ISSN 1648-7788 / eISSN 1822-4180

VILNIUS TECH Vilnius Gediminas Technical University

AVIATION

2026
Volume 30
Issue 2
Pages 97–113
https://doi.org/10.3846/aviation.2026.26800

FROM EMISSIONS TO ILLNESS: AVIATION AND TRANSPORT POLLUTION AND RESPIRATORY MORTALITY IN EUROPE

Tuğba AKBIYIK [1], Tunahan AVCI [2]

[1]Department of Aviation Management, Faculty of Aeronautics and Astronautics, Tarsus University, Tarsus/Mersin, Türkiye
[2]Department of Aviation Management, Faculty of Aeronautics and Astronautics, Erciyes University, Melikgazi/Kayseri, Türkiye

Article History:
- received 5 November 2025
- accepted 21 January 2026

Abstract. This study explores the association between aviation-related CO_2 emissions and asthma mortality in 15 European Union countries with the highest levels of air traffic between 2008 and 2021. The analysis finds a strong and statistically significant relationship: a 1% increase in aviation emissions is linked to up to a 0.125% rise in asthma-related deaths, underscoring the hidden public health burden of air transport pollution. Emissions from road transport and industrial activity also exhibit strong long-run effects; notably, a 1% rise in road transport emissions corresponds to a 0.79% increase in asthma mortality. Economic expansion, measured by GDP, is indirectly associated with higher asthma mortality, likely through increased demand for aviation and growing urban density. Urban population growth itself is also linked to heightened asthma risks in both the short and long term. These findings highlight the health risks posed by transport emissions and support the need for stronger environmental and public health policy responses. Recommended measures include enhancing emission limits for aviation, promoting sustainable aviation fuels, and integrating air quality indicators into urban and transport planning.

Keywords: asthma, aviation emission, CO2 emissions, environmental health, pooled mean group estimation, sustainable aviation, sustainability.

Corresponding author. E-mail: *tugbaakbiyik@tarsus.edu.tr*

1. Introduction

The aviation sector is pivotal in global economic activity, significantly facilitating international trade and interpersonal relationships. Prior to the COVID-19 pandemic, the air transport sector experienced consistent growth. The industry is expected to triple in value by 2050 compared with its 2020 valuation (Gössling & Humpe, 2020). Excluding COVID-19 and its transient impact, the industry's annual increase ranged from 3% to 8%. This signifies a substantial increase in demand for air travel (Berger, 2021). Conversely, the rapid expansion of the aviation industry adversely affects the environment, primarily through the release of greenhouse gases. As a component of the transport industry, aviation is responsible for emitting substantial quantities of greenhouse gases into the environment. These comprise carbon dioxide (CO_2), nitrogen oxides (NO_x), and water vapor. Emissions are critical factors contributing to the onset of climate change.

In addition to aviation, road transport represents one of the largest contributors to air-pollution-related respiratory mortality in Europe, mainly due to high emissions of nitrogen oxides (NO_x) and particulate matter ($PM_{2.5}$), which are directly associated with asthma attacks, reduced lung capacity and premature mortality. According to the European Environment Agency [EEA] (2023), road traffic is responsible for approximately 39% of total NO_x emissions and 13% of $PM_{2.5}$ emissions across EU member states, posing a respiratory burden comparable to, and in some regions greater than, aviation-related emissions. Evidence further suggests that children and elderly populations living close to high-traffic roads experience significantly higher asthma hospitalization rates and mortality risk, underscoring that road-based pollution must be considered alongside aviation when assessing respiratory health impacts in Europe (EEA, 2023).

According to the International Energy Agency (IEA, 2023), aviation accounted for approximately 2.5 percent of global energy-related CO_2 emissions, highlighting this sector as a significant contributor to climate change.In 2005, however, aviation was estimated to account for approximately 4.9 percent of global radiative forcing, and its carbon dioxide emissions were projected to increase by up to 360% from 2000 through the mid-century (Owen et al., 2010). This substantial growth was attributed to the increased demand for air travel and minimal improvements in the average fuel efficiency, as reported by Warnecke et al. (2019). In 2018, the global aviation industry emitted approximately 918 million metric tons (Mt) of CO_2, accounting for about 2.4% of global energy-related CO_2 emissions (IEA, 2020). Within

Europe, commercial aviation emissions increased by over 16% between 2013 and 2019, with international flights being the primary contributors (EEA, 2022). This upward trend in emissions, if unmitigated, is projected to continue despite recent improvements in aircraft fuel efficiency.

In light of these trends, accelerated industrial growth and inadequate fuel efficiency hinder pollution mitigation. Consequently, the aviation industry must use sustainable fuels and adhere to international environmental regulations. The viability of alternatives, such as Sustainable Aviation Fuel (SAF), is contingent upon industry demand. Regulatory and market-oriented initiatives such as the EU Emissions Trading Scheme seek to diminish airplane emissions by 3.8% for economic benefits (Anger, 2010). CORSIA mandates that airlines compensate for emissions via sustainable activities to achieve the 2020 objectives. However, their overall significance and comprehensive implementation continue to pose challenges. The acceptability of environmentally friendly alternatives, such as CO_2-based aviation fuels, is contingent upon public approval, as seen by varying levels of support in Germany, Spain, and Norway, which subsequently impacts the trajectory of sustainable aviation (Arning et al., 2023). The aircraft industry significantly compromises public health and the environment. Aviation pollution, particularly NO_x and ultrafine particles, exacerbates respiratory issues, such as asthma, resulting in increased hospitalizations. Approximately 16,000 premature deaths annually are attributed to air transport pollution, primarily from long-term exposure to NO_x and fine particulate matter, with around 90% of these fatalities occurring near airports (Yim et al., 2013). These figures refer specifically to human mortality and do not include impacts on wildlife. Moreover, aircraft pollution has financial implications: annual expenditures related to healthcare and other social costs amount to approximately 21 billion USD (Barrett et al., 2010). However, the exact components of this cost remain broad, encompassing direct healthcare spending, reduced labor productivity, and long-term public health impacts. This study provides actual data on the direct health impacts of aircraft-related CO_2 emissions, particularly on asthma-related mortality, thereby addressing a significant gap in the literature. Unlike much of the existing research that focuses solely on aviation's climate effects, this study contextualizes CO_2 emissions within broader transport-related pollution debates, emphasizing aviation's contribution to respiratory health outcomes across European countries. It focuses on the 15 countries with the highest airline traffic and regions disproportionately affected by aviation pollution. These nations significantly contribute to aviation-related emissions, as they manage the majority of European passenger and cargo flights. This study offers a focused evaluation of public health and environmental impacts through a national analysis. This study enhances prior models by including CO_2 emissions from manufacturing, building, and road transportation to mitigate potential concerns about omitted variable bias. These enhancements provide a more thorough assessment of how different sources of carbon emissions may affect asthma-related mortality. The analysis guarantees that the effects ascribed to aviation-related emissions are not obscured by other significant emission sources; hence, it enhances the robustness of the findings.

Contemporary studies have primarily examined the impact of aviation on environmental issues, such as global warming and climate change; however, its health consequences, especially concerning respiratory ailments, remain insufficiently addressed within long-term, cross-country empirical research. This disparity is significant, as an enhanced understanding of health implications could inform policies aimed at more effectively mitigating environmental and health risks. This study establishes a foundation for future studies and encourages the exploration of broader societal repercussions of air transportation along with the potential health implications of aviation pollution.

First, by integrating the health consequences of aviation emissions into the environmental impact assessment, and subsequently by providing new perspectives on the effect of CO_2 emissions from commercial aircraft on asthma mortality in several European nations, this study offers a novel contribution. This multidisciplinary approach brings together econometric modeling, public health data, and environmental sustainability analysis, thereby offering a more comprehensive understanding of aviation's broader societal and health-related effects. The study further contributes methodologically through the application of the Pooled Mean Group (PMG) panel ARDL estimation method, which allows for the analysis of both short- and long-term causal relationships while accounting for cross-sectional heterogeneity. Its strength lies in its ability to accommodate variables of mixed integration orders, I(0) and I(1), and to handle temporal and structural fluctuations across countries. Although PMG is widely used in studies concerning economic development, fossil fuel consumption, and carbon emissions (Mensah et al., 2019; Ssali et al., 2019), this study extends its application to the aviation-health nexus, thus introducing methodological novelty and new empirical insights into a previously underexplored domain.

These findings reinforce the urgency of adopting sustainable aviation regulations that simultaneously mitigate environmental degradation and reduce public health risks.

2. Theoretical framework

2.1. Environmental and health impacts of aviation

Aviation and ground transportation exacerbate global greenhouse gas emissions, intensify climate change, and deteriorate air quality. These pollutants pose hazards to the environment and pulmonary health (Ferrer & Thomé, 2023). Ferrer and Thomé (2023) calculated that 15% of anthropogenic emissions originate from transportation, with energy-related global CO_2 emissions potentially increasing this figure to 25%. Advancements in vehicle technology, alternative fuels, and air control systems have mitigated these disadvantages (Agarwal et al., 2011). Mitigating air pollution can lead to a decrease in greenhouse gases emitted from energy, transportation, and agriculture, thereby improving environmental quality and public health (Gao et al., 2023). Assessing and internalizing the costs of traffic pollution are intricate, necessitating a more advanced policy response (Profillidis et al., 2014).

Carbon dioxide emissions from aircraft constitute a significant health and environmental concern. Aviation carbon emissions, particularly those at high altitudes, significantly affect climate. Studies have indicated that aircraft emissions, comprising CO_2 and NOx, facilitate the formation of contrails and cirrus clouds, thereby enhancing radiative forcing and exacerbating global warming. The radiative forcing of high-altitude aircraft, including the resultant cloudiness, constitutes 4.9% of the total human forcing, highlighting their environmental impacts (Lee et al., 2009, 2021).

