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Air Travel and Carbon Emissions: Global Evidence and a UK Policy Evaluation

Ziqing Wang¹²

This study examines the effectiveness of aviation-related fiscal instruments, particularly the Air Passenger Duty (APD), in mitigating carbon emissions from air travel, using a global panel dataset and a focused UK case study. At the global level, we employ Instrumental Variable Quantile Regression (IVQR) to estimate the causal effects of air passenger departures on emissions, addressing potential endogeneity by using the presence of aviation-related taxes as an instrument. The UK analysis further evaluates how air travel demand responds to changes in APD, distinguishing between short and medium-haul and long-haul routes. The findings highlight the potential of aviation taxation as an effective climate policy tool. In addition, global results show that air passenger departures significantly increase CO₂ emissions, with smaller marginal links in relatively high-emitting country. The UK case also shows that APD does not reduce air travel uniformly. It significantly lowers demand for short- and medium-haul flights and for reduced-fare long-haul travel. This heterogeneity highlights the importance of differentiated aviation tax design for achieving climate objectives.

Keywords: Carbon emissions, Instrumental variable quantile regression, climate policy, Panel data analysis, Air passenger duty

Key Policy Insights

Passenger-based aviation taxes can contribute to CO₂ mitigation by reducing air travel demand.

Given the uneven emissions response across countries, differentiated policy designs are preferable to uniform per-passenger charges.

UK evidence shows that APD reduces demand most strongly for short- and medium-haul travel, where the tax represents a larger share of total travel costs and substitution options are available.

APD also lowers demand among long-haul passengers travelling in reduced-fare (economy) classes.

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1. Introduction

As concern over climate change intensifies, aviation as one of the most carbon-intensive transport modes accounts for 2–3% of global CO₂ emissions, a share projected to rise with continued growth in international travel (IATA, 2020). Unlike many sectors where decarbonization technologies are becoming viable, aviation remains reliant on fossil fuels, with sustainable fuels, electric aircraft, and hydrogen propulsion still far from large-scale deployment (Bergero et al., 2023; Bastinho, 2025). In the short term, fiscal measures such as air ticket levies, departure taxes, and carbon-linked charges have emerged as key policy tools, acting as Pigouvian taxes to embed the external costs of carbon emissions into air travel prices (Larsson et al., 2019; Gössling et al., 2021; Sterner, 2007; Santos & Robin, 2010). The importance of such measures is reinforced by the International Civil Aviation Organization's adoption of a Long-Term Aspirational Goal of net-zero emissions from international aviation by 2050, which commits member states to pursue sustained reductions in aviation-related greenhouse gas emissions and constrains national policy choices beyond purely voluntary action.

Globally, a growing number of countries across Europe, Asia, Africa, and the Americas have introduced air-travel taxes or related passenger-based fiscal measures, though their scope and design vary considerably across jurisdictions (see Appendix A). Empirical evidence supports their effectiveness: Mayor and Tol (2007) show that even modest fare increases can prompt modal shifts and reduce emissions without substantially impairing mobility, while Albalade and Bel (2010) find such instruments particularly effective where alternative transport infrastructure, such as high-speed rail, enables feasible substitution. Demand responses, however, are heterogeneous, varying with passenger income, travel purpose, route type, and the availability of substitutes.

Recent studies emphasise the importance of policy design. Using qualitative synthesis and conceptual analysis, Gössling and Higham (2021) argue that uniform aviation tax structures may be suboptimal. Kogler, Thaller & Posch (2025) run scenario analyses to simulate emissions trajectories for Austria. Their results show that demand-side measures and travel restrictions can reduce CO₂ in the short run, but rising leisure demand risks offsetting gains unless policies bite harder. Business travel is more responsive to frequent-flyer charges and strict travel rules. At the global level, using a scenario-based simulation model, Zheng & Rutherford (ICCT, 2022) compare

a flat per-flight APD with a progressive frequent-flying levy (FFL), and find an FFL raises most revenue from the small share of frequent, high-income flyers while aligning the burden with historical emitters. ICAO has adopted a Long-Term Aspirational Goal (LTAG) of net-zero carbon emissions from international aviation by 2050 (ICAO, 2022). Complementing this policy, ICCT's Aviation Vision 2050 roadmap quantifies current aviation CO₂ emissions and projects their future evolution under different technology and policy scenarios, showing that efficiency improvements and sustainable aviation fuels alone are insufficient to offset expected traffic growth (ICCT, 2025). This implies that additional measures, such as APD or frequent-flyer levies, will be required if aviation is to align with climate-stabilisation targets.

Within this global policy landscape, the United Kingdom's Air Passenger Duty (APD), one of the world's first national-level aviation taxes, stands out. Introduced in 1994, the APD applies a tiered structure based on flight distance and travel class. A key feature of its recent evolution is the divergent trajectory of its fares: following a 2014 consultation (HM Treasury, 2014), long-haul duties were restructured and have seen substantial nominal increases, whereas the short and medium-haul reduced fare remained largely frozen, leading to a significant decline in its real-term value (HM Treasury, 2015; 2021). It has attracted substantial scholarly attention: Durbarry (2008), using an ARDL model, found a negative impact on outbound tourism, though demand appeared relatively inelastic, while Song, Seetaram, and Ye (2019) applied compositional data and seemingly unrelated regression techniques to show that travellers reallocate their budgets in response to APD, increasing the share spent on transportation and reducing at-destination spending (e.g., accommodation and food). Büchs & Mattioli (2022) show air-travel taxes are distributionally neutral to progressive, with the most progressive design taxing both flight counts and emissions using a frequent-flyer-style levy. They also flag groups for example some migrants who fly frequently at lower incomes, underscoring the need for careful design.

