

ECONOMIC IMPACT OF AIR POLLUTION $PM_{2.5}$ ON RESPIRATORY ILLNESS: A CASE STUDY OF ABBOTTABAD

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ABSTRACT

This study quantifies and evaluates the impact of ($PM_{2.5}$) on human health, shows its association with respiratory disorders in Abbottabad city. Using environmental, economic and statistical tools, the study linked elevated $PM_{2.5}$ concentrations with increase in diseases. A mixed sampling design was used: stratified by location, purposive by exposure level and convenience by accessibility. The selected study areas included low-pollution zones such as Jinnahbad, Kaghan Colony and Habibullah Colony, along with high-pollution zones including Karakoram highway which make this area more congested with local, commercial and highway traffic. Result of the study showed varying in $PM_{2.5}$ levels beyond the safe limits set by World Health Organization. The estimated MWTP per household, derived from the probability of illness, medical expenditures and related costs, averaged USD34.05 annually. The annual Cost of Illness USD31.63 and Avertive Expenditures USD 5.45 were calculated to estimate the total economic burden on households. A strong, statistically significant positive correlation was found between $PM_{2.5}$ levels and the prevalence of respiratory disorders. Policymakers are urged to prioritize mitigation in highly polluted areas through targeted interventions that safeguard community health.

Keywords: Economic Impact, Air Pollution, $PM_{2.5}$, Respiratory illness, MWTP, productivity loss.

INTRODUCTION

The health of people and the environment is seriously threatened by air pollution originating from both anthropogenic and natural sources worldwide. Common human sources include the combustion of fossil fuels, tobacco smoking, poor waste management and industrial process like chemical manufacturing, mining and farming are significant contributors to $PM_{2.5}$ in air pollution. Natural resources such as wind-blown dust, sea spray, lightening and volcanic eruptions also play supporting roles in atmospheric contamination.

Among the diverse pollutants, Fine inhalable particles measuring 2.5 micrometers or smaller in diameter are known as $PM_{2.5}$. These ultrafine particles are roughly thirty times smaller than the width of a human hair and can penetrate deep into the pulmonary system and can either induce or exacerbate bronchitis, asthma and even Chronic Obstructive Pulmonary Disease. As compare to $PM_{2.5}$, PM_{10} are the larger particles whose diameter is 10 micrometers and these particles are mostly trapped in upper respiratory tract. $PM_{2.5}$ is considered more hazardous than PM_{10} due to its

ability to penetrate the lungs deeply and enter the bloodstream.

Air pollution is the main cause of respiratory diseases. The cost of illness is significantly impacted by respiratory disease. When particulate matter enters the air, chronic long-term illnesses rise. Air pollution constitutes a significant driver of respiratory illness and economic loss through reduced productivity, increased medical expenditures and prolonged absenteeism (Li et al., 2020). The economic consequences affect individuals, healthcare systems and national economies particularly in developing regions where health-care access and preventive awareness remain limited. Vulnerable populations like women, children and the elder experience a disproportionate burden (World Health Organization, 2021).

