

Value of Statistical Life (VSL) to Support Cost-Benefit Analysis of India's Air Quality Management



Sarath Guttikunda Sai Krishna Dammalapati SIM-air working paper series #55-2024

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- Promoting advocacy and raising awareness on air quality management
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Table of Contents

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List of Abbreviations	3
Short Story	4
1. Cost-Benefit Analysis	5
2. Calculating Health Impacts	7
Integrated Exposure Response (IER) curve	8
3. Monetizing Health Impacts	10
Hedley Environmental Index	11
4. What is the Value of Statistical Life (VSL)	13
Factors influencing the WTP value during a survey	14
History of VSL from the United States	17
Extrapolation of VSL to global applications	17
5. India's Value of Statistical Life	20
Benefit transfer method	20
Life insurance proxy method	22
6. Cost of Air Pollution in India	23
7. References	

List of Abbreviations

AQM	Air Quality Management
CBA	Cost-benefit Analysis
CO	Carbon Monoxide
COPD	Chronic Obstructive Pulmonary Disease
DALYs	Disability Adjusted Life Years
GBD	Global Burden of Disease
GDP	Gross Domestic Product
HICs	High Income Countries
IER	Integrated Exposure Response curve
INR	Indian Rupees
IRDAI	Insurance Regulatory and Development Authority of India
LMICs	Low- and Middle-Income Countries
NO ₂	Nitrogen Oxides
PM10	Particulate Matter with diameter < 10 μ m
PM _{2.5}	Particulate Matter with diameter < 2.5 μm
PPP	Purchasing Power Parity
RR	Relative Risk
SO ₂	Sulfur Dioxide
US EPA	United States Environmental Protection Agency
USD	US Dollar
VOCs	Volatile Organic Compounds
VSL	Value of Statistical Life
WTP	Willingness to Pay

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Short Story

Controlling air emissions can be a significant financial burden, making it essential to justify these costs through measurable benefits. This is often achieved by accounting for the health benefits associated with emission reductions. These benefits include the number of lives saved, life years extended, work years not lost due to premature deaths or illnesses, and the medical expenses avoided by preventing or reducing morbidity. By quantifying these benefits, policymakers can demonstrate that the long-term savings and improvements in public health outweigh the immediate costs of implementing air quality controls, making a strong case for investment in cleaner air.

In this working paper, we reviewed the application of the VSL concept in CBA for AQM. We explored the methods through examples to estimate health impacts and monetize them. We examined the complexities involved in establishing WTP, a critical input for estimating VSL, which reflects differences in economic conditions, risk perception, and public health priorities, and how the concept of benefit-transfer method can be used to extrapolate the VSL estimates from countries where the studies are conducted to other countries. Finally, we estimated the VSL for India by analyzing existing data such as income levels, insurance levels, gross domestic product, and other relevant statistics to present a valuation that can effectively balance the costs and benefits of AQM in the Indian context.

The benefits transfer method and life insurance proxy method presented a range of US\$ 0.5 to 1.6 million as India's VSL. A preliminary assessment of the 2.09 million lives lost to air pollution in India, valued at a conservative VSL of \$0.5 million, amounts to an economic cost of \$1,045 billion, or approximately 7% of the national PPP.

These estimates, however, are not definitive and carry significant uncertainties. Contributing factors include fluctuating GDP values; generalized IER curves that may not accurately reflect region-specific data; exposure rates derived from global chemical transport models, which may lack precision in areas with limited monitoring; and the methods for calculating VSL introduce variability, as they often require adapting values from other contexts. While these estimates offer valuable insights, they should be viewed with an awareness of their inherent uncertainties.

1. Cost-Benefit Analysis

In air quality management (AQM), the foremost dialogue factor that often arises is the "cost" of an intervention to control emissions in all the known sources. This cost is typically measured against the potential "benefits" it can provide, both to the city in terms of reduced emissions and pollution levels, and to the public in terms of improved health outcomes. **This is cost-benefit analysis (CBA)**.



The CBA cycle is often depicted as a simple schematic, but each component of this cycle requires extensive input and a deep understanding of the local context. At its core, the process begins by identifying potential interventions aimed at reducing air pollution. Each intervention has associated costs, including financial investments, operational challenges, and potential socio-economic impacts.

Cities have numerous options to control emissions, including transitioning to cleaner fuel for road transport, promoting public transportation, promoting walking and cycling, enforcing vehicle maintenance, promoting the use of electric vehicles, increasing green spaces, transitioning to cleaner fuels for cooking and heating, stricter regulations on open waste burning, paving of roads to reduce dust loading, implementing industrial emission controls, and encouraging energy efficiency at industries.

