days	10.18	+	Duration of illness avoided
Population characteristics			
AGE	43	+/−	Average age
MALE	51.3	+/−	Percentage of male respondents
EDUC	13.2	+/−	Years of schooling
INC	33998	+	Annual household income
Study characteristics			
Elicitation format[a]			
BG	0.20	+	Bidding game (1 = yes, 0 = otherwise)
DC	0.03	+	Dichotomous choice (1 = yes, 0 = otherwise)
PC	0.52	+	Payment card (1 = yes, 0 = otherwise)
Survey method: INTERVIEW[b]	0.77	+	In-person interview (1 = yes, 0 = otherwise)
Geographic area: DEVELOPING[c]	0.22	−	Survey conducted in developing countries (1 = yes, 0 = otherwise)

[a] Open-ended format was the omitted category
[b] A combined mail and phone survey variable was the omitted category
[c] Survey conducted in developed countries was the omitted category

characteristics of each study. The last subgroup comprises descriptive variables on the features of each study, including CV design, geographical areas of the surveys, and publication status.

Table 5 shows the specific variables used when explaining WTP estimates and the summary statistics of the data set for each variable. Theoretically, variables used to describe health risk characteristics and population characteristics should be important determinants of the variation in WTP estimates, whereas the effects of variables in study design characteristics should not be significant. Here, we discuss the independent variables according to the subgroups stated above.

Regarding health risk characteristics in the first subgroup, the two main factors believed to cause the variation of WTP estimates for health effects are the duration of illness (DAYS) and level of severity of the discomfort associated with health effects (QWB). The duration of short-term health effects is shown as the number of days the symptoms were alleviated or avoided. The degree of severity is measured by the health state index through the QWB score (Johnson et al. 1997; U.S. EPA 2000a).

The WTP should positively increase with the duration of illness to be avoided. Concerning severity of illness, it is expected that people should pay more to reduce or avoid the more severe illness than the less severe illness. Accordingly, WTP increases when QWB score moves away from 1 (perfect health) to 0 (death), resulting in a negative correlation (the lower score represents the more severe illness).

It is worthy of note that there is another variable, a conceptual difference in the WTP measure, for whether the study asked for the WTP to avoid future morbidity or to purchase reductions in existing morbidity, which may affect WTP.[16] As noted by Johnson et al. (1997), assuming that the marginal utility of health diminishes as conditions approach perfect health, WTP should vary depending on whether the respondent is valuing the avoidance or reduction of a condition relative to a common reference point: that is, whether the measure is a Hicksian equivalent variation or compensation variation. This analysis tried adding a dummy variable to account for this conceptual difference; however, because of its high correlations with other variables, this dummy variable was omitted in the final models.[17] The magnitude of the difference between WTP to avoid additional days and WTP to reduce the number of days may not be large for short-term conditions that do not result in large changes in overall health status (Johnson et al. 1997).

In addition to the two fundamental independent variables of health risk characteristics, sample population characteristics, which are respondents' socioeconomic variables, would be important determinants on the variation of WTP to reduce or avoid a health effect. Four variables—age, gender, education, income—represent the socioeconomic data of respondents in each study. We selected these variables because they are the typical information reported in individual studies.[18]

Willingness to pay should increase positively with income level because people who have higher incomes are likely to give a higher WTP amount than people with a lower income. Age (AGE), gender (MALE), and education variables (EDUC) may also have some influence on respondents' WTP. However, there is

[16] In our data set of studies, 11 studies measured WTP for the avoidance, rather than the reduction, of a given illness. This accounts for approximately 84% of total observations.
[17] In a linear full model with the ordinary least squares (OLS) estimator, this dummy variable is highly correlated with four variables: Ln(INC) (−0.925), MALE (0.841), INTERVIEW (−0.834), and PC (−0.731). However, when this variable is added to the simple model (only DAYS and QWB), its coefficient is positively significant in double-log models but not in linear models. To some extent, this result indicates that the study that measures WTP for the avoidance of a given illness may have higher WTP than the study that measures WTP for the reduction of a given illness.
[18] Another important variable involves respondents' health status or baseline health. An effort was made to collect data on this variable. However, most CV studies did not report or collect enough information on each respondent's current health endowment (e.g., average number of days per year the respondent experiences). Consequently, we had to omit this variable from our analysis.

no clear-cut conclusion from previous studies on the magnitude and pattern of the relation between WTP and these three demographic variables.

In the last subgroup, variables are constructed to control for variation in study design characteristics that arise through the choice of elicitation formats used in the questionnaires and the survey modes. Previous CV research results show that the open-ended (OE) elicitation format yields a significantly lower average WTP than other elicitation formats: payment card (PC), bidding game (BG), or dichotomous choice (DC). Three dummy variables (BG, DC, PC) are included in the analysis to check for the effect of elicitation formats on WTP estimates, with OE as the omitted variable. The average mean of each dummy variable indicates that more than 52% of the studies use the PC format following by the OE type (25%) and the BG format (20%). Only three studies, accounting for 3%, used the DC format. This finding is contrary to the current trend of CV studies.

In addition to the various elicitation formats, the different modes of surveying used in the primary studies may have caused the variations in the WTP estimates. An "interviewer effect" problem with in-person interviews is one example because people might feel pressed either for time or to say yes to the WTP question and state an unrealistic amount of money (Mitchell and Carson 1989). It is expected that the WTP estimates from in-person interview surveys would be higher than that of other survey methods, including mail and phone surveys. Because only one study (Loehman et al.) used a mail survey, we combined mail and phone surveys into one variable (TELMAIL) and use it as an omitted variable. As shown by the mean, the in-person interview mode is most often used in the CV studies (77%).

Because of the nature of meta-analysis synthesizing various studies, it is necessary to take into account variables that reflect the study characteristics at the meta level. To account for different geographical survey areas, we created a dummy variable: DEVELOPING for studies conducted in developing countries. The omitted variable for this group is developed countries.[19] Although seven studies have been conducted in developing countries, they account for only 22% of the total observations. This is because each of these studies measures WTP for fewer items of morbidity reduced or avoided.[20]

5.2 Regression diagnostics

Typically, meta-analysts employ an ordinary least squares (OLS) regression to obtain values for the regression coefficients. Because the variables underlying

[19] Initially we included data on time differences (YEAR) by separating two periods (before and after 1990) and geographic area according to regions of the studies: U.S., EU, and non-U.S./EU countries. However, because of the high correlations among regressors, the YEAR variable was omitted, and geographical differences are categorized by a broader variable for whether the study is conducted in developed or developing countries.

