AIR POLLUTION, REGIONAL MORBIDITY DAMAGES AND DAMAGE FUNCTIONS#

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I. INTRODUCTION

Epidemiological studies have suggested that morbidity rates are significantly related to the air pollution concentration level.[1] The relationship between air pollution and health can be an acute response, i.e., dramatic increases in air pollution can exert an immediate adverse effect on human health. However, air pollutants continuously react dynamically in the environment, and the effect of pollution on health should be examined over an extended period.

The results of a great number of epidemiological studies have indicated that incidence rates of various kinds of diseases are generally much higher in urban areas than in rural areas, and many of the disparities in morbidity rates between urban and rural areas can be attributed to air pollution.

The effect of air pollution on mortality has been examined recently, for example, by Liu and Yu (1976), Smith (1976) and Lave and Seskin (1973), among others. The damaging effect of air pollution on morbidity on a regional basis, however, has not yet been studied. This paper is an exploratory effort to remedy this gap in the literature by estimating economic damages and damage functions of adult morbidity due to air pollution.

Policymakers need access to national and regional damage cost figures in order to devise optimal pollution control strategies, and a set of internally consistent and fairly accurate damage estimates is particularly useful to policymakers. The purpose of this paper is, hence, to derive such damage estimates. The morbidity damage costs are estimated for the 40 SMSA's which had a sulfur dioxide (SO_2) concentration level equal to or greater than the threshold level, i.e., 25 $\mu g/m^3$.[2] The selection of a threshold level of $25\mu g/m^3$ is primarily based on the consideration that it is the average concentration level reported in the rural areas. In addition, physical and economic damage functions useful for prediction purposes are developed by relating morbidity rates and morbidity costs, respectively, to a host of air pollution, socioeconomic, demographic and climatological variables.

This paper, which represents an exploratory effort to estimate morbid-

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ity physical and economic damage functions, is developed as follows: Section II sets out a theoretical framework for estimating the morbidity damages; Section III provides a simulation and regression analysis for deriving an adult morbidity dose-response function; morbidity costs in the sampled SMSA's and an "average" economic damage function for adult morbidity are estimated in Section IV; and Section V contains the concluding remarks.

II. ENVIRONMENTAL DAMAGE FUNCTIONS: SOME THEORETICAL UNDERPINNINGS

An economic damage function, which is usually derived on the basis of a physical damage function, is defined, for example, by Maler (1974) as the compensating variation or the amount the individual (or society) should be compensated so as to maintain his initial preference level in the presence of a deterioration in the environment. This definition is clearly applicable to any situation in which the effect of environmental degradation enters directly into the individual's utility function.

It is assumed that the consumer's preferences can be represented by a twice differentiable, concave utility function, defined on R^{m+n} as:

$$U = U(C,H(A)) \tag{1}$$

where C is an m-vector representing m private commodities and services, with positive components indicating consumption and negative components representing supply of labor services. H denotes the health status, which is influenced by air pollution and can be viewed as the dose-response function, and A is an n-vector characterizing environmental quality, which is exogeneously given to the community.

Each individual wants to maximize (1) subject to the following budget constraint:

$$PC \leqslant Y \tag{2}$$

where P is the price vector associated with C, and Y is the individual's income.

The economic damage function, as registered in the compensation variations due to changes in the individual's health condition because of changes in A, can be derived by minimizing the total expenditures subject to a given utility level, say $\overline{U}$.

The familiar first-order necessary conditions are:

$$\alpha\ U_i = P_i,\ i = 1, \ldots, m \tag{3}$$

where α is the Langrangean multiplier.

Solving (3) yields the following compensated demand functions:

$$C = C(P,H(A);\overline{U}) \tag{4}$$

The minimum income required to maintain the same utility level when one or several components in A changes is denoted by:[3]

$$I = I(P,A;\overline{U}) \tag{5}$$

If the individual always exhausts his budget, the economic damage function, ED, is derived as the difference between (5) and the individual's initial income, Y:

$$ED = I - Y = f(P,H(A);\overline{U}) \tag{6}$$

Note that the health condition H is generally determined by a set of socioeconomic, demographic and climatological variables in addition to air pollution. Thus:

$$ED = f(H(E,D,S,W,A;\ e),P) \tag{7}$$

where E stands for the economic factors; D, the demographic factors; W, the climatological factors; A, air pollution, e, error term; and P, the commodity prices.

