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Research article

Econometric model derived from meta-analysis to estimate VSL and VOLY associated to air pollution at a global level

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1. Introduction

Air pollution is a key determinant of health. Numerous studies have identified an association between air pollution and negative health effects in the general population (Burnett et al., 2018; Juginović et al., 2021; WHO, 2024a). These negative consequences range in severity from minor subclinical effects to premature death (WHO, 2016). Exposure to air pollution is now the second-largest risk factor of deaths worldwide, accounting for 8.1 million deaths in 2021 (Health Effects Institute, 2024). The major cost within the air pollution control context is the impact on human health (Alberini and Scasny, 2011; Lindhjem et al., 2011). Premature deaths due to exposure to both ambient and household air pollution cost the global economy approximately USD 5.11 trillion in welfare losses (World Bank and IHME, 2016). Although assigning a monetary value to human life may be controversial from an ethical standpoint (OECD, 2012), it provides crucial information for public interventions aimed at reducing premature deaths linked to air pollution.

The Value of a Statistical Life (VSL) and the Value of a Life Year (VOLY) are important metrics in this domain as they quantify the economic value of human life. They represent what individuals are willing to pay for a death risk reduction or an increase in their life expectancy (Viscusi and Aldy, 2003). Specifically, the VSL is an economic parameter that reflects individuals' willingness to trade wealth for a lower risk of mortality. It captures society's collective willingness to pay (WTP) for a marginal reduction in the risk of premature death (Miller, 2000). VSL is derived from aggregating individuals' WTP, typically assessed through surveys, to secure this reduced risk (OECD, 2016). The VOLY refers to the monetized value of a one-year increase in life expectancy. Unlike the VSL, which quantifies the value of reducing the risk of premature death, VOLY provides an economic assessment of life years lost due to early mortality (Lattarulo and Plechero, 2005).

VSL and VOLY values referring to different causes of death can vary significantly (Hammitt, 2006). In fact, these metrics provide policymakers with a quantitative framework to assess the costs and benefits of proposed interventions across various policy fields, including healthcare, transportation, environment, and occupational safety. Air pollution-related valuations take into account a range of contextual factors, such as pollutant type, exposure duration, and demographic characteristics of affected populations, providing a more suitable estimate. It is important, therefore, to focus on a context-specific VSL and VOLY quantification: in this study, VSL represents the value of preventing a premature death caused by exposure to air pollution, while VOLY refers to the change in life expectancy associated with air pollution.

However, establishing reliable VSL and VOLY estimates is challenging due to variations in the methods used across different studies and even within countries. Furthermore, many countries have insufficient and unreliable estimates of VSL and VOLY due to limited data collection on health and air pollution, as well as a lack of studies specific to those regions. The absence of country-specific data and a common methodology makes it difficult to assess climate policy on a global scale. This paper seeks to address this gap by conducting a comprehensive meta-analysis of existing literature, with the aim of developing an econometric model to estimate air pollution-related VSL and VOLY at a country level worldwide. This approach is intended for the estimation of health costs due to air pollution, even in countries where VSL and VOLY studies have not been conducted. Unlike other VSL/VOLY meta-analyses in the literature, this study exclusively focuses on the willingness to pay for reductions in all-cause mortality associated with air pollution.

The remainder of this paper is organized as follows: Section 2 details the development of the database, including the systematic literature

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review process, the inclusion criteria, and the variables used in the meta-analysis. Section 3 outlines the model specification and the statistical methods employed for the analysis. Section 4 presents the database used for the meta-analysis, along with the results and a discussion. Section 5 introduces a method for converting VSL into VOLY values as an alternative parameter for quantifying the health costs of air pollution. Section 6 concludes the paper.

2. VSL and VOLY database development

2.1. Literature search and inclusion criteria

The final database used for the meta-analysis includes monetary assessments of VSL/VOLY, sourced from an extensive and systematic literature review. To avoid any form of bias, the literature review was conducted simultaneously by two researchers. This review was divided into two parts. The first part focused exclusively on peer-reviewed academic papers to ensure the quality of primary valuation studies. The second part reviewed technical reports published by globally recognized authoritative agencies and organizations, aiming to achieve broader global coverage and enhance the review's comprehensiveness.

Peer-reviewed literature was searched using publicly accessible search engines, such as Web of Science (www.webofscience.com), Scopus (www.scopus.com), and PubMed (https://pubmed.ncbi.nlm.nih.gov). The initial phase involved searching for relevant studies published in English up to June 2023. The search strings used were:

(({VSL} OR "Value of Statistical Life") OR ({VOLY} OR "Value of Life Year") AND "air pollution") OR (({VSL} OR "Value of Statistical Life") OR ({VOLY} OR "Value of Life Year") AND ({WTP} OR "Willingness to pay"))

A flowchart diagram summarising the studies selection process is shown in Fig. 1(a). After excluding duplicates, and papers not published in English, 621 peer-reviewed publications remained. The first two steps involved scanning titles and keywords (inclusion criterion 1) and the papers' abstracts (inclusion criterion 2). Afterwards, the full-text documents were downloaded for an in-depth evaluation (inclusion criterion 3). Unlike other meta-analyses found in the literature, this study exclusively considers VSL and VOLY estimates related to air pollution: all papers containing other types of VSL and VOLY estimates were excluded. Furthermore, only studies providing a monetary estimation of VSL and VOLY were retained (inclusion criterion 4). The final criterion was to include only country-level VSL and VOLY estimates, excluding those at the city level (inclusion criterion 5). The final number of peer-reviewed papers in the database is 23.

The selection process regarding technical reports is summarised in Fig. 1(b). Estimates of VSL and VOLY related to air pollution in technical reports were identified through Google searches and on the websites and platforms of authoritative agencies and bodies (e.g., DEFRA, European Commission, OECD, US EPA, WHO, World Bank). Additionally, cross-references from primary peer-reviewed articles were checked. Conference abstracts, newspaper articles and dissertations were excluded. Validity of the source was the initial selection criterion (inclusion criterion 1). This thorough search yielded 24 reports, which were further filtered based on the publication date to include only the most recent reports from each agency/body (inclusion criterion 2). Reports not published in English or lacking VSL/VOLY estimates were excluded. The final number of technical reports in the database is 11. This final selection includes outcomes from CLIMAQ-H (Climate Change Mitigation, Air Quality and Health), a tool developed by WHO/Europe for quantifying the health impacts of air pollution (WHO, 2023). As for the peer-reviewed papers, only reports with country-level VSL and VOLY estimates are included in the final database.