The benefits of these interventions are just as critical to evaluate. These include reductions in pollution levels, improvements in public health, and the potential for enhanced economic productivity due to healthier populations. Quantifying these benefits often requires detailed data on current air quality levels, exposure patterns, health outcomes, and economic valuation methods to estimate savings from reduced hospitalizations, mortality, and productivity losses. These benefits are often monetized, just as the costs of interventions are, to create a comprehensive CBA. The value assigned to calculate the benefits of a statistical life saved from air pollution is called **"value of statistical life" (VSL)** and similarly for other end points in the form of **"willingness to pay" (WTP)**.

However, the process of assigning a monetary value to health impacts and even to human life is a complex and challenging task. It involves numerous assumptions, ethical considerations, and uncertainties, making the evaluation process far from straightforward.

In this working paper, we reviewed the application of the VSL concept in CBA for AQM. We explored various methods used to estimate health impacts and provided examples of how these impacts are monetized. Additionally, we examined the complexities involved in establishing WTP, a critical input for estimating VSL, which reflects differences in economic conditions, risk perception, and public health priorities. Finally, we estimated the VSL for India by analyzing existing data such as income levels, health expenditure patterns (including insurance), gross domestic product, and other relevant statistics to present a valuation that can effectively balance the costs and benefits of AQM in the Indian context.

2. Calculating Health Impacts

In AQM, evaluating health impacts is a crucial step in understanding the full scope of emissions management for policy support. Evaluating and valuing health impacts provides a clear, measurable way to justify policy measures. Using health metrics such as reduced morbidity and mortality allows governments to demonstrate the real-world benefits of air quality interventions, helping to prioritize and implement effective policies. This approach also helps personalize the abstract concept of air quality, making it easier to raise public awareness and drive change.

There are many types of health impacts to consider when assessing air quality: **Chronic effects** from long-term exposure, such as respiratory diseases (e.g., chronic obstructive pulmonary disease) and cardiovascular conditions. **Acute effects** from short-term exposure, which can trigger asthma attacks, irritations, and even hospital admissions. **Occupational impacts** for workers in industries like mining or construction, where prolonged exposure to high pollution levels poses significant health risks. **Personal effects**, which vary based on an individual's vulnerability (e.g., children, elderly, or those with pre-existing conditions) and proximity to pollution sources.



All pollutants have an impact on our health, though the severity varies by pollutant and exposure level. Among them, PM_{2.5} and ozone concentrations are most used to assess the health impacts of chronic exposure. The health effects of

PM_{2.5} range from respiratory issues and cardiovascular diseases to premature mortality, as well as exacerbating conditions like asthma and bronchitis. Chemically, PM_{2.5} carries signatures of various gaseous pollutants, as secondary PM in the form of sulfate aerosols from SO₂, nitrate aerosols from NO_x, organic aerosol from VOCs. Beyond PM_{2.5}, gaseous pollutants also affect human health in different ways: SO₂ can cause respiratory problems and aggravate lung diseases, NO₂ contributes to respiratory inflammation and worsens asthma, CO impairs oxygen delivery to the body, and ozone causes respiratory distress and long-term lung damage. Together, these pollutants have widespread and serious health implications.

Integrated Exposure Response curve

Air pollution affects nearly every part of the human body, with some pollutants contributing to serious health issues. Across the globe, numerous epidemiological studies have been conducted and are ongoing to better understand the linkages between air pollution and a wide range of health impacts, including the incidence of premature death in many cases. These studies are not simple exercises; they require significant time, effort, and collaboration among experts in various fields, such as medicine, data science, statistics, atmospheric science, and the contributions of many volunteers. While this chapter does not delve into the methodologies for conducting such studies, it builds on the knowledge gained from them to explore how we can model these health impacts and use the results for cost-benefit analysis, ultimately helping to inform policy and decision-making.

$$HI_{i} = Y \times AF \times PoP_{i}$$

$$HI = \text{estimated health endpoint impacts in zone i}$$

$$POP = \text{population exposed in zone i}$$

$$Y_{0} = \text{incidence/prevalence rate of health endpoint}$$

$$AF = 1 - \frac{1}{RR}$$

$$RR(z) = 1 \quad \text{for } z \leq z_{cf}$$

$$RR(z) = 1 + \sqrt{1 - e^{-Y}(z - z_{cf})^{\delta}} \quad \text{for } z > z_{cf}$$

Over the past few decades, methodologies for evaluating these health impacts have evolved significantly. The most recent advancement is the development of **Integrated Exposure Response** (IER) functions, linking various levels of air pollution exposure to specific health outcomes across different populations (Cohen et al., 2017; HEI-SoGA, 2024). This library of work was created as part of the Global Burden of Disease (GBD) study led by the Institute for Health Metrics and Evaluation (IHME - <u>https://vizhub.healthdata.org/gbd-compare</u>), in collaboration with the Health Effects Institute (HEI) and a consortium of leading research institutions (<u>https://www.stateofglobalair.org</u>).

