Morbidity Costs of Vehicular Air Pollution: Examining Dhaka City in Bangladesh

WORKING PAPER

No. 47-10

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SANDEE

South Asian Network for Development and Environmental Economics

April 2010

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April 2010

South Asian Network for Development and Environmental Economics (SANDEE)
PO Box 8975, EPC 1056
Kathmandu, Nepal

SANDEE Working Paper No. 47-10

Published by the South Asian Network for Development and Environmental Economics (SANDEE)
PO Box 8975, EPC 1056 Kathmandu, Nepal.
Telephone: 977-1-5003222, 552 6391 Fax: 977-1-5003299

SANDEE research reports are the output of research projects supported by the South Asian Network for Development and Environmental Economics. The reports have been peer reviewed and edited. A summary of the findings of SANDEE reports are also available as SANDEE Policy Briefs.

National Library of Nepal Catalogue Service:

Tanzir Chowdhury and Mohammad Imran
Morbidity Costs of Vehicular Air Pollution: Examining Dhaka City in Bangladesh
(SANDEE Working Papers, ISSN 1893-1891; 2010- WP 47)

ISBN: 978 - 9937 -8218 - 8 - 9

Key words:

1. Air Pollution
2. Health Benefit
3. Health Production Function
4. Cost-of-Illness
5. Panel Data
6. Random-Effects Zero Inflated Poisson Model
7. Random-Effects Tobit Model

The South Asian Network for Development and Environmental Economics

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SANDEE is financially supported by International Development Research Center (IDRC), The Ford Foundation, Swedish International Development Cooperation Agency (SIDA), the World Bank and the Norwegian Agency for Development Cooperation (NORAD). The opinions expressed in this paper are the author's and do not necessarily represent those of SANDEE's donors.

The Working Paper series is based on research funded by SANDEE and supported with technical assistance from network members, SANDEE staff and advisors.

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Abstract

This study estimates the morbidity costs of reduction in air pollution in Dhaka, the capital of Bangladesh, using the Cost-of-Illness (COI) approach. COI is defined as the sum of lost earnings due to workdays lost or restricted activity days and the mitigation expenditure borne due to illness. The data for the research comes from seasonal household surveys using health diaries. We use a random-effects Zero Inflated Poisson regression model to estimate the equation for lost earnings and use a random-effects Tobit Regression to estimate the equation for mitigation expenditure. We find that the annual savings from reducing air pollution to meet national safety standards is Taka 131.37 (USD 1.88) per person from reductions in lost earnings and Taka 150.49 (USD 2.15) per person from reductions in medical expenditure. The annual saving to the population of Dhaka is Taka 2.39 billion or USD 34.09 million. Our estimates, which are based on primary data, provide significantly lower estimates of the benefits of reducing air pollution in Dhaka relative to previous analyses that has relied on the benefit-transfer approach.

Keywords: Air Pollution, Health Benefit, Health Production Function, Cost-of-Illness, Panel Data, Random-Effects Zero Inflated Poisson Model, Random-Effects Tobit Model

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1. Introduction

There has been increasing concern over the years about the effects of vehicular air pollution (VAP) on health. Vehicular emission arises due to the formation of Nitrogen Oxide (NO_2), Carbon Monoxide (CO), Carbon Dioxide (CO_2), Sulfur Dioxide (SO_2), Particulate Matter (PM), Lead (Pb), and other byproducts of combustion such as hydrocarbon (HC) and Black-Smoke. Among the identified short-term effects of these pollutants are increased respiratory syndromes and reduced lung functions (Pope *et al*., 1995b) and irritation, headache, fatigue, asthma and high blood pressure (Brunekreef *et al*., 1995). More importantly, longer-term exposure to particulate matter (PM_{10} and $PM_{2.5}$) can lead to heart disease, cancer, and increasing the mortality risk associated with air pollution (Pope, 2007). Exposure to lead, measured by blood lead levels, has potential effects on both adults and children that include increased blood pressure, damage to the central nervous system, cognitive impairment, and reduced measures of child intelligence (Schwela, 2000). Thus, vehicular pollution can have a negative impact on society; some economic manifestations of these costs can be captured by assessing the loss in working days due to illness[1], the increase in treatment costs of illness, and costs of premature mortality (Pope *et al*., 1995a).

VAP is regarded as the main contributory cause of outdoor air pollution in many large cities around the world with high population due to the large volume of traffic on the roads. The problem is even more pronounced in the developing countries, where the large cities experience rapid improvements in the standard of living as a consequence of higher economic growth. Consequently, there have been quite a few studies conducted on VAP and its impact on health in the context of the developing countries in recent years. A few studies have also attempted to determine the health impact of VAP using the benefit transfer method in Bangladesh, and its capital city Dhaka, which has one of the highest levels of particulate pollution among the South Asian cities. This paper estimates the morbidity costs of outdoor air pollution for the people in Dhaka city using primary data collected through a panel household survey.

A recent report on the environment of Bangladesh by the World Bank shows that by reducing the ambient level of particulate matter (PM_{10}) under two scenarios, a reduction of 20 percent and a reduction to the proposed national standard of 50 $\mu g/m^3$ annually, the number of cases of mortality and morbidity that can be avoided come to between 1,200 to 3,500 and 80 million to 235 million, respectively. The estimated saving from a reduction in the health cost based on Willingness-to-pay (WTP) was found to be USD 169 million and 492 million for these two scenarios respectively (World Bank, 2006). These projected amounts are roughly between 0.34 and 1 percent of the gross national income of the country, which represent a significant saving to the economy.

[1] If the sufferer has access to paid sick leave and health insurance, a fraction of the burden of economic cost is transferred from the individual to the society.

In the context of Dhaka, the main sources of outdoor air pollution are PM_{10} and $PM_{2.5}$, the levels of which are much higher than the proposed national standards. The levels of other air pollutants, CO, SO_2 and Ozone, are well within the standards while NO_2 is very close to the standards. To reduce lead poisoning from vehicular emissions, the Government of Bangladesh (GOB) introduced unleaded gasoline in July 1999, which has brought down the lead level in the air to the revised national standard (Biswas *et al*., 2003). Two other major steps toward reducing VAP in Dhaka city were, the introduction of Compressed-natural-gas (CNG) as an alternative source of vehicle fuel, and the replacement of the two-stroke three-wheelers by CNG-powered three-wheelers with 4-stroke engines, both of which contributed to a significant reduction of particulate pollution in the city. The paper also tries to estimate the health benefits of air pollution reduction due to introduction of CNG in Dhaka.

Even though CNG as vehicle fuel was first introduced in 1985-86 through a pilot project of Bangladesh Petroleum Corporation in collaboration with the World Bank, it did not attract much interest till 1996. During the first decade there were only about 160 CNG-powered vehicles in total, and 4 CNG refilling stations run by the Rupantarita Prakritik Gas Company Limited (RPGCL), the government body for the distribution of natural gas in Bangladesh. Since then, however, CNG-powered vehicles have increased rapidly with a) four private companies obtaining permission to setup 20 refilling stations in Dhaka; b) the RPGCL entering into a foreign joint venture to setup another 51 stations where piped gas was available; c) UNDP supporting a training scheme with RPGCL to expand the CNG conversion program in 2000; and d) an ADB project extending the piped gas network and developing new CNG technology in 2002. In January 2003, the government introduced CNG-powered three-wheelers with 4-stroke engines to replace the highly polluting two-stroke three-wheelers, which led to an immediate reduction of PM levels by more than 30 percent in Dhaka (Begum *et al*., 2006a). At the same time, GOB's mandate to switch all government motor vehicles and public transport, including buses, minibuses and taxis, to CNG-powered engines, as well as the government's incentive through the highly subsidized price of CNG for private motor-vehicle owners to switch to CNG, led to a rapid conversion. The number of CNG-powered vehicles went from about 11,700 in 2002 to 50,500 in 2006 (Hossain, 2006). According to the Bangladesh Road and Transport Authority, today there are more than 300 CNG refilling stations around the country with roughly 200,000 vehicles running on CNG. However, despite all such efforts, PM levels in Bangladesh, especially in Dhaka, still remain well above the national standards.

In this context, the present study estimates the health benefits to the people of Dhaka due to air pollution reduction by calculating the Cost-Of-Illness (COI), defined as the sum of lost earnings due to workdays lost or restricted activity days and the mitigation expenditure due to illness. It uses a two-equation random effect panel regression model to control for the fixed seasonal effects as well as the different observable and unobservable individual characteristics that affect their health. For estimating the equation for lost earning, the paper uses a Zero Inflated Poisson (ZIP) regression, as the dependent variable for restricted activity days due to illness, is a count data variable with excessive presence of zeros. For the mitigation expenditure equation, it uses a Tobit regression to model the zero-censored dependent variable for medical expenditure. The paper also compares these results with the previous estimates of health benefits for Bangladesh derived through the benefit transfer approach, and with estimates from similar studies conducted in other major Asian cities. Finally the paper assesses the economic impact in terms of health benefits of using CNG as an alternative fuel and technology.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on the estimation of health benefits, in particular, existing literature on studies conducted in Bangladesh, while Section 3 provides an overview of the study area, Dhaka, and the air pollution scenario. In Section 4 we discuss the basic health production function model, and Section 5 provides the econometric estimation technique to derive relevant results. In Section 6 we describe the details of the household survey design and data collection and provide descriptive statistics for the data collected, while Section 7 is devoted to analysis and discussion of the results. In Section 8 we conclude with some policy recommendations and directions toward further research.

2. Literature on Estimating the Morbidity Costs of Air Pollution

One way of estimating the health benefits of air pollution reduction is through the following steps suggested by Ostro (1994). The first step is to estimate the dose-response relationship, which relates health impacts to ambient air pollution level. The next step estimates the number of people who are exposed and susceptible to the particular air pollution effect being considered. The third step is to estimate the change in the level of air pollution due to implementation of a particular pollution reducing strategy. The product of these three factors gives us the change in population at risk of health damage due to a change in air pollution level. Finally, the researcher arrives at the monetary valuation by estimating the willingness to pay (WTP) of the affected population for reductions in air pollution.

