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RESEARCH PAPER

Quantifying Air Pollution Vulnerability and its Distributional Consequences: some perspectives from Delhi

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Abstract: This paper estimates Vulnerability Index of air pollution in Delhi taking into account exposure, susceptibility and coping capacity of households. A general health production function model and a vulnerability assessment framework are used for this purpose. Data was collected through a survey of sample households located in close vicinity to 10 air pollution monitoring stations in Delhi. The estimated vulnerability index is used to show the effect of household exposure to air pollution. The vulnerability index takes into consideration sample households' socio-economic status, demographic profile and other characteristics. Result showed that households of lower socio-economic status were the most vulnerable to air pollution and its consequences.

The study also quantifies the economic benefits to Delhi households from reduction in air pollution to the standard safety limits of PM_{10} (100 μg/m3). Estimates show that the total annual economic (health) benefits for a typical household is Rs. 33,978 and for the whole population of Delhi is Rs. 52.4 billion. The study also found that a household of a lower socio-economic status could save much more out of their annual income (4.96 per cent) as compared to a household of a higher socio-economic status (1.97 per cent) from reduced air pollution.

Keywords: Environmental Inequity; Air Pollution; Health Production Function; Vulnerability Framework, Coping Capacity; and Health Benefits

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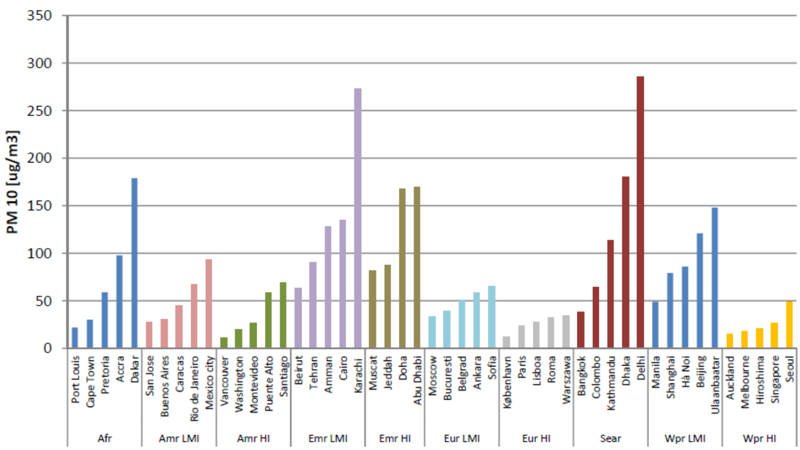
1. INTRODUCTION

1.1. Background

Air pollution has very significant health effects on urban households in major cities of India, especially in the national capital of Delhi. WHO (World Health Organization) (2014) report found that Delhi had the most astounding mean level of particulate air pollution among 1,600 noteworthy urban cities around the world. Delhi had PM_{10} concentration of 286 µg/m3 compared to Beijing's 121 µg/m3 during the period 2008-2012. This is four times more than the permissible limits of PM_{10} (100 µg/m3) as shown in Figure 1. Recently, a report (World Bank 2015) in its study of 381 cities from developing countries globally branded Delhi as the worst in air pollution.

Figure 1: PM_{10} levels (Specific cities, period 2008-2012)



Source: Figure 3 in WHO (2014, 2)

Abbreviations: PM_{10}: Fine particulate matter of 10 microns or less; Afr: Africa; Amr: America; Emr: Eastern Mediterranean; Eur: Europe; Sear: South-East Asia; Wpr: Western Pacific; LMI: Low- and middle-income; HI: high-income.

Amongst the many causes of air pollution in Delhi, industrial and vehicular pollution remain as major factors for emissions of PM_{10}. They emit PM (particulate matter) along with CO_x, NO_x, and SO_x (carbon, nitrogen and sulfur oxides) and metal compounds in the air. A judgment of the Supreme Court of India in 2001, in this regard, compelled all Delhi public transport to run on Compressed Natural Gas (CNG), which led to a reduction in PM_{10} levels. Similarly, the Delhi metro operation also helped to reduce levels of pollution. However, over the years, these gains are seemingly nullified by rapid urbanization and growing vehicular pollution. In 2016, a 15-day "even-odd policy" was also rolled out by the government to ration road traffic and its pollution. Even though this was a good experiment for curbing vehicular air pollution, it was not altogether successful in producing significant results, leaving Delhi still polluted as it was earlier. Previous studies have shown that the health (morbidity and mortality) effects of air pollution are severe in key urban areas of both developed as well as developing countries. However, one important problem is to study the differential effects of air pollution on different socio-economic status (SES) classes of population, which in turn raises a question of – why there might be inequity in air pollution? Inequity in the health effects of air pollution in an urban community could exist due to differences in exposure, susceptibility and coping capacity of different socioeconomic classes. These differences could be due to poor living conditions, material deprivation, already meager health position, heritable predilection and apprehension (psychosocial). Moreover, due to lower levels of social, financial and infrastructural amenities, individuals/ households/ communities with lower SES could also be confronted with lower adaptive or defensive limits to combat the consequences of air pollution.

1.2. Research Evidence

Most studies quantify inequity of health hazards from air pollution by examining the linkage between exposure to air pollution and socio-economic traits, and mostly these are in the context of developed countries. Some other studies, on the other hand, examine SES as a modifier in the association between air pollution exposure and its health impact. A study done by Freeman (1972), using geographic coverage of three cities in the U.S., established that there was an inverse relation between income and SO_2 particulates exposure and the highest exposure was faced by black subpopulation. Gianessi *et al.* (1977) evaluated the distributional aspect of air pollution on a nation-wide basis using an integrated CB (cost benefit) analysis. According to the study, standardization creates redistribution and the net benefits accrue to the low-income groups leading to race and environmental equity. A CB assessment of the impact of the uniform regulation by income groups confirmed a greater welfare support to blacks in the urban polluted residential areas. Harrison and Rubinfield (1978) tried to analyze the dissemination advantages from an air pollution controller technique for Boston using a housing value and health damages technique to estimate the willingness to pay benefits for 7 different income groups.

Results suggested that tangible benefits from upgrading the air quality of urban areas go to the poor rather than the rich, and when measured in pecuniary terms, including workplace benefits, it showed that distribution was much less towards the poor. Another evidence was given by Asch and Joseph (1978), who investigated both inter- and intra-city variations in air quality in the U.S states. Their study shows that exposure to particulates is associated with cities characterized by low income and hence, low education, low property value, and crowded population.

Using generalized linear models (GLMs), Jerrett *et al.* (2004) showed that air pollution was related to expansive deaths in intra-urban zones of low socio-economic characteristics. Also, low education and high manufacturing employment in the zones substantially enhanced mortality impacts of air pollution exposure. Another study by Pratt *et al.* (2015) studied the inequities in exposure to air pollution from traffic and the related risk in the state of Minnesota, America. They found that the risks and exposures were differentially larger than expected value for ethnic minorities and low SES population. In similar studies in Europe, Fecht *et al.* (2015) examined inequities of exposure to air pollution in England and the Netherlands at country, city and regional levels. Results showed a greater concentration of air pollution in those areas of the two countries with more than 20 per cent non-white population and the most deprived neighborhoods in England. A related study in Africa by Rooney *et al.* (2012) examined the spatial patterns of PM and its sources in four neighborhoods of varying SES in Accra using mixed-effects regression model and found that community SES was inversely associated with both $PM_{2.5}$ and PM_{10} levels.