These IER functions quantify the relationship between exposure to certain health risk and the subsequent health outcomes at the population level. The end metric is as both premature morality and disability adjusted life years (DALYs). These functions incorporate epidemiological evidence and dose-response relationships from across the world and information on national disease incidence rates and health management systems. All the inputs to run the IER function for regional and global assessments are available from the State of the Global Air program.

Both outdoor and indoor exposures are critical concerns, particularly in low- and middle-income countries (LMICs), where people face heightened risks due to poor regulatory standards, reliance on biomass fuels, and industrial emissions. Indoor air pollution from sources like cooking stoves is a major issue in many households, compounding the overall health risks in these regions.

The State of Global Air 2024 report reveals that air pollution was responsible for 8.1 million deaths globally in 2021, making it the second leading risk factor for death. Most of these deaths were due to noncommunicable diseases such as heart disease, stroke, and chronic obstructive pulmonary disease (COPD). Vulnerable populations, particularly children under five, were heavily affected, with over 700,000 deaths in this age group attributed to air pollution. Outdoor PM₂₅ and household (indoor) air pollution from solid fuel use are major contributors.

An example tool to estimate health impacts using this methodology is included @ <u>https://urbanemissions.info/tools</u>.

3. Monetizing Health Impacts

Monetizing health impacts translates the abstract concept of air quality into tangible economic terms, making it easier to prioritize and support policy decisions aimed at reducing emissions. We can use the concept of monetizing health impacts in two different ways.

The high costs of implementing interventions to reduce emissions and improve air quality can only be effectively justified by monetizing the associated health benefits and productivity gains. By assigning an economic **value to the benefits**—such as fewer premature deaths, reduced hospital admissions, and lower rates of chronic illnesses like asthma or cardiovascular disease policymakers can make a compelling case for the investment. This approach allows for a CBA where the long-term savings from improved public health, reduced healthcare costs, and increased productivity outweigh the immediate expenses of pollution control measures.

On the other hand, the same concept can be used to highlight the cost of air pollution by calculating the health impacts under prevalent pollution levels. This includes estimating the economic burden of diseases, hospitalizations, lost productivity, and premature deaths caused by current levels of pollution (as demonstrated by the Hedley Index in the following section). When health impacts are assessed for pollution that exceeds safe or regulated thresholds, these are termed **avoidable health impacts** or **the cost of inaction**. These represent the portion of economic losses that could have been prevented if emissions were reduced to meet the local air quality standards. By quantifying these avoidable impacts, policymakers can make the case for stricter pollution control measures, demonstrating that controlling emissions not only yields health benefits but also avoids significant economic losses tied to preventable health issues.

It's important to recognize that the monetized values themselves are also somewhat abstract. Policymakers must be aware that these numbers, while vital for decision-making, cannot fully represent the true value of health and life, making it important to approach cost-benefit analyses with a nuanced understanding of the limitations of monetization.

The Cost of Air Pollution report (IHME, 2013; WB-IHME, 2016) highlights two main methods for estimating the economic impact of air pollution. The Welfare-Based Approach calculates the broader societal loss from air pollution by using the Value of Statistical Life resulting in global welfare losses of \$5.11 trillion in 2013, particularly high in South Asia and East Asia. The Income-Based Approach focuses on the economic productivity loss by calculating the forgone labor output due to premature deaths from air pollution, estimating global losses of \$225 billion in 2013. **Hedley Environmental Index**

The Hedley Environmental Index (<u>https://hedleyindex.hku.hk/en</u>) was launched in 2008 by the University of Hong Kong's School of Public Health, led by Professor Anthony Hedley, who was known for his advocacy for environmental health.

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The Hedley Index is a pioneering effort, as no other country or city in the world is providing real-time estimates of the health and economic costs of air pollution in the same way.

The portal calculates and displays in real-time the number of avoidable premature deaths, hospital admissions, and economic losses caused by air pollution, by converting abstract air quality data into tangible, human-centered outcomes. By assigning a monetary value to these impacts, the index **helps the public and policymakers understand the personal and societal costs of polluted air** and provides a strong basis for justifying stricter air quality controls in Hong Kong.

Integrating real-time air quality data with epidemiological models, the Hedley Index continuously updates the health and economic impacts, making it an important educational tool for raising public awareness and supporting policy advocacy aimed at reducing emissions and protecting public health.

Excerpt from the Hedley Index website on how the economic losses are calculated every day.

We calculated the overall health-related community costs of air pollution using the amount of adverse health effects caused by air pollution which we have so far been able to measure in our population. These costs can be categorized as the direct costs of health care; the indirect costs due to lost productivity and the intangible costs attributable to pain and suffering (defined as "loss of healthy life value").

In our economic appraisal the direct health care costs due to the bad health outcomes attributable to air pollution include public and private hospital admissions (valued as bed days used), public out-patient consultations at general, specialist and accident and emergency clinics for cardiovascular and respiratory diseases (valued as cost of visits plus travel costs) and primary care doctor visits (valued as cost of visits plus travel).