A more general approach to arrive at the benefits of reduction in air pollution is to use a household health production function, developed by Grossman (1972), to determine the demand for health using the human capital model. The model views health as a durable human capital stock and medical care as an input in its production. Cropper (1981) later used this model with pollution as one of the inputs in order to estimate the reduction in health damage from the reduced level of pollution, and Harrington and Portney (1987) provided some important extensions of the basic model of health production function.

The more recent studies on estimating the health benefits from pollution reduction using the health production function usually differ from each other in terms of specification of the utility function and the health (or damage) function. Alberini and Krupnick (2000) defined health production as a function of pollution and averting activities whereas more general models include mitigating activities, stock of health and social capital as inputs in the health production function (Dickie and Gerking, 1991). In the context of South Asia, Murty *et al*. (2003) and Gupta (2008) estimated the benefits from a reduction in urban air pollution in the Indian Subcontinent with primary data from Delhi and Kolkata, and Kanpur, respectively.

Of the studies undertaken on air pollution in Bangladesh, Begum *et al*. (2005) compared the nature and magnitude of VAP between Dhaka and other urban and semi-urban areas in Bangladesh. To analyze the impact of various government policies to reduce VAP in Dhaka, another study demonstrated that the reduction of PM concentration during the period 2000 to 2003 was associated with the introduction of CNG in three-wheelers and the banning of old buses and trucks (Begum *et al*., 2006b). On the other hand, to measure the economic impacts of VAP, Azad et al. (2003) performed a risk assessment of PM_{10} in terms of excess deaths per annum, restricted activity days, respiratory hospital diseases, emergency room visits and respiratory symptom days for residents of Dhaka city and estimated the monetary value of health impacts of air pollution using the benefit transfer method with coefficients from the developed world.

One needs to be very careful while estimating the health impacts using the benefit transfer method as these extrapolations might be inappropriate in some cases and lead to an underestimation or overestimation of the actual health impacts (Cropper *et al*., 1997). Firstly, health impacts associated with a particular air quality might be very different between the low initial air pollution level (experienced in developed countries) and the high initial pollution level (observed in developing countries). Secondly, the average life expectancy is different between developed and developing countries due to various reasons other than air quality, which might in turn lead to a biased estimate of mortality associated with air pollution. Chestnut *et al*. (1997) draw similar conclusions in a study on the transferability of pollution control benefit estimates in the case of Bangkok.

The present study tries to bridge the gap in literature on air pollution studies for Bangladesh, and more generally for developing countries, by estimating the morbidity costs of air pollution with primary data using the health production function approach and comparing the calculated benefits with estimates from benefit transfer studies. Moreover, the study incorporates of the zero inflated Poisson model, widely used in disease studies, for estimating the cost of air pollution in terms of restricted activity days. Because of the large number of observation with no illness this should provide better estimates than the standard Poisson or negative binomial models used frequently in pollution studies.

3. Background to the Study: Air Pollution in Dhaka

The population of Dhaka in 2007 was about 12.3 million and growing at an average annual growth rate of 4.23 percent[2]. Since there are not many manufacturing industries in the city, the main source of outdoor air pollution is VAP. A study on source apportionment of air particulate matter conducted in two different sites in early 2000, a pollution hot spot and a semi-residential area, showed that roughly 36 to 44 percent of coarse and 45 to 48 percent of fine particles are generated from vehicles, out of which 10 to 12 percent comes from two-stroke engine three-wheelers (see Table 1).

The number of registered vehicles in Dhaka before 1995 was 140,000 but had grown to almost 300,000 by the end of 2002. At the end of 2007, the number of vehicles had gone up to 422,000 (Table 2). In a study that compiles a traffic pollution inventory, Karim (1999) measured different VAP concentrations using the Gaussian Plume Model at 82 street intersections in Dhaka. Figure 1 shows the estimated distribution of high PM concentrations at different locations in Dhaka city. A recent vehicular emission inventory for Dhaka in 2004 in the United Nations Environment Program (UNEP) report on the environment of Dhaka (UNEP, 2005) showed that the annual PM10 emission from motor vehicles was 1,515 tons, more than 85 percent of which is contributed by less than 15 percent of the vehicles, that is, the diesel powered buses, minibuses and trucks (Table 3).

The available data on the PM concentration in Dhaka between 1993 and 1994 show that the average PM concentration in a semi-residential area was measured as 123 ±82 for PM_{10} and 51 ±43 for $PM_{2.5}$ (Kojima and Khaliquzzaman, 2002). Although the PM levels were increasing between 1993-94 and 1998-99, they began showing a reverse trend from 2001-02 (Begum *et al*., 2005). Moreover, the removal of two-stroke three-wheelers from Dhaka in the beginning of 2003 caused a reduction in the PM_{10} and $PM_{2.5}$ concentrations in the air by 31 percent and 41

[2] Based on population statistics for Dhaka Statistical Metropolitan Area (SMA) from the Bangladesh Bureau of Statistics (BBS) Census (2006).

percent (Begum *et al*., 2006a). Figure 2 plots the monthly average PM concentrations between April 2002 and May 2007, with some gaps in the data. Although there was a declining trend initially between 2002 and 2003, there has been a slightly increasing trend since then, which can be partly attributed to the rapidly growing number of vehicles even though many of these have been switching to CNG as the alternative vehicle fuel. Figure 3 plots the daily PM trend during the study period, November 2007 to June 2008, which shows that during most days from November to March, both PM_{10} and $PM_{2.5}$ stay above their 24-hour period standard values, which are 150 $\mu g/m^3$ and 65 $\mu g/m^3$, respectively.

4. A Model of Willingness-To-Pay for Health

The theoretical model we use in our study is a simplified version of the general health production function proposed by Freeman (1993), which extends the Harrington and Portney (1987) model to incorporate optimal choice of medical expenditure.

The basic health production function for an individual can be specified as:

$$S = S(Q, M, A; Z) \tag{1}$$

in which the health status of the individual or the number of days spent sick (*S*) is positively related to the level of air pollution (*Q*), and negatively related to the mitigating activities (M) and averting activities (*A*) to reduce exposure to pollution. In the health production function we also include a vector of individual characteristics (*Z*) that captures factors like an individual's baseline health.

Individual's utility (*U*) depends on aggregate consumption (*C*), leisure (*L*) and sick days (*S*):

$$U = U(C, L, S) \tag{2}$$

with $\partial U/\partial C$, $\partial U/\partial L > O$ and $\partial U/\partial S > O$. The individual allocates his non-labor income (*Y*) and labor income between aggregate consumption, averting activities (*A*) and mitigating activities (*M*). The individual's time available for wage earning activities, *T*, is reduced by leisure and days of restricted activity due to illness, *S*. The individual's full income budget constraint is given by:

$$Y + w(T - L - S) = C + p_A \cdot A + p_M \cdot M \tag{3}$$

Here, *w* is the wage rate, while prices of *A* and *M* are given by p_A and p_M, respectively, and the price of aggregate consumption is normalized to one. The individual maximizes *U* by choosing *C*, *L, M* and *A*, subject to budget constraint (3). The first order conditions of the optimization problem yields the following demand functions for averting activity (*A*), mitigating activities (*M*), which depend on prices, wage rate, non labor income, level of pollution, and the vector of individual characteristics:

$$\begin{aligned} A &= A(w, p_A, p_M, Q, Y, Z) \\ M &= M(w, p_A, p_M, Q, Y, Z) \end{aligned} \tag{4}$$

Denoting the marginal utility of income by λ, it is possible to show that the individual's marginal willingness to pay (WTP) for a small change in pollution comprises the individual's marginal lost earning, marginal medical expenditure, marginal cost of averting activities, and monetary value of disutility caused by illness[3]. That is:

$$\mathbf{MWTP} = w \cdot \frac{dS}{dQ} + p_M \cdot \frac{\partial M}{\partial Q} + p_A \cdot \frac{\partial A}{\partial Q} - \frac{U_S}{\lambda} \cdot \frac{dS}{dQ} \tag{5}$$

The estimation of WTP using the above expression avoids the direct estimation of the health production function, which requires not only the data on relevant health outcomes and on ambient pollution level, but also the information on mitigating and averting activities, and the cost of undertaking them. Instead, equation (5) expresses WTP as a function of observable changes in health status, mitigating activities and averting behaviors, along with their observable costs or prices (Freeman, 1993). The first term in WTP measures the lost earnings due to pollution related illness[4], while the second and the third term measures the mitigation and averting expenditure, respectively, and the last term is the monetary value of disutility of the illness.

Because of the difficulty in measuring the disutility of illness, researchers often exclude it from estimation of health benefits and derive a conservative estimate of WTP as:

$$\mathbf{MWTP'} = w \cdot \frac{dS}{dQ} + p_M \cdot \frac{\partial M}{\partial Q} + p_A \cdot \frac{\partial A}{\partial Q} \tag{6}$$

Finally, the lower bound of the benefit estimate consists of the first two terms in equation (5), which measures the Cost-of-Illness (COI) for a small change in the level of pollution:

$$\mathbf{COI} = w \cdot \frac{dS}{dQ} + p_M \cdot \frac{\partial M}{\partial Q} \tag{7}$$

The estimated ratio of WTP to COI for the developed countries varies roughly around 2. However, Alberini and Krupnick (2000) estimated the ratio for Taiwan and found that the ratio for Taiwanese cities varies between 1.6 to 2.26, which is very similar to the estimates from the US, despite the highly dissimilar geographical and socio-economic characteristics between the two.

To estimate COI using the above expression, we need panel data on individual's health status, mitigation activities and related information on individual characteristics that might affect his health, along with the data on ambient level of pollution. The calculation of the first term in equation (7), the lost wages due to pollution related illness, involves estimating the change in health status for a small change in pollution level. This can be computed from the dose-response function, which is the reduced form relationship between health and ambient pollution given the optimal choice of mitigation and averting expenditure by the individual. Thus by substituting the demand functions in equation (4) in the health production function (1), we can derive the dose-response function for the individual as:

$$S = S^*(w, p_A, p_M, Q, Y, Z) \tag{8}$$

The dependent variable in the dose-response function is the health status of the individual (S), which is usually approximated by the workdays lost due to illness to account for the lost earning[5] . But due to the nature of the data, often there are not enough observations on missed work to estimate the dose-response function consistently. Alternatively, we can use the number

3 For details of derivation, see Freeman (1993).

4 Here, the value of the lost earnings includes the value of the lost leisure time due to pollution related illness.

5 By valuing the days of sickness with wages, we are implicitly assuming a zero value to lost leisure time due to illness, since individuals only work for certain hours in a day (Harrington and Portney, 1987).

of restricted activity days due to illness to approximate S. However, using restricted activity days to measure S will overestimate COI because it includes days on which the individual did not miss work in calculation of lost wages. Thus the resulting benefit estimate will include a proxy for the value of leisure time lost due to illness.