[20] We also omitted another dummy variable (PUBLISH), which controlled for differences between published and unpublished studies, due to its high correlation with BG and INTERVIEW. We found that all studies using the bidding game format are published articles.

WTP estimates were based on different data sets and different estimation methods, gross violations of the least squares model assumptions could impair the efficiency or precision of the estimation. Thus, it was important to investigate whether the OLS model applied in this study met assumptions about the structure of the data.

A major concern in meta-analysis studies is the presence of heteroscedasticity, or nonconstant error variance, in the OLS model. This is a common problem because the studies used in meta-analyses may have used different data sets, different sample sizes, and different independent variables, leading to unequal variances of these estimated coefficients (Stanley and Jarrell 1989). Moreover, the effect of influential data points and outliers has been detected in some meta-analysis studies (Smith and Huang 1995; Bowland and Beghin 1999).

The effects of heteroscedasticity and influential data points in the OLS models were examined by regression diagnostics. Residual plots have shown that problems of heteroscedastic error variance and nonnormal distribution occur in the linear OLS model (not reported here). Additionally, the Cook's distance index plot, a measure of each observation's influence on coefficients, identifies several high influential points in the data set.

To confirm the findings from the residual plots, we carried out several tests for heteroscedasticity and nonnormality. The P value of 0 in the White test for homoscedasticity and the Shapiro-Wilk test for normality of error disturbances in the linear OLS estimator indicates that the null hypotheses of homoscedasticity and normal distribution must be rejected.

We use two alternative approaches to tackle regression assumptions violations. The first approach is that we use the OLS estimator with the White consistent covariance estimator.[21] The robust standard errors were computed to allow for correlation among observations across studies. The alternative approach is least absolute deviations (LAD),[22] which can be used to tackle the outliers and influential data as detected in the Cook's distance plot. The LAD regression refers to a general class of statistical procedures designed to reduce the sensitivity of the estimates to gross errors by replacing the squared residuals with another function of the residuals that minimize the sum of the absolute residuals. The likelihood function and standard error estimates are computed as though the true distribution of the disturbances was Laplace; this is by analogy to least squares, where the likelihood function and conventional standard error estimates assume that the true distribution is normal (Hall and Cummins 1999).

[21] This approach was used for the Smith and Kaoru (1990) meta-analysis on travel cost recreation demands. Weight least squares (WLS) with the robust standard errors [a similar approach was used by Mrozek and Taylor (2002) and Blaeij et al. (2000)] were also tried, but the results did not change much. In fact, the WLS model performs even worse than OLS (larger mean absolute residuals). Accordingly, the OLS estimator was used for regression analysis in this study.

[22] The LAD estimator in this study is similar to the minimum absolute deviation (MAD) used in the Smith and Huang (1995) meta-analysis. Bowland and Beghin (1999) used the robust regression, methodology similar to the LAD in their meta-analysis of VSL estimates.

Neither approach comprehensively addresses all of the concerns that arise when dealing with regression. The OLS estimator accounts for heteroscedasticity (when judging statistically significant factors for estimated WTP) but can be expected to be influenced by outlying observations. The LAD estimator is resistant to outliers and influential data points but does not explicitly adjust for heteroscedasticity. We use these two estimators to see the pattern of the effect of each variable across estimators. We focus on the points of consistency among the two estimators.

It is noteworthy that our statistical analysis is different from the previous Johnson et al. (1997) meta-analysis in that Johnson et al. used panel estimators, whereas we used the OLS and LAD estimators. Although the panel estimators (fixed effect and random effects) can account for study-specific correlations among observations, we chose to use the OLS and the LAD because our focus is on investigating the effects of the study design, which are variables omitted in the previous meta-analysis. These dummy variables could not be checked appropriately by the panel estimators in this study.[23]

6 Statistical results

6.1 Results of meta-regressions

To show the appropriateness of using the OLS and the LAD estimators in this study, we first compare our simple models accounting for only health risk characteristics with the previous meta-analysis, the panel model of Johnson et al. As shown in Table 6, the coefficients of both QWB and DAYS (in the logarithm) are comparable to those in the Johnson et al. study and are statistically significant in both OLS and LAD estimators. Nonsignificant P values in misspecification tests (Shapiro-Wilk test, White test) indicate that the double-log OLS does not violate the least square assumptions. The goodness of fit criteria showed that the OLS is not inferior to the LAD estimator. The predicted WTP value for mild cough from our models was close to the predicted WTP from the Johnson et al. study. However, the predicted WTP value for more severe health effect by our models is relatively lower than the value predicted by the Johnson et al. panel estimator. This may be because our data set had more observations and consequently more variations in the WTP estimates.

Table 7 shows the results of the full models together with the simple models (specification 1), accounting for health risk and population characteristics only. We reported both linear and double-log specifications for our full models. Specification 1 represents a simple model controlling for population characteristics

[23] We attempted to use the panel estimators in our analysis by using the SAS and TSP program, but the outcomes were not satisfying. The fixed-effect models become defective when dummy variables were included. Moreover, Hausman's test rejected the null hypothesis of noncorrelation among estimators in random effect models. As this study aimed to investigate the effects of different study designs, the OLS and the LAD were adopted for this analysis.