The implementation of biofuels and enhancement of taxi-out procedures can significantly reduce emissions. Lee et al. (2021) demonstrate that a one-minute reduction in taxi time decreases CO_2 emissions in their airport efficiency model. The CO_2 and NO_x emissions were reduced by 3.9%. Sustainable Aviation Fuels (SAF) have the potential to diminish aviation's lifecycle CO_2 emissions by 50% or greater by 2050, contingent on production and utilization factors (Staples et al., 2018; Jain et al., 2021). These solutions could substantially mitigate aviation pollution. Emissions during takeoff and landing impact the local air quality, whereas in-flight emissions detrimentally influence the environment (Barrett et al., 2010). Particulate matter and chemicals emitted by aircrafts increase the risk of cardiovascular diseases (Pope & Dockery, 2006; Lewtas, 2007). Touri et al. (2013) and Yim et al. (2015) identified that aircraft emissions present health hazards, particularly in proximity to airports where pollution is concentrated. PM2.5, particles measuring 2.5 microns, is a significant pollutant. PM2.5, owing to its diminutive size, can profoundly infiltrate the lungs, resulting in health complications (Loxham et al., 2019; Thangavel et al., 2022). The WHO recommends restricting 24-hour PM2.5 exposure to 25 micrograms per cubic meter (IATA, 2017). Global air traffic is projected to surpass 4.7 billion passengers by 2024, exceeding pre-pandemic figures and creating concerns regarding aviation pollution and health (Airlines, 2023). Airports serve as crucial aviation centers and are susceptible to pollution. Schlenker and Walker (2016) investigated ground-level pollution resulting from aircraft taxation emissions. The correlation between flight frequency, emissions, healthcare expenditures, and asthma-related mortality is associated with aviation pollution and public health on a national scale (Yim et al., 2015). Aviation-associated PM2.5 and ozone emissions result in approximately 16,000 premature fatalities globally, with PM2.5, which is responsible for 87%, and ozone at 13% (Yim et al., 2013). Approximately 5,000 premature fatalities have been associated with airplane emissions within a 20 km radius of major airports. Aviation accounts for only 1–2% of global greenhouse gas emissions. Nonetheless, it significantly affects public health, particularly in places that rely on air travel (Harrison et al., 2015). Although the environmental repercussions of aviation, particularly its role in climate change, have been thoroughly studied, the health effects of aviation toxins such as asthma are increasingly evident. Alleviating aviation-related pollution could decrease healthcare expenses associated with asthma (Jacob et al., 2016). Although PM2.5, is a recognized contaminant, the health implications of other pollutants, like CO_2, remain inadequately understood. This study aimed to elucidate the impact of aviation-related CO_2 emissions on respiratory diseases and healthcare expenditures, thereby enhancing the discourse on the environmental and health hazards associated with air transport.

2.2. Studies on carbon emissions in aviation

Air transportation contributes approximately 5% to the total anthropogenic radiative forcing, mostly through the emission of CO_2, nitrogen oxides (NOx), and the formation of contrails. Although CO_2 persists in the atmosphere for an extended duration, NOx emissions exert a dual influence: their short-term contribution to ozone formation exacerbates warming (Maruhashi et al., 2022). Conversely, particularly in high-traffic regions, such as the North Atlantic, they significantly contribute to the climatic impact of aviation through their radiative forcing effects, which are influenced by meteorological and seasonal factors (Teoh et al., 2022). A recent study employing econometric approaches, including data envelopment analysis, revealed significant disparities in emission efficiency among nations (Junior et al., 2024). Panel data regression approaches have been employed to analyze restrictions, such as the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) (Sharma et al., 2021), and to examine the determinants of aviation carbon emissions. These studies highlight the challenges associated with reducing emissions in this burgeoning business.

Initiatives such as the Union's Emissions Trading Scheme (EU ETS) and CORSIA have demonstrated a minimal effect on reducing demand, reflecting an impact of less than 2% on passengers' price sensitivity; the demand for air travel is relatively inelastic. Initially, CORSIA hampered its effectiveness by focusing on curbing post-2020 growth, rather than achieving substantial reductions. Implementation challenges and external factors, such as the COVID-19 pandemic, which has hindered progress, pose obstacles to both initiatives. Stricter policies are required to significantly reduce aviation emissions (Mendes & Santos, 2008; Maertens et al., 2019). The study conducted by Gonzalez-Garay et al. (2022) examined environmental taxes, trade laws, and energy efficiency improvements in relation to carbon reduction.

The Environmental Kuznets Curve theory posits that air travel emissions from NAFTA countries initially increase with economic development and thereafter decline at higher income levels (Dursun, 2022). The increasing demand for cargo and passenger services has obstructed efforts to achieve carbon-neutrality objectives (Sgouridis et al., 2011). Therefore, to mitigate the climatic impact of aviation, advancements in technology, regulatory measures, and efforts to manage both the CO_2 and non-CO_2 effects, including NOx emissions and contrail formation, are essential. Contrarily, infrared light is retained, while NOx emissions contribute to ozone formation, both of which significantly impact climate change. Enhanced fuel design, forthcoming technologies, and operational methodologies are anticipated to mitigate these effects (Terrenoire et al., 2022). Panel cointegration tests and Granger causality analysis have demonstrated enduring relationships between air transportation, logistics, economic growth, and CO_2 emissions (Song et al., 2023). The energy-intensive nature of international air freight produces between 0.69 and 0.82 kg of CO_2 per ton-kilometer (Howitt et al., 2011).

Despite extensive examination of the environmental impacts of aviation, there is a lack of quantitative and econometric studies on CO_2 emissions from air travel. Ergen et al. (2024) addressed this research gap by employing an ARDL model to analyze the long-term effects of different transportation modes on CO_2 emissions in the United States. Interestingly, their findings revealed a negative association between air transportation and CO_2 emissions, which contrasts with the generally assumed environmental burden of aviation. However, their model focuses solely on aggregated carbon output, without incorporating health-related externalities such as asthma or mortality. The present study fills this gap by shifting the focus from carbon accounting to human health impacts, thereby offering a complementary yet distinct perspective within the transport-environment-health nexus.

3. Data and modelling approach

3.1. Data

The study focuses on the fifteen European Union member states with the highest levels of commercial air traffic: Germany, Spain, France, Italy, the Netherlands, Norway, Sweden, Belgium, Denmark, Portugal, Austria, Poland, Ireland, Finland, and Romania. Annual data from 2008 to 2021 were used. Country selection was based on aviation intensity and data availability to ensure both environmental relevance and methodological consistency.

The dependent variable is asthma-related mortality (ADN), obtained from Eurostat and The Organisation for Economic Co-operation and Development [OECD]. Air transportation intensity is captured using three proxies: total commercial passenger flights (CPAF), cargo and mail flights (FMCAF), and aviation-related CO_2 emissions (ATCO), all sourced from Eurostat. Control variables include GDP per capita and urbanization, drawn from the World Bank. Urbanization is included in levels due to its percentage format (0–100), while all other variables are log-transformed to address skewness and allow elasticity-based interpretation. To isolate the specific contribution of aviation, the models also incorporate two additional sources of CO_2 emissions: manufacturing and construction (MIC) and road transport (RIC). These variables, also obtained from Eurostat, help distinguish the impact of aviation-related emissions from broader industrial and vehicular pollution.

The study estimates six models in a sequential manner to build analytical depth and test robustness. Model 1 includes total CO_2 emissions; Model 2 isolates aviation-specific emissions (ATCO); Model 3 adds GDP and urbanization as controls; Model 4 introduces emissions from road transport (RIC); Model 5 incorporates emissions from manufacturing and construction (MIC); and Model 6 includes NO_x emissions to account for pollutant-specific health impacts. This stepwise modeling strategy minimizes omitted variable bias and enables comparative analysis across different sources of emissions. Due to incomplete sectoral data, Norway is excluded from Models 5 and 6. Specifically, consistent MIC and RIC data were unavailable for Norway between 2008 and 2021. To maintain panel consistency and avoid introducing bias through imputation, Models 5 and 6 were estimated on a reduced sample of 14 countries. As Norway contributes a relatively small share of total EU aviation emissions and asthma-related deaths, its exclusion is unlikely to significantly affect the findings. Nonetheless, this limitation is acknowledged, and future studies are encouraged to revisit the analysis once more comprehensive data become available.

Model-I: Asthma mortality rate = f (CO_2 from air transportation, Commercial Passenger Flights, Urban Population Growth)

$$\text{Model I} = ADN_{i,t} = f\,(ATCO_{i,t},\ CPAF_{i,t},\ URB_{i,t}). \tag{1}$$

Model-II: Asthma mortality rate = f (CO2 from air transportation, Commercial Cargo Flights, Urban Population Growth)

$$\text{Model-II} = ADN_{i,t} = f\,(ATCO_{i,t},\ FMCAF_{i,t},\ URB_{i,t}). \tag{2}$$

Model-III: Asthma mortality rate = f (CO_2 from air transportation, Gross Domestic Product, Urban Population Growth)

$$\text{Model-III} = ADN_{i,t} = f\,(ATCO_{i,t},\ GDP_{i,t},\ URB_{i,t}). \tag{3}$$

Model-IV: Asthma mortality rate = f (CO_2 from air transportation, Commercial Cargo Flights, Gross Domestic Product, Urban Population Growth)

$$\text{Model-IV} = ADN_{i,t} = f\,(ATCO_{i,t},\ FMCAF_{i,t},\ GDP_{i,t},\ URB_{i,t}). \tag{4}$$

Model-V: Asthma mortality rate = f (CO_2 from air transportation, Commercial Cargo Flights, Gross Domestic Product, CO_2 emissions from manufacturing industries and construction)

$$\text{Model-V} = ADN_{i,t} = f\,(ATCO_{i,t},\ FMCAF_{i,t},\ GDP_{i,t},\ MIC_{i,t}). \tag{5}$$

Model-VI: Asthma mortality rate = f (CO_2 from air transportation, CO_2 emissions from road transportation)

$$\text{Model-VI} = ADN_{i,t} = f\,(ATCO_{i,t},\ RIC_{i,t}), \tag{6}$$

where i and t denote the country and data period, respectively. This study utilized Table 1 to provide a comprehensive breakdown of the dataset.