The second term in equation (7), the reduction in mitigation expenditure for a small change in pollution level, can be directly computed from the demand function for mitigating activities in equation (4):

$$M = M^* \left(w, p_A, p_M, Q, Y, Z\right) \tag{9}$$

We can approximate the dependent variable in equation (9) by the total medical expenditure of the individual due to pollution related illness, where medical expenses include expenditure on medicines, doctor fees, diagnostic tests and hospital stay, and their opportunity cost of time. In the next section we discuss the econometric specifications for estimating these two equations.

5. Econometric Specification of the Model

Calculating the health benefits of a small change in the pollution level requires estimating the equations for restricted activity days and medical expenses for pollution related illness using the panel data on relevant health outcomes for individuals and ambient level of pollution. Even though these two equations given by (8) and (9) are not functionally interdependent, they are still likely to be interrelated through unobservable individual characteristics or random-effects that control the health outcome of the individual. However, most health benefits studies avoid joint modeling of random-effects for multivariate latent processes, as it can be computationally expensive, especially for the type of non-linear system that arises due to the nature of the dependent variables. Thus for computational tractability and simplicity of the econometric model, we estimate the equations for the health status (S) and the mitigation expenditure (M) separately, the details of which are given in the following subsections.

5.1 Estimation of Health Status

We need to use a discrete or count data regression model to estimate the equation for health status as the dependent variable for the equation is usually approximated by the number of workdays lost or the number of restricted activity days due to pollution related illness. Suppose, S_{it} denotes the days of pollution related sickness for individual i at time period t. Then it is possible to write the probability of number of sick days for the individual using the Poisson Regression (PR) model as:

$$\Pr\left(S_{it} = S|\mathbf{X}_{it}\right) = f\left(S_{it}|\lambda_{it}\right) = \frac{\lambda_{it}^{S_{it}} \exp\left(-\lambda_{it}\right)}{S_{it}!}; \qquad S = 0, 1, 2, \ldots, 7 \tag{10}$$

$$\log\left(\lambda_{it}\right) = \mathbf{X}_{it}^{'}\beta + u_i; \qquad u_i \sim N\left(0, \sigma_u^2\right) \tag{11}$$

Here, λ_{it} denotes the mean value of the number of illness days due to pollution and equation (11) is known as the log link function. The vector of regression coefficients is denoted by β, while X_{it} is the vector of exogenous independent variables including the exposure to pollution for individual i at time t, and u_i captures the time-invariant unobservable individual specific (random) effect that affects an individual's health status. This way of modeling the random effect additively falls under the General Linear Mixed Model (GLMM), for which the researcher does the estimation through maximization of the marginal or "integrated" log-likelihood function[6].

Given the density function for the random effects, $g(.|\sigma_u^2)$, we can obtain the integrated likelihood function, which is the likelihood contribution for individual i, by integrating out the random effects from the conditional likelihood function for individual i conditional on the random effects:

$$f\left(S_i|\beta,\sigma_u^2\right)=\int\left[\prod_t \frac{\exp\left(\mathbf{X}_{it}'\beta+u_i\right)^{S_{it}}\exp\left(-\exp\left(\mathbf{X}_{it}'\beta+u_i\right)\right)}{S_{it}!}\right]g\left(u_i|\sigma_u^2\right)du_i \quad (12)$$

Here the expression inside the square brackets is the conditional likelihood function for individual i given the random-effects. Finally, we can write the likelihood function for all individuals as a product of the individual likelihood functions:

$$L\left(S|\beta,\sigma_u^2\right)=\prod_i f\left(S_i|\beta,\sigma_u^2\right) \quad (13)$$

We need to maximize L for estimating β and σ_u. In general, the integral in equation (13) will not have an analytic expression, except for some special cases, and thus the equation will not have a closed form solution as well. Usually, researchers approximate the integral as a weighted sum through some numerical integration method such as the Gaussian quadrature and then maximize the likelihood function using an optimization algorithm, among which the most commonly used algorithm is the Newton-Raphson algorithm.

One major problem with the PR model is the assumption of equi-dispersion, that is, the assumption that the mean and variance of the Poisson dependent variable is the same. Therefore, for our model of health status, $E(S_{it}|X_{it}) = V(S_{it}|X_{it}) = \lambda it$, which is a very restrictive assumption. One alternative is to model the health status using the Negative Binomial Regression (NBR) model, which allows for an additional parameter to account for over-dispersion. We can modify our Poisson model to incorporate the NBR framework with additive normally distributed random effect as:

$$\begin{aligned}\Pr\left(S_{it}=S|\mathbf{X}_{it}\right) &= f\left(S_{it}|\alpha,\lambda_{it}\right)\\ &= \frac{\Gamma\left(S_{it}+\alpha\right)}{S_{it}!\,\Gamma\left(\alpha\right)}\left(\frac{\alpha}{\alpha+\lambda_{it}}\right)^{\alpha}\left(\frac{\lambda_{it}}{\alpha+\lambda it}\right)^{S_{it}}\\ \log\left(\lambda_{it}\right) &= \mathbf{X}_{it}'\beta+u_i; \qquad u_i\sim N\left(0,\sigma_u^2\right)\end{aligned} \quad (14)$$

Here α denotes the dispersion parameter, which quantifies the amount of over-dispersion. The mean of the dependent variable in NBR is still given by: $E(S_{it}|X_{it}) =$ it, whereas the variance is denoted by: $V(S_{it}|X_{it}) = \lambda_{it}+\lambda_{it}/\alpha$. We should note that the standard Poisson Model could be derived as the limiting case of NBR with α approaching to infinity. The full likelihood function for the NBR model can be written as:

$$L\left(S|\alpha,\beta,\sigma_u^2\right)=\prod_i\int\left[\prod_t f\left(S_{it}|\alpha,\beta;u_i\right)\right]g\left(u_i|\sigma_u^2\right)du_i \quad (15)$$

where, $f\left(S_{it}|\alpha,\beta;u_i\right)=\frac{\Gamma(S_{it}+\alpha)}{S_{it}!\,\Gamma(\alpha)}\left(\frac{\alpha}{\alpha+\exp\left(\mathbf{X}_{it}'\beta+u_i\right)}\right)^{\alpha}\left(\frac{\exp\left(\mathbf{X}_{it}'\beta+u_i\right)}{\alpha+\exp\left(\mathbf{X}_{it}'\beta+u_i\right)}\right)^{S_{it}}$.

6 see Molenberghs and Verbeke (2005), for a detailed exposition of GLMM and their different estimation techniques

Another problem with the Poisson model is that it cannot account for the excessive occurrence of one of the counts (usually zero) in the data, which is quite often observed in the literature on health or social sciences. The excessive occurrence of zeros in the data is not quite the same as the modeling of over-dispersion, which just specifies an increasing variance, and thus cannot be fully captured by NBR as well. Although there are different models that fit this type of data, the "Hurdle" Model or the Zero Altered Poisson (ZAP) model, for example, the underlying assumptions of the data generating process (DGP) in these models are quite different from that of our model. The data on days of illness in our model suits more the Zero Inflated Poisson (ZIP) model, introduced by Lambert (1992) with applications in manufacturing defects. Later on, Hall (2000) incorporated the random effect in the ZIP model.

In a ZIP model, the excess occurrence zeros are modeled as a separate binary process. In particular, there are two possible states for each observation and the result of a binary trial determines which state has occurred for that particular observation. Suppose in our model, state 1 refers to the absence of illness for individual i at time period t and chosen with probability φ_{it}, whereas state 2 refers to Poisson process of number of sick days, $f(S_{it}|\lambda_{it})$, and chosen with probability $1-\varphi_{it}$. The DGP in our model can then be summarized by:

$$S_{it} \sim \begin{cases} 0 & \text{with probability } \varphi_{it} \\ f\left(S_{it}|\lambda_{it}\right) & \text{with probability } 1-\varphi_{it} \end{cases} \tag{16}$$

Then the probability of a particular number of illness days is given by:

$$\Pr\left(S_{it}=S|\mathbf{X}_{it},\mathbf{Z}_{it}\right)=\begin{cases} \varphi_{it}+\left(1-\varphi_{it}\right)f\left(S_{it}|\lambda_{it}\right)=\varphi_{it}+\left(1-\varphi_{it}\right)\exp\left(-\lambda_{it}\right); & S=0 \\ \left(1-\varphi_{it}\right)f\left(S_{it}|\lambda_{it}\right)=\left(1-\varphi_{it}\right)\frac{\lambda_{it}^{S_{it}}\exp(-\lambda_{it})}{S_{it}!}; & S>0 \end{cases} \tag{17}$$

where,

$$\log\left(\lambda_{it}\right)=\mathbf{X}_{it}^{'}\beta+u_i \tag{18}$$

$$\operatorname{logit}\left(\varphi_{it}\right)=\log\left(\frac{\varphi_{it}}{1-\varphi_{it}}\right)=\mathbf{Z}_{it}^{'}\delta+v_i \tag{19}$$

Here the probability of the no illness state is modeled with a logistic specification, where $\mathbf{Z}_{it}$ denotes the vector of covariates that determine the zero inflation state and δ denotes the vector of regression coefficients. Finally, v_i captures the time invariant unobservable random-effect that affects an individual's zero-state probability, which is jointly distributed with the random-effect for the Poisson process μ_i as:

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim \mathbf{N}\left\langle \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{pmatrix} \right\rangle \tag{20}$$

The mean of the health status in the ZIP model is given by $E(S_{it}|X_{it}) = (1 - \varphi_{it})\,\lambda_{it}$, whereas the variance is given by, $V(S_{it}|X_{it}) = (1 - \varphi_{it})\,\lambda_{it}(1 + \varphi_{it}\lambda_{it}) = E(S_{it}|X_{it})(1 + \varphi_{it}\lambda_{it})$.

