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Linking the Determinants of Air Passenger Flows and Aviation Related Carbon Emissions: A European Study

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Abstract: Increasing global concern regarding the negative consequences of climate change will see the introduction of comprehensive policy governing aviation-related carbon emissions. With demand for air travel set to accelerate over the next three decades airlines are faced with the task of catering to increased demand while simultaneously achieving emission reductions. In this study we identify the determinants of air passenger flows and flight frequency and assess their impact on carbon emissions and carbon efficiency. Confining our analysis to the European market, we employ Fixed-Effects (FEIV) and Random-Effects (REIV) instrumental variables modelling techniques to 150 intra-Europe routes and find that the factors that are significant in influencing the operational planning decisions of an airline often lead to carbon inefficiencies. Our findings have important implications for both airlines and policymakers. For airlines, we show how the decisions they make to optimise operations can have negative environmental consequences, while we make suggestions as to how policymakers can incentivise airlines to achieve emission reductions.

Keywords: environment; aviation; policy; CO₂ emissions; flight frequency; passenger flows

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1. Introduction

The aviation industry has faced a rapidly changing landscape over time and increasing public pressure to mitigate the negative effects of climate change coupled with the anticipated accelerated demand for air travel over the next three decades will lead to further challenges. Consumers increasingly value products and services based on their resource efficiency and in response to changing public sentiment, governments and policymakers are committing to limiting CO₂ emissions. As a high-intensity energy user, the transport sector is under scrutiny to adapt the way in which it operates in order to achieve CO₂ reductions, particularly relevant to airlines given that passenger air travel produces the highest and fastest growth of individual emissions [1]. Deregulation and the dawn of the Low Cost Carrier (LCC) era has put downward pressure on airfare forcing airlines to operate at increasingly tight margins and, notwithstanding the COVID-19 pandemic, demand for global air transport is anticipated to triple between 2020 and 2050 [2]. Airlines therefore are faced with the seemingly antithetical task of catering to the increased demand for air passenger travel while simultaneously achieving a reduction in aviation-related CO₂ emissions. As concerns surrounding the negative impacts of aviation-related CO₂ emissions intensify, a significant shift in policy relating to aviation-induced carbon emissions is on the horizon with the introduction of comprehensive policy. Developed by the International Civil Aviation Organization, the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) aims to control aviation-related CO₂ emissions and will become mandatory for almost all airlines by 2027 [3].

Prior to CORSIA, policy aimed at controlling aviation-related CO₂ emissions has been inconsistent in some regions, and completely absent in others. The most notable policy in operation is the EU-Emissions Trading Scheme (ETS), which has included airlines since

2012 and has been credited by the EU for an aviation sector reduction in the carbon footprint of in excess of 17 million tonnes per annum. However, the EU ETS only applies to flights within the EU and its partners due to opposition from other countries [4], so coverage is far from comprehensive. Evidence into how successful the scheme has been at delivering emissions reductions is mixed with Anger and Köhler [5] and Meleo et al. [6] finding that the scheme is unlikely to achieve significant reductions, while in contrast Seufert et al. [4] find that airlines are more likely to consider their environmental performance if they have to include the direct cost of an ETS. Emission Trading Schemes are not confined to the EU and efforts have been made to establish ETS elsewhere, and there are other countries and regions, for example the US, Australia, and China that have transitorily or continuously implemented ETS that include aviation [4]. However, prior to CORSIA there has been a lack of consistent policy across regions and with over 190 countries included in the scheme [7], CORSIA has a much broader geographical scope than other previous or existing schemes and hence the policy is likely to have a significant impact on airlines.

A large body of literature examines the determinants of air demand and flight frequency, which is crucial for the strategic operational planning of airlines, providing key insights into how to optimally manage changes in passenger flows to maximise the profitability of airlines. A separate strand of literature investigates the environmental consequences of aviation. In this study, we link both by examining the main factors that influence air passenger flows and flight frequency and how the decisions that airlines make to optimise operations may have negative environmental consequences. Airlines will be best placed to develop a framework that satisfies the dual challenge of catering for an increased demand for its services and concurrently reducing CO₂ emissions if they can identify the common factors that influence both air passenger flows and carbon emissions. In this study, we do this by first identifying the determinants of air passenger flows and subsequently investigating whether the factors identified are also important determinants of carbon emissions. Confining our analysis to the intra-Europe market where EU-ETS policy is in place, we empirically investigate the factors that are most influential in determining passenger flows and flight frequency. Specifically, we implement both Fixed-Effects and Random-Effects models with instrumental variables to estimate air passenger flows for 150 intra-Europe air routes, and employ clustering analysis to identify differences between the short-haul and medium-haul routes market. We apply simultaneous equations to solve the endogeneity problem between air passenger flows and flight frequency by using an equation-by-equation estimation method and confirm a two-way positive relationship between air passenger flows and flight frequency. We subsequently implement log-linear modelling to investigate whether the most significant determinants of air passenger flows influence aviation-related carbon emissions.

