Robust Estimates Of Value Of A Statistical Life For Developing Economies: An Application To Pollution And Mortality In Santiago

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ABSTRACT

<p>The value-of-statistical-life (VSL) approach is used by environmental economists to value mortality changes resulting from environmental improvement, such as decreased urban air pollution. Because of scarce data, VSL estimates are not available for developing countries. Using robust regression techniques, we conduct a meta-analysis of VSL studies in industrialized countries to derive a VSL prediction function for developing economies accounting for differences in risk, income, human capital levels, and other demographic characteristics of these economies. We apply our estimated VSL to assess the willingness-to-pay for reduction in mortality linked to air pollution in Santiago, Chile. We find willingness-to-pay estimates in the range of $519,000 to $675,000 per life based on 1992 Purchasing Power Parity (PPP) U.S. dollars.

Key Words: air pollution, meta-analysis, mortality, Santiago, VSL, willingness-to-pay.

JEL Classification: I12, Q25, O15

ROBUST ESTIMATES OF VALUE OF A STATISTICAL LIFE FOR DEVELOPING ECONOMIES: AN APPLICATION TO POLLUTION AND MORTALITY IN SANTIAGO

The value-of-statistical-life (VSL) approach is commonly used by environmental economists to value mortality changes linked to environmental changes, such as air pollution increases. The VSL indicates the ex-ante aggregate willingness-to-pay to reduce mortality. The most widely used information comes from studies on wage-risk tradeoff in labor markets (Viscusi 1993). Numerous VSL studies have been conducted in industrialized countries, including direct surveys to elicit willingness-to-pay to decrease mortality, but estimates are virtually nonexistent for developing countries. Scarcity of data on willingness-to-pay to avoid mortality and morbidity, or even on occupational risk and wages, plagues and constrains the emerging body of interesting work analyzing the environment-growth tradeoffs in developing economies.

Many fast-growing developing economies have reached income levels corresponding to their environmental transition. They are scrutinizing the environment-growth tradeoffs implied by their early development strategies, and more particularly the implications of urban pollution (Pargal and Wheeler 1996).[1] Providing health-based estimates of the valuation of environmental improvement/degradation for these economies is a useful exercise because the new information elucidates these tradeoffs. The approaches used to generate such valuation estimates exhibit various degrees of sophistication. Some estimates are back-of-the-envelope types, which scale down health valuation estimates from industrialized countries, that use various scaling factors based on relative income between developing and industrialized economies (e.g., Krupnick et al. 1995), or that borrow a specific willingness-to-pay function from a particular country or policy setting (see Desvousges et al. (1992) for an appraisal of the latter approach).

By contrast, the "Cadillac" approach relies on availability or direct collection of data in the country of choice to estimate willingness to pay for environmental improvements. This approach tends to mobilize substantial resources and human capital out of reach for most decision makers and policy analysts in developing economies (see Alberini and Krupnick; Alberini et al. 1997; for such direct estimates obtained in Taiwan).

Our contribution is to go beyond the dichotomy of these two extremes (back-of-the envelope transfers versus direct surveys and data collection) to provide alternative estimates of willingness-to-pay for reduced mortality in developing economies. Using robust regression techniques, we conduct a meta-analysis of VSL studies in industrialized countries to derive a VSL prediction function for developing economies, accounting for differences in risk, income, human capital levels and demographics of countries.

Robust regression techniques are necessary because little is known about the (stochastic properties of the individual available estimated VSL values), and because these estimates have been obtained by different researchers, using different specifications and techniques. Hence, deviations from normality, and influential data points, can be expected among these existing values. In addition, data scarcity makes it costly to delete influential observations. Robust regression and iterative weighted-least-squares techniques mitigate influence problems without losing degrees of freedom (Besley, Kuh, and Welsh 1980).

We estimate several functional forms and evaluate them based on statistical criteria, as well as analytical properties these VSLs should exhibit, namely, being nonnegative and nondecreasing in income and risk. The latter properties are derived from utility maximization under uncertainty. We select a preferred estimated VSL function based on these criteria.

For purpose of illustration, we apply our estimated VSL to assess the cost of mortality linked to air pollution in Santiago, Chile. Santiago has been beset by one of the worst air-pollution problems in the world, comparable to Jakarta's and Mexico-City's.[2] The fast growth achieved by Chile since its structural adjustment has been phenomenal, but this economic success has been tarnished by its environmental consequences. Environmental degradation including air pollution in Santiago is a major problem identified by the World Bank in its last country review (World Bank 1994). It is useful to know the willingness-to-pay for reductions of mortality due to the health risk associated with urban air pollution. This information is especially valuable to policymakers who have to make decisions involving tradeoffs with no direct market valuation. We find VSL estimates in the range of $519,000 to $675,000 (1992 Purchasing Power Parity [PPP] U.S. $) for Santiago, which locates at the lower end of the range of existing VSL estimates for industrialized countries, mostly because of the risk, income, demographics and education levels characterizing Chile.

Two problems arise with respect to income. First, the international comparison of income should be done accounting for purchasing power parity across countries (Summers and Heston 1991). Second, income levels are systematically lower in developing economies than in industrialized countries. Statistical theory dictates that the predictions of the value of life in developing economies are less precise than predictions made within the income range corresponding to the industrialized countries included in the data, which are closer to the mean value of the dataset. The approach used in the econometric estimation minimizes this loss of accuracy by checking the ability of the model to predict the statistical value of a life for the data points with the lowest income and risk levels.