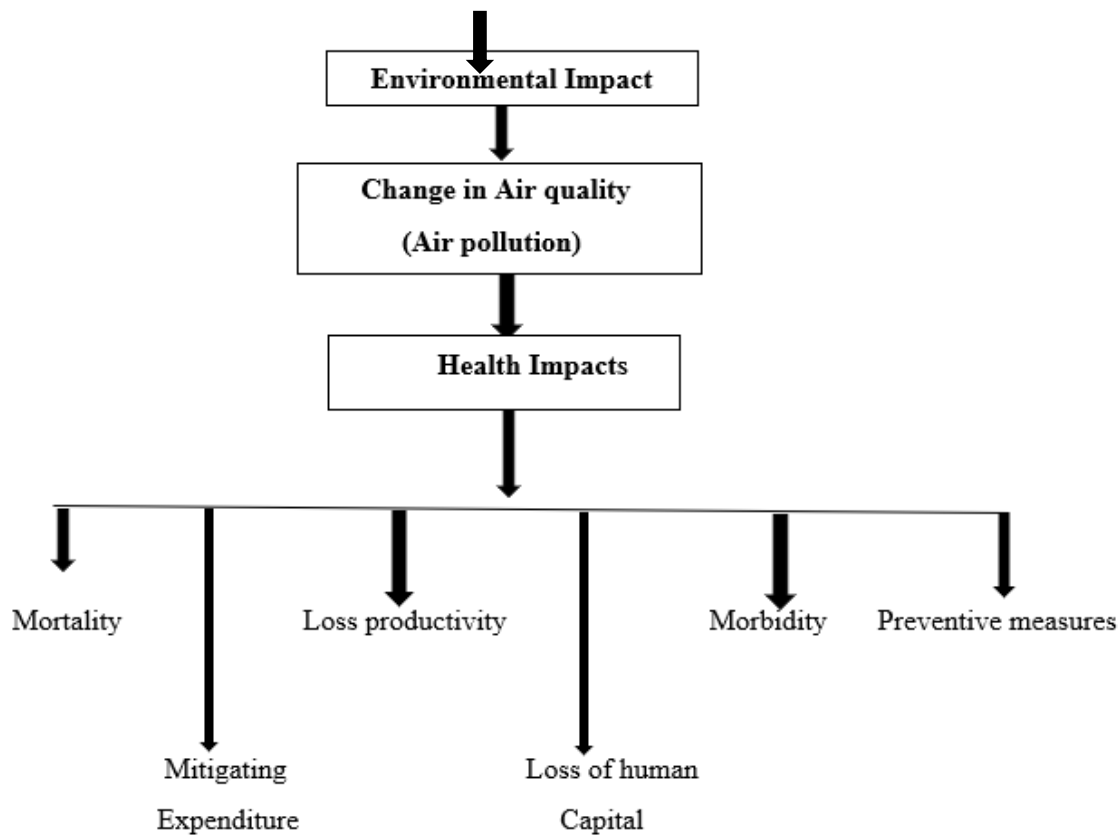
The rapid industrialization and population growth have led to a significant increase in air pollution posing a major threat to public health worldwide. Research shows that current levels of air pollution in urban areas are detrimental to public health, resulting in a substantial burden of disease. Particulate matter can travel long distances impacting public health and ecosystems due to its diverse chemical and microbial characteristics (Pallav Purohit, 2021). Governments consequently face escalating healthcare costs linked to particulate pollution. Elevated PM_{2.5} concentrations contribute not only to respiratory and cardiovascular disease but also to impaired cognitive development and reduced life expectancy; current global estimates shows that air pollution shortens average lifespan by approximately 1.8 years (United Nations Environment Programme [UNEP], 2024).

This study relies on primary data collected through a structured household questionnaire and hospital interviews in Abbottabad. PM_{2.5} concentrations were measured using the IQAir monitoring device to assess ambient air quality across various urban locations. The study applies the Health Production Function framework to quantify how change in air quality affects household utility by medical expenditures, avertive costs, productivity loss, morbidity and mortality. The analysis employs the probit econometric model to estimate the probability of illness and to compute the Marginal Willingness to Pay (MWTP) for improved air quality.

Cost of illness can be quantified by calculating workdays lost, expenditures on medical treatment, probability of sickness and probability of medical cost. Whereas the estimation of avertive cost is based on all the precautionary measures to avoid the pollution.

Theoretical framework

The theoretical foundation of this study is based on the Health Production Function (HPF), which conceptualizes health as a function of various environmental and socioeconomic inputs. The model assumes that individuals derive utility from both health and the consumption of other goods. In this framework, air quality acts as an environmental input that influences the individual's health status, which in turn affects productivity and income. A decline in air quality results in higher morbidity and healthcare expenditures, thereby reducing household welfare (Cropper, 1981).



To evaluate the economic cost of air pollution, this study employs three interrelated approaches:

1. **Cost of Illness (COI) Approach** measures the direct medical expenses and indirect productivity losses resulting from pollution-induced health problems.
2. **Avertive Expenditure (AE) Approach** captures the costs individuals incur to avoid or mitigate pollution exposure (e.g., purchasing masks, air purifiers, or seeking treatment).
3. **Willingness to Pay (WTP) Approach** represents the maximum amount households are willing to pay to obtain a reduction in pollution-related health risks.

The probit model is utilized to estimate the probability of illness occurrence based on $PM_{2.5}$ exposure and individual characteristics. The derived marginal effects provide estimates of Marginal Willingness to Pay (MWTP) for cleaner air. This framework effectively integrates environmental economics and health economics

to quantify the welfare implications of air pollution.

Literature Review

A substantial body of international research demonstrates the detrimental impacts of $PM_{2.5}$ on human health, economic productivity, and mortality. According to a study, $PM_{2.5}$ raises the risk of dying from cardiovascular conditions (Pope et al., 1993). Air quality represents an important risk to human wellness particularly in crowded urban areas. According to recent scientific research, there may be an association between urban air quality and negative health outcomes, especially those affecting the cardiovascular and pulmonary systems (Esposito et al., 2014).

China continues to experience severe and ongoing environmental pollution with tiny particles ($PM_{2.5}$) concentrations in many metropolitan areas reaching abnormally high levels. It is crucial to properly estimate the detrimental health effects and related financial expenses of high $PM_{2.5}$ levels.