Morbidity economic damages in the jth urban area, ED_j, however, can be roughly estimated by:

$$ED_j = \left[MB_j(A) \times pC_j + HS_j(A) \times HC_j + DU_j(A) \times DC_j\right] \times POP_j \tag{8}$$

where MB is the morbidity rate; HS, the hospitalization rate; DU, the drug use rate; pC, the physician cost; HC, the hospitalization cost; DC, the drug cost; POP, the population in the area; and A, the pollution level.

III. PHYSICAL DAMAGE FUNCTIONS OF MORBIDITY AND AIR POLLUTION

This section is concerned with deriving physical damage functions on adult morbidity by the classical least-squares linear regression techniques and the random sampling, simulation method. The data base for the regression analysis is provided by the dose-response observations obtained from the Community Health and Environmental Surveillance System (CHESS) study (Shy, *et al.*, 1974). The aggregate dose-response observation reported in the CHESS study related morbidity prevalence rate to particulates and sulfur dioxide in 1971 for four regions, i.e., Salt Lake Basin, Chicago, Rocky Mountain and New York.[4] However, only the effects of sulfur dioxide on morbidity will be considered in this paper.

To derive the dose-response functions for Salt Lake Basin, Chicago, Rocky Mountain and New York, the adjusted morbidity prevalence rates were regressed on the pollutant by the least-squares technique. The regression results are summarized in Table 1. The regression fit between morbidity and SO_2 for New York, Chicago and Salt Lake Basin is fairly good, with R^2 having the values of 0.50, 0.88 and 0.94, respectively. Furthermore, SO_2 is significant at the 1 percent level for the New York and Salt Lake Basin regression equations.

These regression equations coupled with the mean values and standard deviations of the pollutant and the morbidity prevalence rates as presented in Table 2, were used for a random sampling and simulation study to generate a "national" dose-response function which was used for estimating morbidity damage costs in the 40 selected SMSA's.

"Simulation" is the technique of setting up a stochastic model of a real situation so that sampling experiments can be performed upon the model. A random sampling experiment was performed on the four sample regions which were constructed in the two dimensional space with the aid of the four regional dose-response functions presented in Table 1. Data on the mean values and the standard deviations of the dependent and independent variable (see Table 2) were also used. The four regional sample blocks are shown in Figure 1, in which the vertical axis represents the morbidity rate expressed in number of incidences per 100 residents, and the horizontal axis denotes the SO_2 pollutant concentration level expressed in $\mu g/m^3$. For each sample block, the height of the block is measured by the difference between the morbidity rates computed from the dose-response function, with the coefficient of SO_2 in the function taking the value of (b + s) and (b − s), where b is the coefficient of SO_2 and s is the associated standard error. The width of the block is, however, measured by the mean value of SO_2 plus and minus one standard deviation of the mean, i.e., $(\overline{X} + S)$ and $(\overline{X} - S)$, where $\overline{X}$ denotes the mean value of SO_2 and S is the associated standard deviation.

Thus, the four sample blocks shown in Figure 1 were defined on the basis of the four prior studies regarding the morbidity effect of SO_2 in the four different regions. The construction of these four blocks enables random sampling experiments to be performed. A random sample of 800

TABLE 1
ADULT MORBIDITY LINEAR DAMAGE FUNCTIONS[a]

	$MB(\%) = a + b\ SO_2$		
Regions	a	b	R^2
(1) Rocky Mountain	3.84 (0.94)*	0.001 (0.005)	0.016
(2) Chicago	22.14 (2.49)*	0.018 (0.023)	0.50
(3) New York	4.2 (3.46)	0.21 (0.08)*	0.88
(4) Salt Lake Basin	6.22 (0.46)*	0.075 (0.013)*	0.94

[a]The values below the coefficients are standard errors with * to indicate that they are significant at the 1 percent level.