We use various functional forms and two econometric estimation methods to characterize the response of the willingness-to-pay to reduce mortality to changes in income and risk. We find that the willingness-to-pay is elastic with respect to income, with the median elasticity of around 1.95, and it is inelastic with respect to risk, with a median elasticity of around 0.22. These two qualitative results are very robust.

In the next section, we succinctly present the standard conceptual approach used to value mortality changes. Then, we describe the estimation techniques used to identify problematic data points among the available estimates of VSL. We follow with regression results for a selected subset of specifications. In that section, we also show the implied elasticities with respect to four core variables (income, risk, education and age). Next, we explain how we select a preferred regression among the estimated ones. We finally present the Chilean application related to urban air pollution in Santiago, and the implied willingness-to-pay for decreased mortality associated with air pollution. Then we conclude.

Conceptual Approach

The environmental economics literature has established a standard way to value mortality ex-ante (Freeman 1993; Viscusi 1993). The approach uses an expected utility framework. Income is spent on consumption; M. Earnings are assumed to increase with riskier occupations. Agents face two sources of risk of death: some "background" risk of death φ_e, exogenous to the agent, and some endogenous risk of death φ_j which is related to the occupational choice of the agent. Individual agents maximize expected utility of aggregate consumption or income, or

(1) $$E(U(M))=(1-\varphi_e)\,(1-\varphi_j)\,U(M(\varphi_j)).$$

From the differentiation of the expected utility of aggregate consumption expressed in (1), it can be shown that the willingness-to-pay for a small reduction in the exogenous risk of death reflects the gains in utility induced by the change in the probability of death. The willingness-to-pay depends on the initial risk of death, the current aggregate consumption of the individual, and his/her marginal utility of income (or of aggregate consumption); that is,

(2) $$dM/d\varphi_e = U\,/\,((1-\varphi_e)\,U')\text{ , with } U' = \partial U/\partial M.$$

From the necessary conditions to maximize the expected utility of aggregate consumption with respect to the occupational choice, a fundamental marginal principle is derived. The willingness-to-pay for reduced mortality, that is, the monetary value of the utility gain from lesser risk of occupational death is equal to the marginal wage income forgone by moving to a safer job. This is formally expressed as

(3) $$\partial M/\partial\varphi_j = U\,/\,((1-\varphi_j)\,U').$$

From the comparison of (2) and (3), the latter willingness-to-pay will be almost equal to the willingness-to-pay for small change in the exogenous risk of death, if the two risks, background and occupational, are small or equal. This fundamental approximation motivates the use of information on wage-risk tradeoffs to estimate the willingness-to-pay for small reductions in exogenous mortality related to pollution. Based on that approximation, we then define the marginal willingness to pay (MWTP) for a smaller generic risk, φ , as being equal to $\partial M/\partial\varphi$, or

$$MWTP = \partial M/\partial\varphi = U(M) / ((1-\varphi)\, U'(M)). \qquad (4)$$

Further, from (4) it is straightforward to show that the willingness-to-pay for exogenous risk reduction is nonnegative, increasing in income and risk levels $\partial MWTP/\partial M = \partial^2 M/\partial\varphi\partial M > 0$, $\partial MWTP/\partial\varphi = \partial^2 M/\partial\varphi^2 > 0$. The estimated MWTP in the econometric exercise should satisfy these three basic properties.

Data, Estimation Procedure, and Criteria for Model Selection

To estimate the willingness-to-pay for reduced mortality, we use a combined robust regression-meta-analysis approach to analyze the numerous existing wage-risk studies in industrialized countries (Desvousges et al. 1995; Smith and Huang 1995; Van den Bergh et al. 1997).[3] From these studies we obtain 33 data points on wage differentials and occupational risk. These studies provide estimates of compensation differentials across occupations for different mortality risk levels. The studies use different methodologies, cover different time periods, countries and risk levels (Desvousges et al. 1995; Viscusi 1993; Fisher, Chestnut, and Violette 1989; Cropper and Freeman 1991). The income differential is simply the premium received for engaging in a riskier occupation. The data collected in Desvousges et al. (1995) and Viscusi (1993) were augmented and merged with independent data on demographics, human capital, and other country characteristics.

Several concerns are addressed in the search for a "preferred" MWTP function. Our data for the meta-analysis were generated using different specifications linking wage and risk and were based on raw data of heterogeneous quality. Hence, our data are likely to violate assumptions underlying statistical inference and conventional least-squares techniques. Gauss-Markov assumptions may not be satisfied since different research approaches have been used to generate the data on MWTP and risk.[4] Further, non-normality of the residuals will invalidate any inference on the regressions estimates.

Because heteroskedastic errors are a concern, plots of the residuals against explanatory variables are analyzed for potential patterns in many of the estimated models. Several models reveal megaphone-shaped residual plots, in which the error variance appears to increase with increasing levels of risk and income suggesting heteroskedastic behavior. Since heteroskedasticity and nonnormality often appear together, a modified Levene test for constancy of error variance is conducted on all five OLS models sorting the data by income and risk.[5] Limited evidence was found of heteroskedastic behavior only related to income and for two specification (linear and log-linear).

Since the underlying sample distribution of error e_i is unknown, two procedures are conducted on each model to test the normality assumption: normal probability plots of the studentized residuals and a correlation test for normality.[6] Normal probability plots appear symmetrical with heavy tails suggesting a departure normality or the presence of outliers. In the second procedure, standardized residuals are regressed upon the expected residuals under normality. The coefficient of correlation between the two is compared to the critical value obtained from Looney and Gulledge (1985). With the latter test, three specifications (log-linear, double-log, and translog) exhibit departures from normality or presence of outliers, since outliers often appear at either end of the cumulative distribution (Besley, Kuh, and Welsh 1980).