Table 1. Description of variables, definitions, sample period, and data sources

Definition	Variables	Duration	Source
Asthma mortality rate	ADN	2008–2021	Eurostat (2020) OECD data (2023)
The total count of commercial cargo flights includes both domestic and international routes	FMCAF	2008–2021	Eurostat (2023)
The total count of commercial passenger flights includes both domestic and foreign routes.	CPAF	2008–2021	Eurostat (2023)
Carbon dioxide emissions from air transportation (metric tons)	ATCO	2008–2021	Eurostat (2023)
Gross domestic product (constant 2015 US $)	GDP	2008–2021	World Bank (2023)
Urban population growth (annual %)	URB	2008–2021	World Bank (2023)
CO_2 emissions from manufacturing and construction sectors	MIC	2008–2021	Eurostat (2023)
CO_2 emissions from road transportation	RIC	2008–2021	Eurostat (2023)

3.2. Econometric methods

This study addresses cross-sectional dependency and variable homogeneity issues using advanced econometric techniques to ensure the reliability of the panel data analysis. Given that cross-sectional errors may be correlated, a common scenario when using panel data, we applied the Pesaran CD test (Pesaran, 2004) to detect cross-sectional dependence in the series using the pooled least-squares method. This traditional approach is particularly effective for large datasets. To test for slope coefficient homogeneity across cross-sections, we employed the modified delta-tilde method developed by Pesaran and Yamagata (2008), which is especially useful in understanding cross-country linkages in the presence of panel heterogeneity. To verify the order of integration of the variables and account for cross-sectional dependence, we used the CIPS and CADF unit root tests (Pesaran, 2007). Analyzing the relationships among cross-sectional units helps to determine whether the variables contain a unit root. In this study, we examined asthma-related deaths and CO_2 emissions from air transportation (commercial aviation passengers and freight flights) over an extended period using the Westerlund-Edgerton (Westerlund & Edgerton, 2007) bootstrap cointegration method to test for cross-sectional dependence in heterogeneous panels. The pooled mean group (PMG) model was employed to estimate both short-run dynamics and long-run equilibria using variables integrated of order I(0) or I(1). The choice of the PMG estimator was motivated by both the structural characteristics of the dataset and the theoretical framework of the study. The PMG approach, introduced by Pesaran et al. (1999), assumes homogeneity in long-run coefficients across cross-sectional units while allowing for heterogeneity in short-run dynamics, error variances, and adjustment speeds. This structure is particularly appropriate for our sample of 15 European countries, where long-term environmental and health policy trends are expected to converge, but short-term responses to aviation-related emissions may vary due to national differences in regulatory enforcement, healthcare infrastructure, and local pollution sources.

Compared to alternative estimation techniques such as Fixed Effects (FE) and Generalized Method of Moments (GMM), the Pooled Mean Group (PMG) estimator offers more reliable results for panels with a moderate number of cross-sections (N = 15) and relatively long time series (T = 14 years). While GMM is typically suitable for panels with large N and small T, it may suffer from instrument proliferation and weak instrument bias in settings with limited cross-sectional units (Baltagi, 2008; Cameron & Trivedi, 2005). Similarly, FE models impose strict homogeneity assumptions that may oversimplify the heterogeneity across countries, particularly in long-run dynamics.

To empirically support the use of the PMG estimator over the Mean Group (MG) alternative, the Hausman test (Hausman, 1978) was applied. The test results across all six models failed to reject the null hypothesis ($p > 0.1$), validating the assumption of long-run slope homogeneity. This confirms that PMG provides efficient and consistent estimates in this context, effectively capturing both country-specific short-run heterogeneity and common long-run equilibrium relationships between aviation emissions and asthma mortality.

3.3. Homogeneity and cross-sectional independence tests

The initial assessment of cross-sectional independence was conducted using Pesaran's (2004) CD test. This is useful for determining whether cross-section residuals (across several units in the panels) exhibit autocorrelation, which is often necessary prior to conducting panel data analysis. Neglecting cross-sectional dependence can lead to inconsistent and misleading estimates. This test entails calculating the average pairwise correlation coefficients among the residuals across several cross sections in the context of CD. The CD statistic was calculated by averaging the pairwise correlation coefficients of the residuals within each subarray. Computation of the CD statistic:

$$CD = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho_{ij}}, \tag{7}$$

N is the number of cross-sections and is the correlation between the residuals of cross-sections i and j.

The presence of cross-sectional dependence is indicated by the substantial CD statistic. Tests for cross-sectional independence were conducted, and the investigation subsequently employed the modified delta tilde test proposed by Pesaran and Yamagata (2008) to examine the homogeneity of slope coefficients. This test is essential when analyzing panels with heterogeneous characteristics and facilitates the assessment of slope coefficient variation across units. This equation utilizes multiple delta–tilde tests.

$$\Delta \cong \left(\frac{\sqrt{N}}{2}\right) * \left(\frac{\Sigma^{\wedge}}{\sigma^2} - 1\right). \quad (8)$$

This method evaluates the null hypothesis of slope homogeneity against the alternative hypothesis that slopes differ across units and is expressed as follows: Consequently, pooling and analyzing the data without considering these slope differences may result in erroneous inferences. A statistically significant test result indicated the heterogeneity of the slope.

3.4. Panel unit root tests

Following the implementation of cross-sectional dependence and homogeneity tests, this study assessed the stationarity properties in panel data using the Cross-sectionally Augmented IPS (CIPS) and cross-sectionally augmented Dickey–Fuller (CADF) tests proposed by Pesaran (2007). These methodologies are advantageous because of their capacity to address the prevalent cross-sectional dependence of the panel data. Disregarding this aspect could potentially bias the identification of characteristics that describe series integration. The CADF test extends the standard ADF test by incorporating cross-sectional averages of the variables to account for common factors affecting all cross-sectional units. CADF Regression Equation:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \overline{\gamma}_i y_{t-1} + \delta_i \Delta \overline{\gamma}_t + \epsilon_{it}, \quad (9)$$

y_{it} is the variable of interest for unit iii at time ttt, y_(it-1) represents the cross-sectional averages of yyy, Δγ¯_t is the first difference of the cross-sectional averages, and ϵ_it is the error term.

The CIPS test aggregates the CADF test statistics across all cross-sectional units and calculates their average to provide a more comprehensive assessment of panel stationarity. The CIPS statistic was computed as follows:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i. \quad (10)$$

3.5. Panel cointegration test

Following unit root tests, this study employs Westerlund and Edgerton's (2007) bootstrap cointegration test to establish long-run associations between variables. This test demonstrated robust performance for panels that exhibited cross-sectional dependence and heterogeneity. Subsequently, the cointegration test is predicated on a panel error correction model (ECM), which examines whether deviations from the long-run equilibrium undergo gradual self-correction.

The panel ECM equation used in the Westerlund-Edgerton test is as follows:

$$\Delta y_{it} = \alpha_i + \lambda_i \left(y_{it-1} - \beta_i x_{it-1}\right) + \sum_{j=1}^{p} \delta_{ij} \Delta y_{it-j} + \sum_{k=1}^{q} \theta_{ik} \Delta x_{it-k} + \epsilon_{it}, \quad (11)$$

y_{it} are the dependent and independent variables, λ_i represents the speed of adjustment toward the long-run equilibrium, β_i _ represents the long-run cointegration coefficients, and ϵ_it is the error term.The null hypothesis posits the absence of cointegration, whereas the alternative hypothesis proposes the existence of a long-term relationship. The bootstrap method enhances the reliability of this test, particularly for small samples, by providing robust standard errors that account for the heteroscedasticity and cross-sectional dependence.

3.6. Pooled Mean Group (PMG) estimation results

This study provides both short- and long-term estimations using the Pooled Mean Group (PMG) estimator established by Pesaran et al. (1999). The PMG estimator is suitable when the initial short-run dynamics vary cross-sectionally but common long-run relationships are assumed in a panel setup. This accommodates both I(0) and I(1) variables. The estimation was based on the ARDL model of the PMG:

$$y_{it} = \phi_i y_{it-1} + \theta_i x_{it-1} + \sum_{j=1}^{p} \alpha_{ij} \Delta y_{it-j} + \sum_{k=1}^{q} \beta_{ik} \Delta x_{it-k} + \epsilon_{it}. \quad (12)$$

4. Empirical results

Prior to assessing the stationarity of the variables intended for analysis, it is imperative to elucidate the characteristics of the panel data to facilitate the implementation of appropriate panel unit root tests. Panel unit root tests yield unreliable and inconsistent results if the panel time-series data lack homogeneity and horizontal cross-sectional independence (Dogan & Aslan, 2017). Consequently, a panel data analysis was conducted using the ADN, ATCO, CPAF, FMCAF, URB, and GDP variables after the preliminary tests. The methodological framework of this study is shown in Figure 1.

Descriptive statistics for data from 15 European countries (2008–2021) are presented in the Table 2. Asthma-related deaths (ADN) average 5.280 per 100,000 population (std. dev. 1.033), indicating moderate variability. CO_2 emissions from air transport (ATCO) average 15.235 metric tons per capita, with slight negative skewness (–0.528). Commercial passenger flights (CPAF) and commercial cargo flights (FMCAF) show low standard deviations, suggesting stable air traffic trends. Specifically, FMCAF refers to the total count of commercial cargo flights, including both domestic and international routes, rather than the volume of freight carried. Urban population (URB), not log-transformed, varies significantly (mean: 75.373%, std. dev.: 12.912%). Log-transformed GDP per capita has a

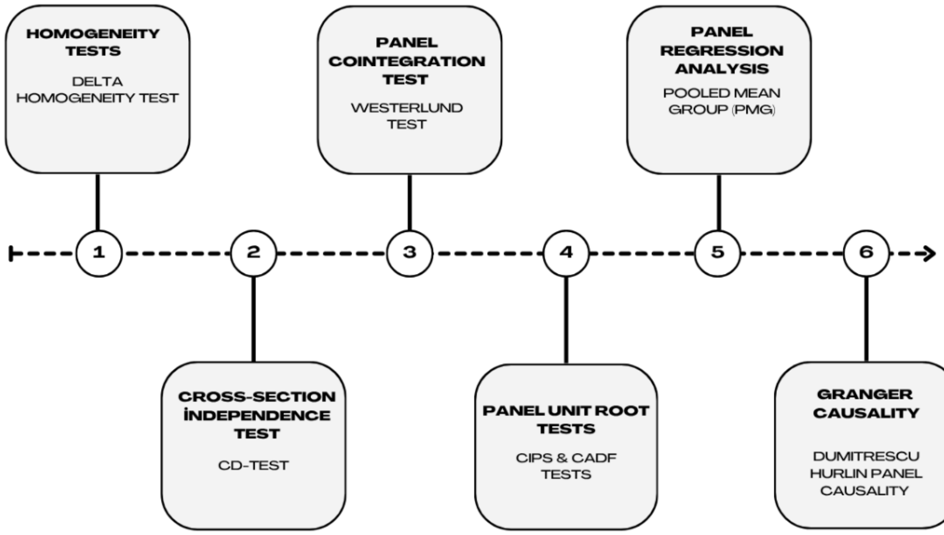

Figure 1. Methodological framework

Table 2. Descriptive statistics of variables, 15 countries, 2008–2021

Parameters	Mean	Min.	Max.	Std. Dev.	Skew.	Kurt.
ADN	5.280	3.526	7.315	1.033	0.455	1.799
ATCO	15.235	11.130	17.243	1.118	–0.528	3.909
CPAF	12.821	11.061	14.372	0.817	0.350	2.348
FMCAF	9.679	6.553	11.941	0.942	0.207	2.689
URB	75.373	53.600	98.100	12.912	–0.129	1.843
GDP	10.451	8.943	11.414	0.565	–1.042	3.415
MIC	2.821	1.295	4.851	1.005	0.324	2.071
RIC	3.427	2.239	5.070	0.910	0.493	1.751

Note: Except for the urban population (URB) variable, all other variables were transformed into logarithmic forms. Data for 15 countries were considered for the period of 2008–2021.

mean of 10.451 and higher negative skewness (–1.042), reflecting more lower-income countries in the sample. CO_2 emissions from MIC average 2.821 metric tons per capita and exhibit mild right skewness, indicating a few countries with heavier industrial output. RIC average 3.427 metric tons per capita, with low dispersion and slight right skewness, suggesting relatively uniform values across countries with a few higher-emission cases. Skewness and kurtosis values indicate approximate normality, supporting the use of panel regression analysis.