TABLE 2
MEAN VALUES AND STANDARD DEVIATIONS OF THE VARIABLES

	Mean Value ($\overline{X}$)	Standard Deviation (S)
Utah		
Prevalence Rate	8.2	1.9
SO_2	26.8	24.2
Chicago		
Prevalence Rate	24.2	2.6
SO_2	110.6	99.8
Rocky Mountain		
Prevalence Rate	4.0	1.3
SO_2	132.8	150.8
New York		
Prevalence Rate	13.2	3.7
SO_2	41.2	16.2

observations was obtained, with 200 chosen from each block, and to eliminate possible bias resulting from the overlapping of the blocks, another random sampling was performed on the 800 observations. A smaller sample of 81 observations, i.e., about 10 percent of 800, was also chosen. These 81 observations were used to develop a nonlinear "average" dose-response function specified as follows:

$$MB = C + EXP\ (a\text{-}b/SO_2) \tag{9}$$

The dose-response function is expressed as an exponential function which is consistent with *a priori* judgment and empirical results of medical experts regarding plausible human dose-responses to changes in pollution levels. The geometrical counterpart of this exponential relation is a long flat "S" curve, implying that while the air pollutant contributes to the morbidity incidence rate, the damaging effect is not proportional. In the presence of an increased SO_2 level, the morbidity rate initially increases and continues to increase but decreases after a certain inflection level.

Of necessity, the C term in equation (9) is assumed to take the value of 11 since 11 is the arithmetic mean of the morbidity rates calculated from the four regional dose-response functions with the explanatory variable, SO_2, being at the threshold of 25 $\mu g/m^3$.

In estimating equation (9), the classical least-squares technique was applied. Since (MB - 11) may be negative and the logarithm of a negative number is undefinable, (MB - 11) was squared prior to its logarithm transformation. The resultant regression equation was then adjusted by dividing the coefficients by 2.

The regression results for equation (9) were obtained as follows:

$$MB = 11 + EXP(\underset{(0.11)^*}{0.65} - \underset{(1.99)^*}{4.96}/SO_2)$$

$$R^2 = 0.072 \tag{10}$$

The figures below the coefficients are standard errors, with * indicating that the coefficients of SO_2 are significant at the 1 percent level. However, the pollution variable SO_2 explains only about 7 percent of the variations in the residual morbidity rate, i.e., (MB - 11).

The nonlinear morbidity dose-response function has a number of distinguishing features: (1) the nonlinear dose-response function is not only more in accord with *a priori* judgment regarding human morbidity response to pollution doses, but it is also more amenable than the linear function to being adjusted with whatever the assumed threshold level of SO_2 is in estimating economic damages; and (2) for the purpose of predicting and estimating the marginal morbidity damages due to SO_2, the nonlinear equation has showed better fit, and hence, will yield more accurate prediction than the linear equation.[5]