The specification of the zero inflation state probability depends on the assumption regarding the DGP, and sometimes little prior information is available on how λ effects φ (Lambert, 1992). In some situations, the process of the zero state can be determined by covariates different from the Poisson process, as specified in equation (19). However, in our model, the health status of an individual for no illness is likely to be determined by the same covariates that affect the number of days of illness. Moreover, as the dose-response function is derived as a reduced form equation by substituting the demand functions for mitigating and averting activities in the health production function, we need to model the Poisson process and the zero state process with the same set of covariates.

Sometimes it is more convenient to reparametrize the above ZIP specification to rewrite the Poisson equation as a truncated Poisson process, while expressing the zero state equation as the probability of observing a positive value (Yau and Lee, 2001). Assuming $p_{it} = (1 - \varphi_{it})(1 - \exp(-\lambda_{it}\text{ it}))$, we can rewrite our ZIP model for health status with same covariates of both Poisson and the logistic process as:

$$\Pr(S_{it} = S|\mathbf{X}_{it}) = f(S_{it}|\beta, \delta; u_i, v_i) = \begin{cases} 1 - p_{it}; & S = 0 \\ p_{it} \cdot \frac{\lambda_{it}^{S_{it}} \exp(-\lambda_{it})}{S_{it}!(1-\exp(-\lambda_{it}))}; & S > 0 \end{cases} \quad (21)$$

with,

$$\log(\lambda_{it}) = \mathbf{X}_{it}^{'}\beta + u_i \quad (22)$$

$$\text{logit}(p_{it}) = \log\left(\frac{p_{it}}{1 - p_{it}}\right) = \mathbf{X}_{it}^{'}\delta + v_i \quad (23)$$

With this specification, p_{it} denotes the probability of being ill, while λ_{it} denotes the conditional mean number of days of illness. Thus, the reparameterization allows us to look at the severity or the duration of illness conditional on being ill, rather than just the unconditional mean duration of illness. Moreover, with this alternative specification with a common set of covariates for both equations, the expected sign of the coefficients for all the variables will be in the same direction for the logistic part as well as the truncated Poisson part. Assuming the joint distribution of the random-effects u_i and v_i is given by equation (20) with joint probability density function $G(u_i, v_i| \sigma_u^2, \sigma_v^2, \sigma_{uv})$, we can write the entire likelihood function for all individuals as:

$$\begin{aligned} L\left(S|\beta, \delta, \sigma_u^2, \sigma_v^2, \sigma_{uv}\right) &= \prod_i \int \left[\prod_{t|S_{it}=0} f(S_{it}|\beta, \delta; u_i, v_i) \right. \\ &\quad \left. \cdot \prod_{t|S_{it}>0} f(S_{it}|\beta, \delta; u_i, v_i) \right] G\left(u_i, v_i|\sigma_u^2, \sigma_v^2, \sigma_{uv}\right) du_i dv_i \quad (24) \end{aligned}$$

We estimate all three models, PR, NBR and ZIP, for the health status equation using the Newton-Raphson algorithm with the adaptive Gaussian quadrature integration method for univariate and multivariate random-effects[7]. There are other variants of the model to incorporate the presence of overdispersion in the zero-inflation framework, such as the Zero Inflated Negative Binomial (ZINB) model and the Zero Inflated Generalized Poisson (ZIGP) model (Famoye and Singh, 2006), but neither model converged for our data.

5.2 Estimation of Mitigating Activities

In order to estimate the demand function for mitigating activities, we need to use a Tobit regression model since the dependent variable, usually approximated by the medical expenditure due to pollution related illness, is censored at zero for several observations. We specify the model for mitigating activities as:

$$M_{it}^* = \mathbf{X}_{it}^{'}\gamma + w_i + \varepsilon_{it}; \qquad w_i \sim N\left(0, \sigma_w^2\right), \quad \varepsilon_{it} \sim N\left(0, \sigma_\varepsilon^2\right) \quad (25)$$

Here, X_{it} is the same vector of exogenous independent variables as for the health status equation, γ is the vector of regression coefficients for the individual's mitigation expenditure and M_{it}^* is the

[7] For a detailed discussion on univariate and multivariate adaptive Gaussian quadrature approximation see Molenberghs and Verbeke (2005).

latent variable, which is observed only when mitigation expenditure is positive, that is,

$$M_{it} = \begin{cases} M_{it}^* & \text{if } M_{it}^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

Note that, *wi* captures the time-invariant unobservable individual specific effect that affects an individual's mitigating expenditure, while ε_{it} is the IID random normal disturbance term.

To estimate the random-effects Tobit model we follow a similar approach of maximizing the integrated likelihood function as before. Hsiao (2003) has given a detailed exposition along with the derivation of the likelihood. Denoting the density function of the standard normal distribution with ϕ(.) and the distribution function with Φ(.), the likelihood function for all individuals is given by:

$$\begin{aligned} L\left(M|\gamma, \sigma_\varepsilon^2, \sigma_w^2\right) &= \prod_i \int \left[\prod_{t|M_{it}=0} \Phi\left(\frac{-\mathbf{X}_{it}'\gamma - w_i}{\sigma_\varepsilon}\right) \right. \\ &\quad \left. \cdot \prod_{t|M_{it}>0} \frac{1}{\sigma_\varepsilon}\phi\left(\frac{M_{it} - \mathbf{X}_{it}'\gamma - w_i}{\sigma_\varepsilon}\right)\right] g\left(w_i|\sigma_w^2\right) dw_i \end{aligned} \tag{27}$$

We estimate λ, σ_ε and σ_w by maximizing equation (27) in STATA using the Newton-Raphson algorithm with the adaptive Gaussian quadrature integration method as with the model for health status. In the next section, we discuss the data used in the study followed by the description of variables used for estimating the health benefits.

6. Household Survey Design and the Data

To estimate health benefits from a reduction in air pollution using the above regression models, we need detailed data on the health status of individuals. We collected the primary data for the study using a household survey based on an administered questionnaire to glean information on health and sickness along with other relevant socio-economic characteristics of individual members of each household.

6.1 Sampling Design

For the household survey, we selected households randomly from four different areas of Dhaka where air pollution monitoring units are located using a two-stage stratified random sampling[8]. For the first stage of stratification, we draw households located in the wards[9] that fall within one-kilometer radius of the monitoring stations randomly, proportionate to the total number of households within the wards surrounding each station. We based the second stage of stratification on the following three types of dwelling, single-storied, multistoried and katcha[10], and we selected households randomly, proportionate to the total number of households in the respective dwelling type in each ward around the monitoring stations. The number of households selected surrounding

[8] It may not be random to select households for the study that are close to the monitoring stations if these stations are located near police stations, fire stations, schools, etc., which may attract particular types of households. However the selection problem is likely to be small and thus can be ignored for our study since the sampling frame covers households located within a large area (one-kilometer radius) surrounding the stations.

[9] Dhaka Municipality area is divided into smaller areas based on wards.

[10] Structure with walls and roof made of bamboo, mud, reeds, thatch, iron or other metal sheets, etc.

each monitoring station was roughly equal and information for a total of 239 households with 1,150 members is available after the survey. Figure 4 gives a map of Dhaka city with the one-kilometer radius around each monitoring stations.

6.2 Data from Household Survey and Secondary Sources

Alberini and Krupnick (2000) used a health diary to collect information repeatedly over a long period of time on the health status, the mitigating and the aversive behavior of the sampled individuals. Two recent studies for this region (Gupta, 2008; Murty et al., 2003) use similar techniques to collect data regarding the individual's health status. Murty et al., have collected data once for households with a recall period of six months whereas Gupta has collected data repeatedly using a health diary for three seasons (summer, autumn and winter) over a total period of eighteen weeks. We collected household data for our study using a health diary from November 2007 till July 2008 over a period of nine months that includes three seasons - winter, summer and the rainy season.

Field enumerators visited the sample households in the first week of each month starting from December 2007 and interviewed the female household head[11] using the health diary to collect information on health status of each family member of the household for each week of the last month. The collected data consists of the number of days of sickness, number of visits to the doctor, expenditure on medicines, doctor fees and diagnostic tests, the hospital visit, and the related travel and waiting time. Data on information regarding the general health status like chronic diseases in the family, the general awareness of the household about diseases caused by air pollution, etc., along with the information on demographic characteristics of households such as family size, age and sex composition, education, occupation, hours of outdoor activity, income and expenditure, dwelling type, usage of kerosene, firewood, repellent, incense, etc., was collected during the initial survey conducted in November 2007. We provide summary information regarding the socio-economic characteristics of the surveyed households in Table 4.

We collected air pollution data for total suspended particulate matter, PM_{10} and $PM_{2.5}$, from the Department of Environment (DOE) of GOB under the memorandum signed between the Department and BRAC University. In 2002 DOE, in collaboration with the World Bank, began an air quality management project in Dhaka City by setting up an air-monitoring network in selected locations of Dhaka City to collect and measure particulate emissions. Currently DOE collects daily data on air quality at four different points within Dhaka City. Among the other relevant secondary data, we collected meteorological data on humidity, temperature, rainfall and wind from the Department of Meteorology. We collected all the relevant census information used in the study from the Bangladesh Bureau of Statistics (BBS) Website[12] , and the data on vehicular fleet size and composition from the Bangladesh Road and Transport Authority (BRTA).

With 1,150 members from 239 households, and 40 weeks of health diary data between November 2007 and July 2008, the study generated a panel data with 46,000 observations. But the data on PM concentration from DOE was available only till June 2008 with gaps in between for some of the monitoring stations due to technical faults. So the final data set used in the study consists of 23,105 observations.

[11] For a detailed discussion on univariate and multivariate adaptive Gaussian quadrature approximation see Molenberghs and Verbeke (2005).

[12] BBS Website: http://www.bbs.gov.bd/

6.3 Variables Used in the Model

The two endogenous variables for our model of health benefits are Health Status (*S*) and Mitigation Expenditure (*M*). We measured Health Status of the individual by the 'number of days of illness or restricted activity' in a week due to air pollution related diseases or symptoms. We did not use workdays lost to approximate health status because there were not enough observations with positive values days of missed work. Mitigation Expenditure on the other hand includes costs of medication, doctor's fees, diagnostic tests, hospitalization, and travel costs for buying medicine or visiting the doctor for air pollution related illness[13] .