Demand for air travel has increased rapidly over the past thirty years and with that trend set to continue, the resulting sharp increase in carbon emissions has led to extensive efforts to mitigate the effects through technological improvements of aircraft. CO₂ is responsible for the majority of the environmental impact from aircraft jet engines [8], and achieving aviation-related emissions reductions has often focused on improved efficiencies through technological advances. Empirical evidence suggests many ways in which airlines can reduce CO₂ emissions including improving the energy efficiency of aircraft, employing greener aircraft with advanced technology, retrofitting existing aircraft, and developing alternative jet fuels [3,9–13]. While technology innovations have resulted in a fall in emissions per passenger of over 50% and improved fuel efficiency over the past decade of approximately 2% per year, the emissions reductions achieved through efficiency improvements will be insufficient to offset the increased emissions generated by the increase in the volume of air travel [14,15]. Hence, airlines may need to look at demand and operations management to achieve further reductions. Lo et al. [16] point out the lack of econometric evidence of the determinants of aviation-related carbon emissions and state that “emissions interact with such factors as economic performance, political motives, and regulations on market entry” and that these factors “influence the possible outcomes of

decisions adopted to limit emissions". We account for this in our study by considering both the determinants of aviation-related carbon emissions and other interacting factors.

Demand for flights broadly follows the business cycle and, over the past fifteen years, the aviation industry has experienced fluctuations in passenger traffic as the global economy has moved from prosperity to crisis and subsequent recovery [17]. Many factors have been identified in the literature as contributing to demand uncertainty [17–23]. Uncertain passenger flows are a major challenge for all stakeholders, in particular the airlines themselves, causing difficulties in terms of both planning operational strategies and revenue management activities. Indeed, the airline industry is a difficult environment in which to make investment decisions due to highly cyclical passenger demand [24]. Therefore, it is essential to analyse the influencing factors that affect passenger flows and the supply behaviour of airlines, particularly in light of the fact that forthcoming CORSIA policy will have to be incorporated into the decision making process. A comprehensive analysis of air passenger flows from both the demand and supply sides can provide managerial insight for airlines in how best to respond to market and policy changes, whether in the short-term or the long-term.

1.1. Demand Side: Air Passenger Flows

Air passenger flows are affected by many influencing factors, with previous studies demonstrating that air passenger flows are primarily reliant on both geo-economic factors and service-related factors [18]. Geo-economic factors are those factors that are determined by the economic activities and geographical characteristics of the area where air transport service takes places, such as GDP and population [17,18]. Service-related factors, on the other hand, are determined by both the quality of service such as the flight frequency, aircraft size, and airfare [17,18,23].

With respect to geo-economic factors, numerous studies find that economic growth has a positive effect on air passenger flows [25–29], while population is another geo-economic factor found to have strong explanatory power [18,23,30,31]. The consensus of these studies is that population has a significantly positive influence on air passenger demand, as would be expected as more populated areas will have a higher passenger flows for transport of any type. While the exchange rate between two currencies has also been offered as an influential factor in determining air passenger flows [32–35], we do not include it in our study as most of the routes included in our sample are either domestic flights or routes between two countries that share a common currency, the Euro.

In the literature, flight frequency, airfare, and low-cost carriers entering the market are all service-related factors found to influence demand. Wei and Hansen [36,37] analyse the effects of aircraft size, flight frequency, and seat availability on air passenger flows and find that rising flight frequency can attract more passengers, and Pitfield et al. [20] also find a positive relationship between passenger flows and flight frequency. Airfare is also a key determinant of demand, with airfare and demand found to be negatively related [22,38]. With the advent of low-cost carriers (LCCs) entering the air service market, air travel has become more accessible to passengers, influencing demand [31,39]. Clewlow et al. [31] and Wang et al. [39] find that LCCs stimulate air passenger demand by making the air service market more competitive. As the presence of LCCs on the air transport market becomes more established, lower airfare on a route results, which subsequently promotes the demand for air travel. Boonekamp et al. [38] also document that the presence of LCCs results in a significant increase in demand, particularly on routes that are active with Europe's leading LCCs such as Ryanair and easyJet.

