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The Effects of Demographic and Environmental Factors on Adult Health in Brazil

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INTRODUCTION

Very little is known about the effects on adult health of environmental conditions in developing countries. Most studies have focused on child health and few have included environmental factors. The shortcomings are associated with difficulties in measuring health status for adults and the limited availability of data on environmental conditions in developing countries. Schultz and Tansel conclude their study stating "the next step in this field of research is to distinguish what variations in public policies or natural variations in environmental conditions combine to explain existing variation in adult morbidity among wage earners."[1] According to UNICEF, over half the population of Brazil live in an unsanitary environment. Worldwide, nearly three billion people do not have access to even a minimally sanitary toilet.[2] This study assesses the effects of demographic factors and key environmental conditions on adult health in Brazil.

The research focuses on morbidity among wage earners and the impact of specific environmental conditions. The analysis is based on a household model developed by Schultz and Tansel and treats work absence due to health problems as a measure of adult health status.[3] The data used are from the 1989 Brazilian National Health and Nutrition Survey and 1989 National Basic Sanitation Condition Survey. The first is a household survey that measured individual health and nutrition. The second survey provides data on basic environmental and sanitary conditions at the municipality level.

Three of the previous studies of adult health in developing countries include Strauss, et. al., Schultz and Tansel, and Thomas, Lavy and Strauss.[4] The first analyzes the demographic determinants of adult ill-health with detailed data for Jamaica. They use as measures of health, self-reported general health plus a variety of measures of problems in physical functioning. Their results show that higher education lowers the probabilities of having problems with physical functioning and other dimensions of health. They also found that location is an important factor, without exploring the reasons.

Schultz and Tansel simultaneously estimate the determinants of adult morbidity and the effect of adult morbidity on labor productivity in Côte D'Ivoire and Ghana.[5] The explanatory variables affecting health include schooling, household assets, community characteristics, food prices, and public health measures. There is only one environmental factor, whether the water supply is sanitary. Thomas, Lavy and Strauss analyze the impact of public policies on child height and weight/height, and also adult body mass index (BMI).[6] They find that the availability and quality of community health services do not affect the BMI of adults. However, local market prices for foods and per capita expenditures have a significant impact on adult health, as reflected in body mass.

Our analysis extends these earlier studies and makes two important contributions. The first relates to the methodology and the second to the empirical results. The measure of adult health status used, self-reported number of days that illness prevented the individual from working, was suggested by Schultz and Tansel.[7] Since standard econometric models are not suitable to deal with dependent variables that express duration outcomes, this analysis uses the statistical analysis of duration data known as the Cox model.[8] The empirical results show that basic environmental and sanitary conditions are essential elements in explaining work absence due to illness. These conditions are captured by a wide range of variables such as the quality of water treatment, the presence of industrial waste in the water source, water testing, sewage treatment, drawing irrigation water from the sewer discharge area, and garbage disposal methods.

THEORETICAL AND ECONOMETRIC MODELS

Theoretical Framework

This model is based on Schultz and Tansel and allows environmental factors to affect health production at the household level.[9] The household maximizes a single period utility function:

$$U = U(H', C, Z, L_2), \tag{1}$$

where H' is current health status, C is endogenous health inputs and care, Z is non-health related consumption goods, and L_2 is time allocated to non-wage activities.

This utility function is maximized subject to budget and time constraints:

$$CP_c + ZP_z = wL_1 + V, \tag{2}$$

and

$$L_1 + L_2 = 1, \tag{3}$$

where $wL_1 + V$ is household income, and savings are ignored in this single period framework. The P's are prices, w is the market wage rate, V is wealth income, L_1 is labor supplied as wage work and the total time endowment equals unity.

Health is produced according to a two-stage process. The cumulative health status of an adult, M, is a function of cumulative nutrition, activity levels, preventive and curative health care received over a lifetime, C, and an exogenous health endowment that is not affected by behavior, H:

$$M = M(C, H). \tag{4}$$

The health stock or endowment H, in this study, is approximated by incapacity to execute normal activities based on self-reported physical functioning and general health.

Recent health status H', the second stage, is influenced by exogenous demographic and environmental factors, A and E, inputs to health and the individual's cumulative health status, M:

$$H' = H'(A, E, M[C, H]). \tag{5}$$

Under the assumption that optimal decisions lead to $C = C(A, E, w, H, P, V)$, the reduced-form health demand function is:

$$H' = g(A, E, H, P, w, V). \tag{6}$$

Prices (P) are omitted in the empirical analysis due to lack of data and per capita household income rather than wealth income (V) is used.[10]

Recent health status is approximated here by the self-reported number of days in the last two weeks that illness prevented the individual from working, T. As in the Schultz-Tansel framework this self-reported indicator of health, T, diverges from the health status, H', by a measurement error, which is viewed here as a random variable uncorrelated with the other determinants of health or behavior. In other words, it is assumed that health status is not directly observed, but instead that H' is a parameter of a conditional probability distribution function, F. The assumption is that $F(t; H')$ fully describes the probability that

an individual misses up to t days of work, conditional on the information that he or she is sick and has a reduced-form health function as specified in (6).