To capture the effect of exposure to air pollution on health status and mitigation expenditure, we used PM_{10} Concentration (X1), which remains in the atmosphere for a long period of time and causes most respiratory illnesses, as one of the covariates in the model[14]. This is the weekly average value of PM_{10} concentration recorded at four different monitoring stations in Dhaka[15]. We have also included meteorological variables along with their lagged values as covariates that are known to affect atmospheric PM concentration as well as individual's health. These are, relative humidity (X2 and X3), rainfall (X4 and X5), temperature variation (X6 and X7)[16], and wind speed (X8 and X9). Inclusion of the meteorological variables also controls for the seasonal effect that might be present in the data. Moreover, we have included a dummy variable for brick production months (X10) to control for the high level of air pollution generated from brick production that takes place just outside Dhaka city during the dry season between November and mid of March. Table 5 provides the sample correlations between PM_{10} and these variables.

To controlled for the various individual characteristics that affects their health status and medical expenditure, we include individual's age (X11) and square of age (X12)[17], and dummy variables for female individuals (X13), individuals who are exposed to passive smoking inside the house (X14), individuals exposed to outdoor air pollution (X15)[18] , and individuals who are suffering from a chronic disease (X16) as covariates. Along with the individual characteristics, household characteristics that might affect individual's health and mitigation expenditure are, household's

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13 When calculating the mitigation expenditure, we did not include the opportunity cost of time for the patient or any accompanying person while visiting the doctor, having a diagnostic test, or buying medicines, since enough information regarding these were not available. Thus the calculated mitigation costs of air pollution related illness in the study provides a conservative estimate.

14 To capture the presence of possible lagged effect of ambient pollution concentration on sickness, we have also included average PM_{10} concentration for the previous week as a covariate. But we did not observe any significant relationship between sickness and lagged particulate pollution. Moreover, the usable sample size reduced significantly after including lagged PM_{10} due to large number missing observations, which forced us to drop this variable from the estimated equations.

15 We could not include SO_2 and NO_2 as covariates since the data for these two pollutants were not available. So in this case, PM_{10} might also capture the effects of these pollutants on health. However, we expect this effect to be insignificant for our study as the levels of both SO_2 and NO_2 in Dhaka are well below the WHO standards.

16 We have measured temperature variation by the difference between daily maximum and minimum temperature, averaged over the week.

17 We have included age and square of age as covariates to capture the non-linear relationship between individuals age and probability of illness as well as medical expenses. We expect the age to be negatively related to *S* and *M*, while the squared-age should be positively related to both, as the probability of illness as well as medical expenditure should go down during the early life and increase during the latter years of life (Zhang and Imai, 2007).

18 It is a dummy variable taking the value 1 for individuals who stay outdoors in the open for more than an hour everyday.

monthly income (X17)[19] , household size (X18)[20], and a dummy variable for frequent use of incense and insect-repellents (X19). We have also included a covariate for awareness index (X20) for the household, which is a variable ranging from 0 to 5 with 0 denoting no awareness regarding air pollution and its effects of health[21] . Finally, to control for the dwelling characteristics that might affect individual's health and mitigation expenditure, we have included dummy variables for houses that are located on a big road with heavy traffic flow (X21), and for houses located in the industrial area (X22) as covariates.

Following Alberini and Krupnick (2000), we have also controlled for pre-existing symptoms and mitigation expenditure to avoid overestimation of health benefits by including dummy variables for illness and positive medicare in the previous week (X23 and X24). However, when calculating the health benefits, we have only focused on new occurrence of illness and medical expenditure at a particular level of air pollution by assuming that the individual was not ill in the previous week and did not incur any mitigation costs.

Table 6 presents the descriptive statistics for these variables used in our model. The average number of restricted activity days for a person due to air pollution related illness (*S*) was 0.23 days per week, and the average expenditure incurred for mitigation of the illness (*M*) for a person was Taka 3.81 per week. However, conditional on being ill, the average number of sickness days per week was 5.09 days, while conditional on incurring a positive medical expense, the average expenditure on medicare was Taka 211.06 per week. The weekly average PM_{10} concentration was 193.74 $\mu g/m^3$.

7. Results and Discussions

7.1 Regression Models

We present the summary results of PR, NBR and ZIP models for health status in Table 7. The coefficient of PM_{10} is positive and significant in all the models, implying a reduction in the expected number of restricted activity days for a reduction in ambient pollution. The dispersion coefficient (α) in NBR model is 16.6954 and it is significant at 1 percent level, suggesting the presence of over-dispersion in the data. The coefficient of PM_{10} in the zero inflation equation is also positive

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19 We have used income brackets instead of gross monthly income, as many households did not report their actual income. Income should be negatively related to *S*, but it can be either positively or negatively related to *M* depending on the dominance of the income effect on medical expenditure over the health effect of higher income.

20 Household size is measured by the number of members in the household to control for the higher number of days of sickness or medical expenditure for a large household. This could be positively related to *S* due to contagiousness of some of the air pollution related diseases. On the other hand it might be negatively related to *M*, as individual's medical expenditure would be lower on average for larger households.

21 The awareness index is constructed using a series of questions regarding outdoor air pollution starting with whether the individual is aware about the air pollution problem in Dhaka. Respondents who answered no to this question received a zero value for awareness. The respondents with a positive answer to the question on the other hand, were then asked to agree or disagree with a series of statements on a 5-point scale regarding the outdoor air pollution situation in the neighborhood as well as in entire Dhaka city, main sources of outdoor air pollution in the city, and various diseases that are related to air pollution. We then created the awareness index for the household by averaging the scores from all the statements. The awareness index might affect health status (*S*) negatively as higher awareness would indicate lower number of days of air pollution related illness. However, the effect of awareness on demand for medicare is ambiguous.

and significant (at 1% level) for the ZIP model, which strongly suggests the choice of the zero inflation model over its counterparts. The expected days of illness is 0.0202 days for the PR model, 0.0274 days for the NBR model, and 0.0714 days for the ZIP model, which suggests that both PR and NBR model underestimates the likelihood of illness. The likelihood ratio test for the presence random effect is significant at 1 percent level for all the models, implying the presence of individual specific unobservable effects that affects individual's health status. Because of the highly significant coefficient PM10 in the zero-inflation equation along with the highest value of the maximized log-likelihood function, we have chosen the ZIP model for the health status equation to estimate the health benefits.

We present the coefficient estimates for the logistic part and truncated Poisson part of the ZIP model for restricted activity days (S) and the Tobit model for mitigation expenditure (M) in Table 8[22]. The coefficient of PM10 for the logistic part and the Poisson part is 0.002 and 0.0011, respectively, for ZIP model, and it is 0.9949 for the Tobit model. It is significant for both equations of the ZIP model at 1 percent level, and for the Tobit model, it is significant 5 percent level.

The coefficient of humidity is positive and significant for all three equations, but the coefficient of lagged humidity is insignificant for all. Rainfall coefficient is positive and significant for both parts of the ZIP model, but lagged rainfall is positive and significant for only the logistic part. However, none of them are significant for the Tobit model. These suggest that, even though an increase in humidity and rainfall usually reduces ambient air pollution, highly humid conditions and higher rainfall significantly increase the likelihood of respiratory symptoms for the people of Dhaka. The coefficient of temperature variation is positive and significant for the logistic part of the ZIP model, suggesting that increase in temperature variation increases the probability of respiratory diseases. But both temperature variation as well as its lagged value are insignificant for the other equations. The coefficients for wind speed and its lag are insignificant for all equations except for the logistic equation, for which the lagged wind speed is negative and significant, suggesting that higher wind speed causes air pollutants to disperse and reduce the probability of illness. The dummy variable coefficient for brick production months is positive and significant for the logistic equation of the ZIP model and the Tobit model as expected.

Among the individual characteristics, age is negative and significant for the logistic and the Tobit equation, while the squared-age is positive and significant for both. This suggests the hypothesis that the probability of illness as well as medical expenditure goes down as individuals get older until a threshold level of age, and increases thereafter[23]. We also find that female individuals have significantly higher probability of illness and higher medical expenses compared to the male individuals. Also individuals who are exposed to passive smoking inside the house are more likely to get ill from air pollution related diseases. Finally, the coefficients of dummy variables for outdoor air pollution exposure and chronic diseases are positive and significant for the logistic and the Tobit equation, which suggests that individuals who are exposed to outdoor air pollution as well as individuals with chronic illnesses face a higher risk of illness and medical expenses due to air pollution related diseases.

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22 When estimating the random-effects panel data models for health status and mitigation expenditure, we are ignoring the possible correlation among the individuals from same house arising from unobservable household level random-effects, as estimation of multi-level random-effects panel data models using the quadrature approximation methods is computationally very expensive.

23 The calculated threshold age for probability of illness is 42.8 years, whereas for medical expenditure it is 40.47 years.

The coefficient of income has a negative sign for the logistic equation and the Tobit equation, but it has a positive sign for the Poisson equation. For the Tobit model, the negative sign of income coefficient suggests the dominance of the negative health effect of higher income through better standard of living over the positive income effect of higher medical expenditure. However the coefficients are insignificant for all three equations. Coefficient of household size is negative and significant for the Tobit model, suggesting that medical expenditure is lower on average for the members of a large household. The coefficient of awareness index is negative and significant for the logistic equation as expected, but it is insignificant for Tobit equation and the Poisson equation. The dummy variable coefficient for frequent use of insect-repellent and incense is positive and significant for the Tobit equation, but it is insignificant for both equations in the ZIP model. Among the dwelling characteristics, main-road dummy coefficient is positive and significant for the mitigation expenditure equation as expected. The coefficient of dummy variable for households located in the industrial area is however negative and significant for the Poisson equation and the Tobit equation, which suggests that individuals residing in the industrial area in Dhaka face lower risk of illness and medical expenses from air pollution related illness.

Finally, the coefficient of dummy variable for presence of illness in the previous week is positive and significant for all three equations, suggesting a higher risk of illness and medical expenditure if the individual was ill in the previous week. The dummy variable coefficient for the medical expenditure in the previous week, on the other hand, is negative and significant for all of the equations, which suggests that the probability of illness and demand for medicare reduces if the individual had positive mitigation expenses in the previous week.