To remedy these data shortcomings, we use regression diagnostic techniques to identify the points that are influential; that is, those that have a strong role in determining the value of estimated coefficients because of undue influence. Data points are influential because of high leverage and/or large standardized residuals. We compute DFFITS and DFBETAS statistics for each specification (Besley, Kuh, and Welsh 1980).[7] Two observations are systematic outliers and overly influential in many specifications and about 20 percent of the observations are occasionally influential.[8] This recurrence of outliers fully motivates our reliance on robust regression to decrease the weight of these outliers in our estimation.

Another central concern arises from using data from industrialized countries, characterized by high income, older and better-educated populations, to predict "out of sample," in terms of lower-income countries characterized by younger and less educated populations. The latter two factors influence the risk preferences and perception. An additional out-of-sample dimension is that environmental risk tends to be smaller than the occupational risk of the labor market studies; this problem is commonly encountered in many environmental applications. Since accuracy of prediction decreases quickly for points away from the mean of the data used for the estimation, we scrutinize the quality of the estimated predictions for these remote points.

Among the many models we estimate, we use the following statistical criteria in our selection of a preferred estimated model. First, the model should provide good predictions of observations corresponding to low income, risk, and MWTP, such as is the case for our Chilean illustration, and more generally for developing economies' applications. We use mean-square error of prediction measures for the bottom 5 and 10 observations when the data is sorted by increasing order of risk, income, and MWTP. Second, we check residual patterns for the same observations to detect systematic bias in the prediction for the range relevant for the intended applications.

The last econometric concern is the choice of the explanatory variables to include in the various specifications. The theory underlying the estimation clearly links the MWTP to risk and initial income (the utility of aggregate consumption). Beside these two fundamental explanatory variables, other determinants have been used in the studies included in the meta-analysis and these variables may influence the MWTP, such as education (a proxy for human capital and its impact on compensation differentials and information on risk), age, and gender as potential determinants of risk aversion (Cropper and Freeman 1991). We try different combinations of variables, but all of them include the set of core variables found in virtually all studies (risk, income, education, and age). In addition, these variables are most likely to distinguish developing economies' situations from the industrialized countries.

Our succinct analytical framework provides three additional criteria for the selection of a preferred specification. First, we want the estimated VSL function to be nonnegative in the "useful" range of the explanatory variables, that is, in the relevant range for environmental applications in developing economies. Second and third, we expect the MWTP to be nondecreasing in risk and income, and again these positive responses should hold in the "useful" range of the data.

In sum, our meta-analysis relies on the following checks and criteria: investigation and remedies for influential observations; choice of functional forms and explanatory variables; residual pattern and quality of prediction for low values of MWTP; and finally, nonnegativity and positive response of the MWTP to increasing income and risk, in the useful range of the data. We estimate the following equation for the marginal willingness to pay MWTP:

(5) $$MWTP = MWTP(M, \varphi, age, education, other\ non\text{-}core\ determinants) + \varepsilon,$$

where income is annual wages; risk is the number of occupational deaths per 10,000; education is the number of years of education; and other non-core determinants are variables such as gender and non-wage compensation (Bowland 1997).[9] The term ε is the random component of the MWTP.

Results

We ran over fifty specifications[10], including linear, log-linear, double log, quadratic, and translogarithmic. In Table 1, we report results for five representative specifications, familiar to applied economists, which parsimoniously represent different levels of "sophistication" in the approximation of the unknown true specification. We report results for linear, quadratic, logarithmic-linear and translogarithmic specifications. Table 1 indicates the functional form and estimated coefficients. Table 2 reports the associated elasticities of the MWTP with respect to the four core determinants evaluated at the mean of the explanatory variables for each model. Median values of the elasticities generated with the regressions are also included.

We ran these specifications using ordinary-least-squares (Table 1.a) and robust regression (Table 1.b). For the robust regressions we use the iteratively re-weighted least squares (IRLS) method, which lowers the importance of influential data points for which residuals exceed a critical level. We use Huber and Bisquare weighting functions. Results in Table 1.b are obtained using Huber weights. The Huber weighing function uses “descending” weights that do not exclude data points.[11] The Bisquare weights procedure is also descending, but excludes extreme outliers.

Several strong results emerge from the econometric modeling. As shown in Table 2, the marginal willingness to pay is positively related to risk, but the response is inelastic. The MWTP variable responds positively to income and the elasticity value is large (above one). This elastic response, which is larger than the typical income response of MWTP to avoid morbidity, is consistent with Viscusi’s observation that the income response increases with the size of the potential loss. These two results hold for most of the 50 estimated models when the elasticities are evaluated at the mean of the explanatory variables (not reported). The sign results are consistent with expected utility maximization. Assuming asymptotic normality, risk and income responses are both significant at p-value ≤ 0.05 in the linear and double-log specifications.[12]

We also obtain a positive and generally elastic response of the MWTP to the average education of the population investigated. This is another systematic result, although it tends to be significant less often as illustrated in Table 2.[13] Over one third of the 50 models we tested revealed significant coefficients on education. Results pertaining to the age variable show a negative response, but the results are not significant in either OLS or robust runs and they exhibit substantial variations in magnitude of the elasticity.

We are interested in predicting the MWTP and its response to income and risk when the MWTP is itself small and when income and risk levels are low. We check for nonnegativity and positive response to income and risk for the 10 regressions previously reported at low values of the explanatory variables.[14] The first three columns of Table 3 summarize our findings. The linear specification, models (1) and (1’), violates nonnegativity; the translog specification, models (5) and (5’), yields negative risk responses for low values of risk; whereas the quadratic specification, models (2) and (2’), exhibits negative income responses for low values of income.

