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Research Article

The effects of macroeconomic and environmental factors on public health: A panel data analysis for OECD countries

Makroekonomik ve çevresel faktörlerin halk sağlığı üzerindeki etkileri: OECD ülkeleri üzerine panel veri analizi

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Abstract

Macroeconomic conditions, environmental risks, and demographic change are among the major determinants of public health. However, comparative studies jointly examining these three factors in relation to mortality across OECD countries remain limited. This study aims to analyse the effects of GDP per capita, PM2.5 exposure, and changes in the proportion of the elderly population on age- and sex-specific mortality. For this purpose, panel data from 14 OECD countries covering the period 2001–2020 were analysed. A fixed-effects model was adopted, and Driscoll–Kraay robust standard errors were used to address autocorrelation, heteroskedasticity, and cross-sectional dependence. The findings show that GDP per capita and PM2.5 exposure have positive and statistically significant effects on mortality. In contrast, the difference in the elderly population variable was not statistically significant. The results highlight the importance of addressing environmental sustainability and public health policies in an integrated manner.

Keywords: Macroeconomic Indicators, Air Pollution (PM2.5), Mortality, Panel Data Analysis

Jel Codes: I15, Q53, C33, I18, E01

Öz

Makroekonomik koşullar, çevresel riskler ve demografik değişimler halk sağlığının temel belirleyicileri arasında yer almaktadır. Ancak bu üç unsurun mortalite üzerindeki etkisini OECD ülkeleri özelinde birlikte inceleyen karşılaştırmalı çalışmalar sınırlıdır. Bu çalışmanın amacı, kişi başına düşen GSYİH, PM2.5 maruziyeti ve yaşlı nüfus oranındaki değişimlerin yaşa ve cinsiyete göre ölüm sayıları üzerindeki etkisini analiz etmektir. Bu kapsamda, 14 OECD ülkesinin 2001–2020 dönemine ait verileri panel veri analiziyle incelenmiştir. Model seçiminde sabit etkiler yaklaşımı benimsenmiş, otokorelasyon, heteroskedastisite ve yatay kesit bağımlılığı sorunlarını gidermek amacıyla Driscoll–Kraay sağlam standart hataları kullanılmıştır. Bulgular, kişi başına düşen GSYİH ile PM2.5 maruziyetinin mortalite üzerinde pozitif ve istatistiksel olarak anlamlı etkiye sahip olduğunu göstermektedir. Buna karşılık, yaşlı nüfus oranındaki değişim anlamlı bulunmamıştır. Sonuçlar, çevresel sürdürülebilirlik ile halk sağlığı politikalarının birlikte ele alınmasının önemine işaret etmektedir.

Anahtar Kelimeler: Makroekonomik Göstergeler, Hava Kirliliği (PM2.5), Mortalite, Panel Veri Analizi

JEL Kodları: I15, Q53, C33, I18, E01

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Introduction

Public health is not explained solely by individuals' health behaviours or biomedical factors; rather, it is closely linked to macroeconomic conditions, environmental quality, and demographic structures (Li et al., 2026; World Health Organisation, 2010). The World Health Organisation's (WHO, 2010) framework on the social determinants of health emphasises that health should not be understood merely as the absence of disease, but rather as an integrated assessment of societal well-being, environmental conditions, and socioeconomic structures. In this context, macroeconomic indicators, environmental quality, and demographic structure are positioned among the key determinants of health.

The United Nations' (UN) "General Comment on the Right to Health" published in 2000 highlights each individual's right to attain the highest possible standard of physical and mental health. This right extends beyond medical care to encompass adequate nutrition, housing, clean water, sanitation, a healthy environment, and safe working conditions (United Nations Committee on Economic, Social and Cultural Rights, 2000). Consequently, public health outcomes are closely linked to structural conditions such as economic welfare, environmental sustainability, and demographic composition. In this context, macroeconomic conditions constitute an important determinant of population health. While higher income per capita improves access to healthcare services and enhances living conditions, inequalities in income distribution may lead to disparities in health outcomes through social determinants (Marmot, 2015). However, the relationship between economic development and health outcomes is not linear. Although improvements in health systems reduce mortality, it has been argued that after a certain income level, the marginal health-enhancing effect of economic growth diminishes; in other words, in high-income countries, economic growth affects population health to a limited extent (Preston, 1975; Deaton, 2003). This suggests that economic welfare alone is insufficient to explain health status and highlights the importance of environmental quality.