As a result of previous findings in the literature we include the growth rate of GDP per capita and population as the geo-economic factors and flight frequency, airfare, and LCCs as the service-related factors affecting the demand side in our study.

1.2. Supply Side: Airlines' Operations

On the supply side, a strand of literature examines how airlines react to changes in air passenger flows and what factors affect airlines' operational strategies [17,20,36,37,40,41]. For example, Wei and Hansen [36] examine the effects of aircraft size, flight frequency, and seat availability on the market share of airlines in the US domestic market and confirm that airlines can achieve greater returns in market share by increasing flight frequency as opposed to increasing aircraft size. Wei and Hansen [37] subsequently show that airlines tend to use the smallest aircraft and increase the flight frequency to adapt to increases in air passenger demand.

Jet fuel price has also been found to be important in influencing the behaviour of airlines, particularly with respect to operational strategies [42]. The effect of the presence of LCCs, particularly for Europe has been widely studied with findings illustrating that the presence of LCCs stimulate demand [38,43–45]. The international development of low-cost airlines is summarised in Francis et al. [43]. Hence, we include jet fuel price, aircraft size, competition, and LCCs as the main influencing factors of an airlines' operations on the supply side.

The remainder of this paper is organised as follows: Section 2 describes the data and variables; Section 3 discusses the empirical models, Section 4 presents the results and discussion, while Section 5 provides concluding remarks.

2. Data

Our study is confined to the intra-Europe market and our sample includes fourteen European Union (EU) members (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom) and one partner country (Norway). It is worth noting that the United Kingdom left the European Union on 31 January 2020, where in this paper, the data selection is from 2004 to 2019, when the UK was still an EU member. The dataset used in this study includes origin-destination (O-D) passenger traffic data for 150 intra-Europe air transport routes (see more details in Appendix A). Data is collected from the Eurostat database [46], EUROCONTROL [47], OECD [48], Cirium, and U.S. EIA [49]. Monthly data is selected and covers the period from January 2004 to December 2019 inclusive. We intentionally omit the year 2020 from our study due to the impact of the COVID-19 pandemic on aviation. The air traffic information of the 150 routes includes both domestic flights and international flights intra-Europe. All routes are single directional from departure airport to arrival airport, based on air passenger transport between the main airports of each country and their main partner airports. A final sample of 28,800 valid "route-time" observations are extracted from the data collection process. The dataset is a panel dataset, each individual route has its own information for both air passenger flows and airlines' operations, and the economic indicators data for a single route is the country's economic indicator of the origin city. The details of variables and descriptive statistics of variables are separately presented in Tables 1 and 2.

For air passenger traffic between airport-pairs, Barcelona to Madrid is the most frequently trafficked route among the 150 intra-Europe routes in our sample, with approximately 126,161 passengers carried in an average month over our sample period, while Helsinki to Malaga, with only about 9002 passengers carried in an average month, is the least trafficked route. With respect to flight frequency between airport-pairs, Barcelona to Madrid (Helsinki to Malaga) has the highest (lowest) flight frequency among all routes. HICP is a proxy for the country-level rate of inflation of the cost of air transport for passengers, with the UK and Austria having the lowest and highest index values respectively. The use of HICP as a proxy for airfare is potentially problematic, as ideally, route-specific airfare should be used although it is not feasible due to a lack of data availability. We follow the advice of Zhang et al. [23] who similarly use a nationwide index as a proxy for airfare and note that the result should be evaluated with caution.

Table 1. Details of research variables ^c.

Variables	Notations	Unit	Data Type	Data Source
Number of departure passengers	Pax	Person	Monthly	Eurostat
Number of departure flights	Flights	Flight	Monthly	Cirium
Average aircraft size	Asize	Seat	Monthly	Cirium
GDP per capita ^a	GDPPC	USD	Quarterly convert to monthly	OECD
Population of origin city ^b	Population	Person	Annually	OECD
HICP by air transport	HICP	Index 2015 = 100	Monthly	Eurostat
Competition (Herfindahl-Hirschman Index)	HHI	-	Monthly	Calculated by authors using Cirium data
Number of LCCs	LCCs	-	Monthly	Calculated by authors using the Cirium data
Jet fuel price	Jet fuel	USD per gallon	Monthly	U.S.EIA
Distance	Distance	Kilometre	-	Cirium
International flights	International	-	Dummy variable	Calculated by authors using Cirium data
CO ₂ emissions per route	CO ₂	Ktonne	Monthly	Calculated by authors using Eurostat and EUROCONTROL data
Total available seat kilometres per route	ASK	Seat*Kilometre	Monthly	Calculated by authors using Eurostat and Cirium data
Total distance of total flights per route	KM	Kilometre	Monthly	Calculated by authors using Eurostat and Cirium data
EU ETS included aviation	ETS	-	Monthly	European Commission

Note: ^b Data for quarterly GDP per capita is adjusted by Industrial production index (IPI); see footnote 3 in [35]; ^a Data for population in 2019 is estimated based on the annual average growth rate of population and data in 2018; ^c Definitions of above research variables are displayed in Appendix B.