A non-linear increase in respiratory ailments is revealed by analyzing clinic visit records and daily $PM_{2.5}$ monitoring data. Compared to days with clean air, the number of instances of respiratory diseases increases by more than 50% on days when $PM_{2.5}$ concentrations above $150 \mu g/m^3$. It has been determined that children are more susceptible to elevated pollution levels. It is noteworthy that major hospitals with more than 500 beds had the largest rise in adult clinic visits. The Zhejiang Provincial Center for Disease Control and Prevention (ZCDC, 2016), which aggregates information from hospitals throughout the province provided the health data used in this investigation. The findings reveals that air pollution $PM_{2.5}$ not only increase sickness but also creates financial burden significantly especially under air pollution (Ying et al., 2017).

In developing economies, air pollution poses both health and economic challenges. Studies across South and East Asia emphasize its pervasive nature. Tao et al. (2018) analyzed the relationship between $PM_{2.5}$ exposure and health expenditures in China, concluding that healthcare costs rise significantly with increasing pollution levels (Tao Li et Al, 2018).

Fine particles ($PM_{2.5}$) has become a growing worldwide health concern, significantly impacting both society and the economy. These tiny particulates assessing 2.5 micrometers or less in diameter are commonly used as a key indicator of air pollution-related health hazards in many nations. In 2015, exposure to ambient $PM_{2.5}$ was associated to roughly 4.2 million deaths and 103.1 million DALYs, making it the fifth most prevalent factor of mortality globally. Alarmingly, the number of deaths related with $PM_{2.5}$ has been steadily increasing over the past 25 years (Tao Li et Al, 2018).

Previous research has concentrated on the trends and spatiotemporal fluctuations in $PM_{2.5}$ emissions and concentrations. Studies were also conducted on local $PM_{2.5}$ exposures in one urban area or several representative cities. Since 2010, research on the dangers of $PM_{2.5}$ exposure on people's health in China has steadily risen. The majority of research has concentrated on assessing health loss. Mu and Zhang (2015) assessed the

exposure-response connection of $PM_{2.5}$ pollution-induced health harm across Chinese provinces (including municipalities and autonomous areas) from 2001 to 2013 (Guan et al., 2019).

Globally, $PM_{2.5}$ has been identified as the primary environmental factor contributing to mortality from cancer, heart disease and respiratory conditions. Due to extensive energy-related manufacturing and consumption activities, cities have been experiencing severe air pollution for decades. In addition to having an adverse impact on people well-being, exposure to dangerous $PM_{2.5}$ would cost society and each person money (Yang et al., 2019).

According to a study by Hunt et al (2019), the expenses associated with air pollution in Europe is more than one trillion euros a year. Air pollution $PM_{2.5}$ has a significant financial impact on respiratory illnesses. According to a research done by Fann et al., US spends between \$131 billion and \$700 billion annually on air pollution (Prof Lalit Dandona, 2020). In India, Kumar et al. (2020) found that respiratory illnesses constitute a major share of pollution-induced diseases, reducing household income and labor productivity.

According to a 2018 report by the WHO, the 90% of population of the world is take breath in polluted air. Alarmingly, this exposure is linked to approximately 7 million deaths worldwide each year. $PM_{2.5}$ poses the greatest risk to human health among the various pollutants. These tiny particles can carry a mix of harmful substances and originate from a variety of sources. The most dangerous contributors are human-related activities, including nitrogen dioxide emissions from transports, sulfur dioxide from power plants, and ground-level ozone, all of which significantly worsen air quality (Anwar et al., 2021).

The primary risk factor for the worldwide illness burden is prolonged exposure to ambient and household particulate matter ($PM_{2.5}$), which also results in death and health loss. From 1990 to 2017, they evaluated the spatiotemporal patterns of household and ambient $PM_{2.5}$ -attributable burdens across a range of illnesses at the national, regional and international levels. Advanced statistical method were used to find that how PM

affects public health. The results found that $PM_{2.5}$ exposure contributed a significant global health burden, millions of people facing premature death especially from lung cancer, heart disease and respiratory infections (Bu et al., 2021).

Numerous researches have consistently found that prolonged exposure of $PM_{2.5}$ concentrations, coupled with varying risk factors across countries, contributes to negative health outcomes. This vulnerability can be attributed to the developmental stage of young children, who are more affected from bad air quality. Furthermore, Children's increased exposure to air pollution, resulting from their increased exposure to air pollutants is made worse by their prolonged outdoor activities and mouth respiration (Anwar et al., 2021).