After the comprehensive review and application of inclusion criteria, 34 publications were selected, yielding 504 value entries: 61 from peer-reviewed papers and 443 from technical reports. Among these, 10 entries exclusively estimate VOLY, all derived from two peer-reviewed papers. Other two papers provide estimates for both VSL and VOLY, namely Desaigues et al. (2007) for France and Orru et al. (2009) for Estonia. Given that VOLY estimates represent only about 2% of the total entries, they are excluded from the regression analysis, which focuses solely on VSL entries from 32 publications. Instead, VOLY values for each country are derived computationally based on VSL values (see Section 5). The practice of computing VOLY from VSL values in the air pollution context is supported by the literature (OECD, 2010; Hurley et al., 2005). Thus, the final database includes 494 value entries from 32 publications, with 51 entries from peer-reviewed papers and 443 from technical reports. Multiple VSL observations for the same country or from the same study are kept if they correspond to different years,

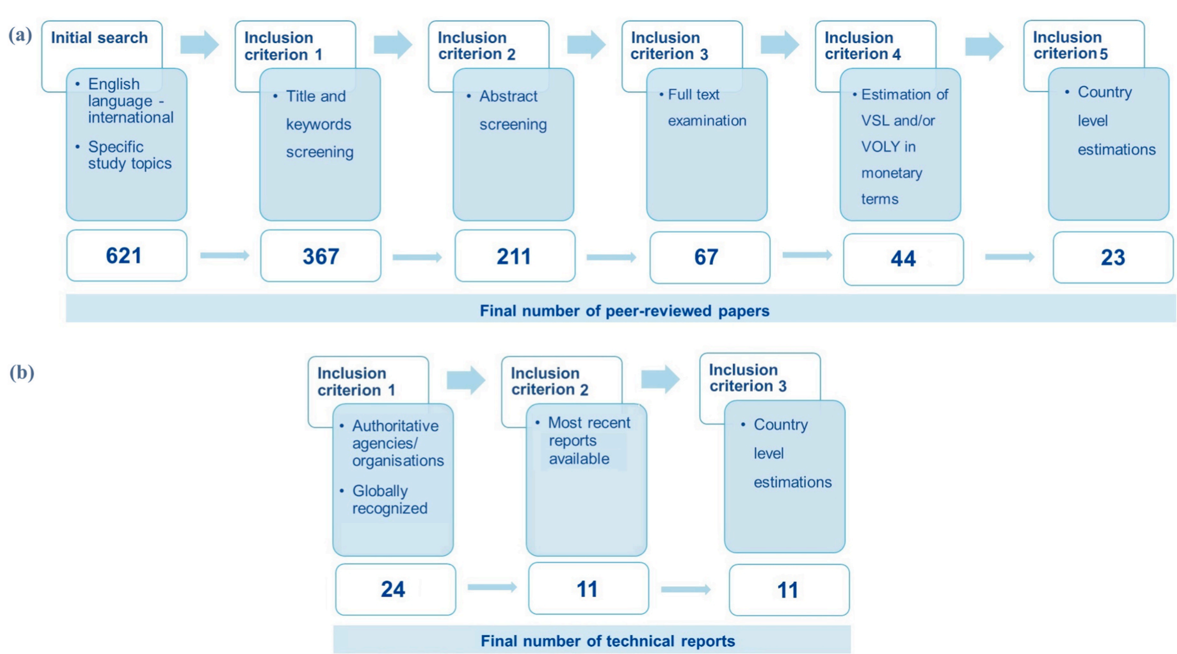

Fig. 1. Systematic literature review flowchart for the selection of peer-reviewed papers (a) and technical reports (b).

methodologies employed or WTP elicitation formats. Refer to Appendix A for the complete list of selected studies and technical reports.

2.2. Variables used in the meta-analysis

In this meta-analysis, the dependent variable is the monetary value of the Value of a Statistical Life (VSL). When studies report both maximum and minimum VSL values, the average of these values is considered.

To compare costs and cost-effectiveness data across various countries and years, adjustments for inflation are necessary to account for changes in currency value. These adjustments are essential for systematic literature reviews, allowing for meaningful comparisons of economic evaluations conducted at different times and in different countries (Kumaranayake, 2000). To standardize the dependent variable across studies, it was converted to 2019 International Dollars (I$). International dollars are preferred over US dollars for cross-country comparisons, as they adjust for variations in location rather than in time (Turner et al., 2019).

Therefore, the dependent variable was first converted to the local currency of the respective country for the year of the analysis (if not already presented in local currency). Subsequently, costs were adjusted for inflation using the country's consumer price index (CPI). Then, conversion to 2019 international dollars was achieved using the purchasing power parity (PPP) exchange rates, which are relatively stable over time, offering an additional advantage of using international dollars (Turner et al., 2019). Both CPI and PPP values were taken from the International Monetary Fund World Economic Outlook Database (April 2023 Edition, accessible at: http://www.imf.org/external/ns/cs.aspx?id=28).

The explanatory variables used in the initial model encompass various categories: economic, socio-economic, health, and environmental variables. These variables, along with their codes (used hereafter in the text), their units of measurement and sources, are detailed in Table 1.

3. Statistical methods

The comprehensive review of articles and reports revisits established methodologies for quantifying air pollution-related all-cause mortality, resulting in a wide-ranging database of empirical data on VSL. Using this updated database, an econometric model was developed, considering each country's distinct characteristics.

3.1. Model specification of the meta-regression

The methodological approach adopted for this meta-analysis is an ordinary least square multiple linear regression model. All the statistical tests and analysis were conducted using R software (version 2023.12.1 + 402). Data exploration was conducted following the protocol described by Zuur et al. (2010) prior to performing the multiple linear regression analysis. Missing values, which constitute less than 5% of the total observations, were excluded from the final database. The presence of outliers was investigated using the Interquartile Range (IQR) method, where all points falling outside the interval [Q1 − 1.5 IQR; Q3 + 1.5 IQR] were classified as potential outliers and, as such, excluded (Hubert and Vandervieren, 2008; Schwertman et al., 2004).