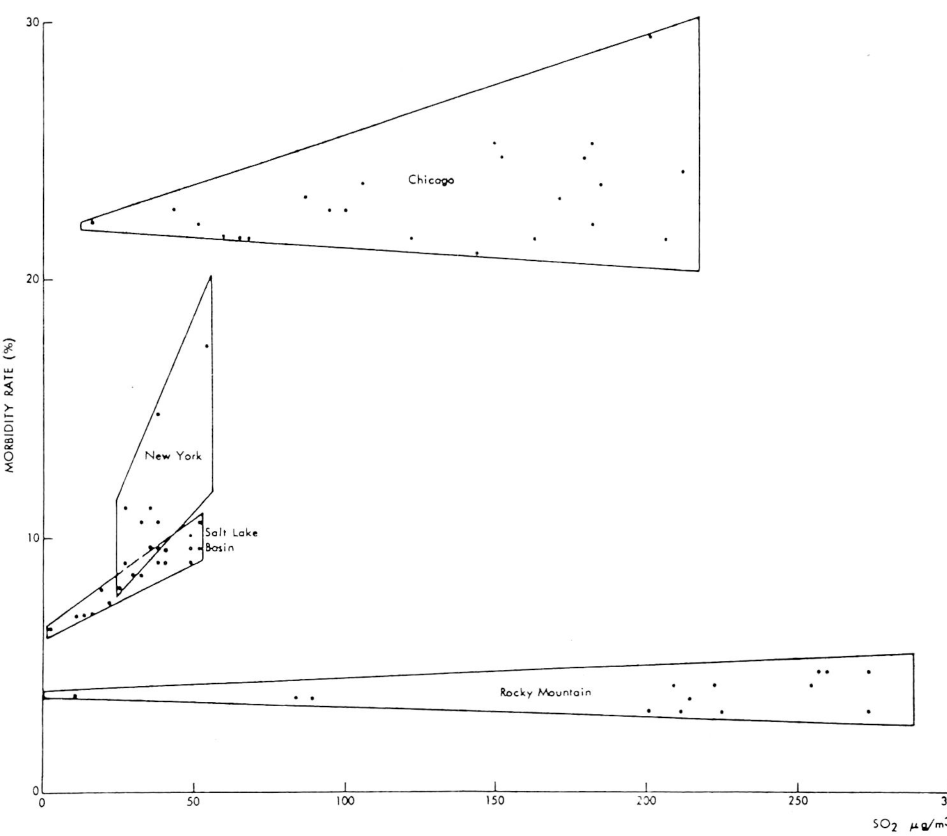

Figure 1 - Sample Observation From Four Morbidity Studies With Respect to SO_2

IV. MORBIDITY DAMAGES AND ECONOMIC DAMAGE FUNCTION

Given the nonlinear physical damage function, the economic costs of diseases attributable to air pollution can be estimated by transforming the "extra" morbidity rate into monetary units.

Morbidity damages generally are comprised of two parts: direct and indirect costs of illness. Included in the direct costs of illnesses are the expenditures for prevention, detection, treatment, rehabilitation, research, training and capital investment in medical facilities. Indirect costs of illness include the loss of output to the economy because of disability and the imputed costs such as opportunities foregone.

Both direct and indirect morbidity costs were estimated. Direct morbidity costs were computed by summing the costs of physician visits, hospitalization costs and drug costs. According to a recent study by Jaksch (1975), the average cost per physician visit for all ages combined in 1970 was $14, and the average cost of a hospital day for all ages combined was $82. To estimate total morbidity costs, further information is needed on the average number of physician visits and the average length of hospital stay per pollution-related disease incidence. In the absence of such useful information, a number of assumptions were made for the damage estimation as follows: (1) each pollution-related morbidity incidence results in one visit to consult a physician; (2) 1 of 8.3 physician visits, i.e., 12 percent, results in hospitalization; (3) drug costs run about 50 percent of the physician costs; (4) if hospitalization is required, each patient stays 1 day in the hospital for treatment.

The conservative nature of both assumptions (1) and (4) possibly leads to underestimations of the morbidity costs. This bias could be partially removed by assuming a greater number of physician visits and a longer hospital stay, however. The estimates presented in this paper can be regarded as *low* estimates for morbidity costs. Assumption (2) is based on the calculated proportion of physician visits resulting in hospital discharge for four categories of diseases related to pollution (Jaksch, 1975). The average of such proportions of physician visits in the four disease categories is 12 percent. Assumption (3) is, however, based on a ratio of total drug costs to total physician costs attributable to the use of an oxidation catalyst as estimated by (Jaksch, 1975), i.e., 11.4/23.2 = 0.5.

The direct morbidity costs attributable to SO_2 were estimated with the aid of the following formulas:

$$PCSO_2 = \$14 \times EXP\left[0.65 - 4.96/(SO_2 - 25)\right] \times POP \times NPV \quad (11)$$
$$HGSO_2 = \$82 \times EXP\left[0.65 - 4.96/(SO_2 - 25)\right] \times 0.12 \times POP \times HSD \quad (12)$$
$$DCSO_2 = 0.5 \times PCSO \quad (13)$$

where $PCSO_2$ denotes physician cost attributable to SO_2; $HCSO_2$ denotes hospitalization cost attributable to SO_2; $DCSO_2$ denotes drug cost attributable to SO_2; POP denotes SMSA population; NPV denotes number of physician visits per incidence = 1 (by assumption 1); and HDS denotes number of hospital stay days = 1 (by assumption 4).

Recall the physical dose-response function for SO_2, as expressed in equation (10), which has an intercept value of 11. If the exponential term in equations (11) and (12) is replaced by the value of the intercept of the dose-response function, then another set of cost estimates for morbidity in the absence of SO_2 can be accordingly estimated.