Table 2. Descriptive information for inputs parameters.

	No. Obs	Mean	SD	Min	Max
Pax_{it}	28,800	36,308.71	19,143.75	506	216,976
$Flights_{it}$	28,800	322.53	166.19	7	2313
$Asize_{it}$	28,800	154.60	23.66	52.22	246.50
$GDPPC_{it}$	28,800	2967.27	1064.23	1117.08	6972.40
$Population_{it}$	28,800	4,002,756.97	3,384,059.73	1,090,513	12,981,056.45
$HICP_{it}$	28,800	94.54	21.35	47.00	202.78
HHI_{it}	28,800	4967.81	1636.54	1369.78	10,000
$Jet\ fuel_t$	28,800	2.10	0.68	0.93	3.89
$LCCs_{it}$	28,800	0.89	0.91	0.00	5
$Distance_i$	28,800	867.81	514.99	174	3357
$International_i$	28,800	0.82	0.38	0	1
CO_{2it}	18,000	8,134,738.68	5,776,266.40	375,636.56	56,392,428.52
ASK_{it}	18,000	38,349,953.12	20,292,250.75	1,729,940	141,772,796
KM_{it}	18,000	234,720	111,177.81	23,496	842,644
ETS_t	18,000	0.80	0.40	0	1

While Europe is a relatively small continent, we acknowledge that our results may be influenced by flight distance. While there is no agreement in the literature as to what distance or flight time constitutes a short-haul flight, the general consensus in terms of flight time is a flying time of up to one and a half or two hours. In terms of distance, we adopt the definition set out by Robeco [50] and designate European routes up to 700 km in distance as short-haul and routes whereas routes over 700 km are designated as medium-haul. The 150 intra-Europe routes in our sample can be clustered into two groups: 73 short-haul flights and 77 medium-haul flights. After the clustering procedure, we separately

estimate both passenger flows and flight frequency equations for the short-haul routes and medium-haul routes.

3. Methodology

In order to estimate the demand and flight frequency, we apply Pooled OLS with instrumental variables (Pooled-OLS-IV), Fixed Effects Instrumental Variables (FEIV), and Random Effects Instrumental Variables (REIV) modelling techniques. Linear regression models are widely implemented to estimate air passenger traffic and flights [17–21,23,29]. While several studies exploit the OLS model to analyse air passenger demand [19,29,38], the potential for endogeneity between air passenger flows and flights is of concern. Several solutions have been offered to address this issue including the two commonly selected two-stage least squares (2SLS) and three-stage least-squares (3SLS) approaches [17,18,20,21,23,29,38]. Considering the heterogeneity between different air routes, the Fixed-Effects model is more efficient in estimating passenger flows and flights in the presence of the unobserved specific variables [23,29,51], because the Fixed-Effects model takes account of any fixed individual differences between different air routes, such as the distance.

To simultaneously estimate both air passenger flows and flight frequency for the intra-European market using the 2SLS approach to control for endogeneity, a valid set of instruments is required. We consult the literature to identify strong and efficient instruments and find that a wide range of instruments have been proposed. These include cost-shifting instruments such as route distance, Stern-type instruments such as the number of airlines serving a route, instruments denoting non-price characteristics of rival products such as the percentage of rival routes that offer direct flights, and the average distance of rival routes [52–54]. For the demand-side estimation, we use jet fuel prices and the Herfindahl–Hirschman Index (HHI), a measure of how competitive the route is, as our instruments because they directly influence flight frequency but are uncorrelated with air passenger flows. For the supply-side estimation, we select the number of low-cost carriers offering service on a route (LCCs), population and GDP per capita as our instruments because LCCs directly influence aircraft size, while population and GDP per capita directly relate to air passenger flows. In the flight frequency equation estimation, the variable LCCs is one of the instrumental variables used to estimate the average aircraft size in the first stage. The presence of LCCs on routes indirectly affects the number of flights but directly affects the average aircraft size. Givoni and Rietveld [40] estimate that the aircraft size is 14% higher on routes where low-cost carriers are present. Thus, we use the information that records the presence and absence of LCCs on routes to estimate the endogenous variable in the flight frequency equation. To obtain the data for the time-varying LCC variable, we hand-collect the monthly information for the presence of LCCs on each route from the Cirium database and observe how many LCCs serve each route for each single month.