Intangible losses for lives lost due to air pollution were based on the average value of a lost life in Hong Kong. This was estimated from population surveys of the willingness-topay to avoid the loss of one statistical life (HK\$10 million or US\$1.28 million). This is a conservative estimate, comparable to the range of US\$0.4 to \$9.7 million reported from Europe, Australia, New Zealand, US and Canada. To this we added the value of avoiding hospital admissions and coughing episodes which were over and above the costs of treatment. These values were also taken from local surveys of the willingness to pay to avoid bad outcomes.

4. What is the Value of Statistical Life?

The Value of Statistical Life (VSL) is an economic concept used to quantify the monetary value that individuals or society are willing to pay to reduce the risk of death by a small amount. It does not refer to the value of an individual's life, but rather to the collective willingness to pay for marginal reductions in mortality risk across a population. For instance, if many people each pay a small amount to slightly reduce their personal risk of dying, those contributions can be aggregated to estimate how much society values saving one statistical life

VSL is determined through WTP studies, where individuals are asked or observed in terms of how much they would spend to reduce their risk of death. These studies use either revealed preferences, such as observing wage differences for risky jobs, or stated preferences, where individuals are surveyed about their willingness to pay for hypothetical risk reductions (Cropper et al., 2023).

For example, suppose a group of 10,000 people is asked how much they would be willing to pay to reduce their individual risk of death by 1 in 10,000 over the next year. Each person states they are willing to pay \$100 for this risk reduction.

- Individual WTP: Each person is willing to pay \$100 to reduce their risk of death by 1 in 10,000.
- Group WTP: For a group of 10,000 people, the total amount they are willing to pay to reduce their collective risk by one statistical death (1 in 10,000 for 10,000 people) is: 10,000 × \$100 = \$1,000,000 dollars.
- VSL Calculation: The total WTP of \$1,000,000 represents the VSL for this group, as it is the amount they are collectively willing to pay to prevent one statistical death.
- If air pollution above the prescribed thresholds results in 58 deaths in the population, then the economic loss due to lives lost is estimated as \$58 million.
- If an emissions control intervention results in saving 40 lives, then the benefits are estimated as \$40 million, against the cost of the intervention.

Ultimately, VSL provides a way to attach a concrete economic value to the otherwise abstract benefits of life-saving policies and interventions, making it easier to prioritize actions that deliver the greatest health and societal benefits.

Factors influencing the WTP value during a survey

Several factors influence the WTP value (\$100 in the above example), which is often determined through a survey. The following factors affect how individuals perceive the value of reducing mortality risks and can vary widely based on personal, cultural, and situational contexts.

- Income level is one of the most significant factors guiding WTP for risk reductions, with higher-income individuals generally placing a greater value on reducing mortality risks due to their increased financial (savings) capacity. This is also reflected in the size of life and health insurance policies they purchase. Higher-income individuals tend to buy more comprehensive policies, reflecting their higher WTP for risk mitigation and financial security, while lower-income individuals often opt for smaller, more basic coverage due to financial limitations.
- 2. Risk perception and the type of risk are closely linked in influencing an individual's WTP for risk reduction. People's perception of the magnitude and immediacy of the risk—whether they see it as a direct and immediate threat, such as air pollution or traffic accidents—can significantly affect how much they are willing to pay to mitigate that risk. Individuals who perceive a higher personal risk or believe that a particular hazard poses a serious threat to their lives are likely to have a higher WTP. For example, often traffic accidents are perceived as a higher risk than air pollution and get a higher WTP value. Also, someone working in freight transport or heavy machinery operations may have a higher WTP for risk reduction due to the more dangerous nature of their job, compared to someone in a general office role or engaged in leisure travel. In essence, how personally relevant and severe individuals perceive a risk, combined with the occupational hazards they face, shapes their overall willingness to invest in reducing that risk. It's important to note that these are perceived values only and do not necessarily translate into actual investments.
- 3. **Health Status and age** are other key factors influencing WTP for risk reduction. Individuals in poor health or with pre-existing conditions often have a higher WTP, as they feel more vulnerable to mortality risks. Similarly, age plays a role, with younger individuals often willing to pay more for interventions that could extend their lifespan, while older individuals may have a lower WTP, though this can vary based on personal priorities and perceived risk. In LMICs, tracking of health status is less common compared to HICs, making it harder to quantify the impact of health on WTP. Additionally, health services in LMICs are often underdeveloped, with many individuals relying on self-support or out-of-pocket payments for medical care. This limited access to healthcare can further influence WTP, as individuals facing greater barriers to care may prioritize risk reduction less due to financial constraints or a lack of available services. Consequently, health status and age

intersect with socioeconomic conditions, shaping how people in different contexts value risk reductions.