Environmental quality has increasingly become another critical factor influencing health outcomes. Air pollution—particularly exposure to fine particulate matter (PM2.5)- has been widely recognised as a major environmental health risk. Numerous studies have shown that exposure to PM2.5 is associated with cardiovascular diseases, respiratory illnesses, and premature mortality (Cohen et al., 2017). Globally, the number of deaths attributable to air pollution is estimated at approximately 8.8 million per year. These findings present strong evidence that environmental factors such as air pollution reduce life expectancy by an average of 2.9 years, an effect even greater than that of smoking (Lelieveld et al., 2020). The results demonstrate that environmental degradation poses profound and structural ecological risks that threaten the stability of societies.

At the same time, demographic change has emerged as a significant challenge for health systems worldwide. The World Health Organisation (WHO, 2025) warns that environmental risks disproportionately threaten public health in low- and middle-income countries. In contrast, in high-income countries, ageing populations and chronic diseases are key challenges. Global demographic change—particularly population ageing—affects both macroeconomic structures and healthcare systems. For example, the increasing proportion of individuals aged 65 and above in OECD countries elevates the burden of chronic diseases, increases the need for long-term care, and raises healthcare expenditures, thereby directly influencing public health status and the sustainability of healthcare systems (Bloom et al., 2015; WHO, 2015; McNicoll, 2002).

Although a growing body of research has examined the relationships between economic conditions, environmental risks, and demographic change in relation to public health, these factors are often analysed separately. Comparative studies simultaneously examining macroeconomic welfare, environmental pollution, and demographic ageing within a unified analytical framework remain relatively limited. In particular, studies employing panel data analysis across comparable groups of OECD countries remain scarce. Therefore, this study aims to examine the effects of GDP per capita, mean PM2.5 exposure, and changes in the proportion of the population aged 65 and over on deaths by age and sex, using panel data from 14 OECD countries covering the period 2001–2020. By integrating macroeconomic, environmental, and demographic determinants within a single empirical framework, this study seeks to contribute to the literature and provide policymakers with evidence-based insights to address public health challenges.

Literature review

Economic development and health outcomes have long been discussed in the health economics and public health literature. One widely accepted view is that increases in income levels may improve health outcomes by providing better living conditions, improved nutrition, and greater access to healthcare services (Marmot, 2015). However, the effect of economic growth on health is not uniform across all income levels. The Preston curve suggests that income significantly improves health indicators at lower income levels, whereas this relationship weakens at higher income levels (Preston, 1975; Deaton, 2003). This indicates that, particularly in developed countries, factors beyond economic conditions must be considered when explaining health outcomes.

Empirical studies have examined the relationship between economic conditions and health outcomes across different country groups. Research focusing on OECD countries has identified various relationships between economic growth and health indicators. For instance, Pritchett and Summers (1996) reported that increases in income levels are associated with improvements in public health indicators. Mujtaba and Shahzad (2021) found that economic growth and environmental factors jointly affect health outcomes in OECD countries. Their findings suggest that while economic development may improve certain health indicators, environmental degradation can limit these positive effects. Similarly, Barnett-Itzhaki and Levi (2021) demonstrated that long-term exposure to air pollution increases mortality risk in 36 OECD countries.

Studies examining the relationship between demographic change and health outcomes also remain important in the literature. O'Connell (1996) analysed the impact of population ageing on healthcare expenditures in OECD countries and found that ageing populations increase financial pressure on healthcare systems. Similarly, Bloom et al. (2015) emphasised that ageing populations increase the burden of chronic diseases and have significant implications for the sustainability of healthcare systems. More recent research by Khan et al. (2024) also indicates that ageing populations place substantial pressure on healthcare systems and increase demand for healthcare services. These findings suggest that demographic change is a key structural factor influencing public health today.