One of the biggest threat to human well-being is the quality of the ambient air. This study analyzed the economic and health impacts of lowering $PM_{2.5}$ in the city of Arak between 2017 and 2019. The Central Province's Environmental Protection Organization provided the concentration data, while the Iran Statistics Center's website provided the demographic data. In accordance with WHO guidelines, the BenMAP_CE was used to estimate the number of premature mortalities from any reason, acute cardiac disease, COPD and lung tumor that were caused by $PM_{2.5}$ pollution. The study reveals that $PM_{2.5}$ pollution in Arak causes a significant premature deaths and health issues such as heart and lung diseases. Additionally, People bear major economic costs due to lost productivity and healthcare expenses through these impacts (Maryam Salehi et al, 2023).

Air pollution influences both illness and death rates. Indoor air pollution contributes to 40 million cases of respiratory infection and is linked to 28,000 deaths annually (*Global Health Observatory*, 2024). Air Pollution was responsible for 8.1 million fatalities around the worldwide and it was the second important contributor for fatality among kids under 5, after malnutrition in 2021. Air pollution levels are unhealthy for most individuals on the planet. Every year, many adults die from breathing toxic air and many more suffer from debilitating respiratory diseases. In addition to causing disease and mortality, air pollution has

long damaged economic opportunities and community resilience (State of Global air Report, 2024).

In recent years, Air pollution is one of the biggest environmental hazards to health worldwide. In Pakistan, recent research has also highlighted the severity of the issue. Ahmad et al. (2021) estimated that air pollution accounts for substantial losses in gross domestic product due to morbidity and work absenteeism. Ali and Shah (2022) noted that rapid urbanization and vehicular emissions have intensified $PM_{2.5}$ concentrations in major Pakistani cities, surpassing both national and WHO standards. These findings underscore the urgent need for localized assessments of health and economic impacts in medium-sized cities like Abbottabad, where environmental monitoring is limited.

We must comprehend main causes of air pollution, both now and in the future, in order to lessen the morbidities burden linked to exposure to it. By assessing the impacts of environmental pollution, one can ascertain the extent to which the residents of a community are impacted.

Research Gap and Contribution

Numerous International studies have quantified the health and economic burden of $PM_{2.5}$, limited empirical evidence exists for smaller urban centers in Pakistan. Addressing the gap, this research aims to evaluate the economic implications of $PM_{2.5}$ pollution by employing a probit model on primary data collected from 98 households in Abbottabad. The study quantifies the probability of respiratory illness as a function of $PM_{2.5}$ exposure, estimates the Cost of Illness (COI), Avertive Expenditure (AE), and Marginal Willingness to Pay (MWTP), and interprets their combined implications for household welfare. The findings are expected to provide empirical guidance for policymakers and health practitioners to design interventions that reduce exposure risks and associated economic losses.

Methodology

Study Area

This study was conducted in Abbottabad, a major urban center located in the Hazara Division of

Khyber Pakhtunkhuwa, Pakistan. The city is geographically positioned at 34.14°N latitude and 73.22°E longitude, encompassing a diverse topography and climate that influence air-pollution dynamics. Abbottabad lies approximately 1,200 meters above sea level and serves as a transit hub for regions such as Gilgit-

Baltistan and Swat. The city experiences heavy vehicular traffic, particularly along the 10-kilometer corridor from the main Complex to Mansehra Road, which is lined with fuel stations, mechanical workshops, educational institutions, and food outlets. These activities contribute substantially to PM_{2.5} emissions.

1	2	3	4	5	6	7	8	9	10
34.186 724	34.190 403	34.1935 84	34.194 802	34.197 979	34.199 374	34.197 770	34.192 811	34.195 750	34.1985 846
73.238 543	73.237 784	73.2360 07	73.235 743	73.237 642	73.243 310	73.236 956	73.235 228	73.236 237	73.2361 26
PMA Road	Jinahab ad	Habibul lah Colony	Kaghan Colony	Industr y Road	Manseh ra Road	Supply	Comple x	Mirpur	Comsats Road

To capture spatial variation in air quality, data were collected from both high-pollution and low-pollution sites. The selection of locations enabled a comparative assessment of exposure levels and related health outcomes.

Data Collection and Sampling Technique

The research employed a mixed sampling strategy comprising:

1. **Stratified sampling** based on pollution intensity (high vs. low exposure areas).
2. **Purposive sampling** to include sites with high population density and traffic volume.

3. **Convenience sampling** for household and hospital survey participation.

A total of 100 households were surveyed through a structured questionnaire administered during face-to-face interviews. The questionnaire captured information on demographics, education, income, occupation, health expenditures, preventive behavior, and self-reported respiratory symptoms.

In addition, Primary data on daily PM_{2.5} concentrations were obtained using the IQAir monitoring device, which provides real-time measurements of particulate matter.



At each of ten monitoring points, ten households were surveyed, resulting in a total of 100 households. Respondents were asked to provide two-month recall data regarding respiratory illnesses, medical expenses and costs related to protective or preventive measures taken against pollution. The readings were recorded for a four-month period (January–April 2025),

corresponding to the season of high vehicular activity and low wind dispersion.