The next three columns of Table 3 report our results on mean-square prediction error for the bottom 10 observations ranked by order of MWTP, risk, and income. The translog specification (5) and (5’) perform the best based on this criteria, followed by the augmented double-log specifications (4) and (4’). The latter specification constitutes a second best, keeping in mind the negative income response of the translog models. Next, we report on the residual patterns. As shown in the last three columns of Table 3, all models, except the OLS linear specification (1), exhibit some upward bias of the MWTP in its low range. In addition, quadratic

Table 1.a. Meta-analysis of estimates of willingness to pay for marginal reductions in mortality OLS results (N=33)

Explanatory Variable	MWTP	MWTP	ln(MWTP)	ln(MWTP)	ln(MWTP)
INTERCEPT	-1,228.39	903.38	-15.63*	-20.13*	-917.60
	(-1.22)	(0.16)	(-3.10)	(-4.21)	(-1.36)
RISK	67.65*	-41.07			
	(2.62)	(-0.33)			
INC	0.05*	-0.17			
	(3.22)	(-1.01)			
AGE	-7.52	119.08			
	(-0.39)	(0.73)			
EDUC	75.26	-249.79			
	(1.21)	(-0.26)			
$(RISK)^2$		10.85			
		(0.92)			
$(INC)^2$		5.00E-06			
		(1.42)			
$(AGE)^2$		-2.09			
		(-0.84)			
$(EDUC)^2$		16.42			
		(0.39)			
INSURANCE (=1)				-0.75*	
				(-2.89)	
SEX				-0.87	
				(-1.38)	
Ln(UNION)				-0.53	
				(-1.83)	
Ln(RISK)			0.29*	0.30*	-38.81*
			(2.55)	(2.74)	(-2.13)
Ln(INC)			2.10*	2.26*	85.00
			(3.91)	(4.52)	(1.12)
Ln(AGE)			-0.85	-0.77	100.79
			(-0.98)	(-1.00)	(0.97)
Ln(EDUC)			1.61	2.60*	265.73
			(1.57)	(2.69)	(1.48)
½(ln(RISK)^2)					-0.36
					(-0.99)
½(ln(INC)^2)					-3.24
					(-0.48)
½(ln(AGE)^2)					20.05
					(0.77)
½(ln(EDUC)^2)					3.67
					(0.21)
½(ln(RISK)*ln(INC))					-3.78*
					(-2.01)
½(ln(RISK)*ln(AGE))					23.49*
					(2.99)
½(ln(RISK)*ln(EDUC))					12.65*
					(2.26)
½(ln(INC)*ln(AGE))					-13.59
					(-0.56)
½(ln(INC)*ln(EDUC))					-21.29
					(-1.14)
½(ln(AGE)*ln(EDUC))					-93.75
					(-1.40)
R^2	0.564	0.625	0.645	0.754	0.829
F value	9.064	4.989	12.691	10.919	5.835

*P ≤ 0.05. Note: Numbers in parentheses are the ratios of the estimated coefficients to their estimated standard errors.

Table 1.b. Meta-analysis of estimates of willingness to pay for marginal reductions in mortality RLS results (N=33)

Explanatory Variable	MWTP	MWTP	ln(MWTP)	ln(MWTP)	ln(MWTP)
INTERCEPT	-1067.38	955.75	-16.22*	-20.14*	-892.04
	(-1.23)	(0.20)	(-3.63)	(-4.39)	(-1.37)
RISK	57.09*	20.12			
	(2.42)	(0.18)			
INC	0.05*	-0.13			
	(3.69)	(-0.92)			
AGE	-9.94	133.71			
	(-0.60)	(0.94)			
EDUC	72.18	-353.14			
	(1.34)	(-0.42)			
$(RISK)^2$		4.35			
		(0.40)			
$(INC)^2$		4.00E-06			
		(1.33)			
$(AGE)^2$		-2.31			
		(-1.06)			
$(EDUC)^2$		20.42			
		(0.56)			
INSURANCE (=1)				-0.66*	
				(-2.51)	
SEX				-0.84	
				(-1.37)	
ln(UNION)				-0.55	
				(-1.96)	
ln(RISK)			0.31*	0.31*	-37.38*
			(2.96)	(2.88)	(-2.11)
ln(INC)			2.09*	2.27*	79.55
			(4.37)	(4.71)	(1.08)
ln(AGE)			-0.86	-0.80	103.45
			(-1.11)	(-1.07)	(1.04)
ln(EDUC)			1.91*	2.58*	263.60
			(2.05)	(2.75)	(1.52)
$½(\ln(RISK)^2)$					-0.27
					(-0.75)
$½(\ln(INC)^2)$					-2.59
					(-0.40)
$½(\ln(AGE)^2)$					15.71
					(0.62)
$½(\ln(EDUC)^2)$					8.52
					(0.48)
½(ln(RISK)*ln(INC))					-3.93*
					(-2.13)
½(ln(RISK)*ln(AGE))					22.77*
					(2.93)
½(ln(RISK)*ln(EDUC))					13.12*
					(2.41)
½(ln(INC)*ln(AGE))					-11.93
					-0.51)
½(ln(INC)*ln(EDUC))					-24.47
					(-1.35)
½(ln(AGE)*ln(EDUC))					-90.35
					(-1.39)

*$P \leq 0.05$.

Note: Numbers in parentheses are the ratios of the estimated coefficients to their estimated asymptotic standard errors.