Environmental conditions are also among the fundamental determinants of public health. In this context, air pollution has gained increasing attention in both academic research and policy discussions in recent years. Fine particulate matter, known as PM2.5, can easily enter the body through the respiratory system and cause serious health problems. Long-term exposure to such particulate matter has been associated with cardiovascular and respiratory diseases as well as premature mortality (Krittanawong et al., 2023; Sangkham et al., 2024; Zhou et al., 2025; Shi et al., 2015; Oh et al., 2025). Busch et al. (2024) further showed that PM2.5 exposure significantly affects all-cause mortality among individuals aged 75 and older. In addition, Kemaloğlu and Bağcı (2022) demonstrated that healthcare expenditures and macroeconomic indicators are closely related and interact with each other. Overall, these studies highlight the significant role of environmental quality in shaping public health outcomes.

However, studies that jointly examine these three determinants using panel data analysis on comparable groups of countries remain relatively limited. In this study, panel data covering the period 2001–2020 for 14 OECD countries are used to analyse the effects of GDP per capita, PM2.5 mean exposure levels, and changes in the proportion of the population aged 65 and over on deaths by age and sex. In this regard, the study aims to make a unique contribution to the literature by holistically examining the effects of macroeconomic and environmental indicators on public health and by providing policymakers with evidence-based insights from a planetary health perspective.

Methodology

In this section, the data set, variables, analytical method, panel data model assumption tests, and the process for obtaining the model results are explained.

Data Set

In this research, the effects of macroeconomic and environmental factors on public health are examined using panel data analysis. In this context, the dependent variable in the analysis is the number of deaths by age and sex (Y). This indicator, as one of the fundamental measures of general public health, represents the health status of the population.

The independent variables in the study consist of macroeconomic and environmental determinants:

- Gross domestic product per capita (GDP per capita, current US$ – X_1),
- PM2.5 mean exposure (µg/m³ – X_2), and
- Population aged 65 and over (percentage of total population – X_3).

Table 1: Description of Variables

Variable	Symbol
Deaths by age and sex – OBS_VALUE	Y
GDP per capita (current US$) – NY.GDP.PCAP.CD	X_1
PM2.5 mean exposure (µg/m³)	X_2
Population aged 65+ (per cent of total population)	X_3

As shown in Table 1, GDP per capita (X_1), one of the independent variables, reflects the level of economic welfare a country provides to its population. Since GDP per capita is measured in current US dollars, the indicator may partly reflect inflation and exchange-rate fluctuations. To reduce potential scale effects and heterogeneity across countries, the variable was included in the regression model in logarithmic form. In addition, the fixed-effects specification controls for time-invariant country-specific characteristics, helping mitigate cross-country differences in economic and demographic conditions. PM2.5 mean exposure (X_2) represents environmental quality and health risks associated with air pollution, and the proportion of the population aged 65 and over (X_3) is included in the model to capture the effects of demographic structure on public health, particularly the increase in age-related mortality. The choice of the absolute number of deaths as the dependent variable is related to the fact that this measure is presented in a standardised, complete form in international databases. Although population-standardised mortality rates (e.g., deaths per 100,000 population) would provide advantages for cross-country comparisons, inconsistencies in population standardisation across years in some countries prevented their use. In addition, by applying a fixed-effects approach in the model, we aim to control for structural differences arising from differences in population size across countries.

In this study, annual data for the period 2001–2020 were obtained from the World Bank (World Development Indicators), the OECD, and the DataSweep database (DataSweep, 2024; World Bank, 2024; OECD, 2024). The panel consists of 14 OECD countries. The countries included are Austria, Belgium, Czechia, Denmark, Finland, France, Italy, the Netherlands, Norway, Poland, Slovakia, Spain, Sweden, and Switzerland. The selection criteria for these countries are as follows:

Availability and comparability of data on mortality, GDP per capita, PM2.5 mean exposure, and the proportion of the population aged 65 and over for the period 2001–2020

Use of similar statistical definitions and measurement methods among OECD member countries;

Differences in economic development, environmental health quality, and the level of demographic ageing among the countries.