Table 6. Panel model of Johnson et al. (1997) and this study's models[a]

Parameter	Johnson et al. panel estimator[b]	This study's OLS	This study's LAD
CONSTANT	10.02*** (10.38)	7.59*** (22.48)	7.89*** (23.96)
QWB	−9.18*** (−6.82)	−5.79*** (−11.50)	−6.18*** (−13.26)
Ln(DAYS)[c]	0.44*** (12.02)	0.54*** (11.94)	0.48*** (15.07)
Adjusted R^2	—	0.69	0.69
AIC	—	128.14	127.92
Log-likelihood	−50.84	−125.14	−124.92
Shapiro-Wilk test	—	0.98 (0.179)	—
White test	—	6.63 (0.250)	—
Predicted WTP			
For mild cough (QWB=0.743)	$25	$27	$27
For severe asthma (QWB=0.622)	$77	$54	$57

[a] Dependent variable is Ln(WTP). Regression coefficients are presented, with t-ratios in parentheses. The t-ratios in OLS estimator are calculated from heteroscedastic-consistent standard errors

[b] Panel estimator is a separate-variances model (SVM), which was selected as the best model for predicting WTP estimates. Predicted WTP estimates are taken from Table 3 in Johnson et al. (1997) and converted to 1995 values

[c] Duration of the illness

The Shapiro-Wilk test is a test on a normally distributed error term, and the White test is a test on a homoscedasticity. These misspecification tests are presented with probabilities in parentheses

AIC, Akaike information criterion; OLS, ordinary least squares (regression); LAD, least absolute deviations

*** Significant at the 1% level

only. Full models are shown in specifications 2 and 3. Specification 2 represents linear models (expecting INC in logarithmic values), and specification 3 represents double-log models.

Two variables of health risk characteristics, the duration of illness to be avoided (DAYS) and the severity of illness (QWB), were highly correlated with WTP values across models, confirming the previous meta-analysis study (Johnson et al. 1997). This result also indicated that WTP estimates derived from the CV studies included in this meta-analysis passed the scope test. That is, changes in WTP estimates respond to changes in the number of sick days reduced or avoided. However, the duration elasticity of the range between 0.46 and 0.54 (specification 1 with LAD in Table 7 and the simple model with OLS in Table 6, respectively) indicates that it is significantly less than unity. This means that WTP increases less than proportionately with the duration of illness to be avoided or reduced. That is, people pay more for reductions in duration of the illness at a decreasing rate.

Willingness to pay is significantly related to the QWB variable with a negative sign, as expected. The negative sign is a result from the QWB score that assigned less score for a more severe health condition. People tend to pay more for the reduction or avoidance of a more severe health condition. The QWB elasticity is

Table 7. Estimated coefficients of WTP to reduce or avoid illness

	OLS			LAD		
	1[a]	2	3[a]	1[a]	2	3[a]
Parameter	Ln(WTP)	WTP	Ln(WTP)	Ln(WTP)	WTP	Ln(WTP)
Constant	−3.50 (−1.61)	703.85 (1.52)	−5.56 (−1.12)	−4.50** (−2.61)	295.64 (1.33)	−3.58 (−1.24)
QWB	−3.57*** (−9.95)	−932.99*** (−5.48)	−3.31*** (−7.94)	−3.87*** (−13.05)	−626.26*** (−8.61)	−3.45*** (−12.17)
DAYS	0.48*** (11.15)	3.65*** (5.13)	0.50*** (12.58)	0.46*** (15.48)	3.68*** (10.87)	0.50*** (17.51)
AGE	0.96* (1.79)	−3.99 (−0.90)	0.83 (0.84)	0.95** (2.31)	2.51 (1.30)	0.13 (0.24)
MALE	−0.44** (−2.35)	2.12** (2.49)	−0.06 (−0.37)	−0.42*** (−2.91)	0.08 (0.14)	−0.19 (−1.39)
EDUC	0.13 (0.31)	8.12 (0.87)	0.57 (0.95)	0.44 (1.14)	11.62** (2.07)	1.33*** (3.16)
Ln(INC)	0.35*** (4.23)	−12.06 (−0.84)	0.26** (2.27)	0.35*** (4.97)	−11.94 (−0.94)	0.18** (2.24)
BG[b]		162.17*** (2.97)	0.58*** (3.50)		48.31** (2.45)	0.80*** (6.94)
DC[b]		136.01** (2.03)	0.41 (1.20)		17.17 (0.41)	0.57** (2.05)
PC[b]		49.07 (1.51)	0.52*** (2.73)		35.22* (1.73)	0.61*** (4.94)
INTERVIEW[b]		96.05** (2.19)	0.78*** (3.16)		56.84** (2.25)	0.52*** (3.53)
DEVELOPING[b]		−104.98** (−2.17)	−0.29 (−1.25)		−33.75 (−1.29)	−0.31* (−1.93)
No.	124	125	124	124	125	124
Adjusted R^2	0.75	0.49	0.81	0.75	0.41	0.79
AIC	116.32	783.24	118.65	113.62	745.79	103.58
Log-likelihood	−109.32	−771.24	−89.65	−106.62	−733.79	−92.01
Shapiro-Wilk test (P)	0.966*** (0.003)	0.82*** (0)	0.97** (0.033)	—	—	—
White test (P)	49.31*** (0.005)	98.18*** (0)	64.00* (0.06)	—	—	—
Residuals	57.7	76.1	55.0	55.5	65.2	50.6

[a] All population characteristics variables are logarithmic values
[b] Dummy variable
Regression coefficients are presented with t-ratios in parentheses; t-ratios in OLS estimator are calculated from heteroscedastic-consistent standard errors
Residuals refer to mean absolute residuals, differences between fitted WTP values (not log-WTP) and actual WTP values
Significance: * At the 10% level. ** At the 5% level. *** At the 1% level

estimated in the range between −3.31 and −6.18 (specification 3 with OLS in Table 7 and the simple model with LAD in Table 6, respectively). This showed evidence of diminishing marginal utility related to health improvements in WTP values, similar to the findings by Johnson et al. (1997). Specifically, people will pay less and less on the margin for improvements closer to perfect health. Alternatively, people will pay more and more for improvements that are farther from perfect health (i.e., become more severe). The double-log models shown in specifications 1 and 3 with both estimators in Table 7 also reflect an interaction between DAYS and QWB. The results indicate that people will pay more to reduce the duration of illness for more severe illness.

Regarding population characteristics, the simple models (specification 1) with both estimators indicate that AGE, MALE, and INC variables have high correlations with WTP, particularly the income variable (INC), which showed statistical significance. EDUC and INC showed significant effects in the full models with the LAD estimator.

The age variable (AGE) showed a positive sign in almost all models (except the linear full model with the OLS estimator) and significance in specification 1 with both estimators and in specification 3 with the LAD. The findings from primary studies seemed to be inconclusive regarding the relation between age and WTP for health. Some studies had a negative sign on age (Dubourg 1998), whereas others found a positive sign (Chestnut et al. 1998; Ready et al. 2001). The results from the meta-regression seemed to suggest that for short-term morbidity the age variable may not be a significant factor on WTP estimates, although it has been a concern in the literature on mortality risk valuation (see discussions on the effect of age on WTP to mortality risk reduction in Pearce 2000 and U.S. EPA 2000a; see CV surveys in Krupnick et al. 1999 and 2000).