- 4. **Cultural and societal norms** also shape how individuals and communities perceive life, risk, and safety. In some cultures, the focus is on collective wellbeing, prioritizing community-level risk reduction, which leads to a different WTP response. For example, in some LMICs, the practice of extended family is common, where multiple generations often live together and make collective decisions. With larger family sizes and a shared sense of responsibility, this can lead to lower individual WTP, as decisions are made with the entire family in mind, and the value of risk reduction may be spread across a larger group. The focus on the family unit often means that risk reductions benefiting the group are prioritized over personal safety measures.
- 5. Level of education—whether at the high school graduate, university graduate, postgraduate, or higher level—strongly affects an individual's knowledge and understanding of the risks they face (such as air pollution and climate change), making them more likely to assign a higher value to reducing mortality risks. More educated individuals tend to be better informed about health and safety issues (such as transportation), which increases their awareness of the potential consequences of inaction, leading to a higher WTP for risk mitigation. The level of education is often closely linked to the type of jobs and income levels individuals attain, which further influences their WTP. People with higher education typically secure higher-paying jobs that offer greater financial security and access to better insurance options (life or health) and out-of-pocket expenditures, which is reflected in their higher WTP.



Average annual salary in India in 2024, by education level (in million Indian rupees) Average annual salary in India 2024, by education level

15

6. **Proximity to risk source** also influences WTP value, as people living near pollution sources or working in high-risk occupations face more immediate threats. Individuals residing close to industrial areas, highways, or regional pollution hotspots are more exposed to pollution, making them more aware of the health risks and more willing to pay for mitigation measures. Similarly, those in high-risk jobs, such as mining or freight transport, have daily exposure to hazards, leading to a higher WTP for safety and health interventions. It's important to note that these are perceived values only and

do not necessarily translate into actual investments.

- 7. **Timeframe of risk** reductions is an important mental game. People tend to place a higher value on short-term improvements in safety or health, as the benefits are more immediate and tangible. In contrast, long-term risk reductions, whose benefits may be realized far in the future, often result in a lower WTP, as the perceived urgency and impact are less immediate. This is particularly true for air pollution, which often loses out to more urgent amenities like access to clean water, food, public transport, or immediate healthcare needs. As a result, people tend to give lower WTP value for air pollution against addressing immediate living needs.
- 8. **Taxation and healthcare systems** also influence the WTP value. People may respond differently based on whether they are asked to contribute through taxes, fees, or voluntary donations. For example, in Scandinavian countries, with universal healthcare systems, where the government provides extensive healthcare services funded through taxes, individuals tend to have a higher WTP for public health initiatives and air pollution reduction efforts. This is because people in these countries are accustomed to contributing through taxes for the collective good, and they trust that their contributions will lead to tangible improvements in public health and safety. In contrast, in countries where healthcare is privatized and is an individual's responsibility, WTP for public health improvements, such as reducing air pollution, may be lower. In such settings, individuals are more focused on personal, out-of-pocket health expenditures, and may be less inclined to support collective health initiatives through additional taxes or fees, which can, in turn, affect the overall WTP for environmental risks.
- 9. During the surveys, **framing of the questions** can greatly impact WTP responses. Positive framing, which emphasizes the benefits of risk reduction (e.g., improved health or longevity due to reduced air pollution), can lead to higher WTP values, as it encourages individuals to focus on the positive outcomes of taking action. On the other hand, negative framing, which highlights the dangers or consequences of not reducing risks (e.g., increased illness or premature death), may result in different WTP values, often driven by fear or a sense of urgency or a reaction to inaction.

History of VSL from the United States

This section is a summary from (Cropper et al., 2023) and their previous works on the same.

The most referred VSL value in studies across the world comes from the methods established for/by the US EPA. The EPA currently uses a VSL of approximately \$8.2 million in its cost-benefit analyses. This figure is adjusted for inflation and income growth over time, but the underlying studies are significantly older.

The EPA's VSL is based primarily on two types of studies: (a) Hedonic wage studies: These studies observe the wage premiums that workers in more dangerous jobs receive, to infer the trade-offs between wages and mortality risks. A large portion of the studies used by the EPA in determining VSL come from this method. (b) Stated preference studies: These surveys ask individuals how much they would be willing to pay for small reductions in mortality risk. This method captures hypothetical risk reduction values.

The report highlights that the EPA's current VSL estimate is outdated, as it is based on 26 estimates from 22 studies conducted between 1974 and 1991—17 of which are from hedonic wage studies and 5 from contingent valuation studies. The report notes that these studies predate the availability of better data and more refined econometric techniques used in more recent research. Many of these studies focus on accidental deaths in the workplace, which are not entirely relevant to the health risks (such as cancer and cardiovascular diseases associated with air pollution) that EPA regulations typically address. Also, about 74% of deaths averted by reducing particulate matter (PM_{2.5}) exposure occur in people 65 years and older (Vollset et al., 2024), a group that is not well-represented in hedonic wage studies. The report calls for a revision of the VSL estimate using more recent data and methods to better reflect the population and risks relevant to current regulations.