This diversity allows for comparisons of the effects of the independent variables on public health. The study used secondary data obtained from publicly accessible databases, including the World Bank, OECD, and DataSweep. No human participants were directly involved, and no individual-level identifiable data were used. Therefore, ethical approval was not required for this study.

Method and procedures

Panel data analysis is employed as the method in this research. Panel data analysis is an econometric technique that allows the analysis of data structures that combine time series and cross-sectional dimensions. While time-series analyses focus on the time dimension and cross-sectional analyses on the unit (country) dimension, panel data methods allow the simultaneous observation of both unit-specific differences and changes over time (Hsiao, 2022; Baltagi, 2008). Using panel data increases the number of observations. It enables more reliable estimation of dynamic relationships among units, while helping control for unobserved heterogeneity (e.g., differences in the health systems of the countries included in the analysis) (Wooldridge, 2010).

In this study, annual data for 2001–2020 for 14 OECD countries (Austria, Belgium, Czechia, Denmark, Finland, France, Italy, the Netherlands, Norway, Poland, Slovakia, Spain, Sweden, Switzerland) were used. Microsoft Excel was used to compile and organise the data, while EViews 12.0 and Stata 16.0 were used for analyses. Given that the study period covers more than 20 years, the panel is classified as a macro panel (Baltagi, 2021). According to Baltagi (2021), micro panels generally cover fewer than 20 time periods, while macro panels have longer time dimensions ($T \geq 20$). Because of the panel's macro structure, both cross-section dependence and stationarity tests were applied, and it was determined that the series satisfies the assumptions of panel data analysis. Indeed, combining variables over a given time span may lead to problems such as multicollinearity, autocorrelation, cross-section dependence, and heteroskedasticity.

In this study, natural logarithms (ln) were applied to the variables. In addition, the elderly population variable was included in differenced logarithmic form to reflect annual demographic change in the model specification. In the notation, "D" denotes differencing and "ln" denotes natural logarithmic transformation. To select the appropriate model, the Hausman test was performed; the null hypothesis was rejected (p = 0.0431), and the fixed-effects model was deemed suitable. Diagnostic tests for the error structure indicated the presence of autocorrelation, based on the Bhargava et al., Durbin–Watson statistic and the Baltagi–Wu LBI statistic, heteroskedasticity (Modified Wald test), and cross-section dependence (Breusch–Pagan LM, Pesaran Scaled LM, and Pesaran CD). Accordingly, parameter estimates were obtained using Driscoll–Kraay robust standard errors, which are consistent in the presence of cross-sectional dependence and serial correlation (Driscoll & Kraay, 1998).

The estimation equation within the fixed-effects framework is as follows:

$$\ln(Y_{it}) = \beta_0 + \beta_1 \ln(X1_{it}) + \beta_2 \ln(X2_{it}) + \beta_3 D(\ln X3_{it}) + \alpha_i + \varepsilon_{it},$$

Where i denotes the country, t the year, and α_i represents the country-specific fixed effects.

Multicollinearity problem

One of the important econometric issues in panel data analysis is multicollinearity, which refers to high correlation among independent variables. High correlation among regressors reduces the reliability of coefficient estimates and may weaken the model's statistical significance (Gujarati & Porter, 2009, p. 339). Therefore, before model estimation, multicollinearity was checked using the Variance Inflation Factor (VIF). For each independent variable, it was, in turn, treated as a dependent variable and regressed on the remaining independent variables to obtain an R^2 value. Then, the VIF for each variable was calculated according to:

$$VIF_i = \frac{1}{1 - R_i^2}$$

The magnitude of the VIF indicates the degree of collinearity among the explanatory variables. While VIF values below 5 are generally considered safe for multicollinearity (O'Brien, 2007), some studies accept values up to 10 (Kutner et al., 2005). The VIF results for this study are presented in Table 2.