In one of the Asian studies highlighting air-pollution inequity, Fan, Lam and Yu (2012) tried to exemplify the spatial variations in Hong Kong's urban population by analyzing the relationship between SES and exposure to vehicular pollution. The study concluded that there was more inequality in private housing lands than their public counterparts. Also, older and low SES population faced relatively greater exposure to air pollution in contrast to higher SES people. However, with all residents clubbed, results showed no status prejudice in air pollution exposure attributable to the housing mechanism in Hong Kong, where the poor live in government-provided housing with relatively better air quality.

There are not many studies on the inequity aspect of air pollution in India. Most studies primarily look at the health consequences and analysis of cost and benefits of improved health from a reduction in air pollution. In a study on Delhi, Cropper *et al.* (1997) estimated a dose-response function of health status of households to pollution levels. Results showed that more than two per cent of non-traumatic deaths in Delhi were related to increased pollution levels (total suspended PM), and that this relationship was significant for children and adults. Similar studies were done by other authors. Kumar and Rao (2001) analyzed the economic benefits of improved air quality in Haryana and found that a representative household has willingness to pay (WTP) Rs. 12 to Rs. 53 per month for reducing particulate matter to the level of WHO standards.

Using health production model and household survey data from Delhi and Kolkata, a study by Murty *et al.* (2003) found the annual health benefits from reducing air pollution levels to safe levels in the urban areas of Delhi and Kolkata as Rs. 4896.6 million and Rs. 2999.7 million, respectively. On similar lines, using a household health production model, Gupta (2006) examined the economic gains from reduction in air pollution in Kanpur and found that a typical city resident would annually save Rs. 165, if pollution was reduced to standard levels and the whole population of Kanpur would gain Rs. 213 million annually. In one of the few studies of its kind, Garg (2011) analyzed the equity aspects of air pollution reduction by examining who bears the cost of pollution abatement and who benefits from it. The study showed that the health effects of air pollution are more detrimental for the poor. The study had quantified mortality and morbidity due to pollution for various socioeconomic groups in Delhi with spatial data on concentrations of PM_{10} and SES. It inferred that health benefits from better air quality laid differentially, more with poor. A contextual study by Makri and Stilianakis (2008) demonstrates the vulnerability to air pollution and its health consequences through risk assessment. According to this study, sub-populace characteristics have a few socio-economic components that enhance vulnerability, impact on exposure, susceptibility and coping capacity factors.

Another study by Kathuria and Khan (2007) investigated the relation between air pollution exposure and socio-economic characteristics. Using a two-step methodology for computing a household-specific exposure index for 347 houses in proximity to pollution monitoring station in Delhi, the study examined the relationship of air pollution exposure with socio-economic and demographic characteristics using a multivariate regression. The results reflected that economically weaker sections were more exposed to air pollution than their counterparts, however, for socially (caste-based) weaker sections, the relationship with air pollution exposure was not significant, and no relation existed with the aspect of religion. A recent study by Foster and Kumar (2011) in Delhi found that people who remained outdoors for long hours had stronger health impacts of air pollution. The study also pointed out betterment in their health following the strict regulation of air quality policies. A meta-analysis of global literature on air pollution by Hajat, Hsia and Neill (2015) provided overall similar results as presented above.

As seen, most of the studies on India have analyzed the health impact of exposure to air pollution and health benefits from its reduction. However, only few limited studies are available on-air pollution and its distributional consequences from a vulnerability context. This paper, aiming to analyze the distributional effects of urban air pollution in Delhi, can be a useful and timely study in the Indian context. It estimates a household Vulnerability Index for determining the role of exposure, susceptibility and coping capacity to air pollution. It also quantifies the relationship between exposure to air pollution and vulnerability in the background of socio-economic and demographic features of the households in Delhi. Finally, it looks at both efficiency as well as equity aspect of reduction in air pollution by estimating the economic health benefits for reduction in air pollution and distribution of these benefits amongst different socio-economic classes of households in Delhi.

2. MATERIALS AND METHOD

2.1. Health Production Function Model: Theoretical Framework

This study uses a simplified version of the health production function model framework for estimating vulnerability from exposure to air pollution and economic benefits from reduction in air pollution to safe limits in Delhi. As proposed by Freeman (1993), the health production function (HPF) and the mitigating demand function (MDF) are implicitly defined by an individual's behavior who wants to maximize utility (U). On similar lines, as used by studies of Freeman (1993), Dasgupta (2001), Murty *et al.* (2003), Gupta (2006), Chowdhury and Imran (2010) and Adhikari (2012), an estimate of marginal willingness to pay (MWTP) of a representative urban household for reducing air pollution to safe-limits can be obtained as follows:[1]

$$dI/dQ = MWTP = w.\, dH/dQ + Pm.\, \partial M/\partial Q + \partial u/\partial H \cdot dH/dQ \cdot 1/\Pi \qquad (1)$$

where U: U (Q, H, I), household utility function, health-status (H): sick-days due to air pollution related diseases, Q: air quality, M: demand function for mitigation, w: wage-rate and Pm: demand price of mitigation.

[1] For derivation, look at Freeman (1993)

MWTP of a household for health benefits from reduction in air pollution (dI/dQ) is obtained by the summation of three terms in equation (1): marginal earning that were lost due to sickness $(w.dH/dQ)$, marginal mitigating cost $(Pm.\partial M/\partial Q)$ and disutility of sickness in money terms $(\partial u/\partial H \cdot dH/dQ \cdot 1/\Pi)$. Estimation of MWTP using this equation requires the estimation of simultaneous equation model consisting of health production function and the demand function for mitigation.

Another possible way is to estimate a reduced form dose-response-function with health as a function of the physical and socio-economic aspects pooled with estimation of demand function for mitigation as a function of common set of variables as from health production function estimation (Freeman 1993; Gupta 2006). This requires estimating the following two reduced form equations of the model[2]:

$$H = H*(w, Pm, Q, I, Z) \tag{2}$$

and

$$M = M*(w, Pm, Q, I, Z) \tag{3}$$

where, Z represents a vector of other household characteristics.

Ignoring disutility that air pollution causes, the paper estimates MWTP or cost of illness (COI) of a household for a small change in air pollution levels as a lower conservation bound:[2]

$$COI = w \cdot \frac{dH}{dQ} + Pm.\frac{\partial M}{\partial Q} \tag{4}$$

Usually, the dependent variable in dose-response-function is workdays lost but due to data unavailability number of days of sickness is taken as a proxy.[3]

[2] Here, the lower bound is due to absence of measure of loss due to averting expenditure. In a general health production framework, demand for averting activities is estimated separately. However, due to difficulty of measuring aversion behavior in monetary terms, it is only implicitly captured in the health production function estimation. The conservative bound is due to absence of disutility term which is not captured because of its difficult to measure tangibly.