The Pesaran and Yamagata (2008) method was employed to assess the homogeneity of slope coefficients in the panel models. The results of the Delta and adjusted Delta (Δ adj) statistics for six model specifications (M1–M6) are reported in the Table 3. In all models, the null hypothesis of slope homogeneity was rejected at the 1% significance level, as all p-values are either 0.000 or below 0.01. This outcome indicates the presence of slope heterogeneity across the cross-sectional units, suggesting that countries in the panel exhibit different behavioral responses in the modeled relationships.

Table 3. Delta homogeneity test results (results from the Pesaran-Yamagata's homogeneity test)

Groups	Test	Statistic	P-value
M1	Δ Δ adj	4.284 5.343	0.000*** 0.000
M2	Δ Δ adj	3.826 4.772	0.000*** 0.000
M3	Δ Δ adj	4.132 5.153	0.000*** 0.000
M4	Δ Δ adj	3.574 4.728	0.000*** 0.000
M5	Δ Δ adj	3.112 4.117	0.002*** 0.000
M6	Δ Δ adj	4.487 5.309	0.000*** 0.000

*Note:****, **, and * indicate stationarity at the 1%, 5%, and 10% levels, respectively.

In addition to the Delta homogeneity test, the presence of cross-sectional dependence (CSD) is a critical concern in panel data analysis. If CSD exists, the application of first-generation panel techniques may lead to biased and inconsistent estimates. Therefore, it is essential to determine whether the data structure supports the use of second-generation econometric methods that are robust to such dependence (Akpanke et al., 2023).

The results of the CD (cross-sectional dependence) test are presented in the Table 4. The p-values for all variables are statistically significant at the 1% level, leading to the conclusive rejection of the null hypothesis of cross-sectional independence. This confirms that the variables analyzed in this study ADN, ATCO, CPAF, FMCAF, URB, GDP, MIC, and RIC exhibit strong and statistically significant cross-sectional dependence.

These findings suggest that shocks or structural changes in one country may influence the same variables in others, underscoring the interdependence of air transportation systems, urban development, industrial activity, and public health outcomes across nations. Among all variables, CPAF recorded the highest CD-test statistic (34.368), indicating intense cross-country interdependence in commercial passenger flight activity. In contrast, ADN presented the lowest statistic (4.834), though it still indicated significant dependence. MIC and RIC also showed substantial cross-sectional dependence, highlighting the shared environmental and infrastructure characteristics among the countries, particularly in terms of industrial emissions and road-based transportation systems.

Given the strong presence of both cross-sectional dependence and slope heterogeneity, the use of first-generation panel data techniques would be inappropriate. To ensure robust and reliable inference, the study employs second-generation unit root tests, specifically the Cross-sectionally Augmented Dickey-Fuller (CADF) and Cross-sectionally Augmented IPS (CIPS) tests, which are specifically designed to address both heterogeneity and cross-sectional dependence in panel structures.

These methodological choices enhance the credibility and accuracy of the empirical findings, ensuring that the estimated relationships between air transport emissions, flight activity, urbanization, economic growth, industrial and road transport emissions, and asthma-related mortality are both statistically sound and policy-relevant in a globally interconnected context.

The results of the CIPS and CADF panel unit root tests, conducted following the detection of cross-sectional dependence are presented in Table 5. The findings from the CIPS test reveal that all variables become stationary at their first differences, indicating that they are integrated of order one, I(1). This includes not only economic and transportation indicators such as GDP, CPAF, FMCAF, and ATCO, but also environmental and demographic variables like MIC (manufacturing emission), RIC (road transport emissions), URB (urban population), and ADN (asthma-related mortality). The results of the CADF test corroborate these findings, showing consistent evidence of first-difference stationarity across the panel.

The convergence of results from both tests confirms the robustness of the unit root diagnostics and satisfies a key precondition for proceeding with panel cointegration analysis. Moreover, the use of second-generation tests like CIPS and CADF is justified given the earlier detection of cross-sectional dependence and slope heterogeneity in the data.

Without estimating the long-run impact relationship, this study employs second-generation (Westerlund) cointegration tests to determine the existence of this relationship. Westerlund's (2005) cointegration analysis is conducted independently for each model, and the test results are listed in Table 6. The cointegration results indicate that all variables in Models 1 through 6 are cointegrated, as the variance ratio statistics are negative and statistically

Table 4. Results of the cross-sectional independence test

	ADN	ATCO	CPAF	FMCAF	URB	GDP	MIC	RIC
CD-test value	4.834	23.747	34.368	5.761	25.461	26.529	18.05	11.89
p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Note: *** p < 0.01, ** p < 0.05, * p < 0.10 indicate rejection of the null hypothesis of cross-sectional independence at conventional significance levels.

Table 5. CIPS & CADF tests (results from CIPS and CADF panel unit root test)

Variables	CIPS		CADF	
	I(0)	I(I)	I(0)	I(I)
ADN	–2.277*	–3.600***	–2.277**	–3.600***
ATCO	–2.471**	–3.215***	–1.932	–3.154 ***
CPAF	–0.410	–2.416**	–0.305	–2.416 ***
FMCAF	–1.431	–3.433***	–1.431	–3.433 ***
URB	–3.623***	–3.078***	–2.886***	–3.078***
GDP	–1.892	–2.885***	–1.966	–3.274 ***
MIC	–2.618***	–3.713***	–2.618***	–3.522***
RIC	–1.240	–2.861***	–1.240	–2.861***

Note: ***, **, and * indicate stationarity at the 1%, 5%, and 10% levels, respectively.

Table 6. Westerlund test for cointegration

N/A	N/A	Statistic	p-value
M1	Variance ratio	–1.9373	0.0264**
M2	Variance ratio	–1.4151	0.0785*
M3	Variance ratio	–2.1371	0.0163**
M4	Variance ratio	–1.4821	0.0692*
M5	Variance ratio	–2.4125	0.0079***
M6	Variance ratio	–2.6780	0.0037***

Note: ***, **, and * indicate stationarity at the 1%, 5%, and 10% levels, respectively.

significant. Specifically, the significance levels for these models were 5% for Models 1 and 3, 10% for Models 2 and 4, and 1% for Models 5 and 6. These findings confirm the presence of a long-run equilibrium relationship among the variables analyzed in each model.

The results of the Westerlund panel cointegration test, as presented in Table 7, indicate that the null hypothesis of no cointegration is rejected in all models, suggesting the presence of long-run equilibrium relationships among the variables analyzed in this study. The test employs four statistics: Gt and Ga assess cointegration at the group level, while Pt and Pa evaluate it at the panel level. Rejection of the null hypothesis by any of these statistics indicates that the variables are cointegrated, i.e., they move together over time in a stable long-term relationship. In Model 1 (M1), the null hypothesis was rejected at the 10% significance level for the Gt, Pt, and Pa statistics, while Ga was not significant. These results provide weak but notable evidence of cointegration. In Model 2 (M2), the null hypothesis was rejected with strong statistical significance. The Gt and Pt statistics are significant at the 1% level, Ga at 5%, and Pa at 1%, providing robust evidence of cointegration in this model. Model 3 (M3) also demonstrates consistent cointegration. The Gt statistic is significant at 5%, Ga at 10%, Pt at 5%, and Pa at 1%, confirming a moderate to strong long-run relationship among the variables. In Model 4 (M4), the null hypothesis of no cointegration was rejected at the 5% level for Gt and Pt and at the 10% level for Pa while Ga remained statistically insignificant. Despite this, the rejection of the other three statistics supports the conclusion of cointegration in M4. Model 5 presents mixed evidence, with Gt significant at the 10% level, Ga and Pt at 5%, while Pa is not significant. Model 6 demonstrates robust cointegration, with all four statistics statistically significant – Gt, Ga, and Pt at the 5% level, and Pa at 1%.

Overall, the Westerlund test results confirm that the variables ADN, ATCO, CPAF, FMCAF, URB, GDP, MIC, and RIC are connected through stable long-run relationships across countries. These findings support the use of long-term panel estimation methods and emphasize the significance of addressing air pollution, industrial activity, and urbanization in relation to health outcomes, particularly asthma-related mortality.

Formally, the Pooled Mean Group (PMG) estimator proposed by Pesaran et al. (1999) was employed to examine the short- and long-run relationships between ADN and a set of explanatory variables, including ATCO, CPAF, FMCAF, URB, GDP, MIC and RIC.

The Hausman test (1978) was used to check the efficiency and consistency of all estimators. In this study, I discuss the ability of the Pool Mean Group (PMG) estimator relative to other mean group estimators. According to the results of the Hausman test, the null hypothesis is accepted, which means that the PMG technique is more efficient than the MG technique. The results of the PMG estimator for Models M1–M6 are presented in the Table 8.

Table 7. Western panel cointegration tests

N/A	Statistics	Gt	Ga	Pt	Pa
M1	Value	–2.370	–4.749	–8.352	–4.465
	Robust P-value	0.060*	0.120	0.073*	0.080*
M2	Value Robust P-value	–2.861 0.000***	–5.257 0.050**	–9.744 0.010***	–5.864 0.010***
M3	Value Robust P-value	–2.436 0.050**	–5.215 0.080*	–9.462 0.020**	–6.655 0.010***
M4	Value Robust P-value	–3.032 0.050**	–3.053 0.160	–8.623 0.030**	–3.110 0.090*
M5	Value Robust P-value	–2.982 0.082*	–3.152 0.045**	–8.262 0.045**	–2.306 0.227
M6	Value Robust P-value	–2.323 0.040**	–6.129 0.030**	–7.616 0.020**	–6.034 0.000***

Note: ***, **, and * indicate stationarity at the 1%, 5%, and 10% levels, respectively.