Table 2: VIF Values for the Variables

Symbol	R^2	VIF
Y	0.51	2.04
X1	0.59	2.43
X2	0.47	1.88
X3	0.43	1.75

The VIF analysis indicates that the variable values range from 1.75 to 2.43. Therefore, it can be concluded that there is no serious multicollinearity problem in the model.

In panel data analyses, choosing the appropriate modelling approach is essential. The literature commonly proposes three basic panel models: pooled ordinary least squares (pooled OLS), fixed effects (FE), and random effects (RE) models (Baltagi, 2021; Wooldridge, 2010). In the pooled model, it is assumed that all units (countries in the present study) share the same intercept. In the fixed-effects model, country-specific, time-invariant differences are controlled via unit-specific intercepts. In the random-effects model, these differences are assumed to be random and incorporated into the error term (Hsiao, 2022). As shown in Table 3, the F-test for poolability rejects the pooled OLS model ($F = 921.27$, $p < 0.001$), indicating the presence of country-specific effects. The Breusch–Pagan LM test further suggests that the random-effects model is preferable to pooled OLS ($\chi^2 = 221.39$, $p < 0.001$). Finally, the Hausman test indicates that the fixed-effects estimator is more appropriate than the random-effects estimator ($\chi^2 = 8.14$, $p = 0.043$). Therefore, the fixed-effects model was selected as the most appropriate specification for the empirical analysis. Accordingly, country fixed effects were included in the model to control for unobserved heterogeneity across countries. Time effects were not explicitly modelled, as the primary focus of the analysis was on structural differences across countries rather than common shocks affecting all countries simultaneously.

Table 3: Model Selection Tests

Test	Statistic	p-value
F-test for Poolability (Pooled OLS vs Fixed Effects)	921.27	0.000
Breusch–Pagan LM Test (Pooled OLS vs Random Effects)	221.39	0.000
Hausman Test (Fixed Effects vs Random Effects)	8.14	0.043

Another problem in panel data models is autocorrelation. Autocorrelation refers to the correlation of error terms over time, indicating a violation of the assumption that errors are independent (Brooks, 2014). Although correlation among error terms does not change the direction of the estimated coefficients, it may cause bias in standard errors and reduce the reliability of statistical significance tests (Gujarati & Porter, 2009). To test for autocorrelation, the Durbin–Watson (DW) statistic proposed by Bhargava et al. (1982) and the LBI (Locally Best Invariant) statistic suggested by Baltagi (2008) were used. In this context, both the Bhargava et al. Durbin–Watson test and the Baltagi–Wu LBI test were applied (Table 4). According to the test results, the Durbin–Watson statistic was calculated as 0.48, while the Baltagi–Wu LBI statistic was 0.57. Since these values fall below the 1.5–2.5 range, it was concluded that the model exhibits positive autocorrelation. This indicates the presence of positive autocorrelation in the model. The hypotheses regarding the autocorrelation test are formulated as follows:

$$H_0: \rho = 0 (\text{no autocorrelation})$$
$$H_1: | \rho | \neq 0 (\text{autocorrelation exists})$$

The test results are reported in Table 4.

Table 4: Autocorrelation Test Results

Test	M1(Y)
	Statistical Value
Bhargava et al. Durbin–Watson	0.48
Baltagi–Wu LBI	0.57

Since these values are below the range of 1.5–2.5, the presence of positive autocorrelation is indicated, and H_0 is rejected.

Cross-section dependence arises when a shock occurring in one country affects the error terms of other countries (Pesaran, 2004). In other words, when economic, environmental, or political linkages exist among countries, this may lead to dependence in the model. To test for cross-section dependence, Breusch–Pagan LM, Pesaran Scaled LM, and Pesaran CD tests were employed. While the Breusch–Pagan LM test can be applied only to fixed-effects models, the CD test developed by Pesaran (2004) is suitable for both fixed- and random-effects models. The hypotheses for these tests are:

$$H_0: \text{No cross-section dependence}$$
$$H_1: \text{Cross-section dependence exists.}$$

The results are presented in Table 5. According to the analysis results (Table 5), the Breusch–Pagan LM ($\chi^2 = 1010.882$, $p = 0.000$), Pesaran Scaled LM ($t = 68.822$, $p = 0.000$), and Pesaran CD ($t = 30.778$, $p = 0.000$) test statistics were found to be significant. These results indicate cross-sectional dependence among countries and that the model's error terms are correlated.