Despite a substantial literature on aviation demand and pricing, important gaps remain in our understanding of how air travel translates into national carbon emissions. Meta-analyses document wide variation in income and price elasticities of passenger air travel across markets (Brons et al., 2002; Gallet & Doucouliagos, 2014). However, econometric evidence linking aviation activity to emissions is still concentrated in a limited set of countries and regions (e.g., Falk, 2021), leaving heterogeneity across the global emissions distribution largely unexplored. Consequently, causal

evidence is scarce on whether international air travel contributes more strongly to total CO₂ emissions in lower-emitting country-years than in higher-emitting contexts, and on whether passenger-based aviation taxes have systematically different effects across emissions levels. This motivates a global panel approach that can test for heterogeneity. Methodologically, we therefore use an instrumental-variable strategy to identify the causal effect of aviation activity and aviation passenger taxes on per-capita CO₂ emissions. We then employ quantile regression to move beyond mean effects and estimate how these causal relationships vary across the conditional distribution of per-capita emissions. In addition, far less is known about how APD affects demand across fare classes and distance bands. We study the UK APD effects with disaggregated quarterly data by band and fare class, applying instrumental variables and seasonal controls to assess impacts on short- and long-haul passenger volumes. This study addresses the following research questions:

1. What is the global impact of international air passenger departures on CO₂ emissions per capita, and how does this impact vary across the emissions distribution?
2. Do aviation-related passenger taxes causally reduce air travel and, through this channel, lower CO₂ emissions?
3. How effective is the UK APD in reducing passenger demand across distance bands and fare classes?

The remainder of the paper is organised as follows. Section 2 describes the data and variables. Section 3 outlines the empirical methods. Section 4 presents the results for the global panel and the UK case study. Section 5 discusses the findings and policy implications. Section 6 concludes.

2 Data and Variables

2.1 Global Data and Variables

Many countries impose taxes or fees on air passengers for a variety of policy objectives. We assemble an unbalanced panel of 117 countries over 2000–2022, including CO₂ emissions per capita, international passenger departures, GDP per capita, energy consumption per capita and population density. For global panel, the dependent variable is total national CO₂ emissions per capita. With the limited data-availability for a full accounting of emissions from residents' air

travel instead, we study how air travel activity is associated with changes in total national emissions. Air passenger numbers are employed as a proxy for aviation activity³. Given the high emissions intensity of air travel per passenger-kilometre, greater departure volumes, and thus higher passenger-kilometres are expected to be associated with higher national CO₂ emissions. GDP per capita is included as a control for income-driven demand and higher incomes typically increase consumption of energy- and travel-intensive goods and services, implying a positive association with CO₂ per capita. A key control is national energy consumption (kg of oil equivalent per capita). We include it because economies with high aggregate energy demand are also likely to have higher baseline levels of mobility and transportation activity. Finally, population density serves as a proxy for urban form, denser countries generally exhibit lower per-capita emissions, so a negative association with CO₂ per capita is expected.

Aviation-related policies are captured by a binary indicator (1 = implemented), with all relevant measures listed in Supplementary Appendix A, Table 1. As shown in Table 1, descriptive statistics reveal large cross-country dispersion in international passenger departures and substantial variation in GDP per capita and energy use per capita, reflecting heterogeneous economic structures and energy systems. Average CO₂ emissions per capita is 4.4 tCO₂/person. Countries record on average is 12.9 million international departures per year. GDP per capita averages is 13,670 US\$. Energy consumption per capita averages are 25,228 kg oil-equivalent per person. Population density also varies largely, spanning sparsely populated countries to very dense city-states.

Table 1. Statistical descriptive statistics for global data (2000-2022)

Variable	Observations	Mean	Std. Dev.	Min	Max
Annual CO ₂ Emissions per Capita	2436	4.389	5.029	0.047	33.975
Air Passenger Number	2,127	2.43e+07	8.35e+07	1593	9.27e+08
GDP per capita	2666	13670.12	19947.37	110.4635	135120.8

³ Since transit passengers, those who arrive and depart the UK within 24 hours without clearing border control, are exempt from the APD, their inclusion in the total is expected to introduce a downward bias in the estimated coefficient for the tax. However, based on stable transit data, for example UK Government reports (2013-2019), we contend that this bias slightly affects the magnitude of the coefficient but not the direction or statistical significance.

Energy Consumption per capita	2604	25227.69	30493.64	105.1101	188294.0
Population Density	2666	430.2709	1924.491	1.5434	21530.0
Aviation-emission related policy (Binary)	231	0.6537	0.4768	0.0	1.0

Table 2. Descriptive Statistics for UK Variables (2010Q1–2024Q4)

Variable	Obs	Mean	Std. Dev.	Min	Max
Carbon emission per capita per quarter	60	1.85	0.27	1.31	2.42
Population (thousand)	60	65865.98	1850.028	62635	69405
GDP (million GBP)	60	524,770.30	91,964.71	396,176	724,724
Unemployment rate (%)	60	5.56	1.65	3.80	8.50
Consumer Price Index (CPI)	60	2.81	2.13	0.30	9.40
Energy consumption (thousand tonnes)	60	35,706.48	5,961.83	23,690.61	47,489.94
APD receipts from Band A (million GBP)	60	192.62	79.63	14.77	428.00
APD receipts from Band B-D (million GBP)	60	521.16	2,655.40	2.95	17,207.00
Reduced Fare Band A Passengers (000s)	60	6347.33	2279.55	240.32	9632.87
Standard Fare Band A Passengers (000s)	60	148.07	73.90	11.89	407.49
Total Band A Passengers (000s)	60	6495.40	2327.02	252.21	9861.45
Reduced Fare Band B-D Passengers (000s)	60	1123.95	465.85	63.50	1799.99
Standard Fare Band B-D Passengers (000s)	60	288.98	131.17	16.20	502.51
Total Band B-D Passengers (000s)	60	1412.93	590.68	79.69	2292.29
Total Passengers (000s)	60	8392.84	2903.49	331.90	12124.07

2.2 UK Data and Variables

The dependent variable in the UK analysis is total CO₂ emission per capita on a residence basis. As showing in Table 2, over the sample period, average emissions amount to 1.85 tonnes per person per quarter, with values ranging from 1.31 to 2.42, reflecting fluctuations in economic activity and structural changes in energy use. APD variables are constructed using band-specific information on passenger numbers and fare rates. Specifically, band A denotes short and medium haul (<2,000 miles from London) and Bands B–D denote long-haul ($\geq 2,000$ miles). Because the statutory band structure changed in 2015 (collapsing B–D) and again in April 2023, introducing Domestic and re-splitting long-haul, we harmonise to two stable analytic groups: A and BCD. This prevents spurious structural breaks and maintains sample size. Within each band, we compute a real APD per passenger by weighting the statutory reduced and standard rates by observed cabin shares. Using UK APD data for 2010 Q1–2024 Q4, Band A averaged 6.50 million passengers per quarter, while Bands B–D averaged 1.41 million passengers per quarter. Total departures averaged

8.39 million passengers per quarter, underscoring the dominance of short-haul travel. Over the same period, APD receipts government revenue from APD, averaged £193 million per quarter for Band A and £521 million per quarter for Bands B. To account for pronounced seasonal patterns in air travel demand, we also constructed seasonally adjusted series for total passengers, Band A, and Bands B–D (see Appendix A, Figure 1). Control variables include population, GDP, the unemployment rate, the consumer price index, and energy consumption, capturing macroeconomic conditions that influence both air travel demand and emissions.