Therefore, the number of days missed from work due to health problems is assumed to be a random variable with a distribution that reflects the individual's recent health status. A person's recent health status is a function of demographic variables, environmental variables, labor wage rate, and health endowment. In the empirical analysis, these factors are assumed to explain the number of days an individual misses work in order to recover from an illness.

The Econometric Approach

One difficulty with explaining work absence is that standard econometric models are not suitable to deal with dependent variables that express duration outcomes. This study uses an approach from the statistical analysis of duration data, known as the Cox model, to resolve this difficulty.[11] Days missed from work due to health problems, our measure of recent health status H', is the duration of an illness that prevented the individual from working. This analysis uses the Weibull family of duration distributions which has been most commonly used.[12]

The specific parametric specification for the conditional probability of recovery, the hazard function, used in this study is:

$$h(t) = \alpha t^{\alpha-1} e^{x'\beta}.$$

The hazard function is time-dependent unless $\alpha = 1$, which is the exponential case. The hazard increases or decreases monotonically according to whether $\alpha > 1$ or $\alpha < 1$. A likelihood function was developed based on this conditional probability that allows for individual heterogeneity.

A special source of difficulty in the analysis is the possibility that some individuals may not be observed leaving the state of illness. In the survey, work absence is recorded in days up to two weeks. Absence longer than two weeks is recorded as "two weeks or more". Such incomplete observation of the failure time is known as censoring and was also considered when creating the likelihood function. The function accounts for the probability that a sick individual is observed returning to work within two weeks, and also the probability that he/she does not leave the state of illness within two weeks.

The likelihood function formed from observations on N people is:

$$L = \prod_{i=1}^{N} \left[\frac{G(t_i+h)}{G(t_i)}\right]^{1-d_i} \left[\frac{h(t_i+s_i)G(t_i+s_i)}{G(t_i)}\right]^{d_i} \tag{7}$$

where

d_i = 1 if person i returns to work within the interval of observation h, two weeks, and zero otherwise,

t_i is the length of the *i*th person in the state of illness before time 0,

s_i is the length of the *i*th person in state of illness after time 0,

$G(\cdot)$ is the survivor function and

G(t) = 1 – F(t), where F(t) is the cumulative distribution function of t.

DATA AND VARIABLES

Two Brazilian data sets are used to conduct this study. The first is the 1989 National Health and Nutrition Survey, undertaken by the Brazilian Geographical and Statistical Institute (IBGE), Institute of Social Economic Planning (IPEA) and by the National Institute of Food and Nutrition (INAM). Approximately 63,000 individuals were interviewed from 17,920 households. The second is the 1989 National Basic Sanitation Condition Survey, undertaken by the Brazilian Geographical and Statistical Institute (IBGE). This survey provides information on sanitary environmental conditions for all 4,425 municipal districts in Brazil in 1989.

Data Management

The final sample used in this study is restricted to people who missed at least one day from work due to health problems. It means that no inference is made regarding the likelihood of an individual becoming sick. To derive insights about the probability of an individual becoming sick would require either massive computations on the whole sample (including people who did not miss work) or computations on a small random subsample of the Health and Nutrition Survey. While the first approach would be costly computationally, the second would reduce significantly the number of sick individuals relative to the number of explanatory variables.

Approximately 47,000 individuals in the Health and Nutrition Survey were employed and 3,584 persons (7.6% of those employed) reported missing work during the two week period before the survey due to health problems. After identifying those people who missed days from work due to illness, another adult in the household was selected. The second adult could be either, the head of the household, a spouse, or another adult in the household older than 15 years old, in that order. Therefore, all households in this study were represented by two people, and at least one of them reported work absence due to health problems. People who lived alone were excluded producing a sample of 3,361 individuals. The Basic Sanitation Condition Survey data were merged by municipality code with the Health and Nutrition Survey data to provide the environmental information for each sick person in the sample. The final regression had 1,561 observations due to missing values for various Health and Nutrition Survey variables.

The Health Variables

In the literature, health status has been measured by clinical measures, disease symptoms, incapacity to execute normal activities, and anthropometric measures. Self-reported measures of general health have been criticized. Self-reported morbidity or health status may be subjectively affected by an individual's social and cultural background given his or her objective clinical health. Moreover, individuals from more educated, wealthier, and socially advanced groups may have a heightened sensitivity to the limitations imposed on them by their health status.

Schultz and Tansel argue that this subjective bias may be minimized by focusing the analysis on only those who are employed in the labor force, for whom missing work because of illness generally implies a penalty in terms of foregone earnings or other direct or indirect consequences.[13] By restricting the analysis to wage earners, for whom work absence conveys a clear cost threshold, the problem of measuring morbidity through self- response is reduced if not eliminated.