The initial model is structured as follows:

$$VSL_{ij} = \alpha + \beta^{E}X^{E}_{ij} + \beta^{SE}X^{SE}_{ij} + \beta^{D}X^{D}_{ij} + \beta^{H}X^{H}_{ij} + \beta^{ENV}X^{ENV}_{ij} + \varepsilon_{ij} \tag{1}$$

Where the dependent variable $\boldsymbol{VSL_{ij}}$ represents the mean Value of Statistical Life expressed in 2019 PPP International Dollars (I$). The subscript $\boldsymbol{i}$ takes values from 1 to the number of studies (N = 32), while the subscript $\boldsymbol{j}$ denotes the observation level, ranging from 1 to 494 as the total number of observations is N = 494.

The variables used in the model are grouped into matrices based on economic, socio-economic, demographic, health, and environmental characteristics (refer to Table 1). The vector $\boldsymbol{X^E}$ includes economic characteristics, namely GDP, GNI and CPI. Additionally, a categorical variable representing income categories is included to capture differences in income elasticities among countries. This variable is included to examine how the WTP for reducing the risk of premature mortality

Table 1
Explanatory variables used for developing the econometric model and their corresponding coding, categories, units of measurement and sources.

Variable	Code	Category	Units	Source
Gross Domestic Product per capita (*)	GDP	economic	PPP (current I$)	International Monetary Fund, 2023
Gross National Income per capita (*)	GNI	economic	PPP (current I$)	World Bank, 2024a
Consumer Price Index (*)	CPI	economic	points	International Monetary Fund, 2023
Income category (*)	income_LM-L income_HM-H	economic	categorical variable	World Bank, 2024b
Unemployment rate	unemp	socio-economic	% of total labor force	ILOSTAT, 2024
GINI Index	GINI	socio-economic	0–1	World Bank, 2024c
Mean years of schooling	school	socio-economic	years	UN Development Programme, 2022
Human Development Index	HDI	socio-economic	0–1	UN Development Programme, 2022
Life expectancy	LE	demographic	years	UN Development Programme, 2022
Population	pop	demographic	millions	International Monetary Fund, 2023
Population density	pop_den	demographic	persons per km^2	United Nations and Department of Economic and Social Affairs Population Division, 2022
Urban population	pop_urb	demographic	% of total population	United Nations and Department of Economic and Social Affairs Population Division, 2018
Number of doctors per capita	doctors	health	n./10,000 people	WHO, 2024b
Current health expenditure	exp_GDP	health	% of GDP	WHO, 2024c
Current health expenditure per capita(*)	exp_capita	health	PPP (US$)	WHO, 2024c
$PM_{2.5}$ concentrations	$PM_{2.5}$	environment	ug/m^3	See Appendix B
O_3 concentrations	O_3	environment	ug/m^3	See Appendix B
NO_2 concentrations	NO_2	environment	ug/m^3	See Appendix B

Notes: The variables marked with (*) were collected for 2019, the baseline year. All other variables were collected for the respective year in which the VSL was estimated.

varies with different income levels across countries. These categories are grouped into two based on the World Bank's GNI per capita classification: income_LM-L, which combines lower-middle-income and low-income countries, and income_UM-H, which includes upper-middle-income and high-income countries. Socio-economic variables, such as unemployment rate, GINI index, mean years of schooling, life expectancy and HDI index, are contained in vector $\boldsymbol{X}^{SE}$. The vector $\boldsymbol{X}^{D}$ refers to demographic characteristics, such as population, population density, and urban population. The vector $\boldsymbol{X}^{H}$ contains health variables, such as the number of doctors per capita and current health expenditure (both as a percentage of GDP and per capita). Finally, $\boldsymbol{X}^{ENV}$ includes environmental variables, namely the concentrations of $PM_{2.5}$, O_3, and NO_2. The error term, represented by $\boldsymbol{\varepsilon}_j$, is the residual for the *j*-th observation.

3.2. Multiple linear regression assumptions

The linear relationship between each predictor variable and the response variable was evaluated using the Pearson correlation coefficients and illustrated with scatterplots. For predictor variables that do not exhibit a linear relationship with the response variable, nonlinear transformations—such as logarithmic, square root, and cubic root transformations—were applied. Unemployment rate, population density, $PM_{2.5}$, O_3, and CPI were excluded from the analysis because after transformation no linear relationship with the response variable was observed (CPI example is illustrated in Fig. S1).

To verify homoskedasticity, residuals were plotted against fitted values to ensure constant variance, with residuals showing consistent dispersion around zero (Zuur, 2012). This assumption holds for the model employed in our analysis, as illustrated in Fig. S2.

Multicollinearity was assessed by calculating the variance inflation factor (VIF) for each predictor variable to ensure that predictor variables were not highly correlated. A VIF >10 was considered indicative of multicollinearity (O'brien, 2007). Unsurprisingly, GDP, GNI, school, LE and HDI were correlated, since HDI is composed of life expectancy, education (mean years of schooling) and GNI indices (UNDP, 2022). As a result, these three variables were excluded from the analysis. There was a positive correlation between HDI and GDP (Ulas and Keskin, 2017), with a mutually influential relationship between them (Elistia and Syahzuni, 2018). Table S1 presents the VIF values for each explanatory variable initially selected. Further VIF analysis confirmed this interdependence, leading to the exclusion of one of these variables from the model. HDI was excluded and GDP was retained for two reasons: studies on VSL values typically account for GDP, and the model showed a higher adjusted R-squared with this variable.

The Durbin-Watson test was used to check for autocorrelation in the residuals (and thus the variables), and the results indicated a violation of the independence assumption. The normality assumption was also violated (see Fig. S3). The Kolmogorov-Smirnov test confirmed this with a very low p-value, rejecting the null hypothesis of normality.

To overcome the non-compliance of the multiple linear regressions assumptions and the outliers leverage effect, a robust regression was employed (R package Robustbase). This regression technique, designed to withstand heavy-tailed errors and outliers, assigns lower weights to less reliable data, thereby minimizing the influence of outliers (Bellavance et al., 2009; Lambert-Lacroix and Zwald, 2011). About 5% of the observations were identified as outliers, with weights having absolute values less than or equal to 4.6 e^{-07}. This indicates that these observations had negligible influence on the regression model due to their very low weights.