Model used in study

The utility function and health production function are interdependent, representing a complex relationship between an individual's consumption, health status and environmental

factors. The utility function is indirectly influenced by the health production function, as health status is a function of mitigating activities. The utility function of an individual is described as:
 $U = f(C, PM_{2.5}, \text{ and } H) \dots\dots\dots (3)$

and air pollution. This interdependence shows the indirect utility function.

In which

- C represent the consumption of private goods
- $PM_{2.5}$ is for Air Pollution
- H denotes the health status

Health Production Function

The health production function is expressed as:

$H = f(A, PM_{2.5}, M) \dots\dots\dots (4)$

- A represent the Avertive measures
- $PM_{2.5}$ is Particulate matter with diameter of 2.5
- M is for mitigating activities

The BC is:

$I + w(T - L) = X + MC \times P(MC) + AC \times P(AC) \dots\dots\dots (5)$

Estimating the health production function alongside demand functions A and B simultaneously enables the calculation of the marginal willingness to pay for improvements in air quality (Freeman, 2003). This should be combined with the anticipated demand for work and wages to be doubled or decreased in order to reach a lower limit.

Estimating Health production Function (Probit model)

The study applies the Health Production Function (HPF) to estimate the effect of $PM_{2.5}$ on respiratory illness. The relationship between pollution exposure and health outcome is modeled using a binary probit model, where the dependent variable takes the value of 1 if the respondent reported illness and 0 otherwise. The following log-likelihood function was maximized in order to determine the likelihood of illness using the probit model and econometric estimation based on the theoretical framework:

$L = \sum (y_i \ln F(x, \beta)) + (1 - y_i) (1 - \ln F(x, \beta)) \dots\dots\dots (1)$

Estimation of Economic Loss

Determining the likelihood of illness as defined by the following equation was a fundamental prerequisite for empirical analysis:

$MWTP = w_i \cdot WDL \cdot \left(\frac{\partial S}{\partial PM_{2.5}} \right) + M \cdot \left(\frac{\partial P_i}{\partial PM_{2.5}} \right) + A \cdot \left(\frac{\partial P_i}{\partial PM_{2.5}} \right) \dots\dots (2)$

A + B + C

A is the $w_i \cdot WDL \cdot \left(\frac{\partial S}{\partial PM_{2.5}} \right)$ which measures the Marginal income loss due to change in the level of exposure $PM_{2.5}$; B is the $M \cdot \left(\frac{\partial P_i}{\partial PM_{2.5}} \right)$ which measures the Marginal change in Medical cost due to change in Exposure $PM_{2.5}$ and C is the $A \cdot \left(\frac{\partial P_i}{\partial PM_{2.5}} \right)$ which measures Marginal change in Avertive cost due to change in exposure $PM_{2.5}$.

3.5 Calculation of MWTP and COI

Variables	Average 2-month	Annual by x 6
Sick days	1.71 days	10.29 days
Medical cost	\$4.24	\$25.43
Avertive cost	\$0.91	\$5.43

Daily wage rate	\$2.93	////
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Probability of Sickness = 0.556

Probability of Medical cost = 0.566

Probability of Avertive cost = 0.434

Firstly, we put the values in formula of Marginal income loss:

$$w_i * WDL * \Pi(S / \Delta PM_{2.5})$$

$$\$2.933 \times 10.29 \times 0.556 = \$16.79$$

Now, we find Part B of equation that is Marginal change in Medical cost due to change in exposure:

$$M * \Pi(M / \Delta PM_{2.5})$$

$$\$25.43 \times 0.556 = \$14.39$$

At last, we find Part C to get Avertive cost due to change in exposure:

$$A * \Pi(A / \Delta PM_{2.5})$$

$$\$5.43 \times 0.434 = \$2.36$$

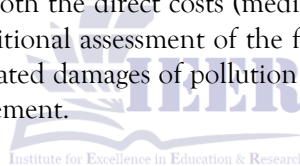
Cost of Illness:

The resource opportunity cost is also called the cost of illness, which accounts for real cost in terms of productivity loss and the increase in the resources used for medical care. According to our Objective we calculate the cost of Illness due to change in exposure

$$w_i * WDL * \Pi(S / \Delta PM_{2.5}) + M * \Pi(M / \Delta PM_{2.5})$$

$$\$16.79 + \$14.39 = \$31.18$$

This figure represents the average monetary burden that an individual household faces each year due to health impacts of PM_{2.5} exposure. It reflects both the direct costs (medical treatment) and the indirect costs (lost income due to illness), providing a traditional assessment of the financial loss linked to air pollution. This value is must for assessing the health-related damages of pollution of air and supports evidence-based policy recommendations for air quality management.