In this study, several variables which reflect a person's incapacity to execute certain activities are used as indicators of health stock or endowment. The data on self-reported incapacity included blindness, deafness, missing a limb, paralysis, difficulty in learning and understanding, mental deficiency, retardation, weight considerations and the individual's hospitalization history for the last twelve months. Due to the large number of variables, preliminary regressions were run to test the significance of the health stock variables. The variables whose coefficients were not significant at the 10% level were dropped from the final regression. The significant variables used to reflect health stock are missing limb, deafness and hospitalization history. These variables are expected to increase absence from work due to health problems. Table 1 presents the percentage of individuals who reported these conditions.

Explanatory Variables

The definitions of all variables and their descriptive statistics are presented in Tables 1 and 2. Table 1 describes the categories for the classification variables and their sample shares in percents. Table 2 describes the quantitative variables and gives their means and standard deviations.

Classification Variables

The surveys have many variables for which the answer is chosen among a fixed set of options. Following Kalbfleisch and Prentice, a class of dummy variables is constructed for each of such questions.[14] These dummy (classification) variables are designed to capture all possible answers in a given class.

Let the list $\{0, 1, 2, \ldots n\}$ represent the set of possible answers to a given question defining a class in the survey. Let $d_1, d_2, \ldots d_n$ be a list of dummy variables such that $d_i = 1$ if the answer is i and $d_i = 0$ otherwise, for $i = 1, 2, \ldots, n$. The variables affect the intercept of the regression by the value $\beta_1 d_1 + \beta_2 d_2 + \ldots + \beta_n d_n$ where β_i is the regression coefficient of d_i. In Table 3 each classification variable has subtitles indicating the reference case ($d_1 = d_2 = \ldots = d_n = 0$) on the right side of versus ("vs").

A statistical test for the joint significance of all dummy coefficients in the class is computed in Table 3. This statistic is constructed as follows. Let $b' = (b_1, b_2, \ldots, b_n)$ be the vector of maximum likelihood estimates for the class and let Σ be the estimated covariance matrix for b.

Then an asymptotic $\chi^2_{(n)}$ statistic is calculated as $b\,\Sigma^{-1}b$, corresponding to the joint significance of $(\beta_1, \beta_2, \ldots, \beta_n)$. As Kalbfleisch and Prentice point out, this statistic does not depend on which answer is selected to correspond to the reference ($d_1 = d_2 = \ldots = d_n = 0$) case.[15]

Similarly, the asymptotic $\chi^2_{(1)}$ statistic in Table 3 for a quantitative continuous variable is formed as the square of the ratio between the associated coefficient and its standard error.

EMPIRICAL RESULTS

Table 3 presents the coefficients, χ^2 statistics, and significance levels of the regression variables for the reduced-form health function based on equation (6) with days missed from work as the dependent variable.

Demographic Variables

The number of days which an individual missed from work clearly depends on his/her health stock measured by deafness and missing a limb. The coefficients estimated for these variables are positive and significant indicating that these physical problems increase work absence. The coefficient for hospitalization history is negative and significant implying that fewer days are missed from work due to health problems when the individual has been hospitalized in the last 12 months. This negative impact was unexpected, but may reflect accessibility to health services which improves the overall health status of the individual.

Smoking has a negative impact on health and increases work absence, as was expected. However, the effect is not statistically significant. Drinking has a significant effect but the signs for the two dummy variables are mixed. This is a classification variable which answers the following question: "Do you think sometimes you should decrease the amount of alcoholic beverages you drink or even stop it?" When the answer is "no," the positive coefficient means that the number of days missed from work increases. Since denial is the reaction of many people with a serious alcohol problem, this result is very interesting. On the other hand, the person who answered "yes" is conscious of his/her drinking problem. They are perhaps more likely to control it and seek treatment if necessary and, therefore, miss fewer days from work.

The age coefficient is highly significant. Age squared (age2) was included to allow for a possible non-linear (parabolic) relationship, but it is not significant. Work absence decreases with age. When a similar regression to the one reported in Table 3 was run without age squared (age2), the coefficient sign of age did not change. As a person gets older, more experience is acquired and the opportunity cost of missing work is higher. Although at some point, a person's health begins to decline with age, most Brazilians may be retired before this becomes an important factor.

Education was represented by the number of years of schooling and the coefficient is positive and highly significant. As education level increases, the number of days missed from work increases. Better educated people are more likely to have jobs which provide sick leave and get paid while ill. Most less-educated workers are not in jobs with such benefits.

The labor market participation of the second adult in the household is a classification variable which answers the following question: "What did you do in the last two weeks?" According to the answer people are classified in three different categories: people who were employed and working for the last two weeks, those who were employed but for some reason did not work for this period, and the third, people who were unemployed. The second adult's (companion's) labor market status is highly significant. The results show a reduction in work absence when the companion is either unemployed or employed but he/she did not work during the period. The negative impact is even larger in the latter case. Recall that the reference case is "employed and working."