3.1. Model Specification for Estimating Air Passenger Flows and Flight Frequency

We apply a set of instruments to estimate the simultaneous equations of air passenger flows and flight frequency by both the Fixed-Effects (FEIV) and the Random-Effects models (REIV). We also conduct analysis using the Pooled OLS model with instrumental variables (Pooled-OLS-IV) to estimate both equations and to compare with FEIV and REIV models. That is, both air passenger flows and flight frequency equations are separately estimated by using the FEIV, REIV, and Pooled OLS models. The system of equations estimated by the FEIV model is constructed as follows:

$$\ln Pax_{it} = \alpha_0 + \beta_1 \ln Flights_{it} + \alpha_1 \ln HICP_{it} + \alpha_2 \ln Distance_i + \alpha_3 International_i + \theta_1 \ln Population_{it} + \theta_2 \ln GDPPC_{it} + \theta_3 LCCs_{it} + \eta_{1i} + \varepsilon_{1it} \quad (1)$$

$$\ln Flights_{it} = \pi_0 + \beta_2 \ln Pax_{it} + \beta_3 \ln Asize_{it} + \pi_1 \ln HICP_{it} + \pi_2 International_i + \pi_3 Distance_i + \lambda_1 \ln Jetfuel_t + \lambda_2 \ln HHI_{it} + \eta_{2i} + \varepsilon_{2it} \quad (2)$$

where the subscript i represents the air route and subscript t denotes the month. The error terms η_{1i} and η_{2i} are the unobserved components, which are specific to individual i . ε_{1it} and ε_{2it} are the random error terms. For more detailed definitions of dependent and independent variables in Equations (1) and (2), please see Appendix B. Equations (1) and (2) can be rewritten as:

$$\ln Pax_{it} = \beta_1 \ln Flights_{it} + \mathbf{X}_{it}\alpha + \mathbf{Z}_{1it}\theta + \eta_{1i} + \varepsilon_{1it} \quad (3)$$

$$\ln Flights_{it} = \beta_2 \ln Pax_{it} + \beta_3 \ln Asize_{it} + \mathbf{X}_{it}\pi + \mathbf{Z}_{2it}\lambda + \eta_{2i} + \varepsilon_{2it} \quad (4)$$

where $\mathbf{X}_{it}$ is the common exogenous variable in both the passenger flows and flight frequency equations. In addition, $\mathbf{Z}_{1it} = (\ln Population_{it}, \ln GDPPC_{it}, \ln LCCS_{it})$ are exogenous variables included in the passenger flows equation but excluded from the flight frequency equation. $\mathbf{Z}_{2it} = (\ln Jetfuel_t, \ln HHI_{it})$ are exogenous variables that determines flights but do not affect air passenger flows.

Without considering the heterogeneity between different routes, error terms η_{1i} and η_{2i} are removed from the Equations (3) and (4), and the system of equations with the REIV and Pooled-OLS model estimation is generated as follows:

$$\ln Pax_{it} = \beta_1 \ln Flights_{it} + \mathbf{X}_{it}\alpha + \mathbf{Z}_{1it}\theta + \varepsilon_{1it} \quad (5)$$

$$\ln Flights_{it} = \beta_2 \ln Pax_{it} + \beta_3 \ln Asize_{it} + \mathbf{X}_{it}\pi + \mathbf{Z}_{2it}\lambda + \varepsilon_{2it} \quad (6)$$

where the instrumental variables selection and the definition of variables are the same as in Equations (3) and (4).

In the passenger flows equation, $\ln Flights_{it}$ is an endogenous variable because air passenger traffic is positively affected by flight frequency at the route level [17,23]. In the flight frequency equation, $\ln Pax_{it}$ and $\ln Asize_{it}$ are endogenous variables for flight frequency (ibid). According to both theoretical and empirical studies, there is simultaneity among the variables $\ln Pax_{it}$, $\ln Flights_{it}$, and $\ln Asize_{it}$ [17,20,21,23], a classical issue in the supply–demand interaction. For the air transport market, there is a two-way causation between air passenger demand and flight frequency and aircraft size, particularly between passenger demand and flight frequency [20,21]. More precisely, this two-way causation generates endogeneity between passenger demand and airlines' service supply.