Table 8. PMG estimation results

Dependent var. (ADN)	M1	M2	M3	M4	M5	M6
Long-run coeff	N/A	N/A	N/A	N/A	N/A	N/A
ATCO	.039	.125**	.070**	.050***	.07***	.12**
CPAF	.112**	--	--	--	--	--
FMCAF	--	.040	--	.011	–.12	--
URB	.034***	.048***	.041***	.039***	--	--
GDP	--	--	.779***	.991***	.81***	--
MIC	--	--	--	--	.66***	--
RIC	--	--	--	--	--	.79***
Short-run coeff	N/A	N/A	N/A	N/A	N/A	N/A
ec	.699***	.674***	.657***	.672***	.61***	.41***
ATCO	–.026	.079	–.023	.012	.22	.05
CPAF	.106	--	--	--	--	--
FMCAF	--	.090	--	.011	–.19	--
URB	.491**	.347	.558***	.489**	--	--
GDP	--	--	1.384*	1.023	–1.58	--
MIC	--	--	--	--	.90**	--
RIC	--	--	--	--	--	.40
Cons	–.464**	.419*	4.654***	6.261***	3.17***	–.26***
Hausman test (pmg, mg)	1.00	2.03	1.45	0.32	0.72	2.85
p-value	0.8011	0.5655	0.6940	0.9884	0.9485	0.2402

Note: ***, **, and * indicate stationarity at the 1%, 5%, and 10% levels, respectively.

PMG estimation results show clear proof of lasting connections between ADN and various environmental, economic, and urban factors in all six model setups (M1–M6). In Model 1, CPAF shows a notable long-run effect on ADN, with a 1% increase in CPAF associated with a 0.112% increase in asthma mortality. URB is connected to ADN in both the long term (0.034%) and short term (0.34%), indicating that living in crowded areas and being in cities leads to ongoing and immediate risks to respiratory health. While ATCO appears positively related, its effect is not statistically meaningful in this specification.

In Model 2, both ATCO and URB display positive long-run impacts on ADN, estimated at 0.125% and 0.048%, respectively. These findings reinforce the role of emissions and urban factors in shaping health outcomes. The addition of FMCAF in this model shows a positive number, but it's not significant, suggesting that the number of cargo flights might not directly affect asthma deaths. In Model 3, GDP is introduced alongside aviation-related CO_2 emissions (ATCO) and urbanization (URB). All three variables show statistically significant and positive long-run effects on asthma mortality (ADN): a 1% increase in GDP is associated with a 0.779% rise in asthma deaths, while ATCO and URB contribute 0.070% and 0.041%, respectively. These findings suggest that economic growth intensifies pollution exposure through increased air travel, urban congestion, and industrial activity, which collectively burden respiratory health. The magnitude of the GDP coefficient aligns with the initial phase of the Environmental Kuznets Curve (EKC), where economic expansion is accompanied by rising environmental and health externalities before potential improvements emerge at higher income levels. In the short run, GDP also shows a strong positive effect, indicating immediate public health impacts of rapid growth in the absence of adequate environmental safeguards.

In Model 4, all three factors, ATCO, URB, and GDP, still show strong long-term connections with ADN, estimated at 0.050%, 0.039%, and 0.991%, respectively. URB also has a positive and important short-term effect (0.489%), highlighting the role of urban factors in both lasting and temporary health results. URB maintains a positive and significant short-run effect (0.489%), again pointing to the importance of urban dynamics in both persistent and transitory health outcomes.

Extending the analysis to Model 5, MIC emerges as a major determinant of ADN. A 1% increase in MIC leads to a 0.66% rise in asthma-related deaths over the long term and a 0.90% rise in the short term, showing that industrial emissions affect both long-term health and immediate breathing problems.

In Model 6, the attention turns to RIC, which also indicates a significant long-term impact on ADN, showing that a 1% increase in road transport emissions is associated with a 0.79% rise in mortality. This result highlights the structural health risk that road-based pollution poses, despite the absence of a short-run effect.

In all models, the negative and significant error correction terms confirm the presence of stable long-term relationships. Additionally, the Hausman test supports the use of the PMG estimator by validating the homogeneity assumption for long-run coefficients.

Overall, the results strongly show that aviation activity, transport-related emissions, industrial pollution, urban growth, and economic development are linked to higher asthma-related deaths. These findings point to an urgent need for integrated policy responses that target emissions control, sustainable urban development, and respiratory public health protection. Overall, the long-run analysis across all model specifications indicates that ATCO exerts a consistently positive effect on ADN, with the exception of Model 1, where its effect is not statistically significant. This finding suggests that countries may mitigate asthma-related mortality by reducing emissions from aviation sources. CPAF was also shown to be an effective predictor in the model where it was included, reinforcing the link between air travel volume and respiratory health risks. URB, which appears in all models, displays a stable and positive relationship with ADN, underscoring the role of urbanization in exacerbating asthma outcomes. GDP, included in Models 3 and 4, also shows a strong long-run effect, indicating that economic expansion may intensify environmental pressures affecting public health. Additionally, adding MIC in Model 5 and RIC in Model 6 enhances the analysis by showing how industrial and road transport emissions affect the results. Both variables demonstrate significant long-run effects, highlighting the structural role of pollution from manufacturing activities and vehicle traffic in driving asthma-related mortality. In the short run, URB maintains a consistent positive impact across nearly all models, while GDP exhibits notable short-run influence in Model 3. These findings reinforce the importance of addressing not only air transport emissions but also broader environmental and urban determinants in developing strategies to reduce the burden of asthma across countries.

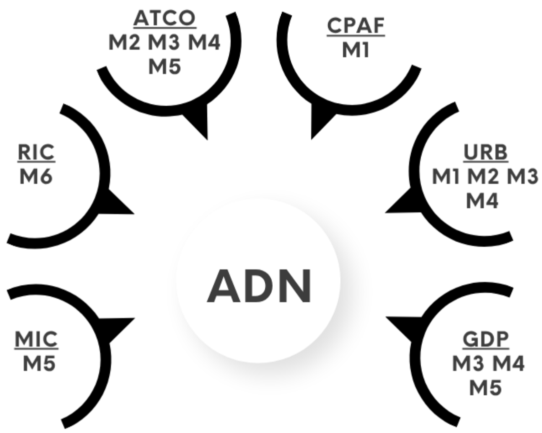

Figure 2. Summary of long-run effects on ADN in PMG model results

The graphical representation of the pooled results from the mean group estimation clearly illustrates the direction and strength of each explanatory variable's effect on ADN across the six model specifications in Figure 2. The visual summary shows that most of the variables have a positive effect on ADN, supporting the findings from the panel estimations and emphasizing how environmental, economic, and urban factors together affect respiratory health outcomes.

This study employs the Dumitrescu-Hurlin test for panel causality to explore the directional predictability among variables related to environmental emissions, transportation, urbanization, economic activity, and asthma-related mortality. Only statistically significant Granger-relationships (10%, 5%, or 1% levels) are interpreted and presented in Table 9.

Table 9. Dumitrescu Hurlin panel causality tests

Causal Direction	Causality Type	W-Stat. / Z-Stat.	Prob.
CPAF → ADN	One-way	5.2664 / 2.1577	0.031**
FMCAF → ADN	One-way	5.3875 / 2.2635	0.0236**
URB → ADN	One-way	6.0103 / 2.8085	0.005***
GDP → ADN	One-way	9.6360 / 5.9803	0.000***
CPAF → ATCO ATCO→CPAF	Two-way Two-way	5.6273 / 2.5602 6.7149 / 3.5451	0.0105 *** 0.0004***
URB → ATCO	One-way	5.7507 / 2.6719	0.0075***
ATCO → GDP	One-way	6.6678 / 3.5023	0.0005***
CPAF → FMCAF	One-way	5.0075 / 1.9989	0.0456**
CPAF → GDP	One-way	5.7893 / 2.7069	0.0068***
FMCAF → URB	One-way	4.7703 / 1.7842	0.0744*
GDP → FMCAF	One-way	6.7524 / 3.5790	0.0003***
URB → GDP	One-way	6.0016 / 2.8992	0.0037***
URB ↔ FMCAF FMCAF ↔ URB	Two-way Two-way	7.3891 / 4.0146 6.7651 / 3.4687	0.00006*** 0.0005***
MIC → RIC	One-way	6.5221 / 3.2562	0.0011***
GDP → URB	One-way	6.1199 / 2.9044	0.0037***
MIC → URB	One-way	6.2719 / 3.0373	0.0024***
RIC → URB	One-way	6.5029 / 3.2393	0.0012***

Note: Only statistically significant causal directions at the 10%, 5%, or 1% levels are included. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results show that GDP, URB, CPAF, and FMCAF each Granger-predict ADN, suggesting a directional association in which increases in economic activity, urbanization, and air transport tend to precede increases in asthma mortality. These findings highlight the public health implications of macroeconomic expansion and mobility-related emissions, not as deterministic causes but as predictive links developing over time.

A bidirectional Granger-relationship between CPAF and ATCO indicates that flight frequency and aviation CO_2 emissions predict one another, meaning variations in one variable systematically follow changes in the other. Similarly, URB was found to predict ATCO, and ATCO was found to predict GDP, showing that environmental factors operate within a reciprocal framework linking infrastructure intensity and economic growth. Likewise, URB significantly predicts ATCO, while ATCO in turn predicts GDP, confirming the role of environmental factors as intermediaries rather than causal determinants between infrastructure and economic development. Directional relationships also emerge from CPAF to GDP and FMCAF, and from GDP to both FMCAF and URB, illustrating how air transport, emissions, and macroeconomic conditions co-evolve across time. MIC was found to predict both RIC and URB, while RIC predicts URB, emphasizing the contribution of industrial and vehicular sources to urban environmental stress.

Collectively, the results establish a robust predictive network rather than strict causality, connecting economic, environmental, and demographic processes with asthma-related mortality. These insights suggest policy relevance in supporting coordination between environmental regulation, transport planning, and public health strategy.