There are at least two possible explanations for this outcome. The first is based on the opportunity cost of work absence. If a companion is not working, then the cost of missing work increases relative to the case in which the companion is employed and working, because there is not an alternative source of income for the household. Hence, when the companion is either unemployed or employed but did not work for the same period, the opportunity cost of missing work is higher and the person misses fewer days from work.

The second explanation is based on the idea that a companion who is at home and can help out more could speed up the recovery of the sick person. The recovery is faster when the companion who stays home is employed but not working, relative to the case when he/she is unemployed. There may be a commitment to higher out-of-pocket expenses when there are two or more incomes in the household. As a result, there would be more pressure for the sick person to return to work as soon as possible.

Another classification variable related to the companion's health status provides information on the past 12 months of his/her hospitalization history. This variable can be classified into three different groups: "delivery," "others" and "no hospitalization." In the delivery group the companion answered that she had been hospitalized in the last 12 months due to pregnancy. In the second group the companion answered he/she had been in a hospital as a patient for any other reason. Finally, the no hospitalization group includes the remaining people who had not been hospitalized in the last 12 months. The companion's hospitalization in the last 12 months increased the number of days the sick person missed from work. If the companion has had health problems in the last 12 months, a lower productivity would be expected in household health production affecting other members in the family.

The theoretical model suggest that the individual's wage rate should have an impact on recent health status. The effect is expected to be negative because of the higher opportunity cost of missing work. However, the estimated coefficient is positive and not significant. The per capita income variable includes the earnings from all members of the household that were participating in the labor market in addition to non-labor income (rent, retirement, etc.). As expected, the coefficient is negative and significant, indicating that the higher the household per capita income level the fewer days an individual will need to recover from an illness and miss work. Higher income allows the purchase of medical care and other goods which are inputs to household health production.

Environmental/Sanitary Variables

All the environmental factors in this data set are classification variables. The first relates to water treatment. There are four possible types of treatment applied to water. The best type of treatment is classified as "conventional treatment," followed by "partial treatment." A conventional treatment station consists basically of a chemical house, screens, floculators, decanters, filters, pH correction, disinfection (chlorination) and fluoridation. "Partial treatment" uses only screen units, slow filtration and posterior chlorination for the production of potable water. The third type of treatment is a "simple disinfection" (chlorination). There is another type which is "no treatment at all." This happens with 20% of the municipal districts in Brazil that have infrastructure for water supply but feature no water treatment.

Water treatment was classified into two groups: "not sanitary" and "sanitary." The "not sanitary" group contains the following three classes: no water supply, no water treatment or simple disinfection (chlorination). The "sanitary" group includes municipalities where the potable water is treated using either conventional or partial treatment. Some 31% of the sample were in municipalities with unsanitary and 69% with sanitary treatment, as shown in Table 1. In Table 3 the type of water treatment affects the duration of time needed for the recovery of an ill individual. The coefficient is positive and significant at a 5% level. Unsanitary water treatment is associated with more missed days from work.

The possibility of industrial waste being present in the water source is reflected in the next variable. The variable assumes the value zero if there was no industrial waste contamination of the water source, and the value one if there was contamination. About 17% of the cases were in the latter category, as shown in Table 1. Contamination negatively and significantly affects health, increasing the number of days a person living in the area needs to recover from an illness.

There are several types of water analysis used to monitor drinking water quality. This data set has information about the type of analysis and the frequency at which each is done. The physicochemical analysis before water treatment checks such characteristics as temperature, turbidity, pH, and hardness. The organic chemistry and the radiological analysis, plus another physicochemical analysis, are conducted after treatment. The organic chemistry analysis tests for the presence of organic pesticides, such as DDT, and oils. The test that relates to the analysis of the potable water (water in the distribution system) is the fecal bacteria analysis.

Each one of these variables can be classified as no analysis, daily, weekly, biweekly, monthly, semi-annually and annually. The results indicate that in most cases as the analysis is executed more frequently, the individual needs to miss fewer work days to recover from an illness. In some municipal districts in Brazil, no analysis is performed. The results show that even in this case, versus annual analysis, there is a reduction in work absence. Not having any analysis does not necessarily imply the water is contaminated or unsanitary, because it may depend on the population and industrial density of the area.

The most interesting result refers to the fecal bacteria analysis of the potable water. When the analysis intervals are shorter, individuals living in these areas miss fewer days from work due to illness. However, when there is no analysis at all the coefficient also indicates fewer days missed from work. This may be reflecting a low population density instead of a lack of quality control. The results for the physicochemical (after treatment) and organic chemistry analysis follow the same pattern.

The radiological analysis coefficients are positive, indicating a larger number of days ill from work. There are very few cities in contact with nuclear power plants or other possible radiation sources in Brazil. One may expect that this type of analysis is done frequently precisely in municipalities for which there is a potential for radiation and probably other pollution is high also. Only about 7% of the sample live in a municipality where radiological analysis was performed (see Table 1). The results for the physicochemical analysis before treatment are similar to those for radiation. This analysis is probably also carried out in urban industrial centers where the quality of the water before treatment is suspicious.