[3] The proxy may overestimate the COI as work-days lost are also included in wage loss reduction $(w.dH/dQ)$ term in equation (4).

2.2. The Vulnerability Framework for Air Pollution

2.2.1. Different Views on Vulnerability

John *et al.* (2008) suggests that there are "three components of vulnerability, namely: differential exposure, susceptibility and coping mechanisms, and these are used to derive an initial vulnerability-framework." IPCC (2012) report views vulnerability as a "universal methodology that defines exposure, susceptibility and societal response capacities as its factors". Commission for Environmental Cooperation (2014) argues that "differential vulnerability to chemical exposures is characterized by the degree of exposure, an individual's susceptibility to the harmful effects caused by the chemical and the capacity to cope with and mitigate chemical risks".

Vulnerability as an idea can be depicted by various indicators and through different channels. Kasperson (2002) considers four main variables which affect the physical as well as social characteristics of the population and make them "vulnerable". These variables are (a) "susceptibility", which refers to an improved probability of maintaining a longer run defensive impact by a sub-populace in comparison to general population; (b) "differential exposure" which includes the behavioral, educational, background and occupational exposures, along with restlessness/disutility which are in some cases disregarded in an evaluation; (c) "differential preparedness" and lastly (d) "coping ability" which includes assets of the communities/populace needed to survive and recover from the environmental impact.

Considering all these views, Vulnerability is defined as a function of Exposure, Susceptibility and Coping Capacity in this paper.

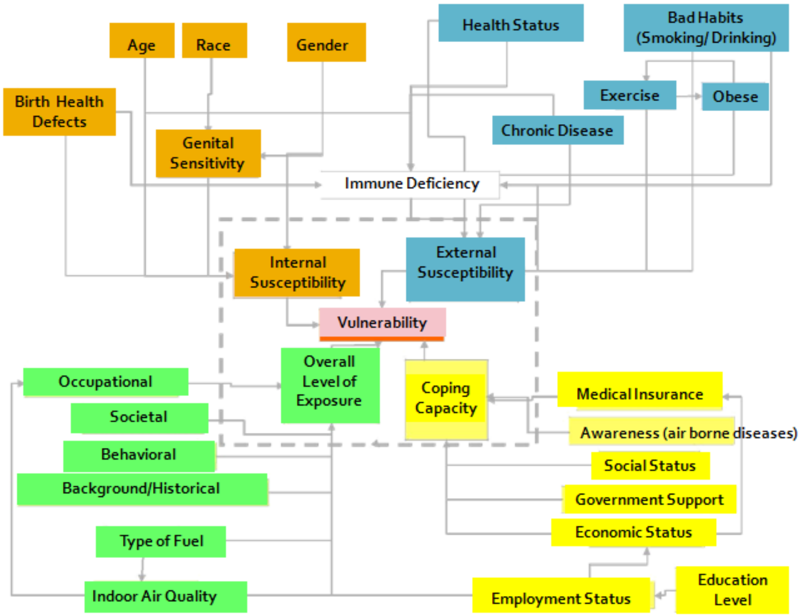
Vulnerability=f (Exposure, Susceptibility, Coping Capacity) (5)

2.2.2. Vulnerability-Framework (A cobweb of factors and sub-factors)

It's important to note that society's vulnerability to air pollution is intricate because of its multi-dimensional connections with ecological behavior inherent as extraneous susceptibility, differential exposure, adjusting and coping capacity (EPA 2003; Kasperson *et al.* 1995). Hence, it is useful to draw a vulnerability-framework template appropriate for reduced-form analysis, yet comprehensive to a universal problem (Turner *et al.* 2003). Many institutions and expert groups have made remarkable advancement in the scheming of these frameworks (Kasperson *et al.* 2001).

Due to the complex multifaceted relationship between factors of vulnerability, it becomes difficult to account for all factors and many sub-factors, implied in the literature, in assessment of vulnerability to air pollution. Therefore, in order to fill this gap, this paper tries to account for all the three vulnerability factors (though all sub-factor may not be considered due to data and other constraints). In line with Kasperson *et al.* (1995), EPA (2003), Turner *et al.* (2003), and John *et al.* (2008), this paper derives the required modified and simplified version of vulnerability-framework for air pollution using the factors of health production model framework explained above, using the framework in Figure 2.

Figure 2: Vulnerability Framework: Differential Exposure, Differential Susceptibility and Differential Coping Capacity to Air Pollution



Source: Adapted from John *et al.* (2008, 6)

As seen in Figure 2, there are numerous channels of assessing vulnerability to air pollution. Regarding susceptibility, the population characteristics which could lead to differential health impacts of air pollution and other chemical encounters are mainly – underlying poor health (past resistant reactions) and disease state, conceivably hereditary predilection, race and gender distribution. This commonly cited variable, "susceptibility" can be internal – if it originates from factors such as age, gender, birth, health defects or race (which is the root for genital sensitivities), as well as external

– which is mainly due to health status, bad habits (such as drinking, smoking, etc.) that could lead to chronic diseases, obesity, etc. (Morata *et al.* 1997; EPA 2003; John *et al.* 2008; Lipfert 2004; Stilianakis 2015). Concerning differential exposure to air pollution, it could be due to behavioral exposures from unhealthy living conditions, exposure to busy traffic/rail road and long hours spent outdoor, indoor air pollution exposure caused by poor fuel type and/or appliances, occupational exposures due to informal or unorganized sector jobs, and finally, exposure due to educational status, family background and deprivation of assets (EPA 2003; John *et al.* 2008; Lipfert 2004; Stilianakis 2015). Finally, the coping capacity, which is the ability to incur abatement expenditures, could be dependents on sub-factors such as socio-economic position, health care access (like medical insurance), awareness of air-borne diseases, economic status (through employment status and educational level) and governmental support (Deguen and Zmirou-Navier 2010; EPA 2003; John *et al.* 2008 and Stilianakis 2015).

Establishing a vulnerability definition along with its parameters remains essential for its assessment. Indicators and sub-indicators have been established based on existing literature, available data, expert judgments and modeling capabilities of the health production function model. This framework will further be used to construct a household specific vulnerability index, which is a feature scale score calculation of sub-indicators (as independent variables of the health production and mitigating demand function models), indicators (as estimated dependent variables of the health production and mitigating demand function models) and final vulnerability index score. The methodology for the construction of this index is given in section 2.4.

2.3. Sample Design and Method of Data Collection

Information on average PM_{10} concentration was collected from Central Pollution Control Board (CPCB), Delhi for 3 months (October-December 2015). As compared to average concentrations of NO_2 and SO_2, which were below safe levels, PM_{10} level was much above the safe limits (100 μg/m^3) of National Ambient Air Quality Standards (NAAQS) and was therefore mainly considered for this study. Of the 17 Pollution Monitoring Stations (PMS) across Delhi, 11 stations provided consistent levels of PM_{10} data. This study is based on PM_{10} data from 10 PMS that capture diverse locations in the West, East, South and North Delhi, both residential as-well-as industrial areas including: Anand Vihar, Mandir Marg, R.K. Puram and Punjabi Bagh monitored by Delhi Pollution Control Board in addition to I.T.O., Siri Fort, Pitampura, Shahzada Bagh, Janakpuri and Shahadra monitored by CPCB.