The meta-analysis was conducted using a robust meta-regression technique with a backward selection process. The resulting model is:

$$VSL_{ij} = \alpha + \beta\, GDP_{ij} + \beta\, GINI_{ij} + \beta\, pop_{ij} + \beta\, doctors_{ij} + \varepsilon_{ij} \tag{2}$$

4. Results and discussion

The final database includes observations from publications estimating VSL values from 1999 to 2020. These years were selected as reference for currency conversion and inflation adjustments. It is important to note that these reference years do not necessarily align with the coverage period of the studies, which is the actual timeframe during which the research was conducted. For survey-based studies, the coverage period refers to the years in which interviews were conducted, while for other types of studies, it pertains to the period during which pollutant concentrations were measured.

Table 2 shows the number of countries covered in each continent and the total number of VSL estimates associated to them. An extensive list of all covered countries is provided in Appendix C, resulting in a database that covers 186 countries, represented in Fig. 2.

Table 3 presents the mean VSL values in 2019 PPP I$ by continent. Africa presents the lowest mean VSL value (737,670 I$), whereas Europe holds the highest (3,489,625 I$). The variation in VSL values across continents may reflect differences in economic conditions, public health investments and cost of living.

Following the removal of outliers through robust regression techniques, the VSL in the database ranges between a minimum of 17,715 PPP I$ (2019) for Nigeria and a maximum of 10,273,480 PPP I$ (2019) for Luxembourg. The median is 1,239,917 PPP I$, with a mean of 1,797,465 PPP I$ (standard deviation of 1,697,635), suggesting a right-skewed distribution.

The final model is outlined in Eq. (3):

$$\begin{aligned} VSL_{ij} = {} & \alpha + \beta\, GDP_{ij} + \beta\, GINI_{ij} + \beta \log\left(pop_{ij}\right) + \beta\, doctors_{ij} \\ & + \beta\, GDP_{ij}\ \ income_{ij} + \varepsilon_{ij} \end{aligned} \tag{3}$$

The model includes GDP, as an indicator of economic growth and the GINI index, as a measure of economic inequality. It also incorporates the logarithm of the country population to ensure a balanced comparison across countries. Additionally, the model includes the number of doctors per capita (every 10,000 people). Starting from the model in Eq. (2), the interaction between GDP and income category is introduced, as it captures the different behaviors of countries based on their income level regarding their WTP for reducing the risk of premature death. This concept is equivalent to income elasticity (Narain and Sall, 2016).

As a robustness check, the potential impact of a year effect on the outcome was examined. The results confirmed the presence of a negligible year effect that was not included in the final model. The final model resulting from the meta-analysis is presented in Table 4.

The outcome of the meta-analysis reveals a positive correlation between the dependent variable, VSL, and GDP. This indicates that individuals in countries with higher economic growth assign a greater value to preventing premature mortality due to air pollution, reflecting a higher willingness to pay for safety improvements. Miller's research highlights the use of per capita GDP as a measure of income to explain variations in VSL (Miller, 2000; in Mrozek and Taylor, 2002). Consequently, VSL tends to increase with higher income levels (Hammitt, 2000; Viscusi and Aldy, 2003). This positive relationship may be attributable to the fact that safety is considered a normal good (Viscusi,

Table 2
Number of countries included in the database and total number of VSL estimates, by continent.

Continent	Countries	VSL Estimates
Africa	52	199
Asia	44	105
Europa	42	131
Oceania	14	16
North America	23	30
South America	11	13
Total	**186**	**494**

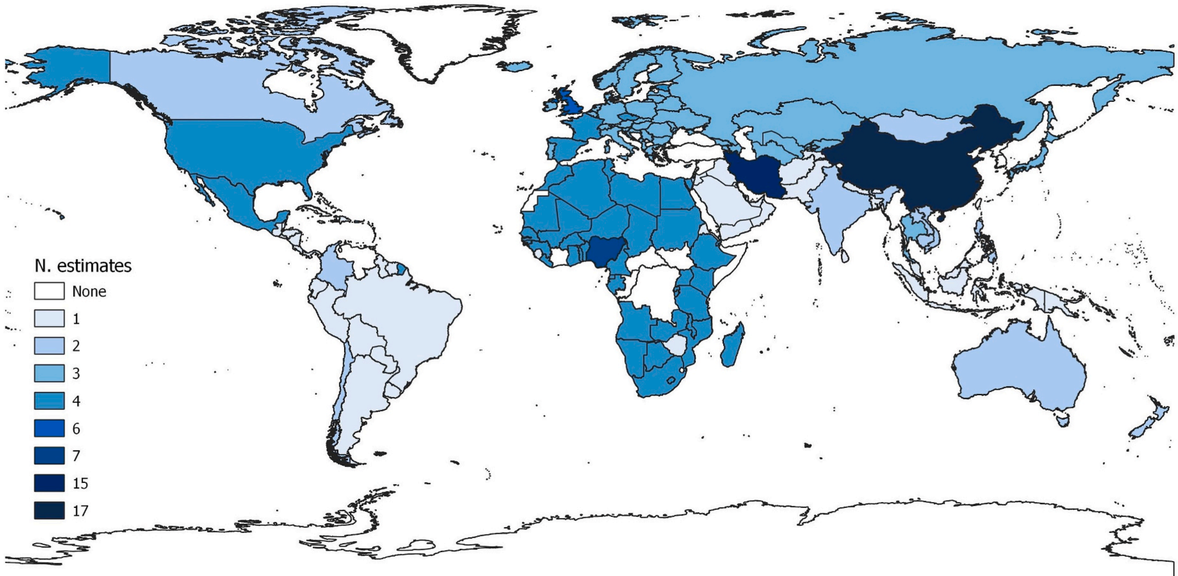

Fig. 2. Countries included in the database. Different colours correspond to the number of VSL estimates collected for each country.

Table 3
Mean VSL (in 2019 PPP I$) values by continent.