3 Methodology

We combine a global country–year panel with a band-level UK time series to identify how air travel affects CO₂ and how the UK’s APD shapes demand.

3.1 Global study

3.1.1 Baseline and Quantile Regression

To assess the relationship between air passenger volumes and carbon emissions, we begin with a baseline panel regression model specified as follows:

$$CO2_{per\ capita_{it}} = \alpha_0 + \alpha_1 Air\ Passengers_{it} + \alpha_2 GDP_{per\ capita_{it}} + \alpha_3 Energyconsumption_{per\ capita_{it}} + \alpha_4 Population\ density_{it} + \epsilon_{2t} \quad (1)$$

This baseline model allows us to isolate the marginal impact of air passenger numbers on national carbon emissions per capita, controlling for economic development, energy intensity, and population density. The coefficient α_1 captures how sensitive CO₂ emissions are to variations in air travel activity. To explore how the relationship between air travel and emissions varies across different levels of national emissions, we also employ quantile regression. This approach estimates the impact of air travel on CO₂ emissions at various points in the conditional distribution (e.g., 25th, 50th, and 75th percentiles), allowing us to capture heterogeneous effects that are often masked in mean-based models like OLS. Specifically, low-emission countries may see a stronger relative impact from air travel, while high-emission countries may already have other dominant sources of emissions, leading to a weaker marginal effect.

3.1.2 Quantile Instrumental Variable Regression (IV-QR)

To make a casual comparison, we use instrumental-variable quantile regression (IV-QR), which isolates the portion of air-travel variation caused by the tax and study whether a tax-induced change in air demand translate into different CO₂ responses in cleaner versus more emission-intensive settings. We use aviation - related tax as an instrument for air-passenger departures, to study when policy moves demand, how does CO₂ respond across the emissions distribution? Specifically, the first stage predicts passengers from APD and control variables; the second stage quantile model relates CO₂ to the policy-induced passenger component.

Step1: We begin by estimating the endogenous regressor (log of air passenger departures) as a function of the instrument (APD) and other exogenous controls: GDP per capita, energy consumption per capita and population density.

$$AirPassengers_{it} = \beta_0 + \beta_1 Aviation - related\ passenger\ tax_{it} + \beta_2 GDP_{per\ capita_{it}} + \beta_3 Energyconsumption_{per\ capita_{it}} + \beta_4 Population\ density_{it} + \epsilon_{2t} \quad (2)$$

Step 2: To allow the causal effect to vary across the emissions distribution, we use a quantile model. For each quantile $\tau = 0.25, 0.50$ and 0.75 , we estimate the following quantile regression:

$$Q_\tau(Z_{it}) = \gamma_0(\tau) + \gamma_1(\tau) * \widehat{Airpassengers}_t + \gamma_2(\tau)GDP_{per\ capita_{it}} + \gamma_3(\tau)Energyconsumption_{per\ capita_{it}} + \alpha_4(\tau)Population\ density_{it} + \epsilon_{3t}(\tau) \quad (3)$$

Where $Q_\tau(Z_{it})$ denotes the carbon emission conditioning on the quantile. Z_t is the vector of control variables. $\widehat{Airpassengers}_t$ denotes the fitted value of air passenger obtained from first stage.

3.1.3 Robustness check

Transit passengers are included in international departure counts but do not pay passenger-based aviation taxes, which could attenuate estimated effects in hub countries with high connecting traffic. To address this issue, we conduct a robustness check by re-estimating all global models after excluding countries that host one of the world's ten largest hub airports (OAG Mega hubs 2025)⁴.

⁴ Specifically, we exclude all countries hosting airports ranked in the global Top 10 Mega hubs: London Heathrow (UK), Istanbul (Türkiye), Amsterdam Schiphol (Netherlands), Kuala Lumpur (Malaysia), Frankfurt

3.2 UK study

3.2.1 APD impact on UK air passenger demands

Using the quarterly UK panel (2010Q1–2024Q4), we estimate band-specific demand elasticities⁵.

$$\ln Airpassenger_{it} = \alpha_0 + \alpha_1 Gdp_{pc_t} + \alpha_2 Apd_{ppi_t} + \alpha_3 Unemployment_t + \alpha_4 Cpi_t + \alpha_5 Q2 + \alpha_6 Q3 + \alpha_7 Q4 + \epsilon_{1it} \quad (4)$$

Where i denotes the passenger band and t represents time. The dependent variable, air passenger numbers, is expressed in logarithmic form. The variable Apd_{pp} refers to the Air Passenger Duty per passenger. Control variables include GDP per capita, the unemployment rate, and the consumer price index. Quarterly dummy variables (Q2, Q3, and Q4, with Q1 as the reference category) are included to account for strong seasonal patterns observed in the data.

3.2.2A 2SLS study on the impact of the air passenger numbers on carbon emissions for the UK

To assess the causal impact of passenger demand on aviation-related CO₂ emissions while accounting for potential endogeneity, we employed a 2SLS estimation strategy. The APD was utilized as an instrumental variable for passenger demand. This analysis was conducted separately for Band A (short and medium-haul) and Band B-D (long-haul) flights, reflecting the differentiated nature of APD and emission profiles.

$$CO2_{per\ capita_{it}} = \beta_0 + \beta_1 \widehat{Airpassengers}_t + \beta_2 GDP_{per\ capita_t} + \beta_3 Energyconsumption_{per\ capita_{it}} + \epsilon_{2t} \quad (5)$$

Where $CO2_{it}$ represents the carbon emissions per capita, especially pertaining to the Band A and Band B-D at time t . $\widehat{Airpassengers}_t$ denotes the predicted passenger demand at time t and is generated from the first-stage regression where actual passenger demand is regressed on the APD as an instrumental variable, along with other exogenous control variables.