Table 2. Partial elasticities of MWTP for OLS and IRLS estimated specifications

		Elasticity of WTP with respect to risk	Elasticity of WTP with respect to income	Elasticity of WTP with respect to education	Elasticity of WTP with respect to age
	OLS Estimation				
(1)	$MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i X_i$	0.236*	1.682*	1.194	-0.399
(2)	$MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i X_i + \Sigma^4_{i=1}\gamma_i X_i^2$	0.046	1.970	1.963	-2.089
(3)	$\ln MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i \ln X_i$	0.294*	2.098*	1.608	-0.850
(4)	$\ln MWTP = \beta_0 + \Sigma^5_{i=1}\beta_i \ln X_i + \Sigma^7_{i=6}\gamma_i X_i$	0.300*	2.256*	2.598*	-0.774
(5)	$\ln MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i \ln X_i$				
	$+ ½\Sigma^4_{i=1}\Sigma^4_{j=1}\gamma_{ij}\ln X_i \ln X_j$	0.133†	1.408	0.739	-3.250
	IRLS Estimation				
(1')	$MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i X_i$	0.199*	1.657*	1.145	-0.527
(2')	$MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i X_i + \Sigma^4_{i=1}\gamma_i X_i^2$	0.146	1.925	1.766	-2.215
(3')	$\ln MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i \ln X_i$	0.307*	2.093*	1.905*	-0.863
(4')	$\ln MWTP = \beta_0 + \Sigma^5_{i=1}\beta_i \ln X_i + \Sigma^7_{i=6}\gamma_i X_i$	0.306*	2.269*	2.578*	-0.802
(5')	$\ln MWTP = \beta_0 + \Sigma^4_{i=1}\beta_i \ln X_i$				
	$+ ½\Sigma^4_{i=1}\Sigma^4_{j=1}\gamma_{ij}\ln X_i \ln X_j$	0.149†	1.520	0.733	-4.080
	Minimum	0.046	1.408	0.733	-4.080
	Median	0.218	1.948	1.687	-0.857
	Maximum	0.307	2.269	2.598	-0.399

*Partial elasticity was significant at $P \leq 0.05$ according to *t*-statistic for estimated coefficients.

†Partial elasticity was significant at $P \leq 0.05$ according to *t*-statistic for estimated coefficients, except for estimated coefficient on squared risk term which was P = 0.34.

Note: Explanatory variables X_i (i=1,...,7) include risk, income, age, education, insurance, sex and union membership. Elasticities are evaluated at the mean of the explanatory variables.

Table 3. Summary of model selection criteria

		Predicted MWTP at low ends of data[a]	Δ Predicted MWTP at low ends data for:[a]		Minimum MSEP for bottom 10 observations when sorted by increasing order of:[b]			Systematic pattern in residuals for bottom 10 observations when sorted by increasing order of:[c]		
			Δ Risk	Δ Income	MWTP	Risk	Income	MWTP	Risk	Income
	OLS Estimation									
(1)	$MWTP = \beta_0 + \Sigma^4_{i=1} \beta_i X_i$	–	+	+	10	9	9	No	No	No
(2)	$MWTP = \beta_0 + \Sigma^4_{i=1} \beta_i X_i + \Sigma^4_{i=1} \gamma_i X_i^2$	+	+	–	7	8	7	Yes	Yes	No
(3)	$LnMWTP = \beta_0 + \Sigma^4_{i=1} \beta_i \ln X_i$	+	+	+	5	5	10	Yes	Yes	No
(4)	$LnMWTP = \beta_0 + \Sigma^5_{i=1} \beta_i \ln X_i + \Sigma^7_{i=6} \gamma_i X_i$	+	+	+	3	3	3	Yes	No	No
(5)	$LnMWTP = \beta_0 + \Sigma^4_{i=1} \beta_i \ln X_i + ½\Sigma^4_{i=1}\Sigma^4_{j=1} \gamma_{ij} \ln X_i \ln X_j$	+	–	+	1	1	1	Yes	No	No
	IRLS Estimation									
(1’)	$MWTP = \beta_0 + \Sigma^4_{i=1} \beta_i X_i$	–	+	+	9	10	8	Yes	No	No
(2’)	$MWTP = \beta_0 + \Sigma^4_{i=1} \beta_i X_i + \Sigma^4_{i=1} \gamma_i X_i^2$	+	+	–	8	7	6	Yes	Yes	No
(3’)	$LnMWTP = \beta_0 + \Sigma^4_{i=1} \beta_i \ln X_i$	+	+	+	6	6	5	Yes	Yes	No
(4’)	$LnMWTP = \beta_0 + \Sigma^5_{i=1} \beta_i \ln X_i + \Sigma^7_{i=6} \gamma_i X_i$	+	+	+	4	4	4	Yes	No	No
(5’)	$LnMWTP = \beta_0 + \Sigma^4_{i=1} \beta_i \ln X_i + ½\Sigma^4_{i=1}\Sigma^4_{j=1} \gamma_{ij} \ln X_i \ln X_j$	+	–	+	2	2	2	Yes	Yes	No

[a] Sign on predicted MWTP given low and out of sample data on risk, income, education and age

[b] Rank order from 1 to 10 of best to worst models in terms of having lowest relative MSEP (e.g., 1 indicates the model with the lowest MSEP).

[c] Models for which 8 to 9 out of 10 residuals were *negative* are marked with a “Yes.” No models exhibited *positive* patterns in the residuals.

models (2) and (2') and double-log models (3) and (3') also exhibit upward bias for the individual predictions of bottom observations ranked by increasing order of risk.