Another dimension of morbidity health costs is the indirect component regarding the changes in earnings and leisure opportunities because of disability and debility. A shortcut to estimate the indirect morbidity cost attributable to pollution was found by applying to the direct morbidity cost a multiplier of 2.4, which is the ratio of the best estimates of total indirect net costs and the total direct costs of morbidity (Jaksch, 1975). Hence, the following formula was used for estimating the indirect morbidity costs attributable to SO_2:

$$IMBCSO_2 = 2.4 \text{ x } (PCSO_2 + HCSO_2 + DCSO_2) \tag{14}$$

The estimated morbidity costs for the 40 SMSA's with SO_2 levels equal to or greater than 25 $\mu g/m^3$, i.e., the threshold level, are presented in Table 3. Columns 1, 2, and 3 present, respectively, the physician costs, hospital costs and drug costs attributable to SO_2. Indirect morbidity costs due to SO_2 are presented in column 4. It should be noted that the figures in column 4 are 24 times the sum of columns 1, 2, and 3. Total morbidity costs due to SO_2 which are calculated by summing columns 1, 2, 3 and 4 are presented in column 5, and per capita total morbidity costs are in column 6. Total morbidity costs in the absence of SO_2, direct and indirect, are presented in column 7. The cost figures in this column were estimated with the aid of equations (11) to (14) with the modification of replacing the exponential term by the intercept term of the dose-response function. Finally, column 8 presents the ratio of total morbidity cost attributable to SO_2 to total morbidity cost with and without SO_2.

Upon examination of the low estimates of morbidity costs in Table 3, it is readily revealed that the annual morbidity costs due to SO_2 range from a minimum value of less than \$1,000 in Cincinnati, Dayton, Evansville and Johnstown to a maximum of \$22 million in New York City. Per capita morbidity costs attributable to SO_2 in 1970 varied between cost of negligible magnitude to \$1.96 in New York City. Total morbidity damages attributable to SO_2 over the 40 SMSA's were at least \$99 million in 1970.

It should again be stressed that the cost figures presented in the table represent *low* estimates for the morbidity damages due to the two conservative assumptions made for the calculation of the costs. If the average number of doctor visits is five instead of one and the average number of days in the hospital is five days rather than one day per pollution-related disease incident, then by assuming the same costs incurred per visit to consult doctors and per hospital day for treatment, the cost figures in columns 1 to 7 should be revised accordingly. In other words, the direct and indirect morbidity costs and the per capita total morbidity cost at-

TABLE 3
MORBIDITY COSTS WITH SO_2 BY SMSA'S, 1970

SMSA	Direct Morbidity Costs Due to SO_2 (in $\$10^3$) PCSO$_2$ (1)	HCSO$_2$ (2)	DCSO$_2$ (3)	Indirect Morbidity Costs Due to SO_2 (in $\$10^3$) IMBCSO$_2$ (4)	Morbidity Cost Due to SO_2 (in $\$10^3$) Total (5)	Per Capita (6)	Total Morbidity Cost Without SO_2 (in $\$10^3$) (7)	Ratio (8)=(5)÷[(5)+(7)] (8)
1 AKR	151	106	75	796	1127	1.66	7834	0.13
2 ALL	125	88	62	660	935	1.72	6269	0.13
3 BAL	468	329	234	2474	3505	1.69	23883	0.13
4 BOS	323	227	162	1708	2420	0.88	31763	0.07
5 BRI	75	53	38	397	563	1.44	4500	0.11
6 CAN	37	26	19	196	277	0.74	4293	0.06
7 CHA	5	4	3	27	39	0.17	2647	0.01
8 CHI	1775	1248	888	9386	13200	1.91	80240	0.14
9 CIN	—	—	—	—	—	—	15973	—
10 CLE	487	343	244	2577	3651	1.77	23809	0.13
11 DAY	—	—	—	—	—	—	9807	—
12 DET	769	541	385	4066	5760	1.37	48280	0.11
13 EVA	—	—	—	—	—	—	2685	—
14 GAR	146	103	73	773	1095	1.73	7305	0.13
15 HAR	152	107	76	806	1142	1.72	7656	0.13
16 JER	148	104	74	782	1108	1.82	7027	0.14
17 JOH	—	—	—	—	—	—	3031	—
18 LAW	52	36	26	274	389	1.67	2681	0.13
19 LOS	1149	808	575	6075	8607	1.22	80920	0.10
20 MIN	332	233	166	1756	2487	1.37	20919	0.11
21 NHA	69	48	34	362	513	1.44	4120	0.11
22 NYO	3021	2123	1511	15900	26600	1.96	133280	0.14
23 NEW	329	231	165	1741	2467	1.33	21414	0.10
24 NOR	1280	900	640	7	10	0.01	7850	—
25 PAT	70	49	35	369	522	0.38	15673	0.03
26 PEO	643	452	322	3	5	0.01	3944	—
27 PHI	1188	835	594	6280	8897	1.85	55420	0.14
28 PTB	551	388	276	2916	4131	1.72	27696	0.13
29 POR	2	1	1	10	14	0.01	11639	—
30 PRO	218	153	109	1150	1629	1.78	10530	0.13
31 REA	29	21	15	156	221	0.74	3419	0.06
32 ROC	117	82	58	616	873	0.99	10181	0.08
33 STL	455	320	228	2407	3410	1.44	27255	0.11
34 SCR	23	16	12	123	174	0.74	2700	0.06
35 SPR	131	92	66	694	982	1.85	6112	0.14
36 TRE	40	28	20	212	301	0.99	3506	0.08
37 WAS	612	430	306	3238	4587	1.60	33001	0.12
38 WOR	40	28	20	214	303	0.88	3975	0.07
39 YOR	39	27	19	204	290	0.88	3801	0.07
40 YOU	53	37	27	282	399	0.74	6182	0.06
Total	15,104	10,617	7,558	69,637	98,633		783,202	