5. Discussion

This study examined the direct impact of carbon dioxide (CO_2) emissions from air transportation (ATCO) on public health, specifically asthma-related mortality (ADN), by analyzing 15 European Union member states with the highest air traffic from 2008 to 2021. The findings revealed strong correlations between air traffic emissions and asthma fatality rates. Advanced econometric techniques were applied to address cross-sectional dependence and variable heterogeneity in the panel data. These included the Pesaran CD test for cross-sectional independence, the modified delta-tilde test for slope homogeneity, CIPS and CADF unit root tests, Westerlund and Edgerton bootstrap cointegration tests, and the Pooled Mean Group (PMG) estimator. The results confirmed cross-sectional dependence, indicating that shocks in one country might have affected others. The CIPS and CADF tests suggested that all variables should have been differenced once to achieve stationarity. Cointegration analysis across all four models confirmed long-term relationships among the variables. ADN was found to be significantly affected by ATCO, which had a consistent and positive effect in models M2–M4. These correlations supported earlier findings by Barrett et al. (2010), who showed through simulation that exposure to aviation emissions increased asthma-related fatalities. Similarly, D'Amato et al. (2014) and Kelly et al. (2015) documented that pollutants from air transport had substantial environmental and economic consequences, contributing to respiratory and cardiovascular diseases. The health burden not only deteriorated population well-being but also placed financial pressure on national healthcare systems (Eckelman et al., 2018). Schlenker and Walker (2015) noted that a one standard deviation increase in pollution levels in specific regions could have resulted in an additional $540,000 in hospitalizations related to respiratory and cardiovascular issues. These findings underscored the economic consequences of rising transport-related emissions.

In Model 1, which focused on commercial passenger flights (CPAF), the strong regression coefficient for ADN indicated a positive association between air traffic volume and asthma-related health outcomes. This result highlighted the importance of considering both emissions and traffic levels when assessing aviation's public health impacts (Kováčiková et al., 2024). Elevated pollution, noise, and stress levels caused by increased air traffic might have worsened asthma symptoms, particularly in adults. Zhu et al. (2011) and Habre et al. (2018) confirmed that aircraft emissions, especially during takeoff, were significant contributors to local air pollution, reinforcing the connection between air traffic operations and public health concerns. This study revealed a clear link between passenger and cargo flights and CO_2 emissions, underlining aviation's impact on respiratory health. With air traffic volume rising, stricter environmental regulations were urgently needed to manage emissions and mitigate both health risks and the associated economic costs (Crump, 2016; Cao et al., 2018; Lo et al., 2020).

Urbanization (URB), used as a control variable, also exhibited a consistent and positive association with ADN in both short- and long-run analyses. This was consistent with prior research indicating that urban environments were linked to higher asthma prevalence due to factors like increased air pollution, reduced green space, and urban-specific risks (Son et al., 2015; Achakulwisut et al., 2019). Su et al. (2019) similarly showed that urban growth, accompanied by rising pollution and declining greenery, increased asthma-related mortality. These findings supported the need for sustainable urban development policies that reduced pollution and improved public health outcomes (Sun et al., 2020; Wang et al., 2021). Cities should have emphasized air quality improvements, promoted public transportation and active mobility (e.g., cycling, walking), and expanded green areas. In addition, policies that prevented urban sprawl and promoted compact, sustainable urban design could have alleviated the environmental and health burdens linked to urban expansion (Nguyen et al., 2021; Alamoudi et al., 2024).

The extended analysis using Models 5 and 6 revealed that emissions from both manufacturing and construction (MIC) and road transportation (RIC) had statistically significant long-term effects on ADN. A 1% increase in MIC emissions led to an estimated 0.66% rise in asthma deaths, while a 1% increase in RIC emissions corresponded to a

0.79% increase. These results underscored the persistent public health risks associated with industrial activity and vehicular emissions.

Recent evidence from European institutional reports confirmed that air transport and related emissions remained a key contributor to respiratory illnesses. The European Environment Agency (2023) and World Health Organization [WHO] Europe (2023) emphasized that aviation and road traffic pollutants significantly affected public health, particularly in urban populations across EU countries. Although MIC and RIC displayed strong and significant long-run effects, the absence of short-run impacts was not unexpected. Industrial and traffic-related pollutants (especially $PM_{2.5}$, NO_2 and ultrafine particles) generated health damage through cumulative biological exposure, where respiratory inflammation and airway remodeling occurred gradually rather than immediately (Brunekreef & Holgate, 2002). Asthma exacerbation and mortality typically responded to chronic exposure thresholds, meaning that pollution-induced health deterioration became visible only after sustained contact rather than short-term fluctuations (Sunyer, 2001). Therefore, the lack of short-run significance likely reflected delayed physiological responses and pollution accumulation dynamics, rather than absence of effect.

The findings were consistent with previous studies highlighting the respiratory health impacts of industrial and road-based air pollution. Exposure to pollutants such as $PM_{2.5}$, NO_2, and SO_2 from industrial sources was shown to exacerbate asthma symptoms, particularly among children living near industrial zones (Buteau et al., 2018, 2020). Similarly, chronic exposure to traffic-related emissions, especially nitrogen oxides and fine particulate matter, was linked to increased risks of asthma, COPD, and premature mortality (Wu et al., 2022). While MIC showed immediate and localized effects, the influence of RIC appeared more cumulative, reflecting long-term exposure and regional pollution spread.

Gross Domestic Product (GDP), another control variable, was positively associated with ADN in models M3 and M4, suggesting a complex relationship between economic growth, industrialization, and respiratory health. While economic development improved access to healthcare, it also increased industrial activity and traffic congestion, which negatively impacted air quality and respiratory health (Chen, 2023). However, it was also important to consider the possibility of reverse causality: higher asthma mortality could, over time, have reduced population growth and transportation demand, potentially decreasing emissions levels. Such feedback loops might have complicated the directionality of the observed associations (Deryugina et al., 2019). Furthermore, the relationship between income growth and environmental degradation might have been nonlinear, as suggested by the Environmental Kuznets Curve (EKC) hypothesis. According to this framework, pollution tended to increase during early stages of economic growth but declined after a certain income threshold was reached, as structural shifts and environmental regulations intensified (Grossman & Krueger, 1995). Although the current study did not explicitly test for EKC dynamics, the potential for such nonlinear patterns deserved further investigation in future research. To balance economic growth with public health, policies should have promoted sustainable development by investing in green technologies, clean energy, and eco-friendly infrastructure (Guan et al., 2016; Luo et al., 2021; Su et al., 2023).

The Dumitrescu-Hurlin panel causality tests supported the main findings, showing causal relationships between GDP, CPAF, freight and mail flights (FMCAF), and ADN. These results offered strong empirical support for the conclusion that changes in economic and aviation activity directly impacted public health, underscoring the urgency of targeted policy measures.

The findings provide a strong rationale for emission-sensitive aviation policies across the EU. Strengthening the integration of aviation into the EU Emissions Trading System (EU ETS), including the reduction of free emission allowances and full inclusion of international flights, could help internalize the public health costs associated with air traffic emissions. Revenue from carbon pricing may also support cleaner aviation technologies and urban health interventions. Additional strategies include establishing emission control zones around major airports to protect nearby populations, encouraging the use of low-carbon aviation fuels to reduce both CO_2 and particulate matter emissions, and expanding real-time health surveillance in high-traffic urban areas. Urban planning efforts should integrate air quality goals by promoting compact cities, expanding green spaces, and encouraging sustainable transport modes. Coordinated action between transport, environmental, and health sectors remains essential to effectively address the aviation health nexus.

While this study offered valuable insight into the aviation health nexus, some limitations were acknowledged. First, although the data were sourced from established institutions such as Eurostat, the EEA, and the IEA, differences in reporting methodologies and time coverage between countries might have limited full comparability. Nonetheless, these datasets were widely accepted and commonly used in cross-country environmental health research. Second, the analysis focused on 15 EU countries with the highest levels of air traffic, with Norway excluded from Models 5 and 6 due to data unavailability. This might have slightly limited the generalizability of extended model results. Third, the use of national-level data might have obscured regional variation, particularly in densely populated or industrialized zones with high localized exposure to pollution. Fourth, some potentially important variables such as $PM_{2.5}$, NO_2, ozone, temperature, and seasonal effects were not available, which might have led to omitted variable bias. Moreover, demographic factors (e.g., age, gender), as well as institutional variation in healthcare access and environmental policy enforcement, were not accounted for and might have independently influenced ADN outcomes. Although cross-sectional dependence was tested, transboundary pollution effects were not explicitly modeled.

To address these limitations, future research was encouraged to utilize subnational data, integrate satellite-derived air quality measurements, and apply advanced methods such as machine learning or nonlinear modeling approaches. Including healthcare system indicators and expanding the scope to non-EU countries would have further enhanced the causal depth and policy relevance of findings.

6. Conclusions

This study investigated the impact of carbon dioxide (CO_2) emissions from air transportation on asthma-related mortality (ADN) across 15 European Union countries with the highest levels of air traffic between 2008 and 2021. Utilizing a comprehensive panel dataset and advanced econometric techniques, the analysis provided robust and consistent evidence of a statistically significant long-term relationship between aviation emissions and adverse public health outcomes.

The empirical approach accounted for cross-sectional dependence and heterogeneity across countries, enhancing the reliability of the estimated results. Unit root and cointegration tests confirmed the presence of stable long-run relationships among the variables. The estimation results indicated that increases in CO_2 emissions from air transportation were associated with higher rates of asthma-related mortality, quantifying the health burden attributable to aviation activity. Notably, the Pooled Mean Group estimation revealed that a 1% reduction in aviation-related emissions corresponded to a 0.05% decrease in asthma-related deaths over the long term.

The analysis was extended to assess the effects of emissions from the manufacturing, construction, and road transport sectors. These sectors also exhibited statistically significant long-term impacts on asthma mortality, underscoring the cumulative influence of multiple emission sources on respiratory health outcomes.

Control variables such as urbanization and gross domestic product demonstrated consistent and measurable effects on asthma-related mortality in both the short and long term. These variables captured key demographic and socioeconomic dynamics that interact with environmental factors to shape public health outcomes.

The study's methodological framework integrating unit root testing, cointegration analysis, and dynamic panel estimation enabled a rigorous evaluation of long-run associations. The consistency of findings across multiple model specifications reinforced the validity and robustness of the results.

In summary, the study established that CO_2 emissions from air transportation, along with emissions from other major economic sectors, contribute significantly to asthma-related mortality across high-traffic European countries. These findings underscore the importance of monitoring emission trends and provide a strong empirical basis for future research on the environmental determinants of public health.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author contributions

Corresponding Author (T. A.): Conceptualisation, Data curation, Methodology, Software, Visualization, Formal analysis, Writing – original draft, Writing – review and editing.

The Second Author (Tu. Av.): Conceptualisation, Methodology, Formal analysis, Writing – original draft, Supervision, Visualization, Writing – review and editing.

Disclosure statement

The authors have no competing interests to declare that are relevant to the content of this article.