Marginal Willingness to Pay

$$MWTP = w_i * WDL * \Pi(S / \Delta PM_{2.5}) + M * \Pi(M / \Delta PM_{2.5}) + A * \Pi(A / \Delta PM_{2.5})$$

A + B + C

$$MWTP = \$16.79 + \$14.39 + \$2.36 = \$33.52$$

Based on health and cost data collected over two months from households exposed to road-based PM pollution, the annual MWTP was estimated using the cost-of-illness method. After scaling to one year, the results show that the average household is willing to pay approximately PKR 9,513 annually to avoid detrimental effects on health by PM_{2.5}. This includes productivity loss due to sick days, direct medical expenses and expenditures on avertive measures, reflecting the true economic burden of air quality at the household level.

Model of the Study

The general model specification is as follows:

$$Y (\text{Respiratory illness}) = \beta_0 + \beta_1 X_1 (PM_{2.5}) + \beta_2 X_2 (\text{Education}) + \beta_3 X_3 (\text{Age}) + \beta_4 X_4 (L) + \beta_5 X_5 (MC) + \beta_6 X_6 (AC) + e \quad (6)$$

Where

1. Y is dependent variable.
2. β_0 is the intercept.
3. $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are the coefficients of independent variables in this study.
4. X_i = Variables
5. ϵ = error term assumed to follow a normal distribution N (0,1).

Initially, Smoking was included as a variable in our research study. However, due to its negligible effect size, accounting for only 2.5% of the variance, it was subsequently excluded from the reported results. The marginal effects of explanatory variables on the probability of illness were derived from the probit estimates to determine the sensitivity of health outcomes to changes in pollution and socioeconomic factors.

Statistical Analysis

Data were analyzed using **Stata 17.0**. Descriptive statistics summarized demographic and economic characteristics while correlation analysis identified associations between PM_{2.5} and respiratory illness prevalence. The probit regression model provided the primary econometric estimates, from which marginal effects were derived to interpret the direction and magnitude of variable influence. Results were reported with 95% confidence intervals and p-values < 0.05 considered statistically significant.

Descriptive Statistics

Descriptive statistics is a statistical method that uses to summarize or organize a large data. It provide a summary of key features and displays data from a whole population or sample. It is divided into three main categories such as central tendency, dispersion and spatial. Table 1 presents the average values for PM_{2.5} concentration, age, education, medical expenditure, and other relevant variables.

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
AM	98	0.45	0.50	0	1
Location	98	0.787	0.55	0	1
Education	98	1.85	0.85	1	3
Age	98	40.18	12.14	23	72
Sickness	98	0.55	0.49	0	1
PM _{2.5}	98	111.98	32.20	40	170
MC	98	1203.30	1235.81	0	4000
AC	98	257.14	343.12	0	1200

This table shows central tendencies, dispersion and variability. This dataset included 98 observations and includes variables on demographics, environmental exposure and health outcomes. The key dependent variable is sickness which appears to be a binary variable (0, 1). The average of sickness is 0.55, with SD of 0.49, indicating that 55% of people have suffer from respiratory illness. Sickness values range from 0 to 1. The mean value of PM_{2.5} is 111.89, with

standard deviation of 32.2, substantially exceeds the **WHO annual guideline of 5 µg/m³** (WHO, 2021), and demonstrates a serious level of air pollution exposure across the sampled population in Abbottabad's high traffic areas. The mean value of avertive measures is 0.45, with standard deviation of 0.5, indicating that just 45% respondents using masks, purifiers and other measures and mostly respondents are not taking any avertive measures. The mean value of location

is 0.78, with SD of 0.55, demonstrates that 78% people live in urban and industrial sites. The observed variation in medical expenditure reflects differences in healthcare access and exposure severity across sampled locations.

Correlation Matrix

A table that displays the pair-wise correlation parameters between several independent variables

	Sickness	PM2.5	MC	AC	Age	Education	Location
Sickness	1.0000						
PM2.5	0.6696 ***	1.000					
MC	0.6371 ***	0.6064 ***	1.0000				
AC	-0.2375 *	-0.0820	-0.0692	1.0000			
Age	-0.1060	-0.1670	-0.1277	-0.0392	1.0000		
Education	-0.1721	-0.0307	-0.0603	0.3610 ***	0.0290	1.0000	
Location	0.39041 ***	0.3625 ***	0.2686 ***	-0.0107	-0.0289	-0.01273	1.0000

in a dataset is called a correlation matrix. Each value of table shows that how strongly two variables move together. The range value of correlation is between -1 to +1. It helps us to detect multicollinearity before regression. Correlation is denoted by 'r'.