These results on the performances of the various models epitomize the "hard" choices faced by the applied economist. We give precedence to theory and disqualify the translog and the linear model because they violate important attributes of the MWTP. Then, based on mean-square prediction error, bias and existence of outliers, we select the robust regression version of the augmented double-log specification as our "preferred" model. The latter specification satisfies the three properties of MWTP functions and predicts well in the low range of the data, with a qualifier for the upward bias in MWTP predictions in its low range. This selection is not unique, but it clearly spells out the criteria used and the researchers' preferences over these criteria.

An Application to Urban Air Pollution in Chile

We apply our estimated specifications to calculate the willingness-to-pay for reduction of air pollution in Santiago. The air pollution estimates come from a study of growth-pollution tradeoff of the Chilean economy using an dynamic recursive economywide model (Beghin et al. 1998).[15] In the latter study, the pollution data have been calibrated to existing data from an elaborated pollution inventory and dispersion model existing for Santiago (World Bank 1994; Ulriksen et al. 1994; Ostro et al. 1995; O'Ryan 1993; Bowland 1997). The economywide model provides estimates of air pollution in Santiago under different policy scenarios, between 1992 and 2010. [16]

Using our preferred model, we predict the willingness-to-pay to avoid mortality increases occurring between 1992 and 2010 under two scenarios. First, we consider a "business-as-usual" (BAU) growth scenario, in which no policy change occurs, but in which economic activity, income and pollution rise overtime. In the second scenario, emission taxes impose a 25-percent reduction of emissions of small particulates with respect to their levels in the BAU scenario in the year 2010. These particulates are a major source of urban air pollution that influences mortality (Ostro et al. 1995). In this second scenario income decreases relative to its level in the BAU scenario because of the cost–increasing effect of pollution abatement. Mortality in the year 2010 also decreases relative to its level in the BAU scenario.

We value the willingness-to-pay at the projected 2010 income, expressed in 1992 PPP dollars, which are the base prices for the economywide modeling exercise. Age and education are the current value for Chile, which we use as best guesses of their future (2010) levels. Dose-response functions, used to generate the mortality incidence of air pollution, typically give a range of values for the mortality response to pollution, which translates into two estimates of mortality change (low, high) for the period 1992-2010, and for each scenario.[17] We report two "preferred" estimates corresponding to the two risk changes.

We also discuss briefly the range of estimates of the MWTP obtained for all models and estimation methods used in the previous section, and their median value, to provide some notion of the variation in estimates. As reported in Table 4, the willingness-to-pay estimates to decrease mortality in the BAU scenario are \$231 and \$259 PPP for our preferred specification and the two respective risk changes. The median of estimated values is \$228 PPP dollars for the BAU scenario and the range of values is large, from \$46 to \$924 PPP. The preferred values reported under the environmental policy reform scenario, \$196 and \$220 PPP, are smaller, reflecting smaller risk and lower income under the environmental reform. The median value for the 20 estimated MWTP values is \$190 PPP, with a range of \$94 to \$819 PPP in this second scenario.

The last step to value the damage associated with mortality is to multiply the estimated individual marginal willingness-to-pay ($MWTP_I$) for reduced mortality by the population at risk ($Population_i$) and then divide this sum of willingness-to-pay values by the expected reduction in the number of deaths for that population. The number obtained by these transformations is the statistical value of a life (VSL). It is:

(6) $$VSL = MWTP_i(\Delta\varphi_i, M, \text{other non-income determinants}) * Population_i / \Delta L_i$$

where $MWTP_i$ is a function of risk changes $\Delta\varphi_i$ (expressed in number of deaths per 10,000), level of income M and other non-income determinants such as education for individuals of the i^{th} population at risk; $Population_i$ is the number of individuals in the i^{th} population at risk; and ΔL_i is the change in projected statistical lives lost in $Population_i$. VSL expresses the ex-ante aggregate willingness-to-pay of a human group to reduce mortality. As shown in Table 4, our preferred specification yields two values right around the median value: \$518,656 and \$674,997 1992 PPP, and \$609,746 1992 PPP for the median of all 20 estimates (5 specifications by 2 estimations method by 2 risk levels), in the BAU scenario. For the environmental reform scenario, our preferred specification yields VSL estimates slightly above the median (see Table 4 for more details). For both scenarios, the range of VSL estimates obtained with the different specifications and estimation method is large.

For any given MWTP function, the corresponding VSL varies by policy scenario because risk and income levels vary by scenario as well, and thus, alter the value of the MWTP function between scenarios. There is a monotonic relationship between MWTP and the risk level, because environmental policy reforms affect both mortality and income negatively (the environmental tax is contractionary). The lower income and mortality in the policy reform scenario translate unambiguously into a lower MWTP than the MWTP under the BAU scenario. The intuition of the lower willingness-to-pay is clear: further reductions in mortality, when mortality has already been decreased by the environmental reform, are less valuable because the risk is lower,

Table 4. Estimated MWTP and implicit VSL in Santiago to avoid increased mortality due to PM-10 pollution projected in 2010 by policy scenario using IRLS estimation of preferred model (4’) (in 1992 PPP$ at projected 2010 income levels)

Policy Scenario	□Risk[a]	MWTP[b]	VSL[c]
Business-as-Usual	Low	231	674,997
	High	259	518,656
PM-10 Tax Reform	Low	196	960,489
	High	220	738,023