References

Achakulwisut, P., Brauer, M., Hystad, P., & Anenberg, S. C. (2019). Global, national, and urban burdens of paediatric asthma incidence attributable to ambient NO_2 pollution: Estimates from global datasets. *The Lancet Planetary Health*, *3*(4), e166–e178. https://doi.org/10.1016/S2542-5196(19)30046-4

Agarwal, D., Singh, S. K., & Agarwal, A. K. (2011). Effect of exhaust gas recirculation (EGR) on performance, emissions, deposits and durability of a constant speed compression ignition engine. *Applied Energy*, *88*(8), 2900–2907. https://doi.org/10.1016/j.apenergy.2011.01.066

Airlines. (2023, 6 December). *Industry outlook upgraded to $25.7 billion profit in 2024*. https://airlines.iata.org/2023/12/06/industry-outlook-upgraded-257-billion-profit-2024

Akpanke, T. A., Deka, A., Ozdeser, H., & Seraj, M. (2023). Does foreign direct investment promote renewable energy use? An insight from West African countries. *Renewable Energy Focus*, *44*, 124–131. https://doi.org/10.1016/j.ref.2022.11.007

Alamoudi, M., Imam, A., Majrashi, A., Osra, O., & Hegazy, I. (2024). Integrating intelligent and sustainable transportation systems in Jeddah: A multidimensional approach for urban mobility enhancement. *International Journal of Low-Carbon Technologies*, *19*, 1301–1314. https://doi.org/10.1093/ijlct/ctae078

Anger, A. (2010). Including aviation in the European emissions trading scheme: Impacts on the industry, CO_2 emissions and macroeconomic activity in the EU. *Journal of Air Transport Management*, *16*(2), 100–105. https://doi.org/10.1016/j.jairtraman.2009.10.009

Arning, K., Engelmann, L., & Ziefle, M. (2023). Ready to fly? Comparing acceptance and behavioral usage intentions of CO2-based aviation fuels in four European countries. *Frontiers in Energy Research*, *11*, Article 1156709. https://doi.org/10.3389/fenrg.2023.1156709

Baltagi, B. H. (2008). *Econometric analysis of panel data* (4th ed.). John Wiley & Sons.

Barrett, S. R. H., Britter, R. E., & Waitz, I. A. (2010). Global mortality attributable to aircraft cruise emissions. *Environmental Science and Technology*, *44*(19), 7736–7742. https://doi.org/10.1021/es101325r

Berger, R. (2021). *The gentle breeze arrives, soaring in the blue sky – supporting China's aviation industry on the path towards*

low-carbon, *green*, *and sustainable development*. Roland Berger, Shanghai.
Brunekreef, B., & Holgate, S. T. (2002). Air pollution and health. *The Lancet*, *360*(9341), 1233–1242. https://doi.org/10.1016/S0140-6736(02)11274-8
Buteau, S., Doucet, M., Tétreault, L. F., Gamache, P., Fournier, M., Brand, A., Kosatsky, T., & Smargiassi, A. (2018). A population-based birth cohort study of the association between childhood-onset asthma and exposure to industrial air pollutant emissions. *Environment International*, *121*, 23–30. https://doi.org/10.1016/j.envint.2018.08.040
Buteau, S., Shekarrizfard, M., Hatzopolou, M., Gamache, P., Liu, L., & Smargiassi, A. (2020). Air pollution from industries and asthma onset in childhood: A population-based birth cohort study using dispersion modeling. *Environmental Research*, *185*, Article 109180. https://doi.org/10.1016/j.envres.2020.109180
Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics*: *Methods and applications*. Cambridge University Press. https://doi.org/10.1017/CBO9780511811241
Cao, X., Zevitas, C., Spengler, J., Coull, B., McNeely, E., Jones, B., Loo, S., MacNaughton, P., & Allen, J. (2018). The on-board carbon dioxide concentrations and ventilation performance in passenger cabins of US domestic flights. *Indoor and Built Environment*, *28*(6), 761–771. https://doi.org/10.1177/1420326X18793997
Chen, Q. (2023). Air pollution, public health service and regional economic development: Evidence from New York. *E3S Web of Conferences*, *424*, Article 04011. https://doi.org/10.1051/e3sconf/202342404011
Crump, D. (2016). Air quality in aircraft: A continuing debate. *Indoor and Built Environment*, *25*(5), 725–727. https://doi.org/10.1177/1420326X16654756
D'Amato, G., Cecchi, L., D'Amato, M., & Annesi-Maesano, I. (2014). Climate change and respiratory diseases. *European Respiratory Journal*, *44*, 735–748.
Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, *109*(12), 4178–4219. https://doi.org/10.1257/aer.20180279
Dogan, E., & Aslan, A. (2017). Exploring the relationship among CO_2 emissions, real GDP, energy consumption and tourism in the EU and candidate countries: Evidence from panel models robust to heterogeneity and cross-sectional dependence. *Renewable and Sustainable Energy Reviews*, *77*, 239–245. https://doi.org/10.1016/j.rser.2017.03.111
Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014
Dursun, E. (2022). Investigating the air transport-induced EKC hypothesis: Evidence from NAFTA countries. *International Journal of Energy Economics and Policy*, *12*, 494–500. https://doi.org/10.32479/ijeep.13347
Eckelman, M. J., Sherman, J. D., & MacNeill, A. J. (2018). Life cycle environmental emissions and health damages from the Canadian healthcare system: An economic-environmental-epidemiological analysis. *PLOS Medicine*, *15*, Article e1002623. https://doi.org/10.1371/journal.pmed.1002623
Ergen, H., Aslan, A., & Ayvaz, E. E. (2024). Can air transportation reach to zero carbon emissions: Comparative econometric analysis between transportation modes in US. *International Journal of Shipping and Transport Logistics*, *21*(1). https://doi.org/10.1504/IJSTL.2025.147885
Eurostat. (2020). *Causes of death – absolute number*. https://ec.europa.eu/eurostat/databrowser/view/hlth_cd_anr__custom_11389087/default/table?lang=en
European Environment Agency. (2023). *Air quality in Europe – 2023 Report*. https://www.eea.europa.eu/en/analysis/publications/europes-air-quality-status-2023
Ferrer, A. L. C., & Thome, A. M. T. (2023). Carbon emissions in transportation: A synthesis framework. *Sustainability*, *15*(11), Article 8475. https://doi.org/10.3390/su15118475
Gao, H., Liu, Q., Yan, C., Wu, Q., Gong, D., He, W., Liu, H., Wang, J., & Mei, X. (2023). Mitigation of greenhouse gas emissions and improved yield by plastic mulching in rice production. *Science of the Total Environment*, *880*, Article 162984. https://doi.org/10.1016/j.scitotenv.2023.162984
Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics*, *110*(2), 353–377. https://doi.org/10.2307/2118443
Gonzalez-Garay, A., Heuberger-Austin, C., Fu, X., Klokkenburg, M., Zhang, D., van der Made, A., & Shah, N. (2022). Unravelling the potential of sustainable aviation fuels to decarbonise the aviation sector. *Energy* & *Environmental Science*, *15*(8), 3291–3309. https://doi.org/10.1039/D1EE03437E
Gössling, S., & Humpe, A. (2020). The global scale, distribution and growth of aviation: Implications for climate change. *Global Environmental Change*, *65*, Article 102194. https://doi.org/10.1016/j.gloenvcha.2020.102194
Guan, W., Zheng, X., Chung, K., & Zhong, N. (2016). Impact of air pollution on the burden of chronic respiratory diseases in China: Time for urgent action. *The Lancet*, *388*(10054), 1939–1951. https://doi.org/10.1016/S0140-6736(16)31597-5
Habre, R., Zhou, H., Eckel, S., Enebish, T., Fruin, S., Bastain, T., Rappaport, E., & Gilliland, F. (2018). Short-term effects of airport-associated ultrafine particle exposure on lung function and inflammation in adults with asthma. *Environment International*, *118*, 48–59. https://doi.org/10.1016/j.envint.2018.05.031
Harrison, R. M., Masiol, M., & Vardoulakis, S. (2015). Civil aviation, air pollution and human health. *Environmental Research Letters*, *10*(4), Article 041001. https://doi.org/10.1088/1748-9326/10/4/041001
Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251–1271. https://doi.org/10.2307/1913827
Howitt, O. J., Carruthers, M. A., Smith, I. J., & Rodger, C. J. (2011). Carbon dioxide emissions from international air freight. *Atmospheric Environment*, *45*(39), 7036–7045. https://doi.org/10.1016/j.atmosenv.2011.09.051
International Air Transport Association. (2017). *Ground air pollution health and safety guide*. https://www.iata.org/contentassets/ccbdc54681c24574bebf2db2b18197a5/ground-air-pollution-health-safety-guide2017.pdf
International Energy Agency. (2020). *Tracking aviation 2020*. IEA.
International Energy Agency. (2023). *Aviation*. IEA. https://www.iea.org/energy-system/transport/aviation
Jain, S., Chao, H., Mane, M., Crossley, W., & DeLaurentis, D. (2021). Estimating the reduction in future fleet-level CO2 emissions from sustainable aviation fuel. *Frontiers in Energy Research*, *9*. https://doi.org/10.3389/fenrg.2021.771705
Jacob, C., Bechtel, B., Engel, S., Kardos, P., Linder, R., Braun, S., & Greiner, W. (2016). Healthcare costs and resource utilization of asthma in Germany: A claims data analysis. *European Journal of Health Economics*, *17*, 195–201. https://doi.org/10.1007/s10198-015-0671-3
Junior, H. D. S. Q., de Souza Celestino, M. A., de Souza, C. F. F., Falcao, V. A., & de Castro Camioto, F. (2024). CO_2 emissions in air transport: A comparative study using data envelopment analysis. *Transportation Research Record*: *Journal of the Transportation Research Board*, *2678*(5), 872–883. https://doi.org/10.1177/03611981231193407
Kelly, F. J., & Fussell, J. C. (2015). Air pollution and public health:

Emerging hazards and improved understanding of risk. *Environmental Geochemistry and Health*, *37*, 631–649. https://doi.org/10.1007/s10653-015-9720-1

Kováčiková, K., Novák, A., Sedláčková, A. N., & Kováčiková, M. (2024). The environmental consequences of engine emissions in air and road transport. *Atmosphere*, *15*(8), Article 903. https://doi.org/10.3390/atmos15080903

Lee, D. S., Fahey, D. W., Forster, P. M., Newton, P. J., Wit, R. C., Lim, L. L., Owen, B., & Sausen, R. (2009). Aviation and global climate change in the 21st century. *Atmospheric Environment*, *43*(22–23), 3520–3537. https://doi.org/10.1016/j.atmosenv.2009.04.024