Table 5: Cross-Section Dependence Test Results

Test	M1(Y)	
	Statistic	**Prob**
Breusch-Pagan LM	1010.882	0.000
Pesaran Scaled LM	68.822	0.000
Pesaran CD	30.7780	0.000

The test statistics are significant, indicating cross-sectional dependence and correlation among the error terms across countries.

Panel unit root tests were conducted to examine the stationarity properties of the variables. The results indicate that Y, GDP per capita (X1), and PM2.5 exposure (X2) are stationary at the level, i.e., integrated of order I(0). In contrast, the proportion of the population aged 65 and over (X3) was found to be non-stationary at the level and therefore integrated of order I(1). Accordingly, the first difference of X3 was included in the regression model to ensure stationarity.

Table 6: Unit Root Test Results

Variable	LLC t* (p)	IPS W-t-bar (p)	Fisher ADF P (p)	Fisher PP P (p)	Result
Y	-1.7501 (0.0401)**	-1.3735 (0.0848)*	44.4062 (0.0253)**	42.7389 (0.0369)**	I(0)
X1	-5.4652 (0.0000)***	-2.9648 (0.0015)***	51.1937 (0.0047)***	31.5025 (0.2952)	I(0)
X2	-2.45 (0.007)***	-2.11 (0.017)**	47.80 (0.012)**	45.20 (0.021)**	I(0)
X3	0.5191 (0.6981)	5.3207 (1.0000)	6.0410 (1.0000)	0.1114 (1.0000)	I(1)

Heteroskedasticity violates one of the econometric assumptions. The presence of non-constant variance in the error terms reduces the efficiency of the model's estimators and the reliability of the standard errors. Therefore, when the fixed-effects approach is adopted in panel data models, the Modified Wald Test, which is designed to detect heteroskedasticity, is used. This test assesses whether the model's error terms exhibit varying variance. In this study, as shown in Table 7, the Modified Wald Test was applied. The test result, χ^2 = 494.17 (p = 0.000), indicates that heteroskedasticity is present in the model.

Table 7: Heteroskedasticity (Modified Wald Test)

Test	Model 1 (Y)	
	Chi²	p-value
Modified Wald Test	494.17	0.000

H_0: There is no heteroskedasticity. H_1: Heteroskedasticity is present

Based on this result, the H_0 hypothesis was rejected, indicating heteroskedasticity. This situation shows that the variance of the error terms differs across units, making it necessary to estimate the model using robust standard error estimators (e.g., Driscoll–Kraay) (Wooldridge, 2010; Baltagi, 2013).

Panel data analysis results

In the scope of the study, panel data analysis was conducted using data from 14 selected OECD countries for the period 2001–2020. Based on the F and Hausman tests performed during the model selection process, the fixed effects (FE) model was identified as the most appropriate estimation approach. The model's fundamental assumptions were tested, and autocorrelation, heteroskedasticity, and cross-sectional dependence were detected. Therefore, to address these issues and obtain reliable estimation results, the analyses were re-estimated using Driscoll–Kraay robust standard errors (Driscoll & Kraay, 1998). The resulting findings are presented in Table 8. In the model, the dependent variable represents deaths by age and sex (LNY). In contrast, the independent variables include gross domestic product per capita (LNX_1), the mean exposure level of PM2.5 (LNX_2), and the first difference of the proportion of the population aged 65 and over ($DLNX_3$).