(Germany), Chicago O'Hare (USA), Atlanta Hartsfield–Jackson (USA), Tokyo Haneda (Japan), and Paris Charles de Gaulle (France).

⁵ Because quarterly series often exhibit serial correlation and heteroskedasticity, conventional OLS standard errors can misstate significance. We therefore report Newey–West (HAC) ⁵standard errors, which are robust to both heteroskedasticity and autocorrelation

4 Empirical Results

4.1 Global Carbon Emission: Global Analysis

4.1.1 Global Panel Analysis with Quantile Regression

This section answers research question 1. In the fixed-effects specification, the quantile regressions reveal a positive and statistically significant relationship between air passenger departures and CO₂ emissions across the conditional distribution. As showing in Table 3, the estimated effect is largest at the lower quantile. Among the control variables, energy consumption per capita is the strongest predictor of emissions in all specifications, driven by within-country variation in the fixed-effects models and by overall variation in the pooled quantile regressions. GDP per capita is positive in the fixed-effects model because it reflects within-country income growth over time, which is typically accompanied by higher consumption and energy use. In the quantile regressions, however, the coefficient becomes negative and statistically significant at higher quantiles, indicating that among higher-emitting country-years, higher income is associated with lower conditional emissions. Population density exhibits a negative and statistically significant association with emissions at the upper quantile.

Table 3 Quantile Regression Estimates of Determinants of Carbon Emissions-Full Sample and Selected Quantiles

Dependent variable: Carbon emission per capita

Variable	Full Sample (FE)	Quantile 0.25	Quantile 0.50	Quantile 0.75
Air passenger number	−0.007 (0.006)	0.105*** (0.007)	0.053*** (0.005)	0.021*** (0.004)
GDP_pc	0.031*** (0.010)	−0.016 (0.017)	−0.066*** (0.012)	−0.018* (0.009)
Energy consumption_pc	0.945*** (0.021)	0.873*** (0.018)	0.981*** (0.013)	0.969*** (0.010)
Population density	0.064 (0.041)	0.005 (0.008)	0.001 (0.006)	−0.023*** (0.005)
Observations	2,137	2,137	2,137	2,137

Note: ***p<0.01, **p<0.05, *p<0.1; Quantiles are reported at the 0.25, 0.50, and 0.75 levels, corresponding to the 25th, 50th, and 75th percentiles.

Before estimation, we assess the time-series properties of the panel variables. Fisher-type panel unit root tests based on the Augmented Dickey–Fuller method indicate mixed integration orders. Accordingly, stationary variables enter the regressions in levels, while non-stationary variables are first-differenced (see Appendix A, Table 2).

4.1.2 IV-QR Regression

This subsection addresses research question 2, asking whether aviation-related passenger taxes can causally affect CO₂ emissions by changing air travel activity. We estimate an instrumental-variable model in which air passenger volume is treated as endogenous and instrumented using the presence of an APD.

Stage 1. The first-stage regression indicates that APD significantly predicts international air passenger activity, confirming that the instrument is relevant. First-stage diagnostics suggest the instrument is sufficiently strong for causal inference: the first-stage F-statistic is 15.69, which exceeds conventional weak-instrument thresholds. Full first-stage results are reported in the Appendix A Table 5.

Stage 2. To examine whether the causal relationship differs across the emissions distribution, we estimate quantile regressions using a control-function IV approach. As shown in Table 4, The quantile results show that the estimated effect of air passengers on emissions is positive throughout the distribution but varies in magnitude and precision. At the 25th and 50th quantiles, the passenger coefficient is positive but not statistically significant. At the 75th quantile, the passenger coefficient is positive and statistically significant (0.089, $p < 0.05$). Energy consumption per capita is a stronger predictor of CO₂ emissions across all models, with elasticities rising from about 0.68 ($\tau=0.25$) to nearly 1.0 ($\tau=0.75$). GDP per capita and population density show clear heterogeneity across the emissions distribution. GDP per capita is positive at lower quantiles but turns negative at higher quantiles, suggesting that income growth raises emissions in low-emitting contexts but is associated with cleaner outcomes in high-emitting countries. Population density reduces emissions at the lower quantile but increases them at the upper quantile.

Table 4 IV-QR for Carbon Emissions

Dependent variable: Carbon emission per capita

Variable	0.25 Quantile	0.50 Quantile	0.75 Quantile
Airpassenger departures	0.0663 (0.0536)	0.0678 (0.0597)	0.0888** (0.0375)
GDP _{pc}	0.1328* (0.0761)	-0.0148 (0.0848)	-0.1118** (0.0533)
Energy consumption _{pc}	0.6754*** (0.0300)	0.8626*** (0.0334)	0.9826*** (0.0210)
Population density	-0.0240** (0.0119)	0.0117 (0.0132)	0.0184** (0.0083)
Resid	-0.0201 (0.0548)	-0.0764 (0.0611)	-0.1051*** (0.0384)
Constant	-7.7570*** (0.2101)	-8.2003*** (0.2342)	-8.6448*** (0.1473)

Note: Dependent variable is CO₂ emissions per capita. Quantile regression is instrumented using fitted values from the first stage. ***p<0.01, **p<0.05, *p<0.1.

4.1.3 Robustness check excluding major-hub countries

Excluding major hub countries does not change our main conclusions, as showing in Appendix B. In the quantile regressions, air passenger activity remains positive and statistically significant across quantiles, with the largest effects at the lower end of the emissions distribution, consistent with the full-sample results. In the IV–quantile estimates, the instrumented passenger coefficient remains positive and is statistically significant at the upper quantile, and its magnitude is larger than in the specification that includes mega-hub countries, and its magnitude is larger than in the estimation that includes mega-hub countries.