The coefficient on gender (MALE) was significant in the simple models, but the sign was not consistent among specifications. The coefficient on education (EDUC) had a positive sign in all models but showed statistical significance only in the LAD full models. This result confirmed the general expectation and the findings in the literature. Ready et al. (2001) valued health effects in five European countries (The Netherlands, Norway, Portugal, Spain, United Kingdom) and reported positive signs in the higher education variable.

The income variable showed a positive sign and strong correlation across models (except the linear WTP models). Having been transformed in the logarithm reflected the magnitude of income elasticity of WTP, which ranged between 0.18 and 0.35 in four models. The range of income elasticity is comparable to the estimates in the primary studies. Loehman et al. (1979) estimated the income elasticity of WTP to range between 0.26 and 0.60, and Alberini et al. (1997) estimated that the income elasticity of WTP to avoid acute illness in Taiwwan was approximately 0.33. In addition, the range of income elasticity in the morbidity literature is slightly smaller than that estimated in the mortality risk literature. A recent meta-analysis of labor market studies (Viscusi and Aldy 2003) indicated an income elasticity of the value of a statistical life from about 0.5 to 0.6.

The results from the meta-regression suggested that, in addition to health risk characteristics, which regressed in the previous meta-analysis, population characteristics (particularly income and education) play an important role in the variation of WTP estimates. This result implied that the meta-analysis based on the benefit transfer function approach, as proposed by Johnson et al. (1997), should take into account not only the health risk characteristics but also the important variables of population characteristics.

A number of CV study design variables were shown to have a significant impact on WTP, including elicitation formats and survey methods. The bidding game and payment card elicitation formats yielded significant coefficients in all models, and the dichotomous choice format was significant in two of four full models. The omitted variable, the open-ended format, tended to give a lower average WTP than other elicitation formats, confirming the general findings in the literature (Desvousges et al. 1988; Batement et al. 1995b).

Concerning the effect of survey methods, using the in-person interview yielded much higher WTP than other survey methods (the omitted variable was TELMAIL, the combination of CV studies using telephone and mail surveys), as it showed a positive sign and was statistically significant across models. This result indicates the effect of in-person interviews on WTP.

With respect to the geographic differences in the CV studies, the coefficient on the developing country variable has a negative relation with WTP estimates in all models. This result confirmed the expectation that WTP estimates from CV studies conducted in developing countries are lower than those from CV studies conducted in developed countries.

6.2 Model selection for policy implication

We believe that the performance of models fit well with our theoretical assumptions and actual data fits. As shown in Tables 6 and 7, the OLS with the White consistent covariance estimates for the standard errors and the LAD reducing the effect of outliers perform comparably well across specifications. The signs for two important variables, DAYS and QWB, are significant across models. However, as shown in Table 6, the LAD estimator provided a wider range of WTP values for different QWB scores. In Table 7, values for the goodness of fit criteria, adjusted R^2, and the Akaike information criterion (AIC) show that double-log simple models (specification 1) are not much inferior to double-log full models (specification 3).

To compare the predictive power and fit between the simple model and the full model, we computed the differences between the predicted and actual WTP values (not log-WTP) for all models and compared the distribution of residuals for double-log models (specifications 1 and 3) according to the QWB score, as shown in Fig. 1. The full models appear to have smaller residuals than the simple models. The OLS simple model often has the largest residuals. The full models therefore perform better than the simple models.

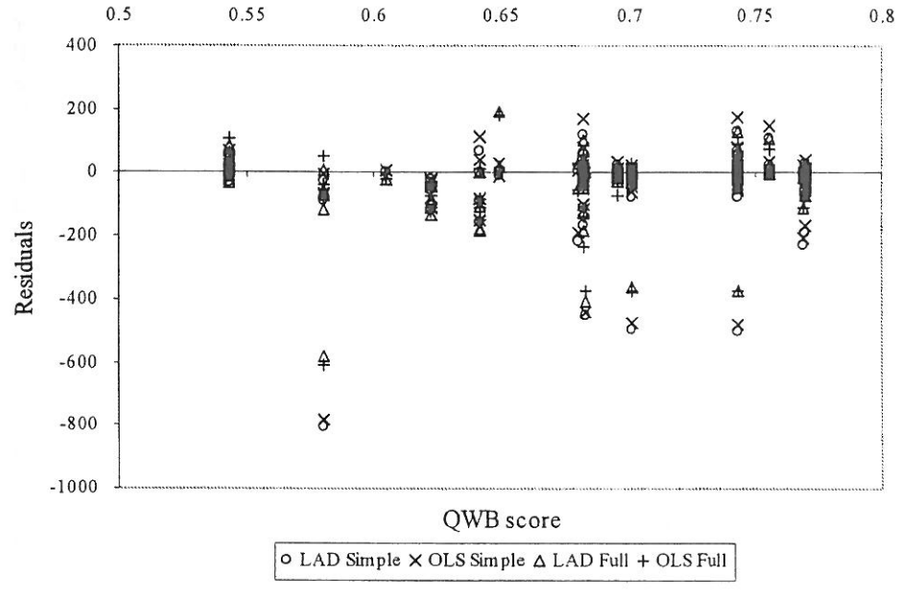

Fig. 1. Residual plots of double-log simple and full models

Now we consider the predictive power and fit between the OLS and LAD estimator in the double-log full models. Based on the residual plots shown in the Fig. 1, both estimators perform similarly, especially for the mild QWB score. However, the residual plots of the two estimators indicated that the LAD has relatively smaller residuals for intermediate and severe QWB scores but larger residuals for mild QWB scores. Because the residual plots showed mixed results, we further compared the mean absolute residual of each model and the predicted WTP for several illnesses to be reduced or avoided.