Table 8: Panel Data Results for Model 1 with Driscoll–Kraay Standard Errors

Dependent variable: LNY Period: 2001–2020 Number of observations: 280 Number of cross-sections: 14				
Variable	**Coefficient**	**Driscoll–Kraay Std. Error**	**t-Statistic**	**p-value**
LNX_1	.251030	.033030	7.60	0.000
LNX_2	.315329	.050675	6.22	0.000
$DLNX_3$	-.737838	.933141	-.79	0.42
C	3.68	.411992	8.94	0.000
R2 : 0.986	F-statistic:1167.793		Prob (F-Statistic): 0.000	

According to the study's findings, the model's F-statistic was 1167.793, with a corresponding p-value of 0.000. These results indicate that the model is statistically significant at the 1% level overall, demonstrating that the independent variables collectively have a significant effect on the dependent variable. The model's R^2 was 0.986, and the adjusted R^2 was 0.985, indicating that the independent variables explain a substantial proportion of the variation in the dependent variable. The high R^2 value obtained in this study is due to the nature of panel data analysis. Indeed, the fixed-effects model incorporates country-specific characteristics (such as health system structures, demographic attributes, and recording systems—factors that do not vary over time) into the equation, thereby enhancing explanatory power (Baltagi, 2013). In this regard, the high R^2 does not imply overfitting; rather, it indicates that the long-term structure of the panel data and unit-specific fixed effects have been effectively captured. Although this provides strong statistical support for the model, note that interpretations are limited to the variables included in the analysis.

The prefix "LN" in the variables indicates the application of a natural logarithmic transformation to the series. At the same time, "D" denotes that the first difference of the variable was taken to achieve stationarity. In this context, the results presented in Table 8 show that the coefficient for LNX_1 is positive and statistically significant ($\beta = 0.251$, $p < 0.01$). This finding suggests that a 1% increase in GDP per capita is associated with approximately a 0.25% increase in mortality. Similarly, the coefficient for PM2.5 mean exposure (LNX_2) is also positive and significant ($\beta = 0.315$, $p < 0.01$). This indicates that a 1% increase in PM2.5 air pollution is associated with approximately a 0.31% increase in mortality. Lastly, the first difference of the proportion of the population aged 65 and over ($DLNX_3$) was found to be statistically insignificant ($\beta = -0.738$, $p > 0.05$). This result suggests that changes in the share of the older population were not statistically significant in the estimated model.

Overall, this research finds that economic factors and environmental exposures—particularly air pollution—have significant effects on mortality, and these relationships should be carefully considered from a public health perspective.

Discussion

In this study, the effects of per capita income level, air pollution (PM2.5), and the proportion of the older population on mortality were examined using panel data analysis across 14 OECD countries for 2001–2020. The findings indicate a positive relationship between GDP per capita and mortality rates. Although some studies in the literature report that increases in income improve individuals' health status (Özer, 2024; Igelström et al., 2024; Preston, 1975; Bor et al., 2017), the Preston curve suggests that beyond a certain threshold, the marginal health-enhancing effect of income growth diminishes in high-income countries (Preston, 2007; Deaton, 2003). Cutler and colleagues (2006), examining the relationship between income and mortality in a historical and international context, argued that during the period 1960–2000, economic growth and health indicators were negatively correlated in some countries. Accordingly, the impact of economic growth on health status appears to be limited in high-income countries. In contrast, even small increases in income can significantly improve life expectancy in low-income settings. In this context, the positive association between GDP per capita and mortality identified in the present study aligns with existing literature, as it reflects the diminishing marginal health returns of income growth in OECD countries. Environmental risks and population ageing may counteract potential health improvements. Pickett and Wilkinson (2015) similarly found little or no association between income inequality and mortality among older adults. Jayawardhana et al. (2025), in a panel data analysis of 25 American countries, reported that the direction and magnitude of the relationship between the older population and GDP per capita vary across countries; in some countries, population ageing constrains economic growth, while in others, economic growth accelerates increases in the older population. Taken together, these studies suggest that in societies with a large elderly population, the influence of economic growth on health outcomes may remain limited. Indeed, factors such as access to healthcare, the burden of chronic diseases, and the capacity of health systems may directly or indirectly affect mortality. Furthermore, the positive association between income level and mortality observed in this study may partly reflect differences in the accuracy and completeness of mortality reporting systems across countries.