The data set contains the type of sewerage treatment for each municipality in Brazil. The possible treatment classifications are: conventional, preliminary, primary, stabilization lagoon, aeration lagoon and digestor. Conventional sewerage treatment basically includes screens, a sand filter bed, primary decanter, activated sludge and/or biological filter, secondary decanter and sludge drying. Preliminary sewerage treatment includes only screens and the sand filter bed. Primary sewerage treatment includes screens, sand filter bed, decanter and sludge drying. A stabilization lagoon uses a process which consists of shallow lagoons where the effluents are held. Through aerobic and anaerobic processes they are oxidized. The aeration lagoon consists of a treatment pond in which mechanical ventilation or diffused aeration is used to supply oxygen. Finally, the digestor is an aerobic biological reactor which can be used in the activated sludge process to hold a reactor in complete mixture.

In Table 1, 69.5% of the individuals in the sample resided in municipalities with no sewerage treatment at all and 9.5% with other (undefined) treatment methods. It is difficult to rank the types of sewage treatment according to their healthiness without taking into account the population density of the municipal district and other factors. A type of treatment that is appropriate for one location is not necessarily appropriate for another. This may explain the alternate signs of the coefficients in Table 3.

In some municipal districts, the drinking water supply (13% of the sample in Table 1) or irrigation water (29%) comes from a source also used as a sewerage discharge area. The first variable takes the value one if the discharge area is used to supply drinking water and zero otherwise. The variable is not significant. For the second, the coefficient is significant at the 1% level and indicates that more days missed from work occur for an individual living in a location where the discharge area is used for irrigation.

The outfall variable indicates whether or not an outfall (a pipe) is used in the sewerage system to carry off the waste matter in the discharge area. In Table 1, 66.4% of the individuals lived in a municipality with an outfall. The presence of an outfall decreases the days missed from work due to illness in Table 3 and is significant at the 10% level.

Garbage collection is provided in most of the municipal districts in Brazil. This variable was classified into two groups according to the risk to the public health. The first is "not sanitary" which includes: no garbage collection system, open dumping, water dumping, or a controlled land fill process of waste disposal. In 80% of the municipal districts in Brazil "open dumping," which is the least sophisticated possible disposal method, is used. A controlled landfill entails dumping the waste and covering it with a layer of soil. The second group is "sanitary" and includes: sanitary landfill, special landfill, composting landfill, recycling facility and incinerator. The garbage destination variable in Table 3 is negative and significant. Individuals living in a place using less sophisticated (unsanitary) waste disposal methods miss more days from work to recover from illnesses.

Time Parameter and Lagrange Multiplier Test

With the Weibull family of duration distributions, the probability of recovering from an illness may be time dependent. When $\alpha = 1$, which is the exponential case, the hazard function is time-independent. The hazard function can be roughly interpreted as the probability that the individual leaves the state of illness in t days, conditional on the state still being occupied at t. The hazard increases or decreases monotonically according to whether $\alpha > 1$ or $\alpha < 1$. In this study, the value for α of 0.78 indicates that the probability that the individual recovers decreases monotonically with time, which means that the more days a person misses work, the more seriously ill they are.

A Weibull model and an exponential model were fit to the hypothesis that $\alpha = 1$. A Lagrange multiplier test statistic was computed to test whether or not this constraint is binding. This statistic is asymptotically distributed as chi square with one degree of freedom under the null hypothesis that $\alpha = 1$. The null hypothesis was rejected at a 0.01% significance level. This test statistic is comparable to the Wald test statistic for testing $\alpha = 1$. The implication is that the Weibull specification is indeed a suitable choice, relative to the exponential case, in explaining work absence due to illness.

Interpretation of Key Environmental Results

In the model the error term has a distribution log normal with mean $1/\alpha$. The expected duration of work absence is:

$$E(T) = \exp\{-x'\beta/\alpha\}.$$

In the computations $x'\beta$ takes the log linear form. As a result the elasticities of the expected duration of work absence are β/α. Thus, if each β coefficient in Table 3 is divided by the time coefficient, α, the elasticities of the expected duration of the days missed from work due to health problems are obtained.[16]

To evaluate the impact of dummy variables on the expected duration of work absence some extra computations are necessary. When a dummy of intercept d_i assumes the value one, the expected duration changes from T_0 to T_1 according to:

$$\log(T_1) - \log(T_0) = \beta_i/\alpha$$

where β_i is the coefficient of d_i. Hence, the percentage change of the expected duration when d_i takes the value of one is $100[\exp(\beta_i/\alpha) - 1]$.

This formula yields the following results for the key environmental/sanitary variables. The last column indicates the percent change in the time missed from work due to illness in response to a change in that environmental factor.