Data on health-status, socio-economic and demographic factors was collected through a household survey conducted in January 2016. A pilot field test was conducted in December 2015 to refine as well as fine-tune the draft questionnaire. For a comparative analysis of the inequity aspect of air pollution, the survey sample households were identified from slums, middle income group areas and high-income group areas. For this, a two-stage stratification was followed as done by Gupta (2006) and Adhikari (2012). In Stage-1, an equal number of households were identified within 2 km radius of each of the 10 PMS. In Stage-2, an equal number of households under different categories were identified on the basis of their locality and accommodation type: high class (independent housing), service class (flat type housing) and slums across each PMS. In this study, 180 households were surveyed; 18 households within 2 km radius of each of 10 PMS. Further, each set of these 18 households were classified into low, middle and high socio-economic categories based on the location and accommodation setting (6 random households for each category under each PMS). Data on health-status, mitigating expenditure as well as averting activities to combat air- pollution impact was collected in the recall period of three months, also capturing information on household members suffering from any chronic disease and their awareness about air pollution related diseases. Comprehensive recall data included – number of days of sickness for each member, household medical expenses (medical expenses, including medicines, doctor's fee, cost of diagnostics, travel, etc., of air pollution related ailments), family health insurance and treatment type. Pollution aversion activities included family opting to stay indoors, travelling extra kilometers, using gas masks, air purifier, air conditioner (AC) transport and other activities such as using a scarf or closing door/windows to avoid air pollution.

For housing characteristics, information collected included – household type, ownership, drinking water, number of rooms and so on. Data on utilization of air conditioner, type of cooking fuel, heaters was also collected to analyze indoor air-quality. For socio-economic characteristics, information obtained included – caste, religion, family background, educational attainment, hours spent outside, unhealthy habits (smoking, drinking, lack of exercise, etc.), occupational profile, wage/income and job being indoor/outdoor. For demographic characteristics, details included – age and gender, household size, number of working and school going family members and so on. Lastly, households' monthly income and other indicators of wealth, i.e., durable assets owned, and monthly family expenditure were also collected.

Another survey of 10 random doctors was conducted in February 2016 to elicit information on severity of health impact (on the population in general) of the 11 chronic diseases that were taken in household survey using a Likert Scale (1-3).

2.4. Econometric Model Specification: Household Health Production Function Model

In the health production function model used in this paper, number of sick days in the household and medical expenses due to air pollution are considered as dependent variables. The data collected for family sick days represent count data and data on medical expenses observed zero censor for several data points. As in studies by Gupta (2006), Chowdhury and Imran (2010), and Adhikari (2012), Poisson Regression (PR) model[4] and Tobit-Regression model could be used for estimation of health status and mitigating expenditure, respectively. However, the assumption of equality of conditional mean and variance acts too restrictive for PR models and is unable to account for over-dispersion of data, leading to a huge standard error of estimation which was corrected using Negative Binomial Regression (NBR) model. Owing to an unequal mean (53.66) and variance in health status suggesting over-dispersion in data, NBR was used for estimating health production function over PR and was validated by a likelihood-ratio test. Also, the data showed only few occurrences with zero mitigating-expenditure (only 16 per cent of sample) and a near normal-distribution with log-transformation. Hence, a log form Ordinary Least Square Regression (OLSR) Model was selected for modelling the mitigating demand function over Tobit-regression. Empirically, this study estimates the household HPF and MDF as represented by the two reduced form equations with health -status, and mitigating expenditure, both dependent on a common set of independent variables:

Reduced Form Equation 1: HPF

$$H = h_0 + h_1 logHEI_i + h_2 CI_i + h_3 HAB_i + h_4 FAM_i + h_5 SES_i + h_6 SUFFER_i + h_7 AWARE_i + h_8 AVERT_i + h_9 SOC_i + h_{10} INS_i + h_{11} GENDER_i + u_i \quad (6)$$

[4] The Poisson Model is given by: (Prob $H_i = h_i/x_i$) = $\mu_i^{h_i} e^{-\mu_i} / h_i$, such that H_i=0, 1, 2.... is a count variable that captures numbers of days of sickness in i^{th} household and h_i is the mean as-well-as variance of sick days.

Reduced Form Equation 2: MDF

$$LogM = m_0 + m_1 logHEI_i + m_2CI_i + m_3HAB_i + m_4FAM_i + m_5SES_i + m_6SUFFER_i + m_7AWARE_i + m_8AVERT_i + m_9SOC_i + m_{10}INS_i + m_{11}GENDER_i + e_i \quad (7)$$

where u_i and e_i represent error terms

These two equations are estimated using cross-sectional regressions - NBR used to estimate the health status and log-form OLSR to estimate the log (Mitigating Expenditure). The description of variables used are as follows:

2.4.1. Dependent Variables

Health-Status(H): The sum of number of days of sickness due to air pollution related diseases in each household over the recall period of three months.

Mitigating-Expenditure(M): The medical expenses of the household in the recall period of three months due to air pollution related diseases on medicines, doctor fees, journey cost to doctor and diagnostic tests.

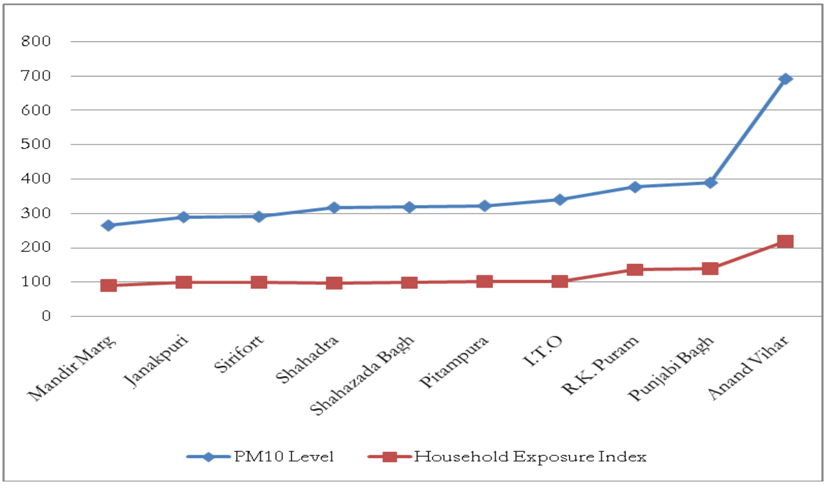
2.4.2. Independent Variables

Household Exposure Index (HEI)[5]: It was constructed using data on mean PM_{10} ($\mu g/m^3$) concentration of the location-specific PMS, household working profile and hours spent outside home by working members assuming differential exposure to air pollution for working members (11 hours) followed by school/college going members (9 hours) and non-working (2 hours). The average HEI was 117.84 $\mu g/m^3$ against PM_{10} average of 360.38 $\mu g/m^3$. Amongst the PMS', Anand Vihar, on an average, was the most polluted whereas Mandir Marg was the least polluted in the study period (see Figure 3).