The findings also show that PM2.5 mean exposure—a key indicator of air pollution—is statistically significantly associated with mortality. This finding is consistent with previous research. Data from WHO (2023) highlights the detrimental effects of PM2.5 exposure on human health. Previous studies have linked such exposure to increased mortality from cardiovascular and respiratory diseases (Agache et al., 2023; Cohen et al., 2017). Particularly in large urban areas, increased exposure to particulate matter may aggravate chronic diseases and other health problems (Luschkova et al., 2022). These results underscore the importance of climate-resilient public health strategies. From a macro-level perspective, regardless of income level, all countries need to integrate air-quality improvement strategies into their health policies to reduce mortality.

The study found no statistically significant relationship between the first difference of the proportion of the population aged 65 and over ($DLNX_3$) and mortality. The coefficient of the differenced share of the population aged 65 and over was not statistically significant in the estimated model. Indeed, population ageing is a long-term process. Moreover, countries' capacities to adapt their health systems to the needs of older populations may vary (Bloom et al., 2015). In other words, when evaluated alongside structural changes such as increases in the chronic disease burden, demand for healthcare services, and care costs, the impact of global ageing on mortality statistics may not be fully captured in the estimated model. Although ageing is theoretically associated with increased mortality, improvements in healthcare systems can reduce the statistical visibility of this effect (Cheng et al., 2020; Xi et al., 2025). Additionally, the lack of statistical significance for the yearly change in the elderly population may be related to the inherently slow pace of demographic ageing. It is also possible that using the differenced form of the variable limited the visibility of long-term structural effects in the model.

Overall, the findings indicate that factors affecting public health are closely linked to economic welfare, environmental quality, and demographic structure. Importantly, given that pollution generated by both developing and developed countries produces global externalities, the impacts extend across borders and affect even less developed countries. From a planetary health perspective (Kalender, 2024), climate-related environmental degradation transcends national boundaries and creates cascading effects on ecosystems and societies.

Conclusion

In this study, the relationship between GDP per capita, PM2.5 mean exposure, changes in the proportion of the population aged 65 and over, and deaths by age and sex was examined using panel data analysis for 14 OECD countries over the period 2001–2020. The findings reveal that economic growth and air pollution are positively associated with mortality. In contrast, changes in the proportion of the older population did not exhibit a statistically significant effect on the model. Overall, the model was found to be statistically significant, with notably high explanatory power.

These results suggest that macroeconomic welfare alone does not automatically improve public health outcomes and should be evaluated together with environmental risks and demographic pressures. Based on these findings, several policy recommendations can be proposed:

Policies aimed at reducing air pollution should be prioritised from a public health perspective. In particular, local and global measures targeting PM2.5 exposure should be intensified.

Economic growth strategies should be evaluated by considering the burden placed on health systems and the implications of global population ageing. In this regard, strengthening health system infrastructure and prioritising chronic disease management and preventive health services are essential.

Public health policies should be designed more holistically, both at the national level and within a planetary health framework. The existing literature indicates that economic growth can improve population health when environmental sustainability and social equity are balanced.

This study has several limitations. Using total death counts as the dependent variable may pose measurement challenges due to differences in population sizes across countries. Although the fixed-effects model controls for time-invariant country characteristics, using absolute death counts rather than age-standardised mortality rates may partially undermine comparability. This choice stems from the fact that, for OECD countries, complete and reliable time-series data were available only for death counts. Future research may enhance comparability by using standardised mortality indicators or population-adjusted measures, when data availability permits.

Another limitation relates to the sample size of 14 countries over 20 years. Some data points were missing due to reporting gaps. GDP per capita was measured using current US dollars due to cross-country data availability and consistency across the study period. However, this measure may also reflect inflation and exchange-rate fluctuations, which could influence the estimated relationship between economic welfare and mortality. Although the variable was included in logarithmic form and country fixed effects were controlled for in the model, these factors should still be considered when interpreting the results. Additionally, only three independent variables were included in the model. Other factors relevant to public health—such as access to healthcare or income distribution—were not incorporated. Future studies could expand explanatory power by integrating such variables into the model.

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