By comparing the mean absolute residuals, the double-log model with the LAD estimator has smaller mean absolute residual than the double-log model with the OLS estimator. When the two models are used to predict WTP for several illnesses to be reduced or avoided, the predicted WTP estimates from the OLS model are higher than those from the LAD model (e.g., the OLS predicts 1-day avoidance for mild coughing at around US$36 compared to US$31 derived from the LAD). Given a conservative basis, an advantage is given to the LAD model, which also has the smallest mean absolute residual.

6.3 Prediction of WTP estimates

To determine the extent that the effects of population characteristics and study design characteristics have on WTP estimates, the selected model was used to

predict WTP to avoid 1-day coughing (DAYS variable was set at 1). Because our data set included CV studies conducted in many countries, the predicted WTP values based on the sample means of total observations may not be appropriate owing to differences in population characteristics between developed and developing countries. To calculate mean values for population characteristics variables, study observations were broadly grouped into country A or country B. Country A represented a group of studies conducted in developed countries, and country B represented a group of studies conducted in developing countries.[24] We asserted here that the income data used in our data set was the average household income deflated to the 1995 base year, not the GDP per capita or the adjusted purchasing power parity (PPP) values.

However, even with the split-sample means, country B's population characteristics may not be a good representative of most developing countries as the average household income and the education attainment level were relatively higher than the average levels of developing countries.[25] We therefore included actual socioeconomic data from Bangkok, the capital of Thailand, for comparison purposes.[26] Bangkok, not Thailand as a whole, was selected because air pollution is often found to be serious in big cities where the income level of people is rising, bringing about a large growth rate in the number of motor vehicles and serious traffic congestion. Urban air pollution is typical in developing countries (e.g., Jakarta, Indonesia; Metro Manila, Philippines; Santiago, Chile).

Table 8 shows that the predicted WTP estimates vary across country groups and study dummy setting. WTP values for the developed country scenario ($31) were higher than those for the developing country scenario ($21) or Bangkok ($11). One main point to note is the differences between the WTP estimate for country A and for Bangkok. Given a proportionality of WTP to income, as is often assumed in policy benefit assessment studies, the income-adjusted WTP for Bangkok based on country A's estimate (US$8) was relatively smaller than that predicted by this study's meta-regression model (US$11).[27] This finding

[24] The estimated means of country A and B were as follows; average age 44.5 and 43.8 years; percentage male 53.0% and 52.6%; average schooling 13.5 and 14.2 years; average 1995 household income US$39171 and US$16077, respectively.

[25] The relatively high income level is due to high income levels of samples used in two studies: Alberini et al. (1997) in Taiwan (US$29102) and Yee (1997) in Hong Kong (US$38049). We also found high education levels of samples in David (1999) in Costa Rica (16 years), Dubourg (1998) in Malaysia (12.9 years), and Meegan (1998) in Iran (14.3). The average schooling in G2 was even higher than that in G1 (13.5 vs. 14.2 years).

[26] The annual household income of Bangkok residents at 1995 prices was US$10236 (the value was deflated by using the GDP deflator for the year 2000 and converted to U.S. currency using the exchange rate of 1995). The median age was 30 years; the percentage of male residents was 49%; the average years of schooling was 8.33 (source: National Statistical Office, www.nso.go.th).

[27] The annual income of Bangkok residents was $10236 (1995 prices), whereas country A's income level was $39171. This gives a Bangkok income level/country A sample group income level ratio of 0.26.

Table 8. Variations of predicted WTP for 1-day of coughing (1995 US$)

Parameter	Country A	Country B	Bangkok (actual case)
Variation 1: sample means for all study design variables[a]	$31 ($25–$38)	$21 ($14–$28)	$11 ($5–$18)
Variation 2: different elicitation formats[b]			
BG = 1	$42 ($36–$49)	$28 ($22–$35)	$15 ($9–$22)
PC = 1	$35 ($28–$42)	$23 ($17–$30)	$13 ($6–$19)
DC = 1	$34 ($27–$40)	$22 ($16–$29)	$12 ($6–19)
OE = 1	$19 ($12–$26)	$13 ($6–$19)	$7 ($0.3–$14)
Variation 3: no in-person interview[c]			
BG = 1	$28 ($22–$35)	$19 ($12–$26)	$10 ($4–$17)
PC = 1	$23 ($17–$30)	$16 ($9–$23)	$9 ($2–$16)
DC = 1	$22 ($16–$29)	$15 ($8–$22)	$8 ($2–$15)
OE = 1	$13 ($6–$19)	$9 ($2–$15)	$5 ($0–$11)

[a] Variation 1 represents input data for study dummy variables using sample means; DEVELOPING variable is set to 0 for country A but 1 for country B and for Bangkok case

[b] Variation 2 adjusted WTP estimates in variation 1 by changing elicitation format dummy one by one; INTERVIEW is set to 1

[c] Variation 3 adjusted WTP estimates in variation 2 by setting INTERVIEW variable to 0

The 95% confidence intervals are in parentheses. Variations 1, 2, and 3 are derived from specification 3 with LAD shown in Table 7. DAYS variable is set to 1. Country A represents population characteristics variables using developed country study samples. Country B represents population characteristics variables using developing country study samples. Bangkok represents population characteristics using Bangkok data

confirmed the general findings that the income elasticity of WTP for morbidity reduction is less than unity (Loehman et al. 1979; Alberini et al. 1997). Adjusting the WTP values for policy evaluation in any target city or country based on the assumption of income proportionality may underestimate the true WTP of people in that city or country.

In addition, Table 8 shows evidence of elicitation effects (indicated as "variation 2") and survey mode effects (indicated as "variation 3") on estimated WTP values. For example, in country A the WTP value increased from US$31 to US$49 if the bidding game (BG) format was used to elicit respondents' WTP (BG dummy variable was set to 1). On the other hand, the WTP value decreased from US$31 to US$19 if the open-ended (OE) format is used. In variation 3, the estimated WTP figures in variation 2 were further adjusted for survey method differences. Instead of using the sample mean, INTERVIEW was set to zero in all cases. The smaller WTP estimates imply that using in-person interviews yield higher WTP estimates than using other survey methods, such as mail and telephone surveys.

Although WTP estimates vary across elicitation formats and survey methods, all the ranges of confidence intervals in variations 2 and 3 were within the reported confidence intervals in variation 1, indicating that they are not signifi-

cantly different measures.[28] Elicitation effects can be viewed as a form of psychological variance around a central economic relation (Bateman et al. 1999). The findings of study design effects indicate that more empirical research is needed to understand how respondents react to different elicitation questions and survey methods.