4.2 UK Carbon Emissions: Policy Impact Analysis

This subsection addresses research question 3, evaluating the effectiveness of the APD in the UK. The results show that APD significantly reduces passenger demand, particularly for short- and medium-haul and reduced-fare travel, with corresponding emissions implications.

4.2.1 APD's Impact on Passenger Demand

In this section, we further examine the impact of APD on passenger behaviour and emissions outcomes by separately analysing Band A and Band BCD passengers. Firstly, ADF tests (Appendix A, Table 3) confirm mixed integration orders, with I(0) and I(1) variables.

In Table 5, APD per passenger is negative and statistically significant across all segments, confirming a demand-reducing effect. For Band A (short and medium-haul), the elasticity is -0.834 (reduced), -0.844 (standard), and -1.234 (total) and the pooled response is largest in magnitude. For Band B–D (longer-haul), the elasticity is -1.246 (reduced), -0.870 (standard), and -0.838 (total), indicating particularly strong sensitivity for the reduced-fare segment.

For other control variables, GDP per capita, as a broad indicator of macroeconomic conditions that influence travel demand, enters positively and significantly throughout. The positive and highly significant GDP per capita coefficients in the air travel demand models indicate that air passenger activity is strongly income-elastic in the long run. A 1% increase in income is associated with a more-than-proportional increase in air travel which is consistent with previous works: Shahbaz et

al. (2022) identify that the income on economic activity can produce elasticities above 1.0, while Burke & Csereklyei (2016) provide direct evidence of such relationships in key sectors for example services, a highly relevant context for the UK's service-oriented economy. unemployment is negative and significant across columns, while CPI and most seasonal dummies are not statistically significant (except Q3 is positive in the Band A total and Band B–D reduced columns).

Table 5 Impact of APD and Economic Factors on UK Air Passenger Demand (2010–2024)

Dependent variable: Air passenger departure

Variable	Band A			Band B-D		
	Reduced Fare	Standard Fare	Total	Reduced Fare	Standard Fare	Total
GDP _{pc}	3.146***	3.737***	2.333***	2.324***	3.019***	3.261***
APD _{pp}	-0.834***	-0.844***	-1.234***	-1.246***	-0.870***	-0.838***
Unemployment	-0.305**	-0.332**	-0.290***	-0.292***	-0.218**	-0.309**
CPI	-0.069	-0.029	-0.172	-0.177	-0.022	-0.060
Q2	-0.111	-0.095	0.189	0.193	0.051	-0.110
Q3	0.044	0.101	0.407***	0.415***	0.169	0.054
Q4	0.136	0.142	0.056	0.062	-0.104	0.134
Constant	-16.492**	-23.072***	-6.103	-5.986	-17.891**	-17.277**
Obs	60	60	60	60	60	60
R ²	0.85	0.88	0.92	0.92	0.89	0.85

Note : Newey-West standard errors with 4 lags; ***p < 0.01, **p < 0.05, *p < 0.1)

4.2.2 Passenger Demand's Effect on CO₂

In the first stage, as showing in table 6, APD has a strong and significant negative effect on passenger demand for both short and medium-haul and long-haul flights, with F-statistics of 11.68 and 8.92 and partial R² values of 0.183 and 0.121. The endogeneity test results are critical for validating the 2SLS approach. For Band A flights, the p-value of 0.012 indicates that passenger demand is indeed endogenous, thus justifying the use of an instrumental variable strategy for short and medium-haul analysis. Conversely, for Band B-D flights, the endogeneity test yields a p-value

of 0.342, suggesting that long-haul passenger demand may not be significantly endogenous in this context, which could explain the lack of significance in the second-stage coefficient for Band B-D. The overidentification tests (Sargan/Hansen) for both Band A ($p = 0.215$) and Band B-D ($p = 0.178$) indicate that our instrument(s) are valid, reinforcing the reliability of the 2SLS estimates where applicable.

The second-stage results, for Band A flights, passenger demand exhibits a positive and highly statistically significant effect on CO₂ emissions. In contrast, for Band B-D flights, the effect is positive but not significant, suggesting that once instrumented, the direct causal link between long-haul passenger demand and CO₂ emissions is not robustly established. This could imply a more complex relationship, or that other unobserved factors play a more dominant role in driving long-haul emission changes.

Table 6 2SLS Analysis of APD's Impact on Carbon Emissions (2010-2024)

Parameter	Band A (Short and Medium-Haul)	Band B-D (Long-Haul)
First-Stage Stats (Dependent variable: Air passenger departure)		
APD coefficient (π)	-1.234*** (0.140)	-0.838*** (0.236)
Partial R ²	0.183	0.121
F-statistic	11.68	8.92
Endogeneity test (p)	0.012	0.342
OverId test (p)	0.215	0.178
Observations	59	59
Second-Stage Results (Dependent variable: Carbon emission per capita)		
$\widehat{Airpassenger}$ departures	0.081*** (0.023)	0.249 (0.193)
GDP _{pc}	-0.817*** (0.083)	-1.568** (0.776)
Energy consumption _{pc}	0.281 (0.215)	-1.078 (1.602)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Discussion and policy implications

Globally, the results show that higher levels of international air travel are associated with higher CO₂ emissions per person. This link is strongest in countries with relatively low overall emissions. Total energy use across countries remains the dominant driver of carbon emissions overall. In the IV–quantile framework, APD reduces departures in the first stage; consequently, the second-stage estimates imply that policy-induced cuts in air travel causally lower CO₂. This effect is strongest in countries that already have relatively high emissions. This pattern suggests that fare-based instruments, such as APD or frequent-flyer levies can deliver meaningful emission reductions by curbing demand, especially where aviation emissions are already high.

In the UK context, time-series analysis reveals that APD has a discernible impact on reducing passenger volumes, especially for short and medium-haul (Band A) flights. These travellers show higher price sensitivity, consistent with prior literature (e.g., Seetaram & Tsvetanova, 2015; Song et al., 2019). One plausible explanation is that, because APD is levied as a largely fixed charge per passenger within each distance band, it may represent a larger proportional increase in total travel cost on routes with lower average base fares where increase in fares is more likely to trigger travel reduction or substitution to alternative modes such as rail or coach. Besides, long-haul reduced-fare (Band B-D) passengers also shows a relatively strong price sensitivity likely because they are budget-conscious travellers such as family visitors, students, or migrant workers, for whom APD adds a meaningful surcharge. In contrast, standard-fare passengers are less responsive, reflecting higher-income or corporate travellers for whom APD is a smaller share of total fare and often employer-funded.