To simultaneously estimate both the air passenger flow (3) and flight frequency (4) equations and control for endogeneity, we select similar instruments to those employed by Mumbower et al. [54] and Zhang et al. [23]. Hence, $\mathbf{Z}_{2it}$ comprises exogenous variables to determine flights that do not directly affect air passenger flows. Similarly, $\mathbf{Z}_{1it}$ are exogenous variables that impact air passenger flows but not flight frequency and are used as instruments to estimate the flights equation.

In the FEIV model, the time-invariant variables are removed from Equations (3) and (4). In the first stage, $\mathbf{Z}_{2it}$ is used as the instrument for estimating the endogenous variable $\ln Flights_{it}$ in the passenger flows equation. For the flight frequency equation, $\mathbf{Z}_{1it}$ is the instrumental variable for estimating the endogenous variables $\ln Pax_{it}$ and $\ln Asize_{it}$ in the first stage. To verify the validation of the instruments in both equations, we check the validity of the instrument validations through the weak instruments test, Wu-Hausman test for endogeneity, and Sargan overidentifying restrictions. The instruments used in the passenger flow and flight frequency equations have passed these three tests, suggesting our instruments are strong, valid, and good for solving the endogeneity issues among $\ln Pax_{it}$, $\ln Flights_{it}$, and $\ln Asize_{it}$.

3.2. Model Specification for Estimating Determinants of Route Carbon Emissions

For CO₂-related analysis, data for CO₂ emissions per route is required. However, we could only access data of total passenger traffic CO₂ emissions by country from EURO-CONTROL since 2010. Due to the above data limits, we estimate route CO₂ emissions by applying the following procedure. Firstly, we separately collect the data of the total depar-

ture flights for air passengers by the reporting country and the number of departure flights by route from Eurostat and calculate the ratio of total departure flights per route to total departure flights by country. We then use this ratio to account for CO₂ emissions by each route of the total state CO₂ emissions (See Equation (7)). Eventually, 18,000 observations of route CO₂ emissions are obtained, covering the period 2010 to 2019.

$$\text{Route CO}_2 = \text{CO}_2 \text{ by country} \times \frac{\text{Total departure flights on a route}}{\text{Total departure flights of the country}} \quad (7)$$

In order to identify the determinants of CO₂ emissions for our sample of European routes, we design two panel data models and estimate using the OLS and Random Effects (RE) estimators. We follow Lo et al. [16] and use the total amount of CO₂ emissions and the emission efficiency, given by the amount of CO₂ generated per available seat kilometre, as out two dependent variables. Equations (8) and (9) below specify the determinants of CO₂ emissions and emission efficiency for European routes.

$$\ln \text{CO}_{2it} = \gamma_0 + \gamma_1 \ln \text{Flights}_{it} + \gamma_2 \ln \text{Pax}_{it} + \gamma_3 \ln \text{Asize}_{it} + \gamma_4 \ln \text{HICP}_{it} + \gamma_5 \ln \text{Jetfuel}_t + \gamma_6 \ln \text{HHI}_{it} + \gamma_7 \ln \text{KM}_{it} + \gamma_8 \text{ETS}_t + \xi_{it} \quad (8)$$

$$\ln \text{CO}_2 \text{ASK}_{it} = \gamma_0 + \gamma_1 \ln \text{Flights}_{it} + \gamma_2 \ln \text{Pax}_{it} + \gamma_3 \ln \text{Asize}_{it} + \gamma_4 \ln \text{HICP}_{it} + \gamma_5 \ln \text{Jetfuel}_t + \gamma_6 \ln \text{HHI}_{it} + \gamma_7 \ln \text{KM}_{it} + \gamma_8 \text{ETS}_t + \xi_{it} \quad (9)$$

where the subscript i represents the air route and subscript t denotes the month. In addition, γ_i represents the coefficients of dependent variables, and ξ_{it} are error terms.

4. Results and Discussion

The results of the panel linear regression models for estimating air passenger flows with three different model specifications: the Pooled OLS model with instruments (Pooled-OLS-IV), the Fixed-Effects with instruments (FEIV) model, and the Random-Effects with instruments (REIV) model are presented in Table 3 below.

Table 3. Estimations for air passenger flows and flight frequency equations.