Chronic Diseases Index (CI): Weighted average of the prevalence of 11 chronic diseases in a particular house including - bones problem, pneumonia, eye-disease, thyroid, diabetes, bronchitis bp, tb, asthma, cancer and heart-disease. Weights are based on the severity score of the diseases calculated using the doctor survey.

[5]The HEI is calculated for particular station and household as: $HEI_{ij} = P_i*(N_w*H_w+N_{nw}*H_{nw}+N_{SOC}*H_{SOC}/24*Family\ Size)$ in i^{th} household and j^{th} pollution monitoring station, where P: Mean PM_{10} ($\mu g/m^3$) N_w: working members, N_{SOC}: school/college going members, N_{nw}: non-working members whereas H_w, H_{SOC} and H_{nw} represent the average hours spent outside by the working, school/college going members, respectively.

Figure 3: Average concentrations of PM_{10} and Household Exposure Index in μg/m3 for 10 pollution monitoring stations in Delhi (October to December 2015)



Source: CPCB, Delhi and Authors' Calculation

Habits (HAB): Unhealthy habits of a household as the ratio of number of family members with unhealthy habits scaled to family size. These habits could either be smoking or drinking or not exercising for any member.

Socio-Economic Status Index (SES): One of the most important variables for the study was SES index which represented the household's social and economic status, computed using a Principal Component Analysis (PCA)[6] method. It facilitated easy interpretation as it presented the data under a single-dimension rather than multi-dimensional framework (Cordova 2009).

The variables used for construction of the SES Index, were captured using highly correlated variables under three household characteristics namely: wealth, housing and socio-economic characteristics (*Table 1*). The data was transformed by dividing it into three quantiles based on the SES Index where top, medium and bottom 33.33 percent were generated to differentiate between the high, middle and lower SES households, respectively.

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[6] In PCA, weights are assigned to each observed variable summed up by determining the data variance direction, as the set of correlated variables are transformed into an uncorrelated component set. PCA captures the maximum amount of information that is identical for all variables to be used as an index that is linear for all variables and provides appropriate weights for every variable such that the index captures the largest variations.

Table 1: Socio-Economic Status Index Variables

Wealth Characteristics		
TV	Washing Machine	Micro-Oven
Fridge	A.C	Heater
Geyser	Music System	Car
Laptop	Phones	
Housing Characteristics		
Rooms	Water Facility	
Socio-Economic Characteristics		
Education	Better Off (Location)	Organized Sector

Source: Authors' Own compilation

Avert (AVERT): The following were taken as a score measured from a household's strategies for averting air pollution: staying indoors, travelling extra kilometers, using gas masks, air purifier, ac-cars v/s public-transport and other activities such as using a scarf or closing door/windows of the households to avoid air pollution.

Gender (GENDER): The ratio of females to family-size.

School/College Going (SOC): The ratio of school or college going members to family-size. This is used in order to capture a demographic factor in the modelling.

Awareness Index (AWARE): It is defined as respondent's awareness of the number of diseases out of the 17 diseases known to be clinically caused by air pollution.

Suffer (SUFFER): It is the ratio of members suffering from air pollution related diseases to family-size. It is used as a physical health control variable.

Health Insurance (HI): A dummy variable defined as '1' if the household has family health insurance, and '0' otherwise.

Family Size (FAM): Number of members in a household.

2.4.3. Vulnerability Index for Air Pollution

The vulnerability framework (explained above in Figure 2) is used to build a household-specific vulnerability index (V) in order to examine the role of exposure, susceptibility and coping mechanism in determining vulnerability to air pollution. This comprises 2 components: model-estimated values of HPF represented by $\hat{H}$ and negative of the estimated value of MDF represented by $\widehat{LM}$. Here, vulnerability is dependent directly on susceptibility factor, captured by $\hat{H}$ and negatively dependent on coping-capacity factor, captured by $\widehat{LM}$. The exposure factor in case of vulnerability to air pollution is not easy to estimate alone, as it does not act as a behavioral variable directly (also due to unavailability of weather-related data) but has linkage to susceptibility and coping capacity factor of air pollution. Hence, the exposure factor of vulnerability to air pollution is captured implicitly as household exposure index by health production and mitigating demand functions, both. The vulnerability index is calculated as a function of the health production function, which captures the exposure and susceptibility factors, and the mitigating-expenditure which will capture the exposure and coping-capacity factors of vulnerability.

Unfortunately, no available study on air pollution computes a vulnerability index at a household level. However, many studies, such as by Christenson *et al.* (2016), Kissi at al. (2015), Baeck (2014) and Kallis *et al.* (2010) have computed vulnerability index for climate change impacts (heat stroke, flood risks, etc.) at a regional or city level. In line with these studies, this study has developed a household-specific vulnerability index/score[7] for air pollution using the following formula:

$$\text{Vulnerability Score} = \text{Susceptibility Score} + (-)\ \text{Coping Capacity Score} \quad (8)$$

Feature scaling score method is used for standardizing the factor scores of susceptibility and coping-capacity[8] making them comparable to get an accurate value of vulnerability index as is done by UNDP (2002) in building the Human Development Index. This is done since $\hat{H}$ has a count unit whereas $\widehat{LM}$ has rupees unit.

The feature scaling is done using the formula given below:

$$\text{Feature Scale Score} = \frac{\text{Value} - \text{Min(Value)}}{\text{Max(Value)} - \text{Min(Value)}} \quad (9)$$

[7] Vulnerability Index is calculated with the supposition that each of the factors have an equal role in determining vulnerability with only contrast being that exposure factor is being captured implicitly in Susceptibility and Coping-Capacity scores.

[8] Susceptibility score and (-) coping capacity score are given by following equations: Susceptibility score $= \dfrac{\hat{H} - \text{Min}(\hat{H})}{\text{Max}(\hat{H}) - \text{Min}(\hat{H})}$ and (-) Coping Capacity score $= \dfrac{\widehat{LM} - \text{Min}(\widehat{LM})}{\text{Max}(\widehat{LM}) - \text{Min}(\widehat{LM})}$.

Here, the $\hat{H}$ represents the predicted value of health status whereas $\widehat{LM}$ represents negative of the predicted value of Log (Mitigating Expenditure).

The summary statistics shows that the mean Vulnerability Index is 0.76.

2.5. Empirical Model of Inequity in Air Pollution

As discussed through literature, air pollution inequity captured by vulnerability is principally dependent on SES of the subpopulation. For a statistical analysis, the paper uses a multivariate regression model with dependent as vulnerability index on independents as socio-economic characteristics (SEC), demographic characteristics (DEC) along with other control variables:

$$V_{ij} = f\,(SEC_{ij}, DEC_{ij}, Controls_{ij}) \qquad (10)$$

where i=1, 2….180 Households and j=1, 2….10 PMS.