Note: —denotes less than $1,000.

tributable to SO_2 should be five times as large as the low cost estimates calculated for the SMSA's.

An "average" economic damage function was derived for the purpose of predicting marginal and average changes in the morbidity costs in response to changes in the pollution or in other variables. The morbidity cost in the presence of SO_2, which is the sum of morbidity costs due to SO_2 and morbidity costs in the absence of pollution, was regressed on a host of socioeconomic, demographic and climatological variables. The stepwise regression results are shown as follows:

$$\begin{aligned} TMBCSO_2 = \; & \underset{(80.3)}{52.4} + \underset{(0.09)^*}{0.60\, SO_2} - \underset{(67.9)^*}{135.0\, PWPO} + \underset{(0.7)^{**}}{1.4\, SUN} + \\ & \underset{(0.6)^*}{1.3\, RHM} - \underset{(0.2)}{0.3\, DTS} + \underset{(0.10)}{0.09\, PCOL} + \underset{(310.4)}{34.4\, PAGE} \\ & R^2 = 0.73 \end{aligned} \qquad (15)$$

where $TMBCSO_2$ denotes the morbidity cost in the presence of SO_2, and the seven explanatory variables are as follows: SO_2 is the sulfur dioxide level; PWPO, the percentage of white to total population; SUN, the number of sunshine days in a year; RHM, the relative humidity; DTS, the number of days with thunderstorms; PCOL, the percentage of the population with college education; and PAGE, the percentage of the population 65 and older.

The values below the coefficients are standard errors, with * and ** indicating that the coefficients are significant at the 1 and 5 percent level, respectively. All coefficients and the corresponding standard errors are reduced by a factor of 10^6. It should be pointed out that equation (15) is derived mainly for prediction purposes. "Wrong" signs as well as other statistical problems need not constitute a problem if they are understood and accounted for.

In predicting and estimating the responsiveness of morbidity damages to changes in any one of the explanatory variables, the partial elasticity of the morbidity cost with respect to the variable of interest merits some discussion. Suppose a policymaker would like to estimate what the marginal changes will be in the morbidity cost if the pollution level of SO_2 in the SMSA's is lowered, on the average, by 1 percent. In order to aid this policymaker in making the prediction, the partial elasticity of the morbidity cost with response to SO_2 ($E_{MCB,SO2}$) is calculated as follows:

$$E_{MCB,SO2} = 0.6 \times 10^6 \times (47.95/22.7 \times 10^6) = 1.27 \qquad (16)$$

where (0.6×10^6) is the coefficient of SO_2 in the economic damage function, and 47.95 and (22.7×10^6) are, respectively, the mean level of SO_2 and total morbidity cost.

In view of the SO_2 partial elasticity value of 1.27, the estimated morbidity cost would decrease by 1.27 percent for every 1 percent reduction in SO_2

level, other things being equal. Stated differently, if the air pollution control program lowers the SO_2 level by 4.7 $\mu g/m^3$ (10 percent reduction), adult morbidity costs on the average would decrease by \$2.72 million, from \$22.7 million to \$19.98 million. In a like manner, the coefficients of other variables in equation (15) can be used to compute the partial elasticities associated with the variables and can be analogously interpreted as conditional marginal impact when others are held constant.