7.2 Benefits from Air Pollution Reduction

In order to estimate the monetary benefits from a reduction in air pollution to the revised national standards of 50 $\mu g/m^3$ from the current level of 193.74 $\mu g/m^3$, we need to compute the "marginal effect" of PM reduction, that is, the change in the expected value of S for a unit reduction in the PM concentration. Denoting PM concentration by x_j, the marginal effect for the PR and NBR is given by $\partial E(S|X)/\partial x_j = \beta_j E(S|X)$, where β_j is the coefficient of β_j. However, for the ZIP model we have estimated, marginal effects are different from the PR and NBR model and it is given by:

$$\frac{\partial \mathbf{E}(S|\mathbf{X})}{\partial \mathbf{x}_j} = (\delta_j (1-p) + \beta_j - \beta_j \exp(-\lambda) \mathbf{E}(S|\mathbf{X})/p) \mathbf{E}(S|\mathbf{X}) \tag{28}$$

Here, β_j and δ_j are the estimated coefficients of PM concentration for the Poisson equation and logit equation, respectively, $E(S|X) = p\lambda/(1 - \exp(-\lambda))$ is the mean number of sick days, with p and λ defined by equation (22) and (23), respectively.

The marginal gain calculated from the ZIP coefficient estimates for a unit reduction in PM_{10} is found to be 0.0002 for a person per month. Given the employment ratio of 33.13 percent in the sample households, the annual gain in workdays from a reduction in PM concentration to the safe level (a reduction of 143.74 $\mu g/m^3$) becomes 0.53 days per year for the employed persons. With the average daily wage at Taka 250.21 (calculated for the sample), the annual gain turns out to be Taka 131.37 for an average working person in Dhaka. The estimated population in Dhaka is 12.3 million. With the employment ratio from our sample, the estimated working population in Dhaka is 4.075 million and the estimated annual monetary gain for the entire working population of Dhaka is Taka 535.35 million.

In order to calculate the economic benefits of reducing air pollution through a reduction in mitigation expenditure, we need to obtain the marginal effect of a unit reduction in pollution on the mitigation expenditure by multiplying the coefficient of PM_{10} in Tobit regression with the probability of incurring medical expenditure. Out of 23,105 observations used for estimating the mitigation expenditure equation, 454 individuals incurred positive medical expenditure, which gives us the probability of using medicare at 0.02. Using this, the estimated benefit for a person in Dhaka of reducing air pollution to the safe level was Taka 2.89 per week and Taka 150.49 per year. The total saving for the entire population of Dhaka then is Taka 1.85 billion.

Thus the total monetary gain, through a reduction in lost earnings and reduction in mitigation expenditure, from reducing air pollution in Dhaka to a safe level amounts to Taka 2.39 billion or USD 34.09 million (using the exchange rate of USD 1 = Taka 70). We ought to note that this is the estimated COI from a reduction in air pollution to a safe level and that it does not include the two other components of WTP, the cost of undertaking averting activities and the disutility incurred due to illness. If we take the ratio of WTP to COI as 2 (a widely used estimate of WTP/COI in studies from the west), the WTP estimate for Dhaka for reducing air pollution to a safe level comes to Taka 4.78 billion or USD 68.18 million. As previously noted, this estimate does not include any costs from pre-mature mortality associated with air pollution.

The estimate of health benefits derived in this study is quite low compared to various WTP estimates for Bangladesh that have been derived through the benefit transfer method. For example, the World Bank report in the Bangladesh Country Environmental Analysis (World Bank, 2006) that morbidity costs saved by reducing outdoor air pollution to the revised national standard in 3 major cities of Bangladesh is USD 380.1 million. Table 9 provides estimates from the World Bank study for various health effects in terms of number of cases and annual savings in million US dollars. If we adjust our WTP estimates with the population (18.2 million) for the 3 major cities and exchange rate (USD 1 = Taka 58) used by the World Bank, the estimated WTP for our study amounts to USD 121.76 million, which amounts to approximately one-third of the estimate obtained using the benefit transfer method. The key difference might have come from the high estimated cost for chronic bronchitis, USD 194.3 million, in the World Bank study, which amounts to more than 50 percent of the total estimated morbidity costs.

7.3 Benefits from Switching to CNG

For estimating the health benefit of switching to CNG as an alternative mode of vehicular fuel, we need detailed data on vehicle fleet size, average vehicle utilization (miles traveled) for different vehicle types, pollution load for each vehicle type, as well as coefficients for translating vehicular emission to ambient pollution concentration. Other than vehicle fleet size, the data for the other measures are not available. Also the vehicle fleet size data that is available is on the number of registered vehicle in Dhaka whereas the actual number of vehicles that ply the streets of Dhaka will be different because there are many vehicles plying the streets of Dhaka without proper registration documents.

Roughly 400,000 vehicles ply the streets of Dhaka. Out of this number, 170,000 are motorcycles, which run on gasoline, while 25,000 are trucks, which run on diesel. The emission inventory in 'Dhaka City State of Environment 2005' (UNEP, 2005) shows that, together they contribute about 33 percent of the PM emission (see Table 3). According to some other sources, 90 percent of the other vehicles, which total roughly 200,000, have switched to CNG already[24]. This includes the more than 6,000 buses and 8,000 minibuses that used to run on diesel and accounted for 57 percent of the vehicular PM emission.

Using the vehicle registration data from Bangladesh Road and Transport Authority (BRTA), and the emission inventory data from the UNEP (2005), we have constructed Table 10 for vehicular PM emissions under two different scenarios: the current state with CNG powered vehicles and the hypothetical scenario without any CNG vehicles. The estimated annual vehicular emissions of PM_{10} are 1,362 tons under the current scenario while it is 3,870 tons in a scenario without CNG. While vehicular emissions contribute to roughly 40 percent of the total particulate emissions in Dhaka (Akhter et al., 2004), the estimated emissions from other sources are 2,043 tons. If these emissions lead to an average PM_{10} concentration of 193.74 $\mu g/m^3$, then the vehicular emissions of 3,870 tons under the scenario without CNG vehicles, along with 2,043 tons of emissions from other sources, could lead to an average PM10 concentration of 336.51[25] $\mu g/m^3$. The resulting saving from the reduction of 142.77 $\mu g/m^3$ (from 336.51 $\mu g/m^3$ to the current level of 193.74 $\mu g/m^3$) due to the use of CNG as an alternative vehicle fuel will be Taka 531.73 million in terms of the gain in workdays and Taka 1.84 billion in terms of reduced medical expenditure, amounting to a total Taka 2.37 billion or USD 33.86 million of benefits. The WTP estimate of this reduction would be Taka 4.74 billion or USD 67.72 million approximately.

We can also calculate the potential benefits from converting the diesel-powered trucks to CNG-powered engines using the estimates from Table 10. Using the same emission factor as CNG-powered buses, converting the trucks to CNG will reduce PM emissions by 662 tons per year. If we continue to assume the same estimated emissions from other sources as 2,043 tons, this would lead to an average PM_{10} concentration of 156.08[26] $\mu g/m^3$, resulting a reduction of PM_{10} by 37.66 $\mu g/m^3$. The estimated saving for this reduction then amounts to Taka 140.26 million in terms of workdays gained and Taka 484.96 million in terms of reduced medical expenses, a total of Taka 625.22 million or USD 8.93 million, and the corresponding WTP estimate is Taka 1.25 billion or USD 17.86 million.

However, these are preliminary estimates of health benefits from switching to CNG-powered engines. A more concrete estimation would require proper data on the vehicular pollution load and receptor modeling results in order to translate vehicular emission into ambient pollution concentration.

8. Conclusion and Policy Recommendations

The present study is the first to have estimated the health benefit of reducing ambient air pollution in Dhaka, the capital city of Bangladesh. The estimated annual gain in terms of the reduction in workdays lost is Taka 131.37 for a working person and Taka 150.49 in terms of reduced medical expenditure for a representative person. Similar studies in this part of the world have shown estimates that are relatively close. In terms of workdays lost per annum from air pollution, the estimated results were 0.43 days in Taiwan (Alberini and Krupnick, 2000), 0.41 days in

[24] We have collected this information from various newspaper articles, as there is no data present from any official sources regarding the total number of vehicles converted to CNG.

[25] $193.74 \times (3,870 + 2,043) \div (1,362 + 2,043) = 336.51 \mu g/m^3$.

[26] $193.74 \times (1,362 - 662 + 2,043) \div (1,362 + 2,043) = 156.08 \mu g/m^3$.

Kolkata and 0.66 days in Delhi (Murty *et al*., 2003), whereas it was 0.53 days in Dhaka. In terms of monetary gain, the estimated annual gain for a working individual was Rs. 544.94 in Delhi (USD 12.11) and Rs. 295.10 in Kolkata (USD 6.56) whereas in Dhaka it was Taka 281.86 (USD 4.03). On the other hand, the estimates from this study are quite low compared to the estimated WTP for reduction in air pollution based on the benefit transfer approach that utilizes studies undertaken in the West. This detail underscores the difficulties of using the benefit transfer method.

The estimated annual health benefits of introducing CNG as an alternative vehicular fuel in Dhaka amounts to Taka 4.74 billion or USD 67.72 million, while the estimated savings from converting the remaining diesel-powered trucks in Dhaka to CNG-powered vehicles is Taka 1.25 billion or USD 17.86 million per annum. This gives us some indication of the potential saving that would accrue from introducing an alternative vehicular fuel in other major cities in Bangladesh with high VAP. However, this benefits need to be compared with potential costs of introducing CNG before implementing any policy. As the literature on cost aspects of CNG introduction is non-existent for Bangladesh, we need studies on the costs of switching to CNG. Further studies are also needed to estimate other pecuniary benefits of introducing CNG accrued through changes in the demand for petroleum imports and savings in foreign reserves. Finally, researchers ought to revisit some of the current government policies such as the high subsidy on CNG prices.

The government has introduced many different policies to tackle the pollution problem in Dhaka and in Bangladesh but the success of these policies depends crucially on the proper implementation of such strategies. This study aims to create further awareness among members of the government and policy makers of the need to design and properly implement policies towards the reduction of air pollution in Dhaka.