	Dependent Variables: $\ln \text{Pax}_{it}$			Dependent Variables: $\ln \text{Flights}_{it}$		
	(1) <i>Pooled-OLS-IV</i>	(2) <i>FEIV</i>	(3) <i>REIV</i>	(4) <i>Pooled-OLS-IV</i>	(5) <i>FEIV</i>	(6) <i>REIV</i>
$\ln \text{Flights}_{it}$	0.568 *** (0.001)	0.568 *** (0.080)	0.651 *** (0.067)			
$\ln \text{Pax}_{it}$				0.821 *** (0.001)	0.821 *** (0.074)	0.833 *** (0.077)
$\ln \text{Asize}_{it}$				−1.369 *** (0.001)	−1.369 *** (0.165)	−1.086 *** (0.361)
$\ln \text{Population}_{it}$	0.606 *** (0.002)	0.606 *** (0.171)	−0.554 ** (0.228)			
$\ln \text{GDPPC}_{it}$	0.572 *** (0.001)	0.572 *** (0.071)	0.228 *** (0.060)			
LCCs_{it}	0.047 *** (0.0002)	0.047 *** (0.010)	0.024 *** (0.007)			
$\ln \text{HICP}_{it}$	0.242 *** (0.0003)	0.242 *** (0.034)	−0.047 (0.031)	−0.157 *** (0.0002)	−0.157 *** (0.022)	−0.091 *** (0.024)
$\ln \text{Jetfuel}_t$				−0.027 *** (0.0001)	−0.027 *** (0.007)	−0.027 * (0.015)
$\ln \text{HHI}_{it}$				−0.074 *** (0.0003)	−0.074 * (0.042)	−0.086 * (0.047)
$\ln \text{Distance}_i$	−0.706 *** (0.003)		1.107 *** (0.382)	−0.044 *** (0.0002)		−0.065 (0.056)
International_i	0.704 *** (0.003)		−1.018 *** (0.368)	0.066 *** (0.0001)		0.053 *** (0.020)
Constant	−3.653 *** (0.007)		7.253 *** (1.357)	5.676 *** (0.004)		4.054 *** (0.940)
Observations	28,800	28,800	28,800	28,800	28,800	28,800
Route-specific dummies	Included	Included	Included	Included	Included	Included
R ²	0.910	0.598	0.935	0.939	0.619	0.953
Adjusted R ²	0.909	0.596	0.935	0.939	0.617	0.952
Residual Std. Error	0.160 (df = 28,645)			0.124 (df = 28,645)		
F Statistic		22,283.510 ***	387,884.600 ***		15,752.950 ***	544,135.800 ***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; the robust standard errors are displayed below the coefficients.

The estimates for air passenger flows are presented in (1), (2), and (3), respectively, and R-squared values of 0.910, 0.598, and 0.935 are observed. We first consider the geo-economic variables included in our analysis: population and GDP per capita. As expected, the coefficient of population is positive and significant at the 1% level in both the Pooled-OLS-IV and FEIV models, suggesting that a larger population size in the origin city generates more passenger flows. The coefficient of GDP per capita is also significantly positive in all models, demonstrating that higher GDP per capita contributes to increased passenger flows [18,23,29]. Hence we conclude that population and GDP per capita drive demand for air travel.

According to our results, the service-related variables included in our analysis are also influential in determining passenger flows. Coefficients on flights are significantly positive in all models, indicating that flights and passenger flows are positively related, consistent with previous findings in the literature [17,20,23,38]. The latter two models consider the heterogeneity between different air routes so the positive, statistically significant coefficient on the flights variable implies that more flights servicing a route can stimulate air passenger flows. The positive coefficient observed on the LCCs variable in all models indicates that more low-cost carriers engaging in the market have the effect of stimulating demand for air travel, consistent with the literature [31,38,43,44]. Finally we look at the airfare proxy, HICP, which captures the price changes of air transport service purchased by passengers and observe a significant and positive coefficient in both the Pooled-OLS-IV and FEIV models. The positive sign of the coefficient in both models is unexpected, as we would expect that higher airfare would lead to lower demand for air service. This unexpected finding is likely due to the use of HICP, a nationwide index, to proxy for airfare, and as Zhang et al. [23] observe, when using such a proxy, the result should be evaluated with caution. While we observe the expected negative sign in the REIV model, the result is insignificant.

We proceed by considering the determinants of flight frequency, the results of which are in (4), (5), and (6). The coefficients of air passenger flows represents the elasticity of flight frequency to passenger traffic, which are 0.821, 0.821, and 0.833, respectively, in the three models, suggesting that an increase in air passenger flows leads airlines to provide more flights. The average aircraft size has a significantly negative impact on the flight frequency in all three models, supporting findings of previous studies [17,20,23,38]. This result is important for the operational strategies of airlines with respect to aircraft choices, the implication being that airlines choose to decrease the aircraft size when they plan to increase the number of flights. A smaller aircraft size allows airlines more flexibility to adjust their operations in response to changes in passenger flows. Like Zhang et al. [23], we find a negative and significant relationship between our airfare proxy and flight frequency in all models. We can offer no explanation as to why this may be the case other than HICP being a weak proxy for airfare and do not have access to route specific data to probe this unexpected finding further.