For this study, the empirical specification of the model is given by:

$$V = v_0 + v_1 logHE1 + v_2 SES_i + v_3 GENDER_i + v_4 HI_i + v_5 INFOUTDOOR_i + v_6 BG_i + v_7 ADULTS_i + z_i \qquad (11)$$

where, z_i is the error term. Socio-economic characteristics of the household are captured by the SES Index and Family Background (BG) as a dummy, 1 for urban and 2 for rural. Demographic characteristics are captured by age (ADULTS) as the proportion of members who are 15 years or older and gender (GENDER). The Household Exposure Index (HEI) measuring the exposure factor was only implicitly accounted in calculating the vulnerability index and hence is taken as an independent control here. Other control variables taken into consideration are informal outdoor occupation (INFOUTDOOR) given by the ratio of members with informal outdoor occupations (like petty traders, construction workers, etc.) to working members and lastly, a Health Insurance (HI) dummy.

The descriptive statistics of the dependent and independent variables used in all the estimation models are provided in Table A1 in Appendix.

3. RESULTS AND DISCUSSIONS

3.1. Household Health Production Function Model

Results of the estimated HPF using the NBR[9] model are given in Table 2. It shows that eight out of eleven parametric estimates have significant relation to health status with expected directions. The coefficient of variable HEI is positive while the coefficient of variable SES Index is negative as expected and they are significant at 5 per-cent and 1 per-cent levels, respectively.

Table 2: Estimates of the Health Status (H: Family Number of Days in Sickness)

Variable	**Negative Binomial Coefficients**
Health Status: Dependent Variable	
Log (Household Exposure Index)	0.45**= h_1
Chronic Index	0.16**
Socio-Economic Status Index	-0.083***
Habits	0.39***
Family Size	0.087**
Suffer	1.16***
Awareness Index	-0.039
Avert Activities	-0.138***
School/College Going	0.87***
1. Health Insurance	0.016
Gender	0.093
Constant	0.46
Ln alpha	-0.76***
Observations	180

Source: Authors' Own Calculation

Legend: * p<0.10; ** p<0.05; *** p<0.01. Likelihood-ratio test of alpha=0: chibar2 (01) = 3194.63 Prob>=chibar2 = 0.000

Table 3 provides the results of the estimated mitigating expenditure function. This reduced form function has common independent variables with HDF function. Ten of eleven independent variables in the model have coefficients with expected signs and significant at 1 to 5 per cent levels. The independent variables HEI and SES Index have positive coefficients as expected which are significant at 5 per cent and 1 per cent levels, respectively. The awareness index has a negative coefficient which is significant at 5 per cent level.

[9] The significant p value of LR-test (as given in Table 2) suggests that NBR is better over a PR Model validating the results of estimation.

Table 3: Estimates of the Log Mitigating Expenditure: Log (M)

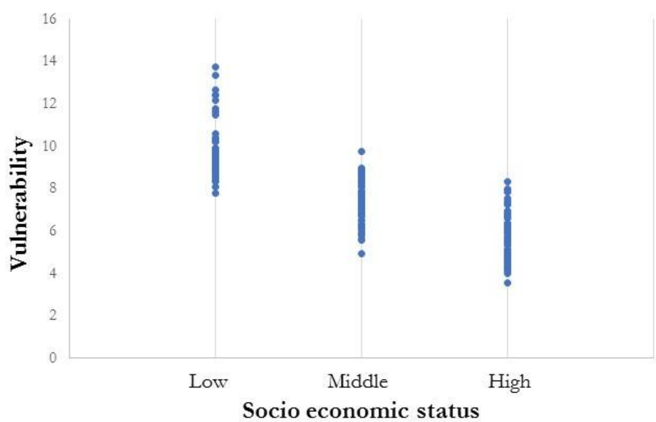
Variable	**OLS (Log-Form) Coefficients**
Log (Mitigating Expenditure): Dependent Variable	
Log (Household Exposure Index)	0.44**= m_1
Chronic Index	0.089
Socio-Economic Status Index	0.16***
Habits	0.39***
Family Size	0.16***
Suffer	1.23***
Awareness Index	-0.103**
Avert Activities	-0.29***
School/College Going	1.03***
1.Health Insurance	0.32**
Gender	0.75**
Constant	4.92***
Observations	177

Source: Authors' Own Calculation
Legend: * p<0.10; ** p<0.05; *** p<0.01

3.2. Estimates of Empirical Model of Inequity in Air Pollution

Estimates show that lower SES households have a mean vulnerability score of 0.97 while the higher SES households have a mean vulnerability score of only 0.58. Figure 4 shows that the households in the lower SES quantile group have higher vulnerability scores as compared to households in the middle and higher SES quantile group.

Figure 4: Scatter Plot between SES Quantiles and Vulnerability Index



Source: Authors' Own Calculation

Table 4 provides the estimates of vulnerability index function. Results show that as socio-economic status of a household decreases, vulnerability to air pollution increases significantly (1 per-cent significance-level). As expected, the parameters of independent variables - pollution exposure, proportion of members with informal outdoor occupation, absence of health insurance and rural family background - are positively and significantly associated with vulnerability to air pollution. However, age shows no significant effect on vulnerability. The parameter gender reflects an unexpected result: it shows that with increased proportion of men in family, vulnerability to air pollution increases which might be because men have a higher working exposure than women in Delhi. The results as hypothesized, found presence of air pollution inequity in the context of Delhi.

Table 4: Estimates of the Vulnerability Index (V)

Variable	**OLS Coefficients**
Vulnerability Index: Dependent Variable	
Log (Household Exposure Index)	0.061***
Socio-Economic Status Index	-0.032***
Gender	-0.18***
Health Insurance	-0.094***
Informal Outdoor Occupation	0.065***
Background	0.041*
Age	0.0302
Constant	0.55***
Observations	180

Source: Authors' Own Calculation
Legend: * p<0.10; ** p<0.05; *** p<0.01

3.3. Estimates of Monetary Benefits from Reducing Air-Pollution to Safe Limits in Delhi

Using equation (4) of the household health production model explained above, the cost of illness (COI) or household health cost of air pollution could be estimated as:

$$COI = W.\frac{\partial H}{\partial HEI} + \frac{\partial M}{\partial HEI} \quad (12)$$

In other words, the health benefits of reduced air pollution consist of reduced cost of work days lost in the family and the reduced mitigating expenditure.

The welfare gains to a typical household from reduced pollution are estimated considering sample mean values of variables: household exposure index (HEI^M), mitigating expenditure (M^M), family size (FAM^M), health status (H^M), family daily wage rate (W^M), and household exposure index safe ($HEI.SAFE^M$)[10]. Table A2 in Appendix provides descriptive statistics variables used in the estimation.

The methodology for calculating total annual benefits to a typical household is given as follows:

A typical household's marginal willingness to pay for reduction in air pollution exposure by 1μg/m³ for last three months recall is calculated by summing up the marginal effect of reduction in wage loss[11] and the mitigating expenditure in last 3 months (recall period) quarter given by:

$$QMWTP=\left(\frac{W^M}{FAM^M}*h1*\frac{H^M}{HEI^M}\right)+\left(m1*\frac{M^M}{HEI^M}\right) \qquad (13)$$

where h1 and m1 represent the estimated coefficient of household exposure index for health production and mitigating demand function regression model, respectively.