Continent	Mean VSL (I$)
Africa	737,670
Asia	1,552,518
Europa	3,489,625
Oceania	2,168,234
North America	2,362,474
South America	1,775,335
Total	**186**

Table 4
Final model. It is the result of a backward selection through a robust regression linear model. ***, **, *, stands for statistical significance at the 0%, 0.1% and 1% level, respectively.

	Final model		
	Coeff.	Std. err	
(Intercept)	361,098.65	231,845.70	
GDP	101.23	7.08	***
GINI	702,603.13	292,758.39	*
pop	− 37,632.67	10,871.18	***
doctors	8,145.65	1,882.33	***
GDP: income (UM-H)	−18.30	6.53	**
Multiple R^2	0.9528		
Adjusted R^2	0.9523		
Robust res. Std. err	324,300		

Notes: The coefficients are rounded to the second decimal figure; "pop" refers to the natural logarithm of the "population" variable.

1978; in Viscusi and Aldy, 2003). As countries experience economic growth and per capita income rises, individuals have more resources to invest in safety measures and risk reduction. Thus, in wealthier nations with greater disposable income, the perceived value of reducing risks due to air pollution also increases.

The higher GDP coefficient (101.23) in low- and lower-middle-income countries shows that VSL grows proportionally or more quickly when income increases in this category of countries compared to those with middle to high-income, reflecting that even a small GDP rise leads to relatively large increases in WTP for risk reductions. While GDP rises, people in low-income countries place greater value on health and safety due to pressing survival concerns and lack of social safety nets (Robinson and Hammitt, 2009; Cropper and Sahin, 2009). In this context—where health risks are higher, and social protections are weaker—the income elasticity of WTP is heightened compared to wealthier countries. Conversely, in upper-middle- and high-income countries, a lower GDP coefficient (82.93) suggests that as GDP grows, VSL rises at a slower rate, indicating a diminishing marginal utility of health and safety investments (OECD, 2016; WHO Regional Office for Europe, OECD, 2015). This trend reflects literature findings that WTP for risk reduction rises more sharply with income growth in low-income countries (Hammitt and Robinson, 2011; Narain and Sall, 2016). Consequently, GDP changes have a more pronounced effect on VSL in lower-income regions.

Moreover, the results indicate a positive relationship between VSL and the GINI coefficient, a measure of income inequality where 0 represents perfect equality and 1 maximum inequality, suggesting that as income inequality increases, the VSL tends to rise. The logarithm of country population shows a negative relationship with VSL, therefore every 1% increase in population, VSL decreases by approximately 376 I$. This slight decrease in VSL may suggest that in countries with larger populations, the average VSL tends to be lower. One potential reason for this relationship is that more populous countries often experience relatively lower GDP per capita (Lianos et al., 2023). Consequently, lower average income levels in these countries can contribute to a reduced average VSL. In contrast, the number of doctors per capita presents a positive relationship with VSL. This indicates that better health conditions contribute to a greater willingness to pay for preventing mortality. This relationship reinforces the notion that as health infrastructure improves and more resources are available, individuals are more inclined to invest in measures that reduce mortality risks.

Including results from different studies for each country in the VSL database implies that VSL variations may occur even within the same countries. This is attributed to the methodological choices each study's authors made, either in the data collection or in data elaboration. These studies may suffer from issues such as sample bias and variations in the choice of the risk variable, as discussed by Bellavance et al. (2009). These varying choices can significantly influence the results and likely account for the wide variability in the published VSLs. Additionally, the results presented in this study are influenced by the choices made by the authors regarding the selection of explanatory variables. A sensitivity analysis was performed to assess the model's uncertainty, using SIMLAB software (Joint Research Centre). Moment-independent sensitivity indices were applied, using both the probability density function method (Plischke et al., 2013) and the cumulative density function method (Pianosi and Wagener, 2015). Since the model variables are correlated, the analysis shows that all variables, with the exception of population, contribute to its uncertainty. GDP stands out as the first one in the variables rank, followed by income and the number of doctors. GINI also affects the uncertainty, though to a lesser extent. Although the parameters that most influence the output distribution are not always those that most impact the variance (Borgonovo, 2007), in this case, their relevance aligns. The variance-based BSPCE method (Shao et al., 2017) reveals that GDP alone accounts for about 37% of the model's uncertainty, while interactions between GDP and the other variables explain 57%.

Moreover, a crucial methodological issue in the meta-analysis literature is the non-independence of estimates across primary studies. This arises because individual studies often yield multiple values, leading to potential within-study correlation among observations (Nelson and Kennedy, 2009). Furthermore, the primary studies may also influence each other, indicating the presence of between-study autocorrelation. In fact, meta-data often include a hierarchical structure, which means that observations can be clustered or nested at some level, such as the study level (i) in this case. For the sake of robustness check, a mixed-model that accounts for this correlation among the same studies was used. The results of the mixed-model are outlined in Appendix D. Although some significancy is lost in the population and income variables, the output confirms the results of the robust model presented in Table 4.

Studies have consistently shown a positive relationship between VSL and GDP, even in contexts unrelated to air pollution, such as cancer risk, accident risk, and wage-risk (OECD, 2010; Milligan et al., 2014; Miller, 2000). However, in the air pollution context, there is no prior evidence in the literature regarding the relationship between VSL and the other variables included in this model which are essential to better grasp the variability between countries. This work is innovative in that it explores how factors beyond GDP can explain variations in VSL, providing new insights into the determinants of VSL values.

5. Deriving VOLY from VSL

Air pollution does not directly cause death but worsens pre-existing conditions, resulting in a reduction in life expectancy and a higher risk of premature death. In cases involving small reductions in life expectancy, such as chronic exposure to air pollution, VOLY is often preferred over VSL (Martinez et al., 2018). This measure is particularly valuable for assessing public health interventions and quantifying the economic impact of mortality linked to air pollution (Bickel et al., 2005). The VOLY is to be applied in combination with the estimation of years of life lost (YLL). The advantage of this approach compared with VSL is that it considers the age of the subject at death giving more emphasis to younger subjects.