Extrapolation of VSL to global applications

Conducting WTP surveys and calculating the VSL for individual countries comes with several challenges.

Cultural and contextual differences, especially in LMICs, affect how people perceive mortality risks, making it hard to standardize WTP estimates. Many individuals prioritize immediate needs, complicating meaningful WTP assessments. Limited data availability, large informal sectors, and technical challenges in designing unbiased surveys add further complexity. Additionally, the high costs of large-scale surveys in diverse regions restrict the scope and representativeness of results. These factors often necessitate the use of proxy estimates or adjustments based on global or regional averages. The **benefit transfer method** is a technique used to estimate the VSL in countries where direct WTP studies have not been conducted. This method involves taking a base VSL from a well-researched context (often a high-income country, like the U.S.) and adjusting it to fit the socioeconomic conditions of another country. The adjustment is typically made based on factors such as income differences and an income elasticity factor.

For example, if the base VSL in the U.S. is \$8.2 million and the GDP per capita is \$85,000, the VSL in a LMIC with a GDP per capita of \$2,000 and using an income elasticity factor of 0.8 is \$400,000 – using the formula below.

$$VSL_{LMIC} = VSL_{HIC} * \left(\frac{GDP_{LMIC}}{GDP_{HIC}}\right)^{e} = 8.2 \ million * \left(\frac{2,000}{85,000}\right)^{0.8} = 400,000$$

The income elasticity factor typically ranges between 0.5 and 1. This means that as income increases by 1%, the WTP for reducing mortality risk generally increases by 0.5% to 1%. However, it is possible for the income elasticity to be greater than 1 in certain cases, which would indicate that WTP increases at a faster rate than income. When the elasticity is:

- Less than 1 (inelastic): WTP for risk reduction increases more slowly than income. This is common when people's basic needs take priority, meaning that even if income increases, their spending on risk reduction does not increase proportionally.
- Equal to 1 (unit elastic): WTP increases at the same rate as income. This implies a proportional relationship between income and the value people place on reducing mortality risk.
- Greater than 1 (elastic): WTP increases faster than income, which may occur in wealthier populations where individuals are more willing to allocate a larger share of their income to improving safety and health as they get richer.

Most studies assume an elasticity value close to 1 for HICs, while for LMICs, an elasticity value below 1 is often used to reflect differences in risk perception and financial priorities.

An example of global economic losses due to air pollution using VSL methodology. Table extracted from (WB-IHME, 2016)

TABLE 3.11Total Welfare Losses from Air Pollution in Low- andMiddle-Income Countries, Base Case VSL Estimates versus Using VSLfrom Middle-Income Country Studies: 2013

% GDP equivalent

Region	Base case	Using mean VSL from middle-income countries	Using median VSL from middle-income countries
East Asia and Pacific	8.7 (6.9–11.0)	6.3 (5.7–7.0)	9.0 (8.0–10.1)
Europe and Central Asia	5.6 (4.7–6.8)	4.1 (3.6–4.8)	5.8 (5.0–6.9)
Latin America and Caribbean	2.4 (2.0–2.9)	1.7 (1.5–2.0)	2.5 (2.1–2.9)
Middle East and North Africa	2.6 (2.1–3.3)	1.9 (1.7–2.2)	2.7 (2.4–3.1)
South Asia	7.4 (5.0–11.1)	5.4 (5.1–5.8)	7.6 (7.3–8.0)
Sub-Saharan Africa	3.7 (2.5–5.8)	2.7 (2.5–3.0)	3.9 (3.6–4.2)

Sources: World Bank and IHME.

Note: Range in parentheses indicates range of welfare losses estimated by assuming a range of income elasticity values from 1.0 to 1.4 for the transferred VSL; central estimates assume elasticity of 1.2. Only low- and middle-income countries are included. GDP = gross domestic product; VSL = value of statistical life.