The total column pools reduced- and standard-fare passengers. When APD rises, many standard-fare travellers downshift to reduced fares, and some reduced-fare travellers cancel altogether. That within-band reallocation plus cross-mode substitution amplifies the *aggregate* response, so the pooled (total) elasticity is larger in magnitude than either reduced or standard on their own. The higher price sensitivity we estimate for short and medium haul is consistent with the real decline in Band A APD, while the stronger response on long-haul standard tickets aligns with the upward path of long-distance APD.

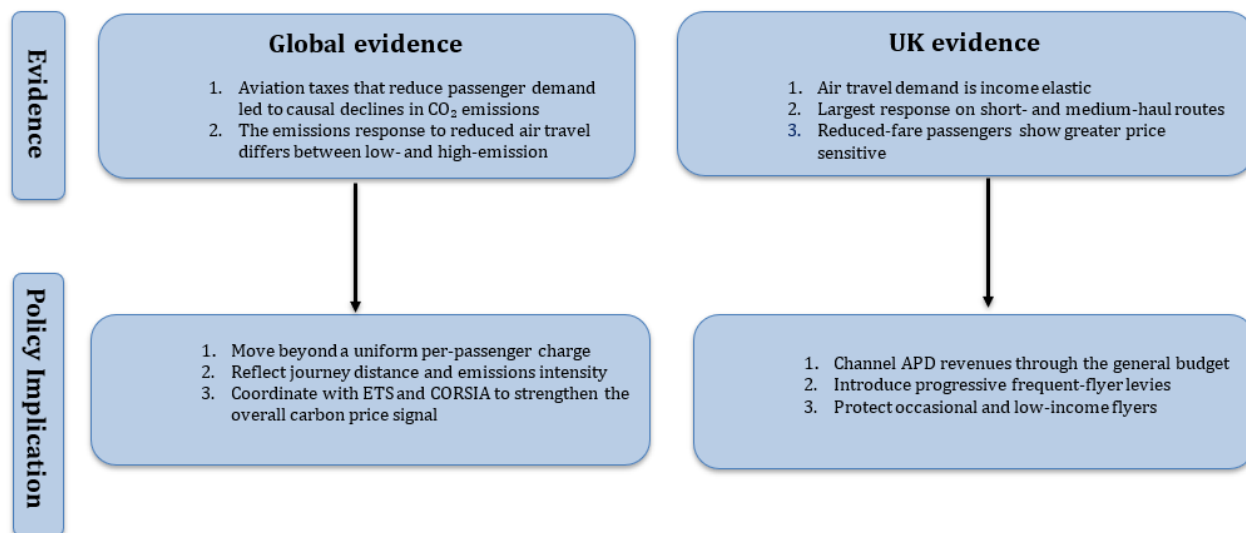
Policy implications

In the context of the goal of achieving net-zero emissions by 2050, demand-side instruments such as APD play a necessary supporting role in aviation climate policy. The evidence points to two complementary levers, as summarized in figure 1.

First, policy-induced reductions in air travel causally lower emissions, with heterogeneous effects across countries at different emission levels, and the strongest impacts observed in high-emission countries. indicating that simple correlations likely understate the relationship. These findings suggest that moving beyond a uniform per-passenger charge toward a structure that better reflects journey distance and emissions intensity could improve environmental targeting. Additionally, because passenger-based taxes influence travel behaviour but do not directly cap emissions, these results also motivate coordination with tonne-based schemes (e.g., European Union Emissions Trading System and Carbon Offsetting and Reduction Scheme) to reinforce the overall carbon-price signal.

Secondly, these are income elasticities of air travel demand. As incomes rise, passenger volumes grow more than proportionally. Higher-income travellers take more discretionary or long-distance trips and upgrade fare classes more when incomes rise. This pattern is broadly consistent with prior findings (Gallet & Doucouliagos (2014); Valdés (2015)) that income elasticities for air travel are often above one and tend to be higher for international/long-haul markets and higher-fare segments. These findings suggest that aviation taxation can be designed to both improve equity and enhance effectiveness. Channelling APD revenues into the general budget can help support low-income households, who benefit disproportionately from well-funded public services. At the same time, a progressive frequent-flyer levy, under which tax rates rise with the number of flights taken, could further concentrate the tax burden on high-frequency, high-emitting travellers while leaving occasional flyers largely unaffected. In practice, this approach could be complemented by targeted measures such as lifeline rebates or tax-credit top-ups for low-income households, rising marginal APD rates on repeat trips, and the use of aviation-tax revenues to reduce rail fares and improve service quality on short- and medium-haul corridors where substitution away from air travel is feasible.

Figure 1. Policy Implications of Air Passenger Duty from Global and UK Evidence



6 Conclusion

This study provides empirical evidence that aviation-related fiscal instruments, especially the UK's APD can reduce carbon emissions by shifting passenger behaviour. Using global panel data and a focused UK case, we show that air travel materially raises CO₂. Our global estimates imply that a 10% APD-induced reduction in passenger departures lowers CO₂ emissions by roughly 1–2%. While this demonstrates that APD contributes to mitigation, the reduction is modest when compared with the 4–5% annual growth rate of global air travel prior to the pandemic (IATA, 2019a, 2019b). The results show it can play a meaningful supporting role in near-term climate policy with broader decarbonisation measures and longer-term technological change. Several limitations could be considered. First, the dependent variable reflects total national CO₂ emissions rather than aviation-specific emissions. Because aviation represents only a small share of total emissions, changes in overall CO₂ are influenced by developments in other sectors, meaning our estimates identify the marginal impact of air travel on national emissions under standard inventory conventions rather than isolating aviation's footprint in a strict sense. Second, in future work, more targeted indicators, such as real median wages, would allow closer alignment with the household-level concept of income elasticity. Finally, more international studies, especially those comparing different taxation schemes, are needed to identify best practices and design coordinated approaches for sustainable aviation policy.