By controlling for population characteristics and study design characteristics, WTP values for the reduction or avoidance of illnesses were estimated and compared with original WTP values reported in primary studies. Based on the average population characteristics in country A (representative of developed countries), most WTP estimates from this study were comparable to the WTP estimates reported in primary studies; most estimates reported in primary studies fell within the confidence intervals of this study's estimates (Table 9). When compared to the WTP estimates from the Johnson et al. meta-analysis, this study's WTP estimates were relatively larger than their estimates in the case of mild health effects (e.g., mild cough, mild headache, eye irritation). For the more severe health effects, this study's WTP estimates were smaller than those found by Johnson et al. The differences may come from the larger variation in WTP estimates in our larger data set. Nevertheless, most central values reported in the Johnson et al. study fell within the confidence intervals.

We also compared our WTP estimates with the original estimates from studies conducted in developing countries (Table 10). Although there were more items of health condition valued in the primary studies, only health conditions commonly estimated in several studies (e.g., respiratory illness or cold, cough, eye irritation) were compared. Most original estimates fell within the confidence intervals of this study's estimates. The predicted WTP provided a central estimate for the health conditions that had wider variations in primary studies, such as cough and eye irritation.

7 Conclusions

This study employed meta-analysis to review and synthesize the literature on WTP estimates for the reduction or avoidance of short-term morbidity associated with air pollution. The analysis extended the Johnson et al. (1997) meta-analysis, providing a method linking WTP values to the QWB index, which allows different health effects to be compared along a common scale.

Our extensions to the previous meta-analysis were (1) updating the data set by adding 11 new studies to the previous work; (2) including more information on population and study design characteristics from the original studies to examine the effects of these characteristics on the variation of WTP estimates; and (3) controlling these variables by the estimated function as a benefits transfer function across countries.

[28] Except the range of WTP estimates for country A in variation 3 where OE was set to 1.

Table 9. WTP values for 1 day of avoidance of various illnesses: developed country case (1995 US$)

Health effect (QWB score)	This study[a] General	Previous meta-analysis[b] USA	David (1999) Portugal	Dickie et al. (1987) USA	Loehman et al. (1979) USA	Navrud (1998) Norway	Ready et al. (2001) EU[c]	Rowe & Chestnut (1985) USA	Tolley et al. (1986) USA
Mild cough (0.743)	$31 ($24–$38)	$25	$70	$15	$12	$15	—	—	$33
Severe cough (0.682)	$42 ($35–$49)	$45	—		$34	—	$43	—	—
Mild headache (0.756)	$29 ($22–$36)	$23	—	$25	$20	—	—	—	$53
Severe headache (0.695)	$39 ($32–$46)	$40	—		$47	$26	—	—	—
Mild shortness of breath (0.743)	$31 ($24–$38)	$25	—	$9	$35	—	—	—	—
Severe shortness of breath (0.622)	$58 ($51–$65)	$77	—	—	$64	$40	—	—	—
Eyes irritation (0.77)	$28 ($21–$35)	$20	$86	—	—	$20	$58	—	$37
Severe asthma attack (0.622)	$58 ($51–$65)	$77	—	—	—	$85	—	$60	—
Throat irritation (0.83)	$21 ($14–$28)	—	—	$22	—	$15	—	—	$39

[a] Calculated from double-log full model with LAD estimator (specification 3 in Table 7). The input data on population characteristics are means of country A (developed country group) in our data set, and average means of the total sample are inserted into study dummy variables except DEVELOPING are set to 0

[b] We select only the mean estimates given in Table 4 in the Johnson et al. (1997) study

[c] WTP values are average means of WTP estimates from five European countries: The Netherlands, Norway, Portugal, Spain, and United Kingdom

The 95% confidence intervals are in parentheses. DAYS variable is set to 1

EU, European Union

Table 10. WTP values for 1 day of avoidance of various illnesses: developing country case (1995 US$)

Health effect (QWB score)	This study[a] General	Alberini et al. (1997) Taiwan	Chestnut et al. (1998) Bangkok	David (1999) Costa Rica	Dubourg (1998) Malaysia	Ibanez & McConnell (2001) Colombia	Meegan (1998) Iran
Mild respiratory illness (0.743)	$21 ($14–$28)	$21	$17	—	—	$11	—
Severe respiratory illness (0.682)	$26 ($19–$33)	$32	—	—	—	$13	—
Mild cough (0.743)	$21 ($14–$28)	—	—	$31	$18	—	$3
Eye irritation (0.77)	$18 ($11–$25)	—	—	$43	$27	—	$6

[a] Calculated from double-log full model with LAD estimator (specification 3 in Table 7). The input data on population characteristics are means of country B (developing country group) in our data set, and average means of the total sample are inserted into study dummy variables, except DEVELOPING is set to 1

The 95% confidence intervals are in parentheses. DAYS variable is set to 1

Based on the 16 studies reviewed, this analysis provided some useful information for the theoretical development of a nonmarket valuation method, the contingent valuation survey, regarding differences in elicitation formats and survey methods. Results from the meta-regression analysis indicated that not only health risk characteristics (i.e., duration and severity of a given illness to be reduced or avoided) but also population and study design characteristics cause variations in WTP values.

In addition to reviewing the literature related to diverse WTP estimates, this study provided meta-regressions, which can be used to generate summaries or benefits transfer functions. By controlling for the population and the study design characteristics variables, our meta-analysis-based transfer function can be used to generate more precise WTP estimates by inserting local population characteristics, thereby providing a better adjustment to benefits transfer in the area of short-term morbidity valuation.