	Country	VSL range	Cost of death (%		Country	VSL range	Cost of death (%
_		0.06.07	of GDP)	26			
	Afghanistan	0.06 - 0.3	0.4	26	Kazakhstan	0.9 - 4.8	1.0
2	Algeria	0.4 - 2.2	0.4	27	Kyrgyzstan	0.1 - 0.7	1.7
3	Argentina	1.2 - 6.1	2.3	28	Mexico	1 - 5.2	5.3
4	Bangladesh	2.2 - 1.1	0.3	29	Morocco	0.4 - 1.8	0.3
5	Belgium	5.2 - 26	9.7	30	Netherlands	5.8 - 29.2	4.0
6	Bolivia	0.4 - 1.9	4.7	31	Nigeria	0.2 - 1.1	0.1
7	Brazil	1-5	6.6	32	Pakistan	0.2 - 0.8	0.4
8	Canada	5.1 - 25.5	2.7	33	Panama	1.6 - 8.2	4.9
9	Chile	1.6 - 8.2	6.6	34	Peru	0.7 - 3.7	9.3
10	China	1.1 - 5.7	0.0	35	Philippines	0.4 - 2.1	0.4
11	Colombia	0.7 - 3.6	4.2	36	Poland	1.7 - 8.3	0.6
12	Dominican Republic	0.9 - 4.4	1.7	37	Portugal	2.5 - 12.7	1.9
13	Ecuador	0.7 - 3.3	4.1	38	Romania	1.4 - 6.9	2.0
14	Egypt	0.3 - 1.5	0.5	39	Russian Federation	1.2 - 6.2	1.3
15	France	4.7 - 23.3	5.2	40	Saudi Arabia	2.5 - 12.5	1.2
16	Germany	5.3 - 26.6	1.3	41	South Africa	0.7 - 3.3	2.7
17	Guatemala	0.5 - 2.5	1.8	42	Spain	3.3 - 16.7	7.0
18	Honduras	0.3 - 1.3	1.9	43	Sweden	6.1 - 30.6	6.7
19	India	0.2 - 1.2	0.5	44	Switzerland	9.4 - 46.9	2.3
20	Indonesia	0.4 - 2.2	0.3	45	Turkey	1.1 - 5.3	0.9
21	Iran	0.6 - 2.9	2.9	46	UK	4.7 - 23.3	6.8
22	Iraq	0.6 - 3.2	1.9	47	Ukraine	0.4 - 1.8	0.6
23	Ireland	6.8 - 34.1	3.1	48	USA	7.2 - 36.1	6.1
24	Italy	3.8 - 18.9	6.7	49	World	1.3 - 6.4	1.2
25	Japan	4.6 - 22.9	0.1				

Another example use of VSL for evaluating the health costs of COVID-19 deaths is illustrated in (Sweis, 2022) summarized in the extracted table below.

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The relationship between VSL and the cost of total deaths as a share of country's annual GDP is not a linear function, as illustrated in this plot (of the same data presented in the table).



5. India's Value of Statistical Life

Benefit transfer method

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We used the following function for two elasticity values (0.5 and 0.8) and calculated VSL's at the national and state level, using the corresponding GDP values. Reference HIC value is from the United States – US\$ 8.2 million for VSL and US\$ 86,600 for GDP per capita.

$$VSL_{LMIC} = VSL_{HIC} * \left(\frac{GDP_{LMIC}}{GDP_{HIC}}\right)^{e}$$

Per capita national income across India from financial year 2015 to 2022, with estimates until 2024 (in 1,000 Indian rupees)

Per capita national income in India FY 2015-2024







Change rate of per capita net national income at constant prices India FY 2013-2024

S. No.	State/Union	GDP (2023-24)	Projected	GDP per	VSL (e=0.5)	VSL (e=0.8)
	Territory	(INR in crores)	Рор	capita (USD)	(million USD)	(million USD)
1	Andhra Pradesh	1,439,674	53,156,000	3,303	1.6	0.6
2	Arunachal Pradesh	35,107	1,562,000	2,741	1.5	0.5
3	Assam	570,243	35,713,000	1,947	1.2	0.4
4	Bihar	854,429	126,756,000	822	0.8	0.2
5	Chhattisgarh	505,887	30,180,000	2,044	1.3	0.4
6	Goa	89,130	1,575,000	6,901	2.3	1.1
7	Gujarat	2,203,419	71,507,000	3,758	1.7	0.7
8	Haryana	1,095,535	30,209,000	4,423	1.9	0.8
9	Himachal Pradesh	207,430	7,468,000	3,387	1.6	0.6
10	Jharkhand	461,010	39,466,000	1,425	1.1	0.3
11	Karnataka	2,500,733	67,692,000	4,505	1.9	0.8
12	Kerala	1,146,109	35,776,000	3,907	1.7	0.7
13	Madhya Pradesh	1,363,327	86,579,000	1,920	1.2	0.4
14	Maharashtra	4,044,251	126,385,000	3,902	1.7	0.7
15	Manipur	40,243	3,223,000	1,523	1.1	0.3
16	Meghalaya	53,057	3,349,000	1,932	1.2	0.4
17	Mizoram	30,690	1,238,000	3,023	1.5	0.6
18	Nagaland	37,150	2,233,000	2,029	1.3	0.4
19	Odisha	853,524	46,276,000	2,249	1.3	0.4
20	Punjab	744,899	30,730,000	2,956	1.5	0.6
21	Rajasthan	1,528,385	81,025,000	2,300	1.3	0.5
22	Sikkim	48,937	689,000	8,662	2.6	1.3
23	Tamil Nadu	2,721,571	76,860,000	4,318	1.8	0.7
24	Telangana	1,501,981	38,090,000	4,809	1.9	0.8
25	Tripura	82,625	4,147,000	2,430	1.4	0.5
26	Uttar Pradesh	2,547,861	235,687,000	1,318	1.0	0.3
27	Uttarakhand	346,206	11,637,000	3,628	1.7	0.6
28	West Bengal	1,700,939	99,084,000	2,093	1.3	0.4
29	Andaman & Nicobar	11,669	403,000	3,531	1.7	0.6
30	Chandigarh	54,988	1,231,000	5,447	2.1	0.9
31	Delhi	1,107,746	21,359,000	6,325	2.2	1.0
32	Jammu & Kashmir	241,133	13,603,000	2,162	1.3	0.4
33	Puducherry	47,902	1,377,000	4,242	1.8	0.7