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Appendix A

Appendix A Table 1 Aviation and Borderline Taxes Summary

Aviation-Related Tax		
Country	Year Introduced	Tax type
Philippines	1993	Terminal Fee
United Kingdom	1994	Air Passenger Duty (APD)
Indonesia	1994	Passenger Service Charge
Jordan	2000	JD10 exit tax
Turkey	2000	Citizens' exit tax
Peru	2001	TUUA Fee
Romania	2005	Airport Infrastructure Tax
France	2006	Solidarity Air Ticket Tax
Luxembourg	2006	Solidarity ticket tax (Unitaid)
South Korea	2006	Solidarity air ticket tax
Cameroon	2006	Unitaid solidarity ticket levy
Chile	2006	Unitaid solidarity ticket levy
Netherlands	2008	Passenger Tax, repealed 2009, reintroduced 2021
Ireland	2009	Air Travel Tax
Austria	2011	Flugabgabe
Norway	2016	Passenger Tax
Sweden	2018	Flygskatt (Flight Tax)
Japan	2019	Sayonara Tax
Portugal	2021	Carbon levy on air passengers
Czechia	2021	Environmental air tax
Spain	2021	Green APT (regional)
Hungary	2022	Green passenger tax
Poland	2024	Green APT (budget 2024)
Slovakia	2024	Passenger flight levy (planned)
Slovenia	2024	Environmental air tax (planned)
Denmark	2025	Passenger Tax (approved in 2023)
Borderline Tax		
Country	Year Introduced	Notes
Costa Rica	1970	Departure tax
Mexico	1974	International Departure Tax
Australia	1978	Departure Tax (renamed PMC)
Dominican Republic	1993	Tourist Card / Departure Tax
Nepal	1994	Airport service tax
Morocco	1996	Departure tax
Russia	1999	Departure tax
South Africa	2000	International departure tax

Namibia	2000	Passenger service tax
Ecuador	2001	Departure tax phased out in 2012
Mozambique	2001	Departure tax
Paraguay	2001	Departure tax
Canada	2002	Air Travellers Security Charge
Kenya	2002	Departure tax
India	2003	Travel Tax under Finance Bill
Argentina	2004	Tourism Fund Tax
Italy	2005	Municipal surcharge on airline tickets
Panama	2005	Departure Tax
Vietnam	2006	Departure tax
Thailand	2007	Departure tax
Zambia	2008	Departure tax
Germany	2011	Luftverkehrsabgabe
China	2011	Departure tax included in fare
Fiji	2011	Departure tax
Ukraine	2011	Departure tax
Cuba	2015	Departure tax included in fare
New Zealand	2016	Border Clearance Levy
Jamaica	2016	Departure tax
Lebanon	2017	Departure tax
Egypt	2019	Departure tax (~£410)
Uganda	2021	Departure levy proposed
Belgium	2022	National Departure Tax

Note: We distinguish between targeted per-passenger aviation taxes and broader departure levies, both of which influence ticket prices. Our baseline analysis includes the full set.

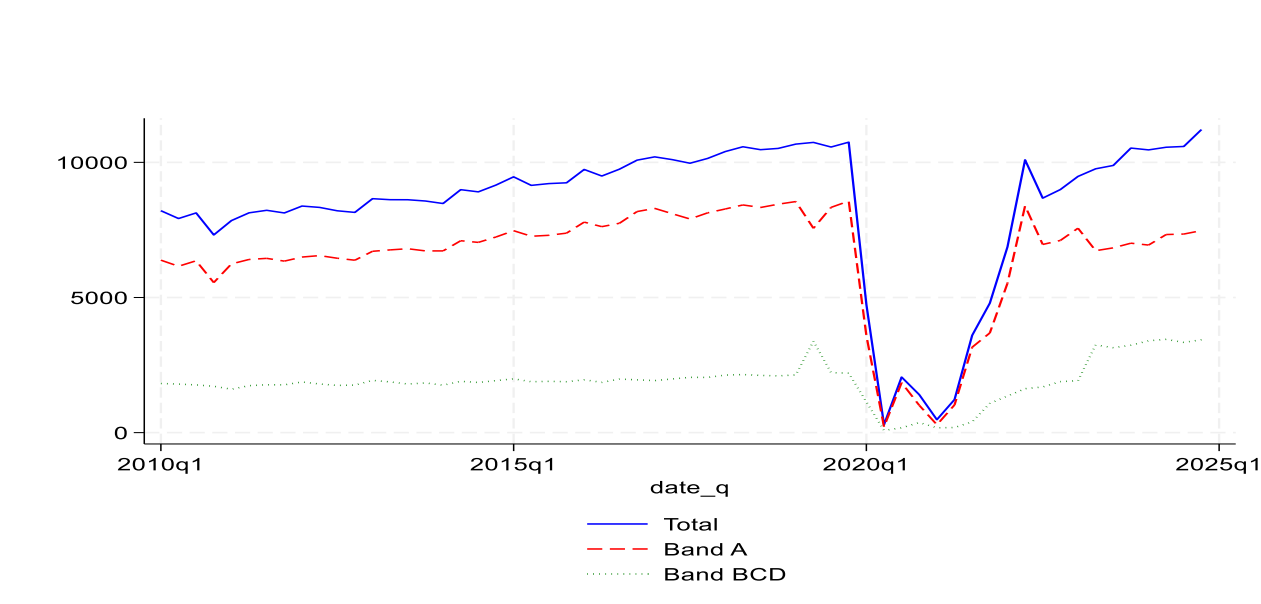
Appendix A Table 2 Panel Unit Root Test Results for Global Data

Variable	P-value	Order of Integration
ln_co2_pc	0.130	I (1)
ln_passenger_numbers	0.000	I (0)
ln_energy_pc	0.485	I (1)
ln_gdp_pc	0.996	I (1)
ln_pop_density	0.000	I (0)