Environmental Factors	β_i/α	Effect on the expected work absence
Water treatment (not sanitary vs. sanitary)	0.15	16%
Industrial contamination of water source (yes vs. no)	0.16	17%
Irrigation draws from discharge area (yes vs. no)	0.25	28%
Presence of outfall (yes vs. no)	–0.20	–18%
Garbage destination (not sanitary vs. sanitary)	0.15	16%

People suffer 16% more time missed from work to recover from illness when they reside where the water treatment is unsanitary, 17% more time if there is industrial contamination of the water source, and 28% more if irrigation water is drawn from the sewerage discharge area. Those who reside in municipalities with a sewerage outfall require 18% less time to return to work when they are absent due to illness. Individuals with an unsanitary municipal garbage facility take 16% longer to return to work.

Under the assumption that one day of work corresponds to 8 hours and the mean days missed from work in this sample is 4.5 days, the average hours of work absence is about 36 hours. The 16% increase in work missed due to unsanitary water treatment corresponds to an increase of 5.8 hours of absence from work. More precisely, among persons who missed at least one day of work due to illness, an individual living where the water treatment is not sanitary misses 5.8 hours more from work on average.

In Table 2 the average wage rate per hour is $1.07 U.S. Thus, $6.20 (5.8 hours x $1.07 per hour) is the increased cost of living where the water treatment is not sanitary for people who miss at least one day from work due to illness. Following the same approach $6.53 (6.1 hours x $1.07) is the increase in cost (per person who misses work) of living in a place where the water source is contaminated by industrial waste. The increase in cost of living in a place where irrigation draws from the discharge area is $10.81 (10.1 hours x $1.07). With respect to the use of an outfall, there is a decrease in cost per person of $6.96 (6.5 hours x $1.07). Finally, the cost per person is $6.20 (5.8 hours x $1.07) when living in a place where the garbage disposal method is unsanitary.

The estimated costs in lost wages of poor environmental conditions are substantial. Moreover, these calculations reflect only the cost of missing additional time from work for people who were absent at least one day from their jobs due to ill health. There are many other potential health costs which are not accounted for here.

CONCLUSIONS

This study estimated the impact of demographic and environmental factors on adult health in Brazil. The specific measure of morbidity used was the number of days those employed missed from work due to poor health. The analysis included measures for major sanitary/environmental conditions by merging data from the 1989 Brazilian Basic Sanitation Condition Survey with the 1989 National Health and Nutrition Survey by municipality. Since days missed from work is a duration outcome, the Cox model for the statistical analysis of duration data was used.

No inferences are made concerning the probabilities of become ill. The sample is limited to those who missed at least one day from work due to health problems in the two weeks preceding the survey. The likelihood of becoming sick is an important but different issue, deserving future research. The demographic factors found to have a significant effect on adult health include physical disabilities, previous hospitalization, a possible drinking problem, age, education, the companion's labor force status and hospitalization history, and per capita income.

Most importantly, the results of this analysis show that poor environmental conditions common in developing countries clearly have a detrimental effect on adult health. People miss more days from work to recover from an illness when they reside where the water treatment is not sanitary, the water source is subject to industrial contamination, irrigation water is drawn from the sewerage discharge area, an outfall is not used for the sewerage discharge, or the garbage disposal method is not sanitary. The impact of various tests on the drinking water is complicated, since their frequency may be related to suspected problems.

The wages lost due to the work absence caused by these environmental problems are substantial. In addition to the cost to the individual, the economy suffers a loss in productivity. Moreover, this analysis accounts for only a small portion of the total health effects of poor environmental conditions and their economic costs. These results, however, do suggest the large potential health and economic benefits to infrastructure investments and other measures that improve environmental conditions in developing countries.

ENDNOTES

[1]T. Paul Schultz and Aysit Tansel, "Measurement of Returns to Adult Health: Morbidity Effects on Wage Rates in Côte d'Ivoire and Ghana." Discussion Paper No. 663, Economic Growth Center, Yale University, New Haven, CT, 1992, p. 22.

[2]Barbara Crossette, "Half the World Lacks Sanitation, says UNICEF," *The New York Times*, July 23, 1997.

[3]Schultz and Tansel.

[4]John Strauss, P. Gertler, O. Rahman and K. Fox, "Gender and Life-Cycle Differentials in the Patterns and Determinants of Adult Health." *The Journal of Human Resources*, 28 (1993): 791-837; Schultz and Tansel; and Duncan Thomas, Victor Lavy and John Strauss, "Public Policy and Anthropometric Outcomes in Côte d'Ivoire," *The Journal of Public Economics*, 61 (1996): 155-192. Jere Behrman and Anil Deolalikar, "Health and Nutrition," in *Handbook of Development Economics*, ed. Holis Chenery and T. N. Srinivasan (New York: North Holland, 1988), 1: 631-711 provide an excellent review of work in this area.

[5]Schultz and Tansel.

[6]Thomas, Lavy and Strauss.