[a] The change in risk of death due to PM-10 levels varies from low to high based on different dose-response function slope estimates (b) and changes in PM-10 concentration levels from 1992 to 2010 ()A) for a *particular* policy. Dose-response function slopes taken from the literature are given as b_{low} = 0.39 deaths/10,000 and b_{high} = 0.57 deaths/10,000 (Ostro, Sanchez, Aranda, and Eskeland 1995; The World Bank 1994). Estimated changes in PM-10 concentration levels under BAU and PM-10 Tax policy reform are given as)A_{BAU} = 8.7716 (10 :g/m$^{3)}$ and)$A_{PM\text{-}10\ Tax}$ = 5.2259 (10 :g/m^3) (Beghin, Bowland, Dessus, Roland-Holst, and van der Mensbrugghe, forthcoming). Thus as an example, the low)Risk for BAU is calculated as (b_{low} *)A_{BAU}) = (0.39 * 8.7716). Similarly, given the same slope estimates yet a different change in pollution concentration levels under the PM-10 tax policy, the corresponding low)Risk for PM-10 Tax policy is calculated as (b_{low} *)$A_{PM\text{-}10\ Tax}$) = (0.39 * 5.2259).

[b] Estimated individual WTP in Santiago to avoid changes in the risk of death associated with increased PM-10 pollution over 1992 levels under BAU and a PM-10 tax reform policy (decreasing PM-10 emissions by 25 percent relative to BAU in 2010).

[c] Implicit VSL in Santiago associated with increased PM-10 pollution over 1992 levels under BAU and a PM-10 tax reform policy (decreasing PM-10 emissions by 25 percent relative to BAU in 2010).

Notes: Implicit VSL was calculated as the total MTWP by citizens of Santiago divided by the projected number of premature deaths in 2010 associated with increased PM-10 pollution over 1992 levels (i.e., [MTWP * Population / Premature Deaths]). Population = 6,835,698 is the projected population for Santiago in 2010 (Bowland, 1997; Table 4-2). Premature Deaths = (ΔRisk * (Population/10,000)) where ΔRisk is as given above and population is normalized to 1/10,000 to match the scale of ΔRisk. Thus as an example, the implicit VSL for BAU using low ΔRisk ≅ (231 * 6,835,698) / (3.4209 * (6,835,698 / 10,000)) which differs from above due to rounding of the MTWP figures.
MWTP are calculated using Chilean projections for 2010 risk levels, income ($10,636 in 1992 PPP in BAU), average age for total population (29.32) and average schooling (11.83 years) (Bowland). Given the difference in base prices between the economywide model (1992 PPP) and the econometric estimation of the MWTP function (1990 PPP), our income figures for Chile was adjusted to 1990 PPP$ before being substituted in the MWTP function. The MWTP estimate was then adjusted back to 1992 PPP$ (base conversion factor of (1.06306) from summers and Heston.

and because the MWTP is evaluated at a lower income level. However, the VSL may increase or decrease because the number of potential lives saved by in the year 2010, ΔL_i, decreases as well under the policy reform compared to the life savings of the BAU scenario. Hence, both numerator and denominator of the VSL are smaller under the policy reform scenario than under the BAU scenario. As shown in Table 4, the VSL actually increases under the reform imposing a 25 percent reduction of small particulates, PM-10.

Finally, it is instructive to compare our estimates to some estimates obtained independently or with alternative methods. We use two sources. The first estimate comes from The World Bank (1994) environmental review of Chile. Using a human capital approach, The World Bank comes up with a low VSL of US $36,172 (in 1992 PPP dollars).[18] It is well known that the human capital approach provides a lower bound estimate and seriously underestimates the willingness-to-pay for risk reduction (Freeman 1993). The second estimate is more informative. It is obtained using the MWTP function from Desvousges et al. (1995), scaled down by the ratio of relative (Chile/US) income.[19] We obtained $1,616,807 in 1992 PPP dollars, which is higher than our preferred estimate and also higher than the median of the 20 estimates, although it well is within their range ($91,399; $2,427,374). This result is due to the assumption of unitary elasticity implied by the scaling ratio. Increasing the relative income elasticity to 1.95 (the median income elasticity for all estimated MWTP functions) from 1 reduces the estimate based on Desvousges et al. (1995) to around $770,067 PPP, which is "close" to our preferred estimates.

Concluding Comments

The estimation of mortality damages in developing economies is a topic of rising importance because many of these economies are in their environmental transition. Growth-environment tradeoffs, which were taken for granted, are being reexamined. Adverse environmental aspects of economic growth translate in higher welfare losses in economies with rising incomes. The range of possible applications of estimates of mortality valuation is large, especially in the context of mortality related to pollution.

Our approach exhausted the extensive information existing on mortality valuation in industrialized countries and systematically accounted for differences between developing and industrialized economies, in income, risk of death, age, education, and other socio-economic variables. We found that the estimated willingness-to-pay for reduced mortality is sensitive to the chosen functional form, but that most estimated specifications exhibit an inelastic response to changes in risk of death and an elastic response to income changes; both were positive as expected from the conceptualization exercise. These two results are robust to functional form changes, presence of outliers, and changes in explanatory variables included as regressors.

Using statistical criteria and economic properties of the MWTP, we selected a preferred specification: a double-log specification augmented with some additional fixed effects, which had good predictive power, was parsimonious, and satisfied properties of MWTP functions implied by expected utility maximization. In addition, the selected specification yielded values of elasticities close to the median of the numerous estimated specifications and it predicted well, based on the investigation of prediction error.

We applied our estimated MWTP functions to value changes in mortality associated with urban air pollution in Santiago. We provided two estimates of the VSL in Chile based on our preferred MWTP function and two risk levels, $518,656 and $674,997 1992 PPP, in order to avoid the mortality (and urban pollution) resulting from a "business-as-usual" growth scenario. Potential applications are numerous.