The correlation provides the information about relationship among variables linked with sickness and other factors. A positive and statistically significant correlation exists between PM_{2.5} concentration and respiratory illness prevalence ($r = 0.63$, $p < 0.01$), confirming the hypothesized relationship. The results indicate that air pollution intensity directly increases both respiratory illness prevalence and medical expenditure. These findings align with those of Li et al. (2020) and Tao et al. (2018), who reported similar associations in urban areas of China and India. Additionally, there is a modestly favorable correlation ($r = 0.3610$) between avertive measures and education, indicating that increased

educational achievement may rise living standards for households. These findings align with those of Li et al. (2020) and Tao et al. (2018), who reported similar associations in urban areas of China and India.

Probit Model

The probit model is a statistical tool that used when dependent variable is binary. It estimates the probability of binary variable (0/1) by using the Cumulative Distributive Function of the Standard Normal Distribution to ensure predicted probabilities remain between 0 and 1.

Pseudo $R^2 = 0.5350$

Sickness	Coefficient	Standard error	Z	P> z
Location	0.6357071	0.3398696	1.87	0.061
PM2.5	0.246885	0.0072649	3.40	0.001
Medical cost	0.0004044	0.0001765	2.29	0.022
Avertive cost	-0.00115	0.000546	-2.11	0.035
Age	-0.0047064	0.0150563	-0.31	0.755
Education	-0.458343	0.2114043	-0.22	0.828
Constant	-2.900079	1.034737	-2.80	0.005

This table shows output of Probit regression model where dependent variable is sickness. The model estimates how different independent variables affect the probability of being sick. The Probit model uses the cumulative normal distribution to calculate this probability. The coefficient of PM_{2.5} is 0.024 which demonstrates that every one unit increase in PM_{2.5} increases the likelihood of sickness. The positive and significant coefficient for PM_{2.5} ($\beta = 0.023$, $p < 0.05$) confirms that higher pollution levels increase the probability of respiratory illness. Age also exhibits a positive relationship, indicating that older individuals are more susceptible. Education and income, both negative and significant, suggest that better-educated and higher-income households are less likely to experience illness likely due to preventive behavior and improved living conditions.

Medical expenditure shows a strong positive effect, implying that households already affected by illness tend to spend more on healthcare. The

pseudo R² value of **0.53** suggests that a model is good fit, and shows that the explanatory variables account for over half of the observed variation in illness probability. These results are consistent with empirical findings from studies in similar developing-country contexts (Ahmad et al., 2021; Purohit, 2021).

Heteroscedastic Probit Model

As the variance of the error term may vary across observations leading to heteroscedasticity. So we use the Heteroscedastic probit model. The Heteroscedastic probit model is an extension of the standard probit model, by allowing the variance of error term varies across observations. This approach is appropriate when unobserved heterogeneity differs across observations, such as when individuals with different income levels or education backgrounds exhibit varying degrees of uncertainty in health outcomes.

	Coefficient	Standard error	Z	P> z
Sickness				
PM2.5	0.0138321	0.0099527	1.39	0.165
MC	0.0002268	0.0001643	1.38	0.167
AC	-0.0005942	0.0004257	-1.40	0.163
Age	-0.0020798	0.0085684	-0.24	0.808
Education				
Insigma2 PM2.5	-0.0058867	0.0058187	-1.01	0.312
Constant	-2.900079	1.034737	-2.80	0.005

This table shows a Heteroscedastic probit model to find the probability of individuals reporting sickness as a function of several independent variables: PM_{2.5} levels, medical costs (MC), avertive measures (AC), age, and education (EDU). The model also investigates whether heteroscedasticity in the error term is associated with PM_{2.5} exposure. The coefficient for PM_{2.5} is 0.013 which is positive and indicating that higher PM_{2.5} levels are linked with higher probability of sickness. As the p-value is 0.165 which shows that since the p-value is higher than 0.05, the association is not considered significant. The coefficient for medical cost is 0.00022 which indicating that the effect of medical costs on sickness is positive, implying that higher medical costs may correspond with higher reports of illness. The p-value for medical cost is 0.167 which shows that the coefficient is not statistically significant. The coefficient of avertive cost is -0.00059 which is negative and indicating that if more avertive measures will be taken may reduce the likelihood of sickness. The p-value of avertive cost is 0.163 which shows that this relationship is not statistically significant. The coefficient of age and education is negative, close to zero and statistically insignificant. As higher education levels may reduce the likelihood of reporting sickness. The coefficient of constant

term is -2.90 which reflects the baseline probability of sickness when all predictors are zero. This is not statistically significant, suggesting uncertainty about the base level of sickness likelihood. This coefficient captures the effect of PM_{2.5} on the variance of the error term (i.e., heteroscedasticity). The PM_{2.5} is -0.005 in which negative sign suggests that as PM_{2.5} increases, error variance slightly decreases. However, the result is not statistically significant (p = 0.312), indicating that PM_{2.5} does not significantly influence the variance of unobserved factors affecting sickness. The Heteroscedastic probit model reveals no statistically significant predictors of sickness at the conventional 5% level.