9. Acknowledgements

This research project was funded by the South Asian Network for Development and Environmental Economics (SANDEE). We are grateful for the valuable inputs into the research from our advisor Dr. M. N. Murty and we thank Dr. Jeff Vincent, Dr. Enamul Haque and Dr. Priya Shyamsundar for their constant support and comments during the project. We are thankful to the Department of Environment (DOE), the Government of Bangladesh and the Project Director of the Air Quality Management Project of DOE, Dr. Mohammed Nasiruddin, for providing us with the data on air pollution in Dhaka, without which the project could not have been completed. We would also like to thank Dr. Anwarul Hoque, Chairperson of the Department of Economics and Social Sciences at BRAC University, for providing the institutional support for the project, and the SANDEE Secretariat for their administrative support. Finally we are grateful to the anonymous reviewer of SANDEE for the valuable comments on the final paper.

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TABLES

Table 1: Average Percentage Contributions of the Sources in Dhaka

Source Profile	Hotspot Site Coarse	Hotspot Site Fine	Semi-residential Site Coarse	Semi-residential Site Fine
Sea Salt	9.41		4.45	1.00
Soil Dust	48.70	1.00	43.00	10.20
Road Dust			7.30	19.40
Two-stroke Engine	12.90	2.41	3.78	9.36
Metal Smelter			1.21	9.96
Motor Vehicle	23.40	43.00	40.20	38.20
Re-suspended Pb	2.29	3.30		
Construction Cement	3.20			
Biomass Burning		37.50		11.90
Unknown Sources		12.70		

Source: Akhter *et al.,* (2004)

Table 2: Vehicle Feet Size in Dhaka, 1995 – 2007

Vehicle Type	Pre 1995	2002	2003	2007
Motor Car	36,998	81,703	87,866	115,880
Jeep/Microbus	17,937	30,581	32,391	46,728
Taxi	787	4,389	9,369	10,672
Bus	269	2,240	2,614	6,152
Minibus	2,009	6,409	7,460	8,098
Truck	9,775	18,214	20,342	25,193
Three-wheeler	8,359	29,120[1]	10,687	13,521
Motor-cycle	61,478	112,060	119,299	173,637
Others[2]	2,063	9,257	12,514	21,816
Total	**139,675**	**293,973**	**302,542**	**421,697**

Source: Bangladesh Road and Transport Authority (BRTA)

Notes:

1. 26,429 Two-stroke Three-wheelers were removed from Dhaka, on January 1, 2003, and Four-stroke CNG-powered Three-wheelers were introduced.
2. Others include Human Haulers and Covered Vans.

Table 3: Emission Factors and Annual Emission Estimates for Different Vehicle Types in Dhaka

Vehicle Type	Number (2004)	Avg. Usage (Km/day)	Emission factor (gm/day)	PM Emission (Tons / year)	Relative Emission
Motor Car	127,105	40	0.1	185.57	0.079
Taxi (CNG)	9,892	130	0.03	14.08	0.005
Three-wheeler (CNG)	13,031	130	0.03	18.55	0.007
Light-duty Diesel	7,828	60	0.8	137.15	0.186
Bus	3,393	130	1.6	257.60	0.389
Truck	21,779	60	1.6	763.14	0.281
Motor-cycle	127,171	30	0.1	139.25	0.053

Source: Dhaka City State of Environment Report 2005 (UNEP, 2005)

Table 4: Socioeconomic Characteristics of Sample Households

Variable	Mean	Std. Dev.	Min	Max	Obs
Houshold Characteristics					
HH Size	5.6748	3.0789	1	22	239
Num of Females	2.8409	1.8324	1	12	239
Num of employed	1.8661	1.3804	0	7	239
Income	22,826.36	19,480.33	2,000	150,000	239
Expenditure	17,145.15	11,416.68	1,500	79,000	239
Aware regarding AP	0.6192	0.4866	0	1	239
Dwelling Characteristics					
Num of rooms	2.8870	1.6295	1	14	239
Floor number	1.6485	1.0381	1	5	239
Dummy Pucca	0.7699	0.4218	0	1	239
Dummy Industrial	0.2134	0.4106	0	1	239
Dummy Mainroad	0.2971	0.4579	0	1	239
Member Characteristics					
Age	27.5017	17.6678	0	95	1150
Years of schooling	8.0330	5.4700	0	16	1150
Hrs of exposure outdoor	1.7270	2.3676	0	20	1150
Dummy Chronic Disease	0.2774	0.4479	0	1	1150

Table 5: Sample Correlation between PM_{10} and Meteorological Variables

	PM10	Humidity	Rainfall	Temp. Variation	Wind speed	Brick Prod. Dum
PM_{10}	1.0000					
Humidity	-0.3276	1.0000				
Rainfall	-0.3917	0.5981	1.0000			
Temp. Variation	0.4388	-0.8104	-0.5422	1.0000		
Wind speed	-0.3740	0.1569	0.2495	-0.3155	1.0000	
Brick Prod. Dum	0.6255	-0.4668	-0.4931	0.6115	-0.2975	1.0000

All correlation coefficients are significant at 1% level

Table 6: Descriptive Statistics of the Variables Used in the Model

Variable	Obs.	Mean	Std. Dev.	Min	Max
Restricted Activity Days (S)	46,000	0.2323	1.1460	0	7
Cond. Restricted Activity Days[1]	2,098	5.0944	2.0068	1	7
Mitigation Expenditure (M)	46,000	3.8083	99.2640	0	13180
Cond. Mitigation Expenditure[2]	830	211.0627	709.1823	2	13180
PM_{10} (X1)	23,105	193.7375	88.3098	59.86	509
Humidity (X2)	46,000	71.8188	7.7658	57.29	88.57
Rainfall (X4)	46,000	5.9759	10.1076	0	47
Temperature Variation (X6)	46,000	8.9936	2.1856	5	12.71
Wind speed (X8)	46,000	3.2130	0.5205	2.14	5
Brick Production Dum (X10)	46,000	0.6000	0.4899	0	1
Age (X11)	46,000	27.5017	17.6604	0	95
Female Dum (X13)	46,000	0.4991	0.5000	0	1
Passive Smoke Dum (X14)	46,000	0.2609	0.4391	0	1
Exposure Dum (X15)	46,000	0.6217	0.4850	0	1
Chronic Disease Dum (X16)	46,000	0.2774	0.4477	0	1
Income Range (X17)	46,000	5.2409	1.8864	1	10
Household Size (X18)	46,000	5.6748	3.0776	1	22
Awareness Index (X19)	46,000	2.5604	1.9440	0	4.91
Repellent-Incense Dum (X20)	46,000	0.3765	0.4845	0	1
Main-road Dum (X21)	46,000	0.3035	0.4598	0	1
Industrial Area Dum (X22)	46,000	0.1930	0.3947	0	1

Notes:
1. Restricted Activity Days conditional on having at least one day of illness
2. Mitigation Expenditure conditional on having positive mitigation expense

Table 7: Summary Results for Health Status Equation (*S*)

Estimates	Poisson	NBR	ZIP
PM_{10} Coefficient	0.0023***	0.0024**	0.0011***
(Standard Error)	(0.0003)	(0.0010)	(0.0003)
Dispersion Coefficient		16.6954***	
(Standard Error)		(0.8396)	
PM10 Coefficient Logistic Equation			0.0020***
(Standard Error)			(0.0007)
Expected number of Sick Days	0.0202	0.0274	0.0714
LR Chi2 test for Random Effect = 0	2850.32	254.34	319.068
Prob. > Chi^2	< 0.001	< 0.001	< 0.001
Log Likelihood	-10663.80	-6598.28	-4954.883
Wald Chi2 (24)	4712.4	628.175	149.591
Prob. > Chi^2	< 0.001	< 0.001	< 0.001

*** Significant at 1% level
** Significant at 5% level

Table 8: Parameter Estimates for Health Status (*S*) and Migration Expenditure (*M*)

Covariate	Coefficient	SE	Coefficients	SE	Coefficient	SE
PM_{10} (X1)	0.0020***	0.0007	0.0011***	0.0003	0.9949**	0.4112
Humidity (X2)	0.0380***	0.0093	0.0112***	0.0037	17.5927***	5.2802
Lag Humidity (X3)	0.0117	0.0100	-0.0043	0.0040	-0.1149	5.6595
Rainfall (X4)	0.0147**	0.0075	0.0056*	0.0030	4.0659	4.1210
Lag Rainfall (X5)	0.0196***	0.0071	0.0035	0.0027	4.1660	4.1134
Temperature Variation (X6)	0.0710*	0.0389	-0.0199	0.0142	5.2947	21.3775
Lag Temp. Variation (X7)	-0.0202	0.0434	-0.0020	0.0167	-1.5673	25.3862
Wind speed (X8)	0.0174**	0.0852	-0.0357	0.0327	16.4036	48.0043
Lag Wind speed (X9)	-0.1564***	0.0742	0.0318	0.0297	-15.7971	43.0617
Brick Production Dum (X10)	0.5664***	0.1559	0.0485	0.0649	224.1072***	85.1066
Age (X11)	-0.0745***	0.0088	-0.0016	0.0026	-32.5705***	4.4227
Age-squared (X12)	0.0009***	0.0001	0.0000	0.0000	0.4024***	0.0634
Female Dum (X13)	0.3281**	0.0982	0.0232	0.0314	99.5378**	50.4630
Passive Smoke Dum (X14)	0.2636***	0.1039	-0.0041	0.0336	87.4171	53.4433