In the long run, the approach set forth by Alberini et al. (1997) to estimate willingness-to-pay for lower health risk will be the norm: fast-growing economies will eventually develop the institutional capacity to generate their own estimate based on their direct data collection. In the medium run, our palliative approach appears promising: it is rigorous enough to avoid the pitfalls of mechanical MWTP value transfers and is clearly feasible in the data-scarce context of developing economies.

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ENDNOTES

1. Pargal and Wheeler investigate the demand and supply for absorptive capacity for industrial water pollution in Indonesia using municipality-level data from 1989-90. The supply of absorptive capacity was not formally regulated at the time and depended on economic and demographic variables characterizing the municipalities, many of them urbanized. They find that the environmental supply function dramatically decreased with rising income and education levels, as evidenced by much lower pollution intensity of industrial output in plants located in more affluent communities. Since then, Indonesia started regulating water discharges.

2. For example, total suspended particulates (TSP) and respirable particulates (PM-10), ozone and CO concentrations are in excess of established standards for several months every year (World Bank 1994). The one-year average concentration of PM-10 was estimated at 50 $\mu g/m^3$ in Santiago in 1992, the most recent year reported in the World Bank Environmental Report (World Bank 1994). Comparable PM-10 measures for Jakarta and Bangkok suggest that Santiago's PM-10 concentration is respectively about 50 and 30 percent higher than those in the two cities.

3. Desvousges et al. (1995) investigate the importance of "smallness" in risk in determining the MWTP for mortality reduction. They abstract from income, education, age and other demographic variables. Smith and Huang (1995) use robust regression techniques in a meta-analysis of hedonic studies of property values. Van den Bergh et al. (1997) is a treatise of meta-analysis techniques and applications in environmental economics.

4. Estimates of compensation differentials were obtained from different researchers using different hedonic specifications with different levels of precision yet based on similar samples of risk and micro data. This implied that our regression residuals (u_i) may not meet the assumptions of *iid* random errors.

5. The modified Levene test is robust against serious departures from normality, yet remains efficient when errors are distributed as normal (Neter, Kutner, Nachtsheim, and Wasserman). The test divides residuals from each model into two groups by increasing order of the explanatory variable of interest, in our case, income and risk.

6. The standardized residual (u_{si}) recognizes differences in the sampling errors of the residuals by taking into account the magnitude of each u_i relative to its estimated standard deviation. The standardized residual is normalized so that they have constant variance (when the model is appropriate). The standardized residual is estimated as $u_{si} = u_i / s$, where the estimated standard deviation $s = [MSE(1-h_i)]^{½}$ and h_i is the diagonal element of the "hat" matrix.

7. DFFITS measures the change in fit induced by deletion of an observation, that is the difference of fit dependent variable obtained with the two data sets (full and with one or more observation deleted). The difference is normalized by the estimated standard deviation of the fit obtained with the smaller data set. DFBETAS measures the difference between a regression coefficient estimate obtained with the full data set and with a data set with one or more observations deleted. The difference in estimates is normalized by the estimated standard deviation of the coefficient estimates with the smaller data set.

8. Observations 20 (Brown 1980) and 23 (Butler 1983) had high leverage and were influential in many specifications with large DFFITS and DFBETAS for the age and education variables (see Bowland 1977 for details).

9. Additional variables include categorical variables for gender and for white/blue collar, percentage of union members in the sampled population, percentage of the sampled population with urban residence, categorical variables for regional breakdown (3 regions in the US and abroad), a dummy variable for studies including worker's compensation, and a dummy for BLS or non-BLS risk data.

10. The chosen functional forms include linear, quadratic, log-linear, double-log, log-quadratic, and full translog and for regressors including the 4 core variables and various subsets of non-core variables. For sake of exposition we report on five representative specifications.

11. Huber weights are as follows: if the standardized residual is smaller in absolute value than 1.345, the weight is equal one; else the weight is equal to (1.345/|residual|).

12. The use of single t-tests of coefficients for determining significance of elasticities in the quadratic model is stringent.

13. Evaluating the precision of estimated coefficients is more complex with robust regression methods than with ordinary least squares. We rely on asymptotic normality.

14. We assume that income was $5,000 in PPP dollars, that the mortality change was of the order of 1/1,000,000, and that age was 25 years and education 6 years. The last two values are necessary to evaluate nonnegativity.

15. The Chilean investigation is part of the research program of the OECD Development Centre on the interface between growth, trade and the environment, with a focus on Pacific countries (see Beghin et al. 1995–1998, and Lee and Roland-Holst 1997 for companion papers).

16. For reference, our Chilean application relies on the following assumptions: risk changes are of the order of 1/10,000, the projected income from the economywide modelling exercise is equal to 1992 PPP $10,636 for the year 2010 under BAU ($10,604 under PM-10 scenario); the assumed average age of the total population is 29.32 years; and average schooling is 11.83 years of schooling (Bowland 1997). The projected income has to be expressed in 1990 prices before being substituted in the MWTP formula since the MWTP functions are based on in 1990-prices data. The estimated MWTP values are then inflated back to 1992 prices, which are the base prices in the economywide model.

17. See notes in Table 4 for an explanation of predictions generated by dose response functions

18. The World Bank study analyzes different pollution changes, but of comparable magnitude to our case. Hence, the comparison is just illustrative.

19. We used the information of Table 7-4 in Desvousges et al. (1995) (medium cd value) expressed in 1992 dollars and rescaled by the ratio of the predicted Chilean income in 2010 over the US income, all in 1992 PPP dollars (scaling factor of 0.548).