Given the limited number of studies directly reporting VOLY estimates in the air pollution context— in this study's final database representing only about 2% of the total entries (12 out of 504)—it is considered more appropriate to estimate VOLY from VSL values. This approach is well-supported by the literature, both within the air pollution context (Andersen, 2017; OECD, 2010; Hurley et al., 2005; Lattarulo and Plechero, 2005) and in other fields (Abelson, 2003; Ananthapavan et al., 2021). In this study, VOLY values were computed using the following formula (Ananthapavan et al., 2021):

$$VOLY = \frac{VSL}{\left(\frac{1-(1+r)^{-n}}{r}\right)} \tag{4}$$

The discount period n was determined by subtracting the median age of a country's population in the collection year from the corresponding life expectancy for that country in the same year. Country's specific median age was downloaded from the MNCAH Data Portal (WHO, 2024d). Given the diverse methodologies employed in deriving VSL across different studies, along with the necessity to account for respondents' perceptions of payment timing (Desaigues et al., 2011), the selection of an appropriate discount rate r is not straightforward. For this reason, VOLY estimates were calculated using three different discount rates: 3%, 7%, and 10%.

The result shows VOLY values consistent with the literature (Abelson P., 2008; US EPA (2003) in Hurley et al., 2005). At a 3% discount rate, on average VSL values are about 23 times higher than VOLY. This ratio is approximately 13 times higher with a 7% discount rate and about 10 times higher with a 10% discount rate. The discount rate used for the final VOLY database construction is 3% because these results are aligned with existing literature in the air pollution context. Belis et al. (2023), using this same discount rate, report VSL values that are 23 times greater than VOLY values for both Czechia and OECD countries. Similarly, VSL values are found to be approximately 20 times greater than VOLY in France (Desaigues et al., 2007) and about 26 times greater in Estonia (Orru et al., 2009). Moreover, a city-level study conducted for Skopje reports a VSL value approximately 25 times higher than the corresponding VOLY (Martinez et al., 2018). Additionally, the European Commission's NewExt study (Friedrich et al., 2004), which analyses different risk scenarios across three countries (UK, Italy, and France), shows that VSL values are, on average, 20 times greater than VOLY.

The approach adopted in the present study led to a worldwide database with 494 country-specific VOLY values derived from VSL estimates. However, this approach is widely debated in the literature because estimating VOLY from VSL is not straightforward; the risks valued in the solicitation of VOLY and VSL differ, contributing to significant uncertainty in the VOLY estimates. Consequently, the monetary valuation carries a high degree of uncertainty (Leksell and Rabl, 2001; Hein et al., 2016). Another challenge with VOLY is the variability in estimates, depending on the methods used (Ananthapavan et al., 2021), particularly regarding the selection of discount rates and discount periods.

6. Conclusion

The methodology adopted in this study is fit for the purpose of developing a comprehensive worldwide database, including 494 country-specific VSL estimates related to air pollution from 186 countries. These estimates were used to develop an econometric model that accounts not only for economic variability across countries, represented by GDP, but also for other key country specific socio-economic, demographic and healthcare factors. Specifically, the model incorporates the GINI index and income categories, based on the World Bank GNI per capita classification, to capture income inequality. It also includes population size as a demographic factor, and the number of doctors per 10,000 people as a proxy for healthcare access. This approach enables the estimation of health costs associated with air pollution, with country detail, at a global level, even in countries without available or up-to-date VSL estimates.

The literature review conducted in this work builds up on prior reviews and meta-analyses (Jaafar et al., 2018; Hein et al., 2016; OECD, 2012). However, unlike previous studies, this model focuses exclusively on air pollution-related VSL estimates and accounts for country-specific differences beyond GDP alone. While GDP remains a key factor, the model shows that other variables also play a role in shaping VSL. Specifically, individuals in countries with higher economic growth (GDP) place a greater value on preventing premature mortality due to air pollution, reflecting a higher willingness to pay for safety improvements. As economies grow and per capita income rises, individuals in wealthier nations are more likely to invest in risk reduction and safety measures, resulting in a higher perceived value of reducing air pollution risks. However, the income elasticity, incorporated in the model through the classification of countries into different income categories, indicates that GDP has a greater impact on VSL in lower-middle-income and low-income countries than in upper-middle-income and high-income countries. The model also highlights the role of income inequality, revealing a positive correlation between the GINI coefficient and VSL: as income inequality increases, the VSL tends to rise. Furthermore, the analysis reveals that countries with larger populations tend to have a lower average VSL, likely due to their often lower GDP per capita. Lastly, better access to healthcare increases the willingness to pay for mortality risk reduction, emphasizing that improved health conditions lead to a higher value placed on preventing air pollution-related deaths.

Additionally, a VOLY database was developed specifically for the context of air pollution. All estimates in this database have been derived from VSL estimates to address the limited number of direct VOLY studies. The resulting database comprising 494 VOLY values (with a discount rate of 3%), represents a valuable alternative tool for assessing health costs associated with air pollution while considering each country's median population age and life expectancy.

While the model presented in this paper does not directly calculate the health impacts of air pollution, it provides unitary costs at the country level, based on the input variables that are available at this scale. Our model was designed with an international scope, aiming to be applicable to as many countries as possible. An upcoming study will apply this model to quantify the economic costs of air pollution-related mortality, accounting for variations in pollution exposure across the countries analysed, thereby demonstrating its practical application. However, the model can also be downscaled to specific regional or local contexts, provided that data at this level of detail is available.

The VSL/VOLY databases and the econometric model developed in this study offer a valuable tool for both researchers and policymakers. Researchers gain access to two comprehensive global databases focused exclusively on air pollution studies. For policymakers, the model's outputs are essential for forecasting the financial burden of air pollution on health, facilitating more informed decisions on resource allocation to reduce premature mortality associated with air pollution.

CRediT authorship contribution statement

Sara Ciarlantini: Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Vito Frontuto:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Alessandro Pezzoli:** Supervision. **Andreas Gavros:** Data curation. **Claudio A. Belis:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Data availability

Data will be made available on request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.124824.

Appendix A

Table A.1
Complete list of selected peer-reviewed papers (n. 21) and technical reports (n. 11).