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Appendix 2. Annotated overview of studies used in this meta-analysis

Health condition	No. of days	Mean WTP[a]	QWB score	Income (annual)	Age (year)	Male (%)	Education (years)	Elicitation format[b]	Survey method[c]
Alberini et al. (1992)[d]									
Respiratory illness (cold)	1	21.22	0.743	29 102.2	42.36	46.9	11.07	BG	I
Respiratory illness (cold)	5	35.94	0.743	29 102.2	42.36	46.9	11.07	BG	I
Respiratory illness	1	31.81	0.701	29 102.2	42.36	46.9	11.07	BG	I
Respiratory illness	5	53.83	0.701	29 102.2	42.36	46.9	11.07	BG	I
Chestnut et al. (1985)									
Angina	1	133.2	0.641	29 322.2	61.5	100	12	OE	T
Angina	2	219.7	0.641	29 322.2	61.5	100	12	OE	T
Chestnut et al. (1996)									
Respiratory symptom day	1	16.81	0.743	7 497.6	40	10.32	10	PC	I
Reduced activity day	1	28.76	0.682	7 497.6	40	10.32	10	PC	I
Respiratory work loss day	1	59.27	0.605	7 497.6	40	10.32	10	PC	I
Barton (1998)									
Cough	1	70.96	0.743	14 290.0	36.36	44	14	PC	I
Eyes irritation	1	86.52	0.77	14 290.0	36.36	44	14	PC	I
Barton (1999)									
Cough	1	30.97	0.743	14 110.0	31.92	51	16	PC	I
Eyes irritation	1	42.94	0.77	14 110.0	31.92	51	16	PC	I
Dickie et al. (1985)									
Cough	1	15.25	0.743	71 194.4	47.57	92.7	14.71	PC	T
Throat irritation	1	22.1	0.83	71 194.4	47.57	92.7	14.71	PC	T
Sinus congestion	1	17.51	0.83	71 194.4	47.57	92.7	14.71	PC	T
Wheezing	1	15.31	0.743	71 194.4	47.57	92.7	14.71	PC	T
Shortness of breath	1	9.2	0.743	71 194.4	47.57	92.7	14.71	PC	T
Pain on deep inspiration	1	35.55	0.701	71 194.4	47.57	92.7	14.71	PC	T
Chest tightness	1	26.09	0.701	71 194.4	47.57	92.7	14.71	PC	T
Cannot breathe deeply	1	19.63	0.743	71 194.4	47.57	92.7	14.71	PC	T
Headache	1	25.03	0.756	71 194.4	47.57	92.7	14.71	PC	T

Appendix 2. *Continued*

Health condition	No. of days	Mean WTP[a]	QWB score	Income (annual)	Age (year)	Male (%)	Education (years)	Elicitation format[b]	Survey method[c]
Dubourg (1995)									
Influenza bed day	3	81.04	0.543	15 306.4	34.6	44	12.9	PC	I
Respiratory hospital admission	8	214	0.47	15 306.4	34.6	44	12.9	PC	I
Cough	1	18.1	0.743	15 306.4	34.6	44	12.9	PC	I
Respiratory ER visit	5	312.8	0.498	15 306.4	34.6	44	12.9	PC	I
Eye irritation	1	26.75	0.77	15 306.4	34.6	44	12.9	PC	I
Ibanez & McConnell (2000)									
Respiratory illness (mild)	1	11.36	0.743	2 528.5	40.5	41.5	11	DC	I
Respiratory illness (severe)	1	13.39	0.701	2 528.5	40.5	41.5	11	DC	I
Kartman et al. (1994)									
Angina	45	395.2	0.641	29 291.9	68	63.9	14.0	DC	T
Angina	45	323.2	0.641	29 291.9	68	63.9	14.0	BG	T
Liu et al. (1995)									
Respiratory illness (cold)	6.5	37.3	0.656	22 590.9	40.8	None	9.09	DC	I
Loehman et al. (1975)									
Cough/sneeze (mild)	1	12.32	0.743	37 507.4	42.4	48.6	14.1	PC	M
Cough/sneeze (mild)	7	40.58	0.743	37 507.4	42.4	48.6	14.1	PC	M
Cough/sneeze (mild)	90	108.1	0.743	37 507.4	42.4	48.6	14.1	PC	M
Cough/sneeze (severe)	1	33.99	0.682	37 507.4	42.4	48.6	14.1	PC	M
Cough/sneeze (severe)	7	88.84	0.682	37 507.4	42.4	48.6	14.1	PC	M
Cough/sneeze (severe)	90	214.6	0.682	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (mild)	1	35.29	0.743	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (mild)	7	87.18	0.743	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (mild)	90	237.7	0.743	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (severe)	1	72.11	0.622	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (severe)	7	213.3	0.622	37 507.4	42.4	48.6	14.1	PC	M
Shortness of breath (severe)	90	501.6	0.622	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (mild)	1	20.17	0.756	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (mild)	7	42.57	0.756	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (mild)	90	117.1	0.756	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (severe)	1	47.45	0.695	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (severe)	7	92	0.695	37 507.4	42.4	48.6	14.1	PC	M
Head congestion (severe)	90	322.5	0.695	37 507.4	42.4	48.6	14.1	PC	M
Meegan (1997)									
Cough	1	2.94	0.743	3 809.0	34.26	59	14.3	OE	I
Shortness of breath	1	7.66	0.743	3 809.0	34.26	59	14.3	OE	I
Eye irritation	1	5.64	0.77	3 809.0	34.26	59	14.3	OE	I
Sore throat	1	7.22	0.83	3 809.0	34.26	59	14.3	OE	I
Headache	1	11.37	0.756	3 809.0	34.26	59	14.3	OE	I
Chest pain	1	10.9	0.701	3 809.0	34.26	59	14.3	OE	I
Asthma attack	1	14.23	0.683	3 809.0	34.26	59	14.3	OE	I
Navrud (1996)									
Cough	1	14.96	0.743	44 724.9	41.5	50.05	14.9	OE	I
Cough	14	40.36	0.743	44 724.9	41.5	50.05	14.9	OE	I
Sinus congestion	1	29.47	0.769	44 724.9	41.5	50.05	14.9	OE	I
Sinus congestion	14	83.58	0.769	44 724.9	41.5	50.05	14.9	OE	I
Throat congestion	1	14.96	0.83	44 724.9	41.5	50.05	14.9	OE	I
Throat congestion	14	37.33	0.83	44 724.9	41.5	50.05	14.9	OE	I
Eye itching	1	19.8	0.77	44 724.9	41.5	50.05	14.9	OE	I
Eye itching	14	65.75	0.77	44 724.9	41.5	50.05	14.9	OE	I
Headache	1	26.29	0.695	44 724.9	41.5	50.05	14.9	OE	I
Headache	14	115.9	0.695	44 724.9	41.5	50.05	14.9	OE	I
Shortness of breath	1	40.35	0.682	44 724.9	41.5	50.05	14.9	OE	I
Shortness of breath	14	123.6	0.682	44 724.9	41.5	50.05	14.9	OE	I
Acute bronchitis	1	30.53	0.622	44 724.9	41.5	50.05	14.9	OE	I
Acute bronchitis	14	84.94	0.622	44 724.9	41.5	50.05	14.9	OE	I
Asthma attacks	1	84.64	0.622	44 724.9	41.5	50.05	14.9	OE	I
Asthma attacks	14	253.8	0.622	44 724.9	41.5	50.05	14.9	OE	I
Asthma attacks	1	175.6	0.622	44 724.9	41.5	50.05	14.9	OE	I
Asthma attacks	14	267.8	0.622	44 724.9	41.5	50.05	14.9	OE	I