Now, a typical household's marginal willingness to pay for reduction in air pollution exposure by 1μg/m3 is annualized by weighting[12] the last quarter (3 months recall period) as compared to the other three quarters of the year:

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[10] The household exposure index at safe level of PM_{10} is given by $HEI.SAFE_{ij}$ = 100*(N_w*H_w+N_{nw}*H_{nw}+N_{SOC}*H_{SOC}/24*Family Size) in i^th^ household and j^th^ PMS , where 100 μg/m³ is the safe PM_{10} limits given by CPCB (NAAQS), N_w: working members, N_{SOC}: school/college going members, N_{nw}: non-working members whereas H_w, H_{SOC} and H_{nw} represent the average hours spent outside by the working, school/college going members, respectively.

[11] The marginal effect of reducing air pollution exposure (from reduced work days lost) by 1 unit for a typical household is multiplied by family wage rate and divided by family size in order to get the benefits for just the working members. This is because health status has been taken as proxy of work days lost.

[12] For annualizing the marginal willingness to pay, a rank sum method was incorporated to calculate the weight for the three months recall period data. Since, the household survey was conducted around winter season (October-December 2015), studies and air pollution seasonal trend analysis by CPCB has shown that winter season traditionally has been the most severe in terms of air quality levels. According to the report "NAQI Status of Indian Cities in 2015-16" by CPCB, the national air quality of Delhi around winter season was seen in severe/ worst category. Hence, the highest rank was assumed for the study period last quarter out of the four yearly season quarters and was used to calculate weight for it. The

$$\text{MWTP} = \frac{\text{QMWTP}}{0.4} \qquad (14)$$

For calculating the total annual economic benefits for a typical household from reducing air pollution exposure from current (study period) level (HEI) to safe level (HEI.SAFE at PM_{10} of 100μg/m^3), the MWTP for 1 unit fall in air pollution exposure is multiplied by the change in exposure from current level to safe level:

$$\text{Total Annual Economic Benefit} = \text{MWTP} * (\text{HEI}^{M} - \text{HEI.SAFE}^{M}) \qquad (15)$$

For inferring economic benefits for the whole population in Delhi, extrapolation is done using data of Census (2011) in India, which shows the population in Delhi as 0.0168 billion and workforce participation rate (percentage of people employed in the population) as 33.4 per cent. The particulars of the calculated economic benefits from reduction in air pollution are provided in Table A2 in Appendix.

The above formulation and information gives the annual economic benefits from the reduction in workdays (sick days taken as a proxy here [13]) lost from pollution exposure to safe levels (100 μg/m^3) as Rs. 28,820.35 for a typical-household, and as Rs. 6,080.24 for a representative working individual. Entire working population of Delhi gets benefits worth Rs. 34.11 billion from reduced workdays lost, if a typical household's benefit is extrapolated using working participation rate as 33.4 percent (Census 2011). Similarly, the annual economic benefits from reduced mitigating expenses for a typical household due to reduction in air pollution exposure to safe level is estimated as Rs. 5,157.77 and Rs. 1,088.13 for a representative individual. The extrapolated benefits for entire Delhi population from reduced mitigating expenses are estimated as Rs. 18.28 billion. Hence, the total annual monetary gain from reduced air pollution exposure (from current to safe level) to the National Capital of India is Rs. 52.4 billion. To a typical household and an individual, the total annual gain amounts to Rs. 33,978.12 and Rs. 7,168.37, respectively. An estimate of share of annual benefits from reduced air pollution to safe levels comes to about 2.54 percent of annual income of a typical Delhi household.

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formulae used for weight of the last quarter is (Rank of the last Quarter/Sum of all ranks) $= \frac{4}{10} = 0.4$

[13] The proxy may overestimate the economic benefits, as work-days lost are also included in wage loss reduction $(W.{}^{dH}\!/_{dQ})$ term shown in equation (12).

3.4. Distribution of Economic Benefits

The annual economic benefits to a typical household from reduced air pollution exposure from current to safe levels (100 μg/m^3) are quite high as shown above. However, the question that remains is - who actually gains the most from pollution reduction? To answer this question, the shares of total annual economic benefits for the three different SES quantile of the households (Low, Middle and High SES) in Delhi are estimated. *Figure 5* provides the distribution of economic benefits due to reduction in air pollution amongst different socio-economic classes of households in Delhi.

As shown in Table 5, estimates of annual economic benefits from reduction in pollution exposure to safe levels for a typically lower socio-economic household is Rs. 8,701.33 which is much lower than that of a higher SES household which saves as high as Rs. 50,631.95, while a typical middle-class household gains a mediocre amount of Rs. 28,376.92. This means that in absolute terms a higher SES household gains the most out of pollution exposure reduction. This estimate though essential does not show the true and real depiction of the distribution of gains and reality could be inferred by looking at the gains in relative terms, estimating the annual benefits share as a percentage of annual income for the three classes of households. These estimates show that a lower SES household saves 4.96 percent out of their annual income which is much larger than a higher SES household saving which is merely 1.97 per cent out of the annual family income, if pollution exposure is reduced to safe levels. For a middle-class family the saving rate out of income is estimated as 2.23 per cent.

Table 5: Distribution of Economic Benefits by Reduction in Air-Pollution amongst different Socio-Economic Classes of Households

SES	Annual Benefit	Annual Benefit Share (%)
Low	Rs. 8,701.33	4.96
Middle	Rs. 28,376.92	2.23
High	Rs. 50,631.95	1.97

Source: Authors' own Calculation

4. CONCLUSIONS AND POLICY SUGGESTIONS

The econometric results show that ceteris paribus, households with lower SES have a higher vulnerability to air pollution and its consequences. Vulnerability is more prominent for household members with informal outdoor occupations and families who have higher air pollution exposure.

Moreover, households with health insurance have lower vulnerability to air pollution which could be due to lower mitigating expenditure and better coverage of health facilities. However, age shows no significant effect on vulnerability. These results conclude that households/communities with lower educational attainment, pronounced deprivation of wealth assets, higher proportion of people in unorganized job sectors and poor living conditions (such as living near busy roads or in slums, having unhealthy water facilities) will be the most vulnerable to air pollution and its impacts. The results are in line with the findings of Landrigan and Goldman (2011) and Hajat *et al.* (2015).

Estimates of economic benefits (in terms of health) from air pollution reduction to safe limit (100μg/m^3) from current levels (study period) for a typical household amount to Rs. 33,978.12 and for the entire population of Delhi it is Rs. 52.4 billion. A typical household can save about 2.54 per cent per year of their annual income from reduction in pollution exposure to safe levels.