N. study	Type	Title of publication	Year of publication	Authors	Journal/Organisation	N. VSL estimates
1	paper	The economic cost of particulate air pollution on health in Singapore	2003	Quah E. and Boon T.L.	Journal of Asian Economics	1
2	paper	Health Burden and economic impacts attributed to $PM_{2.5}$ and O-3 in China from 2010 to 2050 under different representative concentration pathway scenarios	2021	Wang, Y. et al.	Resources, Conservation & Recycling	1
3	paper	Cost-Benefit Analysis of Reducing Premature Mortality Caused by Exposure to Ozone and $PM_{2.5}$ in East Asia in 2020	2015	Chen, F. et al.	Water, Air, & Soil Pollution	10
4	paper	What is the health cost of haze pollution? Evidence from China	2019	Hao, Y.; Zhao, M.; Lu, Z.	The International Journal of Health Planning and Management	1
5	paper	Priming and the value of a statistical life: A cross country comparison	2023	Andersson, H. and Ouvrard, B.	Journal of Behavioral and Experimental Economics	2
6	paper	An Economic Analysis of the Environmental Impact of $PM_{2.5}$ Exposure on Health Status in Three Northwestern Mexican Cities	2021	Becerra-Perez, L. A. et al.	Sustainability	1
7	paper	Health impact and related cost of ambient air pollution in Tehran	2019	Bayat, R. et al.	Environmental Research	1
8	paper	The value of a statistical life in Mexico	2020	De Lima, M.	Journal of Environmental Economics and Policy	1
9	paper	Monetary value of a life expectancy gain due to reduced air pollution: Lessons from a contingent valuation in France	2007	Desaigues, B. et al.	Revue d'économie politique	1

(continued on next page)

Table A.1 (*continued*)

N. study	Type	Title of publication	Year of publication	Authors	Journal/Organisation	N. VSL estimates
10	paper	The Economic Value of Air-Pollution-Related Health Risks in China: A Contingent Valuation Study	2006	Hammitt, J. K. and Zhou, Y.	Environmental & Resource Economics	1
11	paper	Estimating Mortality and Economic Costs of Particulate Air Pollution in Developing Countries: The Case of Nigeria	2012	Yaduma, N.; Kortelainen, M.; Wossink, A.	Environmental & Resource Economics	3
12	paper	Health and economic impacts of ambient air particulate matter ($PM_{2.5}$) in Karaj city from 2012 to 2019 using BenMAP-CE	2022	Kianizadeh, F. et al.	Environmental Monitoring and Assessment	8
13	paper	A health impact assessment of long-term exposure to particulate air pollution in Thailand	2021	Mueller, W. et al.	Environmental Research Letters	1
14	paper	Health impact assessment of particulate pollution in Tallinn using fine spatial resolution and modeling techniques	2009	Orru H. et al.	Environmental Health	1
15	paper	Estimating health co-benefits of climate policies in China: An application of the Regional Emissions-Air quality-Climate-Health (REACH) framework	2020	Qu, C. et al.	Climate Change Economics	1
16	paper	The economic benefits of fulfilling the World Health Organization's limits for particulates: A case study in Algeciras Bay (Spain)	2019	Roman-Collado, R. and Jimenez de Reyna, J.	Journal of the Air & Waste Management Association	1
17	paper	Health impact assessment and evaluation of economic costs attributed to $PM_{2.5}$ air pollution using BenMAP-CE	2022	Safari, Z. et al.	International Journal of Biometeorology	1
18	paper	Valuation of Mortality Risk Attributable to Climate Change: Investigating the Effect of Survey Administration Modes on a VSL	2012	Ščasný, M.and Alberini, A.	International Journal of Environmental Research and Public Health	1
19	paper	Estimation of economic costs of air pollution caused by motor vehicles in Iran (Isfahan)	2021	Soleimani, M. et al.	Environmental Science and Pollution Research	1
20	paper	Health benefits of improving air quality in Taiyuan, China	2014	Tang, D. et al.	Environment International	10
21	paper	Economic valuation of air pollution health impacts in the Tehran area, Iran	2008	Karimzadegan, H. et al.	Iranian Journal of Public Health	3
22	report	Valuation of Health Benefits Associated with Reductions in Air Pollution	2004	Chilton, S. Covey et al.	Department for Environment, Food and Rural Affairs (Defra)	2
23	report	The cost of air pollution in Africa	2016	Roy, R.	OECD	144
24	report	The Cost of Air Pollution	2014	–	OECD	36
25	report	Economic cost of the health impact of air pollution in Europe	2015	–	WHO Regional Office for Europe, OECD	23
26	report	Western Balkans Regional AQM - Western Balkans Report – AQM in Bosnia and Herzegovina	2019a	–	World Bank	1
27	report	Western Balkans Regional AQM - Western Balkans Report – AQM in North Macedonia	2019b	–	World Bank	1
28	report	Western Balkans Regional AQM - Western Balkans Report – AQM in Kosovo	2019c	–	World Bank	1
29	report	Environmental Health Costs in Colombia: The Changes from 2002 to 2010	2014	Golub, E. et al.	World Bank	1
30	report	Policy Assessment for the Review of the Particulate Matter National Ambient Air Quality Standards	2011	–	U.S. Environmental Protection Agency (U.S. EPA)	1
31	report	Mortality, morbidity and welfare cost from exposure to environment-related risks	2023	OECD Data Explorer	OECD	185
32	report	Climate Change Mitigation, Air Quality and Health (CLIMAQ-H)	2023	European Centre for Environment and Health (ECEH)	WHO Regional Office for Europe	48

Appendix B

$PM_{2.5}$, O_3 and NO_2 concentrations calculation.

We calculated the country weighted averages for the following pollutants: $PM_{2.5}$, NO_2 and O_3. In order to calculate the timeseries needed for our analysis, we made use of widely acknowledged air pollution datasets. For $PM_{2.5}$ we analysed the annual Gridded mean $PM_{2.5}$ concentrations dataset from Atmospheric Composition Analysis Group. The data are available at 0.01° × 0.01° resolution for the years 1998–2022 and were obtained by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, SeaWIFS, and VIIRS with the GEOS-Chem chemical transport model by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, SeaWIFS, and VIIRS with the GEOS-Chem chemical transport model (Shen et al., 2024).