Appendix 2. *Continued*

Health condition	No. of days	Mean WTP[a]	QWB score	Income (annual)	Age (year)	Male (%)	Education (years)	Elicitation format[b]	Survey method[c]
Ready et al. (2001)									
Respiratory hospital admission	8	400.7	0.47	29 967.6	44	43	12.7	PC	I
Respiratory ER visit	5	180.6	0.498	29 967.6	44	43	12.7	PC	I
Influenza bed day	3	100.8	0.543	29 967.6	44	43	12.7	PC	I
Cough	1	40.19	0.682	29 967.6	44	43	12.7	PC	I
Eyes irritation	1	56.81	0.77	29 967.6	44	43	12.7	PC	I
Respiratory hospital admission	8	425.4	0.47	36 260.9	41	49	13	PC	I
Respiratory ER visit	5	337.8	0.498	36 260.9	41	49	13	PC	I
Influenza bed day	3	168.2	0.543	36 260.9	41	49	13	PC	I
Cough	1	51.21	0.682	36 260.9	41	49	13	PC	I
Eyes irritation	1	43.17	0.77	36 260.9	41	49	13	PC	I
Respiratory hospital admission	8	424.4	0.47	19 290.1	46	36	9.6	PC	I
Respiratory ER visit	5	261.4	0.498	19 290.1	46	36	9.6	PC	I
Influenza bed day	3	123.7	0.543	19 290.1	46	36	9.6	PC	I
Cough	1	39.41	0.682	19 290.1	46	36	9.6	PC	I
Eyes irritation	1	98.5	0.77	19 290.1	46	36	9.6	PC	I
Respiratory hospital admission	8	602	0.47	22 076.2	43	46	10	PC	I
Respiratory ER visit	5	206.6	0.498	22 076.2	43	46	10	PC	I
Influenza bed day	3	159.3	0.543	22 076.2	43	46	10	PC	I
Cough	1	54.63	0.682	22 076.2	43	46	10	PC	I
Eyes irritation	1	74.27	0.77	22 076.2	43	46	10	PC	I
Respiratory hospital admission	8	231.8	0.47	24 367.2	47.8	44	11	PC	I
Respiratory ER visit	5	184.7	0.498	24 367.2	47.8	44	11	PC	I
Influenza bed day	3	117.3	0.543	24 367.2	47.8	44	11	PC	I
Cough	1	28.13	0.682	24 367.2	47.8	44	11	PC	I
Eyes irritation	1	19.18	0.77	24 367.2	47.8	44	11	PC	I
Rowe & Chestnut (1983)									
Asthma	9.5	571.2	0.683	39 173.8	43.56	51.86	13.66	PC	I

Tolley et al. (1984)									
Cough	1	33.55	0.743	40 716.5	44.49	45	14.25	BG	I
Cough	30	221.7	0.743	42 891.3	42.15	51	13.83	BG	I
Sinus congestion	1	46.67	0.769	40 716.5	44.49	45	14.25	BG	I
Sinus congestion	30	353.7	0.769	42 891.3	42.15	51	13.83	BG	I
Throat congestion	1	38.57	0.83	40 716.5	44.49	45	14.25	BG	I
Throat congestion	30	274.6	0.83	42 891.3	42.15	51	13.83	BG	I
Eye itching	1	36.92	0.77	40 716.5	44.49	45	14.25	BG	I
Eye itching	30	313.6	0.77	42 891.3	42.15	51	13.83	BG	I
Drowsiness	1	41.93	0.68	40 716.5	44.49	45	14.25	BG	I
Drowsiness	30	423.4	0.68	42 891.3	42.15	51	13.83	BG	I
Headache	1	53.39	0.743	40 716.5	44.49	45	14.25	BG	I
Headache	30	650.1	0.743	42 891.3	42.15	51	13.83	BG	I
Nausea	1	66.95	0.649	40 716.5	44.49	45	14.25	BG	I
Nausea	30	247.7	0.649	42 891.3	42.15	51	13.83	BG	I
Angina (mild)	1	87.99	0.701	40 716.5	50.33	50	13.2	BG	I
Angina (mild)	10	205.5	0.701	40 716.5	50.33	50	13.2	BG	I
Angina (mild)	20	647.5	0.701	42 891.3	42.15	51	14.15	BG	I
Angina (severe)	1	164.6	0.58	40 716.5	50.33	50	13.2	BG	I
Angina (severe)	10	348.7	0.58	40 716.5	50.33	50	13.2	BG	I
Angina (severe)	20	1124	0.58	42 891.3	42.15	51	14.15	BG	I
Yee (1997)									
Respiratory diseases	7	84.86	0.682	38 049.4	40.78	56.38	9.82	OE	I
Respiratory hospital admission	1	131.2	0.47	38 049.4	40.78	56.38	9.82	OE	I
Cardiovascular diseases	7	175.1	0.58	38 049.4	40.78	56.38	9.82	OE	I
Cardiovascular hospital admission	1	200.3	0.428	38 049.4	40.78	56.38	9.82	OE	I

Source: See references of all studies in Appendix 1

[a] Mean WTP estimates in Alberini et al. actually are median values, as no mean values were reported in the study

[b] Four types of elicitation formats of CV survey: BG, bidding game; OE, open-ended; DC, dichotomous choice; PC, payment card

[c] Three survey methods: I, in-person interview; T, telephone survey; M, mail survey

[d] These figures refer to the year of data, except for Ready et al. where the year of the study was used because of missing data