It can be concluded that reduction in pollution (in Delhi) can have critical monetary benefits through improved health status and lowered medical expenses on air pollution related illness by the households and the population of Delhi. There are already a few other studies done in the past which show similar results, though, with much lower annual benefits in the context of other cities. For instance, Gupta (2006) found the economic benefits for the city of Kanpur to be around Rs. 200 million per year. This highlights the plausibility of a high estimated value of economic benefits for the whole population, given Delhi being amongst the most polluted as well as highly populated cities in the world. However, these estimates only provide information about the gains to a typical household or population from pollution reduction. The critical question is who gains the most from economic benefits of pollution reduction and whether the policies that lead to air pollution reduction can also lead to "pro-equity" benefits to all socio-economic segments along with overall "pro-efficiency" benefits to a typical household of Delhi. Distribution of the economic gains from air pollution reduction reflects that in absolute terms a typically higher SES gets higher annual benefits which may be since these have higher annual income and hence will save more in absolute terms. In reality, looking at the gains in relative terms by estimating the annual benefits share as a percentage of annual income for the three classes of households, estimates shows that a lower SES household saves the maximum proportion of its annual income, i.e., 7.93 per cent as compared to higher SES household for which annual benefit share is merely 3.15 per cent of the annual family income if exposure to air pollution is reduced to safe limits.

Thus, it can be concluded that a lower SES household with a higher vulnerability to air pollution will benefit the most from reduced air pollution (in relative terms). Studying the impact of socio-economic position on vulnerability to air pollution can help assess policy implications in tackling the menace of air pollution and population's vulnerability to it. A cooperative strategic policy can help economically poor households use appropriate defensive behavior and activities to reduce the severity of air pollution consequences and thus, reduce inequity in the environmental aspect along with the reduction in air pollution.

In recent years, several significant studies have addressed policy suggestions for air pollution in the context of Delhi. A recent source apportionment study by TERI (2018) identified multiple sources for the variation in $PM_{2.5}$ and PM_{10} concentrations during summer and winter months - transport, biomass burning, industries and dust being the significant ones. It proposed several interventions, ranging from liquified petroleum gas penetration, introduction of gaseous fuels and enforcement of new and stringent $SO_2/NO_x/PM_{2.5}$ standards for industries using solid fuels, inspection and maintenance of vehicles, strong implementation of BS-VI (Bharat Stage) norms to congestion management, etc. Further, attention has been given at the national and sub-national level to issues of proper management of crop-residue burning such as implementing blanket ban, promoting subsidies and compensation programs for farmers to buy advanced and modern equipment for *in situ* crop residue management, initiatives to diversify the crop production and straw management, creating market for agri-residues, while focus given to embedded socio-economic, cultural and behavioral elements responsible for widespread practice of burning of agri-residues has been limited (Kumar *et al.* 2015).

Looking at the course of action from the distributional aspect, social variables that have prompted air pollution inequity as shown in the study should additionally be given due importance along with those policies that will help in reduction of air pollution. Ujjwala scheme has been promoted by the government for higher penetration of liquified petroleum gas in the households from lower SES. More attention is needed for reducing occupational exposures, thereby, improving the working conditions of people. Legal structures also need to be effectively designed to protect workers in outdoor jobs and other vulnerable groups. Another strategy prospect could be more focused awareness creation about consequences of air pollution and procurement of more information on the health impacts of air pollution, which affect individual's adaptive and mitigating capacity to combat with it.

This study found it important to analyze efficiency as well as equity matters of air pollution in Delhi. A general observation made by authors such as Blank (2002) is that the trade-off between equity and efficiency only exists in the shorter run (as efficiency can only be persistent in the longer run when these are balanced); in the long run, both go hand-in-hand (Berg and Ostry 2011; Krugman 2014). In terms of air pollution inequity, the gap between the two can be minimized by implementing pro-poor policies with support from the community and government, through policies that mandate efficient pollution control standards and finally, through redistribution of payments via- subsidies, health insurance facilities and increasing education investment to reduce both distributional vulnerability to air pollution along with reduction in overall exposure.

Vulnerability to air pollution and its consequences cuts across various sectors at different scales, and thus calls for coherence and integration at the policy level to deal with such an imminent problem. This study serves as a potential for reviewing new developments in further research and use the outcomes of the analysis for policy implications that act as a toolkit for the government at a micro level to base decisions at a macro level in the longer run.

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Appendix

Table A1: Descriptive Statistics of Variables used in Estimation of Health Production Function and Mitigating Demand Function Model, and in Estimation of Vulnerability to Air Pollution Model

Variable	Mean	Std. Dev.	Min	Max
Health Status	53.66	50.58	0	255
Mitigating Expenditure	6506.63	9317.5	0	60950
Vulnerability Index	0.76	0.197	0.35	1.37
Household Exposure Index	117.054	44.96	46.15	288.304
Chronic Index	0.531	0.69	0	4.3
Socio-Economic Index	-9.31e-10	3.206	-4.48	11.39
Habits	0.74	0.54	0	3
Family Size	4.74	1.77	1	11
Suffer	0.63	0.29	0	1
Awareness	10.47	2.52	0	16
Avert	1.73	1.36	0	5
School/College Going	0.24	0.2006	0	0.75
Health Insurance	0.55	0.49	0	1
Gender	0.49	0.18	0	1
Outdoor Job	0.29	0.41	0	1
Background	1.32	0.47	1	2
Adults	0.81	0.19	0.33	1

Table A2: Estimates of Total Annual Economic Benefits and Annual Benefit Share (%) for Reduction in Air-Pollution

h_1	m_1	Mean Values								
		Last Three Months				FAM^M	W^M	INC^M		
		HEI^M	HEI. $SAFE^M$	H^M	M^M					
Estimated coefficient of Household Exposure Index for HPF regression model	Estimated coefficient of Household Exposure Index for MDF regression model	Household Exposure Index	Household Exposure Index Safe	Family Days of Sickness	Mitigating Expenditure (Rs.)	Family Size	Family Wage Rate (Rs.)	Annual Household Income (Rs.)	Delhi Population* (Billion)	Delhi Working Participation Rate *
0.45	0.44	117.05	32.7	53.67	6506.63	4.74	3139.64	1337399	0.0168	33.4

Annualized Economic Benefits (Rs.) to a typical household for reduction in pollution exposure by 1 μg/m3		
Gain from Reduction in Sick Days (For Working Family Members)	Gain from Reduction in Mitigating Expenses (For all Family Members)	Annual Willingness to Pay (Household)
Rs. 341.67	Rs. 61.14	Rs. 402.82

Annualized Economic Benefits (Rs.) to a typical household for reduction in pollution exposure from current to safe level (100 μg/m3, PM10)		
Gain from Reduction in Sick Days (For Working Family Members)	Gain from Reduction in Mitigating Expenses (For all Family Members)	Total Annual Economic Benefits (Household)
Rs. 28820.35	Rs. 5157.77	Rs. 33978.12

Annualized Benefits Share (%) to a typical household for reduction in pollution exposure from current to safe level (100 μg/m3, PM10)	4.06%

Annualized Economic Benefits (in Rs. Billion) to Delhi Population for reduction in pollution exposure from current to safe level (100 μg/m3, PM10)		
Gain from Reduction in Sick Days (For Working Population)	Gain from Reduction in Mitigating Expenses (For Entire Population)	Total Annual Economic Benefits (Delhi)
Rs. 34.11 Billion	Rs. 18.28 Billion	Rs. 52.4 Billion

Source: Authors' Calculation

* Population and Working Participation Rate, Census (2011)