[7]Schultz and Tansel.

[8]D. R. Cox, "Regression Models and Life Tables." *Journal of the Royal Statistical Society*, Series B, 34, (1972): 187-220 and D. R. Cox and D. Oakes, *Analysis of Survival Data* (London and New York: Chapman and Hall, 1984).

[9]Schultz and Tansel. The model is also similar to that used by Duncan, Lavy and Strauss. The basic theoretical foundation for these household models is Gary Becker, "A Theory of the Allocation of Time," *Economic Journal* 75 (1965): 493-517, and *A Treatise on the Family* (Cambridge, MA: Harvard University Press, 1981). The important early work applying a household model to health includes Michael Grossman, *The Demand for Health: A Theoretical and Empirical Investigation* (New York: National Bureau of Economic Research, 1972) and "On the Concept of Health Capital and the Demand for Health," *Journal of Political Economy* 80 (1972): 223-255.

[10]Per capita household income is used rather than wealth (non-labor) income. Since the latter is difficult to measure, the former may better reflect the economic resources available to the household. See Thomas, Lavy and Strauss.

[11]Cox; and Cox and Oakes (n. 8 above); also Regina C. Elandt-Johnson and Norman L Johnson, *Survival Models and Data Analysis* (New York: John Wiley and Sons, 1980).

[12]Tony Lancaster, *The Econometric Analysis of Transition Data* (Cambridge, England: Cambridge University Press, 1990) and "Econometric Methods for Duration of Unemployment," *Econometrica* 47 (1979): 939-956.

[13]Schultz and Tansel (n. 1 above).

[14]John D. Kalbfleisch and Ross L. Prentice, *The Statistical Analysis of Failure Time Data* (New York: John Wiley and Sons, 1979).

[15]Kalbfleish and Prentice.

[16]Lancaster, 1979, pp. 946-947.

Table 1: Categories for Classification Variables
Definition and Sample Shares in Percents

The Health and Nutrition Survey Variables:

Variable	Category Definition	%
Deafness	Individual reports partial or total deafness	4.1
	No deafness reported	95.9
Missing limb	Individual is missing a limb	1.0
	No missing limb reported	99.0
Sick person's hospitalization history	Individual has been hospitalized in the last twelve months	16.8
	No recent hospitalization reported	83.2
Drinking	Thinks should reduce or stop drinking	17.6
	Thinks should not stop drinking	18.6
	Individual does not drink	63.7
Companion's labor status	Employed and working in the last two weeks	86.0
	Employed and not working	12.7
	Unemployed	1.3
Companion's hospitalization history	Has been hospitalized in the last twelve months for delivery	1.6
	Has been hospitalized in the last twelve months for any other reason	15.0
	Has not been hospitalized in the last twelve months	83.4

Table 1-continued: Categories for Classification Variables
Definition and Sample Shares in Percents

The Basic Sanitation Condition Survey Variables:

Water treatment	Not sanitary (if in the municipality there is no water supply or no water treatment or a simple disinfection of the potable water is done)	31.1
	Sanitary (if in the municipality there is either conventional or partial treatment of the potable water)	68.9
Industrial contamination of water source	There is industrial waste contamination of the water source	17.4
	There is no industrial waste contamination	82.6
Physicochemical analysis of water before treatment	No analysis	18.4
	Daily	38.9
	Weekly	8.4
	Biweekly	7.6
	Monthly	16.9
	Semi-annually	7.9
	Annually	1.9
Physicochemical analysis of water after treatment	No analysis	18.4
	Daily	42.3
	Weekly	6.4
	Biweekly	7.7
	Monthly	17.5
	Semi-annually	5.2
	Annually	2.5
Organic chemistry analysis of water after treatment	No analysis	70.6
	Daily	2.8
	Weekly	1.5
	Biweekly	1.4
	Monthly	0.7
	Semi-annually	16.2
	Annually	6.8

Table 1-continued: Categories for Classification Variables
Definition and Sample Shares in Percents

The Basic Sanitation Condition Survey Variables (cont.):

Radiological analysis of water after treatment	No analysis	93.0
	Daily	4.8
	Monthly	0.4
	Semi-annually	0.3
	Annually	1.5
Fecal bacteria analysis of potable water	No analysis	33.0
	Daily	25.8
	Weekly	16.4
	Biweekly	8.0
	Monthly	13.5
	Semi-annually	1.5
	Annually	1.8
Sewerage treatment	No treatment	69.5
	Conventional	8.9
	Preliminary	2.7
	Primary	0.8
	Stabilization lagoon	3.8
	Aeration lagoon	3.7
	Digestor	1.1
	Others	9.5
Water source draws from discharge area	Draws from discharge area	13.1
	Does not draw from discharge area	86.9
Irrigation draws from discharge area	Draws from discharge area	29.2
	Does not draw from discharge area	70.8
Presence of outfall	Outfall is present	66.4
	Outfall is not present	33.6
Garbage destination	Not sanitary (if there is no garbage collection system in the municipality, or if the destination is one of the following: open dumping, water dumping or controlled landfill)	92.4
	Sanitary (if the destination is one of the following: sanitary landfill, special landfill, composting facility, recycling facility or incinerator)	7.6