Lee, D. S., Fahey, D. W., Skowron, A., Allen, M. R., Burkhardt, U., Chen, Q., Doherty, S. J., Freeman, S., Forster, P. M., Fuglestvedt, J., Gettelman, A., De León, R. R., Lim, L. L., Lund, M. T., Millar, R. J., Owen, B., Penner, J. E., Pitari, G., Prather, M. J.,… & Wilcox, L. J. (2021). The contribution of global aviation to anthropogenic climate forcing for 2000 to 2018. *Atmospheric Environment*, *244*, Article 117834. https://doi.org/10.1016/j.atmosenv.2020.117834

Lewtas, J. (2007). Air pollution combustion emissions: Characterization of causative agents and mechanisms associated with cancer, reproductive, and cardiovascular effects. *Mutation Research/Reviews in Mutation Research*, *636*(1–3), 95–133. https://doi.org/10.1016/j.mrrev.2007.08.003

Lo, P., Martini, G., Porta, F., & Scotti, D. (2020). The determinants of CO_2 emissions of air transport passenger traffic: An analysis of Lombardy (Italy). *Transport Policy*, *91*, 108–119. https://doi.org/10.1016/j.tranpol.2018.11.010

Loxham, M., Davies, D. E., & Holgate, S. T. (2019). The health effects of fine particulate air pollution. *BMJ*, *367*, Article l6609. https://doi.org/10.1136/bmj.l6609

Luo, R., Ullah, S., & Ali, K. (2021). Pathway towards sustainability in selected Asian countries: Influence of green investment, technology innovations, and economic growth on CO2 emission. *Sustainability*, *13*(22), Article 12873. https://doi.org/10.3390/su132212873

Maertens, S., Grimme, W., Scheelhaase, J., & Jung, M. (2019). Options to continue the EU ETS for aviation in a CORSIA-World. *Sustainability*, *11*(20), Article 5703. https://doi.org/10.3390/su11205703

Maruhashi, J., Grewe, V., Frömming, C., Jöckel, P., & Dedoussi, I. C. (2022). Transport patterns of global aviation NO_x and their short-term O_3 radiative forcing – a machine learning approach. *Atmospheric Chemistry and Physics*, *22*(21), 14253–14282. https://doi.org/10.5194/acp-22-14253-2022

Mendes, L. M., & Santos, G. (2008). Using economic instruments to address emissions from air transport in the European Union. *Environment and Planning A*: *Economy and Space*, *40*(1), 189–209. https://doi.org/10.1068/a39255md

Mensah, I. A., Sun, M., Gao, C., Omari-Sasu, A. Y., Zhu, D., Ampimah, B. C., & Quarcoo, A. (2019). Analysis on the nexus of economic growth, fossil fuel energy consumption, CO_2 emissions and oil price in Africa based on a PMG panel ARDL approach. *Journal of Cleaner Production*, *228*, 161–174.

Nguyen, P. Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *International Journal of Environmental Research and Public Health*, *18*(21), Article 11028. https://doi.org/10.3390/ijerph182111028

Owen, B., Lee, D. S., & Lim, L. (2010). Flying into the future: Aviation emissions scenarios to 2050. *Environmental Science and Technology*, *44*(7), 2255–2260. https://doi.org/10.1021/es902530z

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Pesaran, M. H. (2004). *General diagnostic tests for cross-section dependence in panels* (Cambridge Working Papers in Economics No. 1229). University of Cambridge. https://doi.org/10.2139/ssrn.572504

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section independence. *Journal of Applied Econometrics*, *22*(2), 265–312. https://doi.org/10.1002/jae.951

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Pope III, C. A., & Dockery, D. W. (2006). Health effects of fine particulate air pollution: Lines that connect. *Journal of the Air & Waste Management Association*, *56*(6), 709–742. https://doi.org/10.1080/10473289.2006.10464485

Profillidis, V. A., Botzoris, G. N., & Galanis, A. T. (2014). Environmental effects and externalities from the transport sector and sustainable transportation planning – A review. *International Journal of Energy Economics and Policy*, *4*(4), 647–661.

Ssali, M. W., Du, J., Mensah, I. A., & Hongo, D. O. (2019). Investigating the nexus among environmental pollution, economic growth, energy use, and foreign direct investment in 6 selected sub-Saharan African countries [Retracted article]. *Environmental Science and Pollution Research*, *26*, 11245–11260. https://doi.org/10.1007/s11356-019-04455-0

Schlenker, W., & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies*, *83*(2), 768–809. https://doi.org/10.1093/restud/rdv043

Sharma, A., Jakhar, S., & Choi, T. (2021). Would CORSIA implementation bring carbon neutral growth in aviation? A case of US full service carriers. *Transportation Research Part D*: *Transport and Environment*, 97, Article 102839. https://doi.org/10.1016/j.trd.2021.102839

Song, M.-J., Seo, Y.-J., & Lee, H.-Y. (2023). The dynamic relationship between industrialization, urbanization, CO_2 emissions, and transportation modes in Korea: Empirical evidence from maritime and air transport. *Transportation*, *50*, 2111–2137. https://doi.org/10.1007/s11116-022-10303-x

Staples, M., Malina, R., Suresh, P., Hileman, J., & Barrett, S. (2018). Aviation CO_2 emissions reductions from the use of alternative jet fuels. *Energy Policy*, *114*, 342–354. https://doi.org/10.1016/j.enpol.2017.12.007

Sgouridis, S., Bonnefoy, P., & Hansman, R. J. (2011). Air transportation in a carbon constrained world: Long-term dynamics of policies and strategies for mitigating the carbon footprint of commercial aviation. *Transportation Research Part A*: *Policy and Practice*, *45*(10), 1077–1091. https://doi.org/10.1016/j.tra.2010.03.019

Son, J. Y., Kim, H., & Bell, M. L. (2015). Does urban land-use increase risk of asthma symptoms? *Environmental Research*, *142*, 309–318. https://doi.org/10.1016/j.envres.2015.06.042

Sun, S., Sarkar, C., Kumari, S., James, P., Cao, W., Lee, R., Tian, L., & Webster, C. (2020). Air pollution associated respiratory mortality risk alleviated by residential greenness in the Chinese Elderly Health Service Cohort. *Environmental Research*, *183*, Article 109139. https://doi.org/10.1016/j.envres.2020.109139

Sunyer, J. (2001). Urban air pollution and chronic obstructive pulmonary disease: A review. *European Respiratory Journal*, *17*(5). https://doi.org/10.1183/09031936.01.17510240

Su, S., Qamruzzaman, M., & Karim, S. (2023). Charting a sustainable future: The impact of economic policy, environmental taxation, innovation, and natural resources on clean energy consumption. *Sustainability*, *15*(18), Article 13585. https://doi.org/10.3390/su151813585

Teoh, R., Schumann, U., Gryspeerdt, E., Shapiro, M., Molloy, J., Koudis, G., Voigt, Ch., & Stettler, M. E. (2022). Aviation contrail climate effects in the North Atlantic from 2016 to 2021. *Atmospheric Chemistry and Physics*, *22*(16), 10919–10935. https://doi.org/10.5194/acp-22-10919-2022

Terrenoire, E., Hauglustaine, D. A., Cohen, Y., Cozic, A., Valorso, R., Lefèvre, F., & Matthes, S. (2022). Impact of present and future aircraft NO_x and aerosol emissions on atmospheric composition and associated direct radiative forcing of climate. *Atmospheric Chemistry and Physics*, *22*(18), 11987–12023.

Thangavel, P., Park, D., & Lee, Y. C. (2022). Recent insights into particulate matter (PM2.5)-mediated toxicity in humans: An overview. *International Journal of Environmental Research and Public Health*, *19*(12), Article 7511. https://doi.org/10.3390/ijerph19127511

The Organisation for Economic Co-operation and Development [OECD]. (2023). *Health status*: *Causes of mortality*. https://stats.oecd.org/?lang=en

Touri, L., Marchetti, H., Sari-Minodier, I., Molinari, N., & Chanez, P. (2013). The airport atmospheric environment: Respiratory health at work. *European Respiratory Review*, *22*(128), 124–130. https://doi.org/10.1183/09059180.00005712

Wang, P., Goggins, W. B., Shi, Y., Zhang, X., Ren, C., & Lau, K. K. L. (2021). Long-term association between urban air ventilation and mortality in Hong Kong. *Environmental Research*, *197*, Article 111000. https://doi.org/10.1016/j.envres.2021.111000

Warnecke, C., Schneider, L., Day, T., Theuer, S., & Fearnehough, H. (2019). Robust eligibility criteria essential for new global scheme to offset aviation emissions. *Nature Climate Change*, *9*, 218–221. https://doi.org/10.1038/s41558-019-0415-y

Westerlund, J. (2005). New simple tests for panel cointegration. *Econometric Reviews*, *24*(3), 297–316. https://doi.org/10.1080/07474930500243019

Westerlund, J., & Edgerton, D. L. (2007). A panel bootstrap cointegration test. *Economics Letters*, *97*(3), 185–190. https://doi.org/10.1016/j.econlet.2007.03.003

World Health Organization. (2023). *Health effects of air pollution in Europe*: *Burden of disease report*. World Health Organization Europe. https://www.who.int/europe/publications

World Bank. (2024). *World development indicators*. https://databank.worldbank.org/

Wu, X., Vu, T. V., Harrison, R. M., Yan, J., Hu, X., Cui, Y., Shi, A., Liu, X., Shen, Y., Zhang, G., & Xue, Y. (2022). Long-term characterization of roadside air pollutants in urban Beijing and associated public health implications. *Environmental Research*, *212*, Article 113277. https://doi.org/10.1016/j.envres.2022.113277

Yim, S. H. L., Lee, G. L., Lee, I. H., Allroggen, F., Ashok, A., Caiazzo, F., Eastham, S. D., Malina, R., & Barrett, S. R. H. (2015). Global, regional and local health impacts of civil aviation emissions. *Environmental Research Letters*, *10*, Article 034001. https://doi.org/10.1088/1748-9326/10/3/034001

Yim, S. H. L., Stettler, M. E. J., & Barrett, S. R. H. (2013). Air quality and public health impacts of UK airports. Part II: Impacts and policy assessment. *Atmospheric Environment*, *67*, 184–192. https://doi.org/10.1016/j.atmosenv.2012.10.017

Zhu, Y., Fanning, E., Yu, R. C., Zhang, Q., & Froines, J. R. (2011). Aircraft emissions and local air quality impacts from takeoff activities at a large International Airport. *Atmospheric Environment*, *45*(36), 6526–6533. https://doi.org/10.1016/j.atmosenv.2011.08.062