Appendix A Table 3 ADF Unit Root Test Results for UK data

Variable	Level P-value	1st Diff P-value	Order of Integration
ln_co2_pc	0.2187	0.0006	I (1)
ln_gdp_pc	0.5763	0.0316	I (1)
ln_energy_pc	0.5274	0.0472	I (1)
ln_BandAPassenger	0.0850	N/A	I (0)
ln_BandBCDPassenger	0.1428	0.0051	I (1)
CPI index	0.3807	0.0085	I (1)
Unemployment rate	0.9564	0.0694	I (1)

Appendix A Figure 1 De-seasonalized UK Air Passenger Demand by Flight Band (2010Q1–2024Q4)



Appendix A Table 4 Data sources

Variable	Description	Data Source
Global data		
CO ₂ emissions per capita	Annual carbon dioxide emissions per capita (metric tons)	World Bank (World Development Indicators) https://databank.worldbank.org/metadataglossary/world-development-indicators/series/EN.ATM.CO2E.PC
Passenger departures	Number of international air passenger departures per year	International Civil Aviation Organization (ICAO) https://data.worldbank.org/indicator/IS.AIR.PSGR
GDP	Gross Domestic Product	World Bank https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
Energy consumption per capita	Annual energy consumption per capita (kg of oil equivalent)	World Bank https://databank.worldbank.org/metadataglossary/world-development-indicators/series/EG.USE.PCAP.KG.OE
Population density	People per square	World Bank https://data.worldbank.org/indicator/EN.POP.DNST

	kilometer of land area	
Air Passenger Duty (APD)	Binary indicator of whether APD is in effect	National-level official website Compiled from national official government tax authority publications
UK data		
CO ₂ emissions (CO ₂ emissions per capita = CO ₂ emissions/Population size)	Total carbon dioxide emissions (CO ₂)	Office for National Statistics https://www.ons.gov.uk/economy/environmentalaccounts/bulletins/experimentalestimatesofquarterlygreenhousegasemissionsresidencebasisuk/julytoseptember2024 (Table 3: Estimates of total carbon dioxide emissions (CO ₂) (residence basis))
Consumer Price Index (CPI)	Annual average Consumer Price Index	Office for National Statistics https://www.ons.gov.uk/economy/inflationandpriceindices
GDP	Gross Domestic Product	Office for National Statistics https://www.ons.gov.uk/economy/grossdomesticproductgdp
Unemployment rate	Annual unemployment rate (%)	Office for National Statistics https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/unemployment
Energy consumption	Energy use per capita (kg of oil equivalent)	UK Department for Energy Security and Net Zero (DESNZ) https://www.gov.uk/government/collections/energy-consumption-in-the-uk
Energy price	Domestic energy price index	UK Department for Energy Security and Net Zero (DESNZ) https://www.gov.uk/government/statistical-data-sets/monthly-domestic-energy-price-statistics
APD receipt	Annual APD receipts in £ million	HMRC (2025). Air Passenger Duty statistics. https://www.gov.uk/government/statistics/air-passenger-duty-bulletin/air-passenger-duty-statistics-commentary-march-2021
Band A Passenger	Annual Band A (short and medium haul) passenger numbers	HMRC (2025). Air Passenger Duty statistics. https://www.gov.uk/government/statistics/air-passenger-duty-bulletin/air-passenger-duty-statistics-commentary-march-2021
Band B-D Passenger	Annual Band B-D (long-haul) passenger numbers	HMRC (2025). Air Passenger Duty statistics. https://www.gov.uk/government/statistics/air-passenger-duty-bulletin/air-passenger-duty-statistics-commentary-march-2021

Appendix A Table 5: First-Stage Regression Results for Global data IV-QR

Dependent variable: ln (air passenger departures)

Variable	Coefficient	Robust Std. Error
APD	-0.972***	(0.224)
ln(GDP per capita)	0.866***	(0.212)
ln(Energy consumption per capita)	0.358**	(0.147)
ln(Population density)	0.093	(0.067)
Constant	2.148**	(0.931)

Diagnostic Tests	Statistic
F-test of excluded instruments	15.682***
Kleibergen–Paap rk LM	21.013 ***

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All tests reject the null of weak instruments at the 1% level.

Appendix B Robust test

Quantile Regression Estimates of Determinants of Carbon Emissions excluding the mega hubs

Dependent variable: ln (Carbon emissions per capita)

Variable	Full Sample (FE)	Quantile 0.25	Quantile 0.50	Quantile 0.75
ln_airpassengernumber	-0.0067 (0.0061)	0.0984* (0.0069)	0.0603* (0.0063)	0.0238* (0.0042)
ln_gdp_percapita	0.0329* (0.0124)	-0.0246 (0.0177)	-0.0660* (0.0161)	-0.0164 (0.0108)
ln_energycon_percapita	0.9168* (0.0226)	0.8686* (0.0182)	0.9711* (0.0166)	0.9739* (0.0111)
ln_popdensity	0.0688 (0.0479)	0.0035 (0.0080)	-0.0070 (0.0073)	-0.0261* (0.0049)
Constant	-8.637* (0.221)	-9.353* (0.179)	-8.441* (0.164)	-8.101* (0.110)

Note: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Full sample estimated using fixed-effects OLS; quantile regressions estimated at $\tau = 0.25, 0.50, \text{ and } 0.75$.

IV-Quantile Regression Results for Carbon Emissions excluding the mega hubs

Dependent variable: ln (Carbon emissions per capita)

Instrument: Aviation Passenger Duty (APD)

Variable	IV-QR Quantile 0.25	IV-QR Quantile 0.50	IV-QR Quantile 0.75
ln_airpass_hat	0.0703 (0.0600)	0.0760 (0.0578)	0.1143*** (0.0307)
ln_gdp_percapita	0.120 (0.0725)	0.0249 (0.0698)	-0.1022*** (0.0371)
ln_energycon_percapita	0.6640*** (0.0399)	0.8308*** (0.0384)	0.9632*** (0.0204)
ln_popdensity	-0.0214 (0.0141)	0.0205 (0.0136)	0.0462*** (0.0072)
Residual	-0.0415 (0.0619)	-0.0827 (0.0597)	-0.1377*** (0.0317)
Constant	-7.605*** (0.297)	-8.384*** (0.287)	-9.022*** (0.152)

Note: Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.