Table 2: Quantitative Variables
Definition, Sample Mean and Standard Deviation

		Mean	Standard Deviation
(Health and Nutrition Survey Only)			
Age	Age of the sick person in years	35.46	15.02
Smoking	Number of cigarettes smoked by the sick person per day	5.79	9.23
Wage Rate	Sick person's wage in dollars per hour	1.07	2.53
Education	Sick person's years of schooling	4.56	4.11
Per Capita Income	Household per capita income per month in dollars	96.59	183.82

Table 3: Regression Results
Days Missed From Work Due to Health Problems

Variable		Coefficient	χ^2 Statistic	Pr > χ^2 %
Constant		1.5006	13.00	0.03***
Deafness	yes vs. no	0.3051	7.54	0.60***
Missing limb	yes vs. no	0.4014	2.68	9.99*
Sick person's hospitalization history	yes vs. no	-0.4509	22.64	0.01***
Drinking	yes vs. doesn't drink	-0.0582	9.11	1.05**
	no vs. doesn't drink	0.1409		
Smoking		0.0037	2.31	12.82
Age		-0.0216	9.04	0.26***
Age^2		0.0001	2.38	12.27
Education		0.0169	6.01	1.42**
Companion's labor status			230.44	0.01***
	unemployed vs. employed & working	-0.6746		
	employed & not working vs. employed & working	-1.1523		
Companion's hospitalization history			8.00	1.83**
	delivery vs. no hospitalization	0.4940		
	others vs. no hospitalization	0.0250		
Wage rate per hour		0.0104	0.86	35.49
Per capita income		-0.0004	5.79	1.61**
Water treatment	not sanitary vs. sanitary	0.1195	4.01	4.53**
Industrial contamination of water source			3.11	7.79*
	yes vs. no	0.1291		

Significance levels: *10%, ** 5% and *** 1%.

Table 3-continued: Regression Results
Days Missed From Work Due to Health Problems

Variable	Coefficient	$\chi 2$ Statistic	$Pr > \chi 2$ %
Fecal bacteria analysis of potable water		21.45	0.15***
no analysis vs. annually	-0.3703		
daily vs. annually	-0.3836		
weekly vs. annually	-0.3917		
biweekly vs. annually	-0.1728		
monthly vs. annually	-0.5692		
semi-annually vs. annually	-0.1508		
Physicochemical analysis of water after treatment			
no analysis vs. annually	-0.2950		
daily vs. annually	-0.4156		
weekly vs. annually	-0.4366	21.14	0.17***
biweekly vs. annually	-0.1034		
monthly vs. annually	-0.0373		
semi-annually vs. annually	-0.7941		
Organic chemistry analysis of water after treatment		15.49	1.67**
no analysis vs. annually	-0.2283		
daily vs. annually	-0.5866		
weekly vs. annually	-0.1575		
biweekly vs. annually	-0.0136		
monthly vs. annually	-0.7923		
semi-annually vs. annually	-0.0505		
Radiological analysis of water after treatment		21.89	0.02***
no analysis vs. annually	0.7237		
daily vs. annually	1.0113		
monthly vs. annually	1.9986		
semi-annually vs. annually	0.4152		

Significance levels: *10%, ** 5% and *** 1%.

Table 3-continued: Regression Results

Days Missed From Work Due to Health Problems

Variable		Coefficient	χ^2 Statistic	$Pr > \chi^2$ %
Physicochemical analysis of water before treatment			12.25	5.66*
	no analysis vs. annually	0.3365		
	daily vs. annually	0.4633		
	weekly vs. annually	0.4361		
	biweekly vs. annually	0.2284		
	monthly vs. annually	0.1633		
	semi-annually vs. annually	0.6239		
Sewerage Treatment			15.20	3.35**
	conventional vs. no treatment	0.2026		
	preliminary vs. no treatment	-0.1340		
	primary vs. no treatment	0.3375		
	stab. lagoon vs. no treatment	-0.2075		
	aeration lagoon vs. no treatment	0.2348		
	digestor vs. no treatment	-0.2492		
	others vs. no treatment	0.1027		
Water source draws from discharge area			1.69	19.42
	yes vs. no	0.1192		
Irrigation draws from discharge area			7.81	0.52***
	yes vs. no	0.2010		
Presence of outfall	yes vs. no	-0.1570	3.82	5.07*
Garbage Destination			3.04	8.10*
	not sanitary vs. sanitary	0.1177		
Time (α)		0.7862		
Lagrange Multiplier Test for Exponentiality (α=1)			203.40	0.01***
Log Likelihood for Weibull		-2019.80		

Significance levels: *10%, ** 5% and *** 1%.