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Notes: unit conversion used 1 US\$ = 82 INR; State level GDP and projected population numbers are extracted from Ministry of Statistics and Program Implementation (MoSPI, Government of India).

State level GDP per capita numbers ranged US\$ 3,332 \pm 1,724 State level estimated VSL numbers ranged US\$ 1.6 \pm 0.4 million (@ e = 0.5) State level estimated VSL numbers ranged US\$ 0.6 \pm 0.2 million (@ e = 0.8)

Life insurance proxy method

Conducting a full-scale survey of a large population to determine WTP is the classical method for assigning a VSL, providing direct insights into how much individuals value mortality risk reductions. In the absence of such extensive surveys, a benefit transfer method can be used (as demonstrated in the last table), where VSL values from other countries are adjusted to the local setting. A useful local proxy can be life insurance policy values, where the insurance premiums reflect how individuals value financial protection against mortality risks and offer a measurable basis for calculating VSL in contexts with limited data. The following notes are based on annual reports from the Insurance Regulatory and Development Authority of India (IRDAI - https://irdai.gov.in), a statutory body responsible for protecting policyholders' interests and ensuring the regulated, systematic growth of the insurance industry in India.

According to the IRDAI annual report, the total business value of life insurance premiums in India grew significantly, from INR 314,300 crores in FY2012-13 to INR 782,500 crores in FY2022-23. The value of new premiums, paid annually, also rose from approximately INR 29,500 to INR 130,500 over the same period. For a typical office-going employee, annual life insurance premiums for an INR 1 crore policy range between INR 15,000 and INR 30,000. This suggests that the likely WTP for life insurance in 2012-13 was around INR 1 crore to INR 2 crores, which increased to approximately INR 4 crores to INR 8 crores in 2022-23, assuming consistent growth.

Converted to USD, this value in 2022-23 translates to approximately US\$ 0.5 to US\$ 1 million, a value closely aligned with VSL estimates derived from the benefit transfer method.

6. Cost of Air Pollution in India

The State of Global Air report for India highlights that air pollution is a major risk factor, contributing to nearly 2.09 million deaths in 2021, which amounts to about 18% of all deaths in the country (https://www.stateofglobalair.org/resources). Of this, 43% of the deaths due to air pollution are in children under 5 years of age. Outdoor PM₂₅ is the second-leading risk factor for mortality, while household air pollution (HAP) ranks as the top cause among pollution-related health impacts (50%). India's annual average PM₂₅ concentration far exceeds health guidelines, with most of the population exposed to levels well above the WHO's least stringent interim target of 35 μ g/m³ and the national standard of 40 μ g/m³.

The health impacts are severe, with 148 deaths per 100,000 people attributed to air pollution, surpassing the global average. Specifically, 39% of stroke deaths, 20% of diabetes deaths, 38% of ischemic heart disease deaths, 67% of chronic obstructive pulmonary disease (COPD) deaths, 31% of lung cancer deaths, 38% of lower respiratory infection deaths, and 33% of neonatal deaths, in India are linked to air pollution exposure.

A preliminary assessment of the 2.09 million lives lost as an economic cost at a conservative VSL value of US\$ 0.5 million is US\$ 1,045 billion (approximately 7% of the national PPP).

These estimates are not definitive and come with a wide range of uncertainties. Various factors contribute to this uncertainty, including the GDP values used in economic assessments, which can fluctuate based on economic conditions and data quality. The IER curves applied to estimate health impacts also introduce variability, as they rely on general models that may not fully capture regionspecific health and pollution data. Exposure rates are derived from global chemical transport models, which estimate pollutant levels but may lack precision in areas with limited ground monitoring. The methods used to calculate the VSL further add uncertainty, as they often involve adapting values from other countries or contexts and rely on assumptions about income elasticity and willingness to pay. Collectively, these factors mean that while the estimates provide valuable insights, they should be interpreted with an understanding of their inherent uncertainties.

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