For NO_2 we analysed the Nitrogen Dioxide Surface-Level Annual Average Concentrations V1 (SFC_NITROGEN_DIOXIDE_CONC) dataset, which provides annual global NO_2 surface values (ppb) at a very high resolution of 0.0083° × 0.0083° for every year since 2000. The values of this dataset were obtained through the use of a Land Use Regression (LUR) model (based on 5220 NO_2 monitors in 58 countries) for the years 2010–2012 (Anenberg, 2023). For the O_3 analysis we used the TROPESS Chemical Reanalysis dataset provided by NASA. The spatial resolution of this dataset is significantly lower compared to the other two datasets (1.125° × 1.125°) but we considered that the available resolution is sufficient for the needs of this study. The data are available in 2-h format for each year (2005–2021), so this added an additional step of calculation since we created the annual average of the hourly values for each available year (Miyazaki, 2024).

All the air quality files that were used in the analysis were in the form of ncdf4.

Population-Land weighted values calculation.

The population weighted values were calculated in the following way. For each grid cell of the map we multiplied the population value and the pollutant concentration value. We then took the sum of the of all these calculations for a single country and we divided the result with the total population for this country:

$$Population\ Weighted\ Pollutant\ Conc. = \frac{\sum grid\ population \times grid\ pollution\ concentration}{Total\ country\ population} \quad \text{Eq.(B.1)}$$

For the land weighted values we applied the same logic, replacing the population with the land surface value:

$$Land\ Weighted\ Pollutant\ Conc. = \frac{\sum grid\ land\ surface \times grid\ pollution\ concentration}{Total\ country\ land\ surface} \quad \text{Eq.(B.2)}$$

Appendix C

Table C.1
List of countries included in the final database and the corresponding number of studies conducted in each.

Country	N. studies	Country	N. studies	Country	N. studies	Country	N. studies
Afghanistan	1	Dominican Republic	1	Liberia	4	Saint Lucia	1
Albania	3	Ecuador	1	Libya	4	Saint Vincent and the Grenadines	1
Algeria	4	Egypt	4	Lithuania	3	Samoa	1
Angola	4	El Salvador	1	Luxembourg	3	San Marino	1
Antigua and Barbuda	1	Equatorial Guinea	4	Madagascar	4	Sao Tome and Principe	4
Argentina	1	Eritrea	1	Malawi	4	Saudi Arabia	1
Armenia	3	Estonia	4	Malaysia	1	Senegal	4
Australia	2	Eswatini	4	Maldives	1	Serbia	3
Austria	3	Ethiopia	4	Mali	4	Seychelles	4
Azerbaijan	3	Fiji	1	Malta	3	Sierra Leone	1
Bahamas	1	Finland	3	Marshall Islands	1	Singapore	2
Bahrain	1	France	4	Mauritania	4	Slovakia	3
Bangladesh	1	Gabon	4	Mauritius	4	Slovenia	3
Barbados	1	Gambia	4	Mexico	4	Solomon Islands	1
Belarus	3	Georgia	3	Micronesia	1	South Africa	4
Belgium	3	Germany	3	Moldova	3	South Korea	3
Belize	1	Ghana	4	Mongolia	2	Spain	4
Benin	4	Greece	3	Montenegro	3	Sri Lanka	1
Bhutan	1	Grenada	1	Morocco	4	Sudan	4
Bolivia	1	Guatemala	1	Mozambique	4	Suriname	1
Bosnia and Herzegovina	4	Guinea	4	Myanmar	2	Sweden	3
Botswana	4	Guinea-Bissau	4	Namibia	4	Switzerland	3
Brazil	1	Guyana	1	Nauru	1	Tajikistan	1
Brunei	1	Haiti	1	Nepal	1	Tanzania	4
Bulgaria	3	Honduras	1	Netherlands	3	Thailand	3
Burkina Faso	4	Hungary	3	New Zealand	2	Timor-Leste	1
Burundi	4	Iceland	3	Nicaragua	1	Togo	4
Cabo Verde	4	India	2	Niger	4	Tonga	1
Cambodia	2	Indonesia	1	Nigeria	7	Trinidad and Tobago	1
Cameroon	4	Iran	15	North Macedonia	4	Tunisia	4
Canada	2	Iraq	1	Norway	3	Turkmenistan	3
Central African Republic	4	Ireland	3	Oman	1	Tuvalu	1
Chad	4	Israel	2	Pakistan	1	Türkiye	3
Chile	2	Italy	3	Palau	1	Uganda	4
China	17	Jamaica	1	Panama	1	Ukraine	3
Colombia	2	Japan	3	Papua New Guinea	1	United Arab Emirates	1
Comoros	4	Jordan	1	Paraguay	1	United Kingdom	6
Congo	4	Kazakhstan	3	Peru	1	United States	4
Costa Rica	1	Kenya	4	Philippines	2	Uruguay	1
Croatia	3	Kiribati	1	Poland	3	Uzbekistan	3
Cyprus	3	Kosovo*	1	Portugal	3	Vanuatu	1
Czechia	4	Kuwait	1	Puerto Rico	1	Vietnam	2
Côte d'Ivoire	4	Kyrgyzstan	3	Qatar**	1	Yemen	1
Democratic Republic of the Congo	1	Laos	2	Romania	3	Zambia	4
Denmark	3	Latvia	3	Russia	3	Zimbabwe	1
Djibouti	4	Lebanon	1	Rwanda	4	**Total**	**494**
Dominica	1	Lesotho	4	Saint Kitts and Nevis	1		

Notes: *This designation is without prejudice to positions on status, and is in line with UNSCR 1244 and the ICJ Opinion on the Kosovo declaration of independence, as on the official website of the European Union.
**Qatar is the only country excluded, considered an outlier, after applying the robust regression model.

Appendix D

Table D.1
Mixed-model's output used as robustness check for within-study correlation among observations.***, **, *, stands for statistical significance at the 0%, 0.1% and 1% level, respectively.

	Mixed-model		
	Coeff.	Std. err	
(Intercept)	−920,479.35	239,150.31	***
GDP	86.24	6.05	***
GINI	634,328.06	249,391.22	*
pop	6,743.59	9,935.98	
doctors	11,161.20	1,787.62	***
GDP: income (UM-H)	−3.62	5.58	

Notes: The coefficients are rounded to the second decimal figure; "pop" refers to the natural logarithm of the "population" variable.

Data availability

Data will be made available on request.

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