V. CONCLUDING REMARKS

The objective stated at the outset of this paper, the derivation of a set of internally consistent and fairly accurate damage estimates for the 40 selected SMSA's, has been accomplished. Physical and economic damage functions instrumental for prediction purposes were developed by relating morbidity rates and morbidity costs, respectively, to a host of air pollution, socioeconomic, demographic and climatological variables. Theoretical underpinnings for environmental damage functions were also explored to provide a useful basis for the empirical estimation.

This study, which represents an exploratory effort to derive a morbidity damage function and regional morbidity damage costs, was conducted by using dose-response observations collected in prior epidemiological studies. Many such studies confirmed that urban areas have higher disease incidence rates than rural areas. The ratio of urban incidence to rural incidence of morbidity, which has been termed the urban factor, has been used for estimating total health damage due to air pollution for this nation. The rationale for the urban factor technique is that if air pollution levels in the urban areas could be reduced to the rural levels, then the differences between the urban and rural morbidity rates adjusted for smoking, age, sex and race should be eliminated.

The crucial question is determining what portion of this urban factor is attributable to air pollution. In a pioneering study of air pollution damage, Ridker (1965) assumed that 100 percent of the urban factor is attributable to air pollution and derived a damage value of \$2 billion for 1958. Williams and Justus (1974) assumed that a minimum of 10 percent and a maximum of 50 percent of the urban factor is due to air pollution and estimated that the total 1970 nationwide health cost due to air pollution was between \$62 million and \$311 million. These figures are much lower than the estimate of \$6.22 billion for respiratory disease in the United States.[7] The damage estimates derived by using the urban factor of health deterioration due to air pollution are apparently subject to a large margin of error because of the difficult assignment problem of the urban factor. The urban factor method is also replete with several other conceptual and practical difficulties. For example, the distinction between urban and rural pollution levels is hard to define because of the existence of a continuous scale of pollution intensity instead of a simple dichotomy between urban and rural pollution levels. Thus, after all, the question of what percentage of this urban factor is actually accounted for by air pollution remains largely unresolved.

Footnotes

[1]The diseases which are known to be related to air pollution include the following: bronchitis and emphysema; pneumonia, tuberculosis and asthma; total respiratory diseases; lung cancer; nonrespiratory-tract cancers; and cardiovascular diseases.

[2]The 40 selected SMSA's are as follows: Akron, Allentown, Baltimore, Boston, Bridgeport, Canton, Charleston, Chicago, Cincinnati, Cleveland, Dayton, Detroit, Evansville, Gary, Hartford, Jersey City, Johnston, Lawrence, Los Angeles, Minneapolis, New Haven, New York, Newark, Norfolk, Paterson, Peoria, Philadelphia, Pittsburgh, Portland, Providence, Reading, Rochester, St. Louis, Scranton, Springfield, Trenton, Washington, Worchester, York and Youngstown.

[3]Equation 5 was labeled by Maler as the expenditure function. The analytical properties of such expenditure functions are delineated in Maler (1974).

[4]The methodological procedures employed in the CHESS study involve statistical analysis with varying pollutant gradients and concentration levels. Each CHESS set, which consists of a group of communities selected to represent an exposure gradient for designated pollutants, generally includes High, Intermediate, and Low Exposure communities. For a general description of the EPA's CHESS Program, see Shy and Finklea (1973).

[5]A linear morbidity equation was also fitted, with the regression result shown as follows:

$$MB = \underset{(1.28)^*}{12.06} - \underset{(0.01)}{0.01}\, SO_2 \qquad R^2 = 0.011$$

Comparing the linear and nonlinear regression results, it can be concluded that the exponential specification of the dose-response function is apparently a better fit than the linear one because the former showed an explanatory power seven times larger than the latter equation. Further, the coefficient of SO_2 in the exponential equation is statistically significant, whereas it is insignificant and has a wrong sign in the linear equation. Thus, the empirical results suggest that the nonlinearity in the dose-response relation is more consistent with *a priori* judgment regarding human health responses to pollution doses.

[6]A comprehensive framework for calculating the direct and indirect economic costs of illness and disability has been developed by Rice (1966) and others.

[7]For a detailed discussion of some of the problems of using the urban factor for calculating health costs, see William and Justus (1974). The figure $6.22 billion was derived by William and Justus by adjusting Ridker's value of $2 billion for 1958.

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