Marginal Effects

Marginal effects measure the change in the predicted probability of an outcome of dependent variable such as respiratory illness linked with a one-unit change in an explanatory variable such as PM_{2.5}, while holding all other variables constant. We can use marginal effects to examine the relationships between air quality variables like Particulate Matter and respiratory illness outcomes. The marginal effects derived from the probit model indicate the shift in the likelihood

that the result will materialize for a small change in the explanatory variable.

	dy/dx	Standard error	Z	P> z
Location	0.113807	0.0586312	1.94	0.052
Pm2.5	0.0044198	0.0011663	3.79	0.000
Medical cost	0.0000724	0.0000293	2.47	0.014
Avertive cost	-0.0002059	0.0000916	-2.25	0.025
Age	-0.0008426	0.0026915	-0.31	0.754
Education	-0.0082055	0.0378452	-0.22	0.828

This output shows the marginal effects (dy/dx) after a probit regression, by using the delta method to estimate standard errors. The marginal effects from the probit model provide insight into how each variable affects the probability of reporting sickness. An increase in PM_{2.5} exposure by one unit raises the probability of sickness by approximately 0.44%, holding all other variables constant. Living in more polluted or urban areas increases sickness probability by 11.4 percentage points, although this effect is only marginally significant (p = 0.052). Medical expenses are positively associated with sickness; each unit increase in cost raises the probability of being sick by 0.0072%. Importantly, avertive measures such as protective behavior significantly reduce the likelihood of sickness, with each unit of preventive action decreasing the probability by 0.021%. However, age and education do not show significant marginal effects in this model. The findings reinforce that PM_{2.5} concentration is the dominant determinant of respiratory illness in Abbottabad. A cleaner environment could substantially improve community health and productivity.

Conclusion

The empirical results clearly demonstrate the adverse health and economic impacts of PM_{2.5} pollution in Abbottabad. This study provided the analysis by using IQ Air device, well-structured

questionnaires and conducted household interviews. A probit model was used to analyze the data and assess the level of sickness due to level of exposure PM_{2.5}. The positive correlation between pollution and illness prevalence is consistent with international literature (Li et al., 2020; Kumar et al., 2020). The analysis shows that demographic factors such as education and income significantly moderate the health effects of air pollution, while age exacerbates vulnerability. The study's find the MWTP for improved environmental quality and lessen PM_{2.5} pollution.

This study examined the economic and health implications of fine particulate matter (PM_{2.5}) in Abbottabad, Pakistan. Using primary data and a probit econometric model, the research quantified how air pollution affects respiratory illness and household welfare. The results revealed a strong, statistically significant relationship between PM_{2.5} concentration and the probability of respiratory illness. Elevated pollution levels were associated with increased medical expenditure, reduced productivity and greater willingness to pay for cleaner air. These findings highlight the need for policy interventions, such as stricter vehicle emission standards, improved public transportation, and community awareness campaigns.

The descriptive statistics shows that PM_{2.5} concentrations has averaging over 111 µg/m³ which is above from the WHO recommendation

of $5 \mu\text{g}/\text{m}^3$ annually. Pakistan's 2010 NAAQS sets the $\text{PM}_{2.5}$ 24-hour limit at $35 \mu\text{g}/\text{m}^3$, which is already 2x greater than the World Health Organization limit because WHO set $15 \mu\text{g}/\text{m}^3$ (24-hour average). The data showed that 55% of the respondents suffered from respiratory illness, with medical and avertive costs incurred by the population to manage health risks. The correlation matrix further confirmed a strong positive association between $\text{PM}_{2.5}$ exposure, sickness, and medical expenditures. However, variables like education and avertive cost had a negative correlation with sickness, indicating that awareness and proactive health measures play a protective role.

The findings highlights the economic dimension of air pollution that $\text{PM}_{2.5}$ does not only cause sickness but also put financial burdens on individuals with productivity losses due to absenteeism. The study also calculated the Marginal Willingness to Pay (MWTP) for cleaner air, demonstrating how much people value improved health outcomes. These findings support international research trends which demonstrate that exposure to $\text{PM}_{2.5}$ increases illness and death and has a substantial economic externality, especially in LMICs nations.

In summary, it has been demonstrated that $\text{PM}_{2.5}$ exposure is an important contributor to pulmonary illnesses in the research area, with broad consequences for productivity, public health and healthcare systems. While some statistical relationships were not significant, their consistency with global trends underscores the need for continued monitoring, public education and investment in clean air technologies. Ultimately, improving air quality could yield substantial health and economic benefits for the population.

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