Exposure Dum (X15)	0.3285***	0.1078	-0.0042	0.0337	101.7899*	55.3463
Chronic Disease Dum (X16)	0.5961	0.1123	0.0222	0.0359	167.0383***	58.1207
Income Range (X17)	-0.0405	0.0292	0.0005	0.0094	-19.2079	15.3030
Household Size (X18)	0.0247***	0.0175	-0.0002	0.0046	-23.1588**	10.8529
Awareness Index (X19)	-0.0723	0.0271	0.0022	0.0088	6.1064	13.8105
Repellent-Incense Dum (X20)	0.0071	0.0992	0.0011	0.0324	94.7512*	50.2650
Main-road Dum (X21)	-0.0797	0.1073	-0.0454	0.0370	108.4856**	52.8203
Industrial Area Dum (X22)	-0.0485***	0.1771	-0.3095***	0.0611	-304.7981***	109.6842
Lag Sickness Dum (X23)	3.1178*	0.1065	0.2837***	0.0331	1316.2900***	78.1534
Lag Med Cost Dum (X24)	-0.2805***	0.1448	-0.1550***	0.0407	-774.2025***	118.6512
Constant	-7.6851	1.3657	0.9728*	0.5153	-3576.3210***	792.4580
sigma-*u*			0.1380***	0.0293		
sigma-*v*			2.4025***	0.1215		
sigma-*uv*			-0.2628***	0.0576		
LR Chi2(3) test of sig-u = sig-v = sig-uv = 0 (p-value)			319.068***	(< 0.001)		
sigma-*e*					1008.6050***	37.3112
sigma-*w*					235.3594***	43.3364
LR Chi2(1) test of sig-w = 0 (p-value)					9.896***	(0.001)
Log-likelihood				-4954.883		-4998.81-5
Wald Chi2(24)				149.591		363.921
p-value				< 0.001		< 0.001
Non-zero Obs.				1038		454
Zero Obs.				21459		22043
Number of Obs.				22497		22497
Number of Groups				1150		1150
Obs. Per Group				6 - 33		6 - 33

*** Significant at 1% level
** Significant at 5% level
* Significant at 10% level

Table 9: Estimated Number of Cases and Annual Costs of Morbidity in the World Bank (2006) Study

Health Effects	Number of Cases	Monetary Savings (Million USD)
Chronic Bronchitis	57,133	194.3
Resp. Hospital Admission	18,127	1.3
Asthma Attack	2,462,278	2.7
Emergency Room Visits	355,595	0.8
Restricted Activity Days	53,212,396	49.2
Lower Respiratory Illness	975,213	0.7
Respiratory Symptoms	170,839,796	131.1
Total	227,920,538	380.1

Source: World Bank (2006)

Table 10: Emission Estimates with and without CNG Vehicles

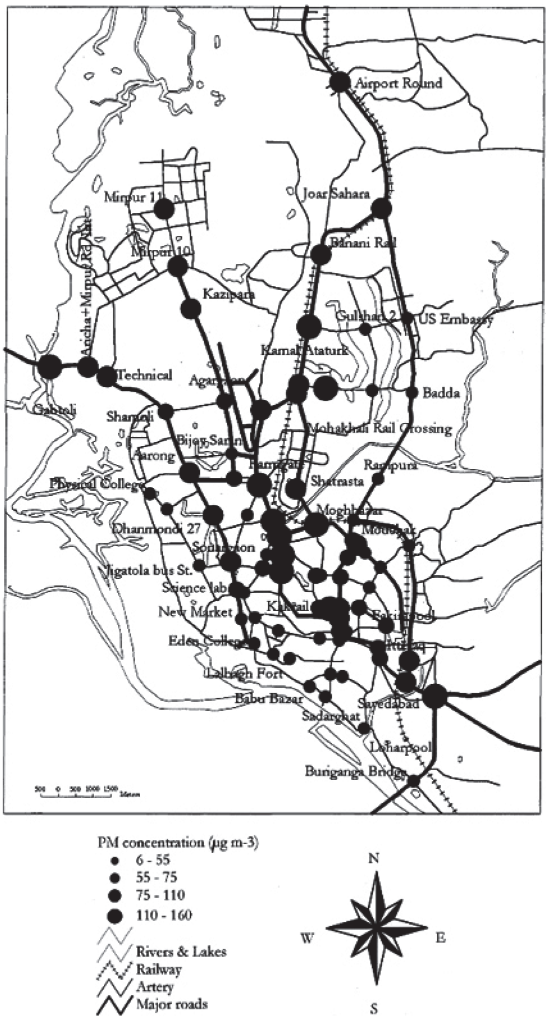
Source	Vehicles (2007)	Avg. Usage (Km/day)[3]	Emission Factor[3]	PM Emission (Tons/year)	Relative Contribution
With CNG					
Motor Car (Petrol)	16,261	40	0.1	24	0.017
Motor Car (CNG)	146,3471	40	0.03	64	0.047
Taxi (CNG)	10,672	130	0.03	15	0.011
Three-wheeler (CNG)	13,521	130	0.03	19	0.014
Bus (CNG)	6,152	130	0.4	117	0.086
Minibuses (CNG)	8,098	60	0.2	35	0.026
Truck (Diesel)	25,193	60	1.6	883	0.648
Motor-cycle (Petrol)	173,637	30	0.1	190	0.140
Others (CNG)	21,816	60	0.03	14	0.011
Total	421,697			1,362	
Without CNG					
Motor Car	162,608	40	0.1	237	0.068
Taxi	10,672	130	0.1	51	0.015
Three-wheeler	40,0002	130	0.8	1,518	0.326
Bus	6,152	130	1.6	467	0.134
Minibuses	8,098	60	0.8	142	0.041
Truck	25,193	60	1.6	883	0.253
Motor-cycle	173,637	30	0.1	190	0.054
Others	21,816	60	0.8	382	0.109
Total	438,176			3,870	

Source: Contingent estimates from various sources

Notes:
1. According to different newspaper sources, ninety percent of the total private motorcars use CNG
2. This includes the 26,429 Two-stroke Three-wheelers that were removed from Dhaka in 2003
3. Emission coefficients and average vehicle usage estimates are taken from the 'Dhaka City State of Environment 2005' (UNEP, 2005)

FIGURES

Figure 1: PM Concentration Map of Major Traffic Intersections in Dhaka



Source: Karim (1999)

Figure 2: Monthly PM Concentration in Dhaka, April 2002 - May 2007

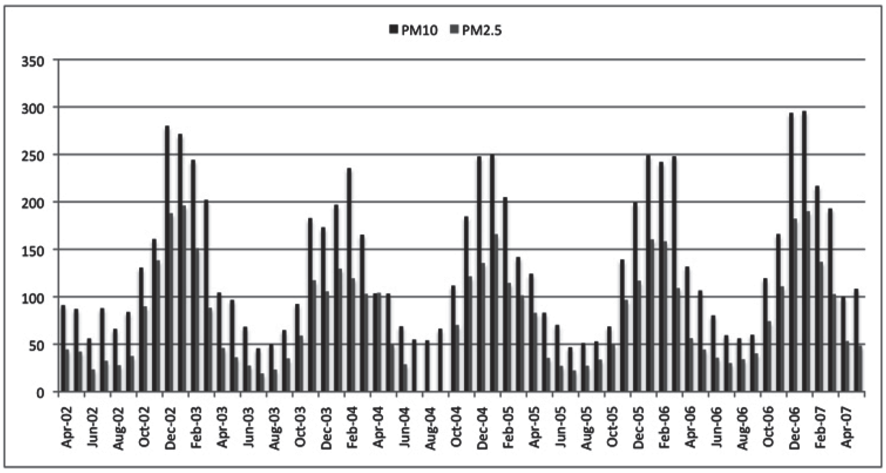


Figure 3: Daily PM Trend in Dhaka, November 2007 - June 2008

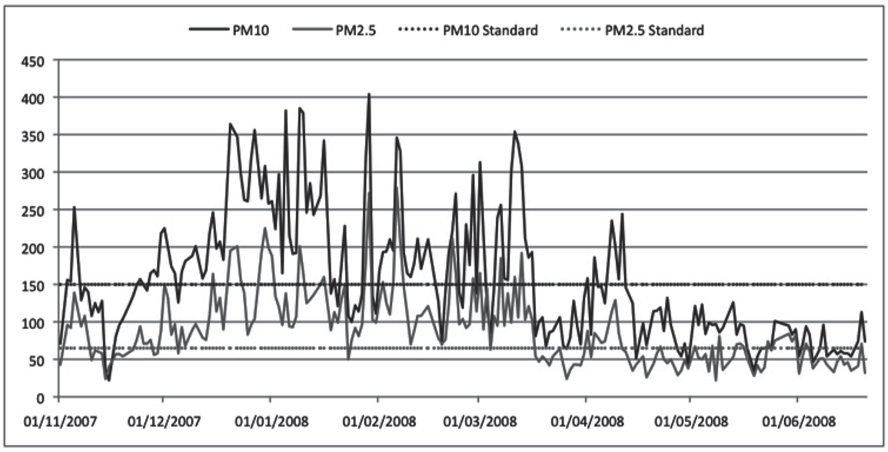
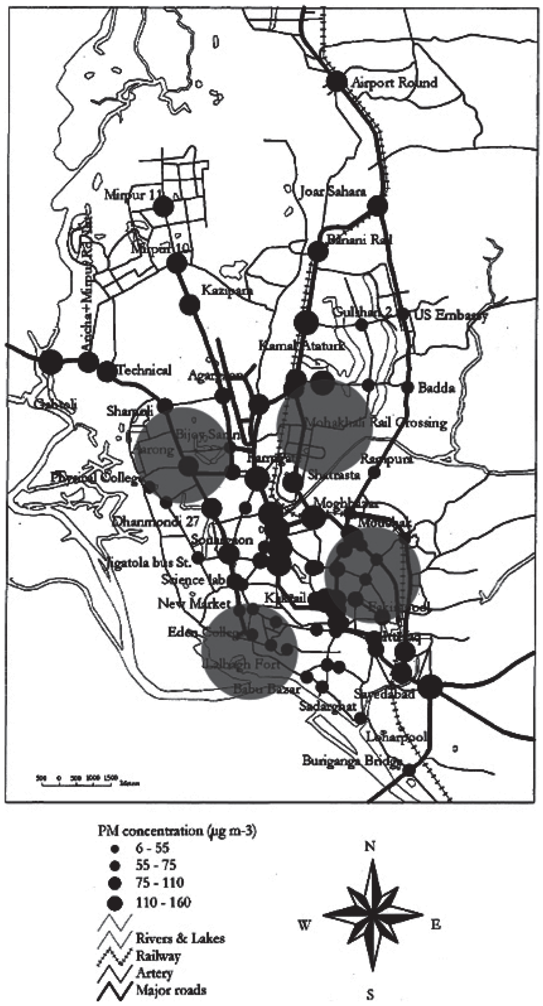


Figure 4: Map of Dhaka with the Sampling Areas



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