As expected, the price of jet fuel has a significantly negative effect on flight frequency, indicating that when fuel becomes more expensive, airlines will decrease flight frequency. The Herfindahl–Hirschman Index (HHI) is frequently used to measure the degree of competition in an industry, with high index values indicating lower degrees of competition. When we consider the effect of HHI on flight frequency, the coefficient is negative and significant in all three models. This finding suggests that increased competition on a route leads to an increase in flight frequency. Finally, the coefficient on distance is negative and significant, indicating that the longer the flight distance the lower the flight frequency. We explore our findings further by clustering our sample between short-haul and medium-haul routes and re-estimating our equations, the results of which are presented in Table 4.

Table 4. Clustering analysis of route distances.

Panel A: Air Passenger Flows Equation						
	Short-Haul Routes			Medium-Haul Routes		
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Pooled-OLS-IV</i>	<i>FEIV</i>	<i>REIV</i>	<i>Pooled-OLS-IV</i>	<i>FEIV</i>	<i>REIV</i>
$\ln Pax_{it}$	0.461 *** (0.0004)	0.461 *** (0.123)	0.534 *** (0.106)	0.634 *** (0.000)	0.634 *** (0.115)	0.697 *** (0.100)
$\ln Population_{it}$	0.113 *** (0.001)	0.113 (0.235)	−0.661 ** (0.316)	1.044 *** (0.000)	1.044 *** (0.226)	0.037 (0.290)
$\ln HICP_{it}$	0.195 *** (0.00002)	0.195 *** (0.065)	0.014 (0.063)	0.266 *** (0.000)	0.266 *** (0.034)	−0.023 (0.032)
$\ln GDPPC_{it}$	0.604 *** (0.0001)	0.604 *** (0.108)	0.351 *** (0.102)	0.580 *** (0.000)	0.580 *** (0.095)	0.264 *** (0.073)
$International_i$	−0.052 *** (0.001)		−1.071 ** (0.453)	−0.570 *** (0.000)		0.122 (0.249)
$LCCs_{it}$	0.045 *** (0.00004)	0.045 *** (0.013)	0.032 *** (0.011)	0.045 *** (0.000)	0.045 *** (0.012)	0.024 ** (0.010)
Constant	0.466 *** (0.011)		15.430 *** (5.073)	−14.042 *** (0.000)		3.782 (3.958)
Observations	14,016	14,016	14,016	14,784	14,784	14,784
Route-specific dummies	Included	Included	Included	Included	Included	Included
R ²	0.900	0.548	0.921	0.893	0.642	0.924
Adjusted R ²	0.899	0.545	0.921	0.893	0.640	0.924
Residual Std. Error	0.155 (df = 13,938)			0.164 (df = 14,702)		
F Statistic		7679.706 ***	152,778.600 ***		15,860.370 ***	168,006.800 ***
Panel B: Flight frequency equation						
	Short-Haul routes			Medium-Haul routes		
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Pooled-OLS-IV</i>	<i>FEIV</i>	<i>REIV</i>	<i>Pooled-OLS-IV</i>	<i>FEIV</i>	<i>REIV</i>
$\ln Flights_{it}$	0.764 *** (0.0002)	0.764 *** (0.070)	0.800 *** (0.072)	0.936 *** (0.000)	0.936 *** (0.145)	1.116 ** (0.456)
$\ln Asize_{it}$	−0.999 *** (0.0003)	−0.999 *** (0.149)	−0.577 ** (0.238)	−1.774 *** (0.000)	−1.774 *** (0.341)	−2.447 (1.501)
$\ln HICP_{it}$	−0.218 *** (0.00004)	−0.218 *** (0.024)	−0.157 *** (0.033)	−0.140 *** (0.000)	−0.140 *** (0.048)	−0.138 (0.099)
$\ln Jetfuel_i$	−0.008 *** (0.00003)	−0.008 (0.008)	−0.009 (0.014)	−0.055 *** (0.000)	−0.055 *** (0.018)	−0.075 (0.060)
$\ln HHI_{it}$	−0.107 *** (0.00004)	−0.107 *** (0.036)	−0.136 *** (0.038)	−0.031 *** (0.000)	−0.031 (0.077)	0.082 (0.238)
$International_i$	0.084 *** (0.00001)		0.067 *** (0.021)	−0.022 *** (0.000)		0.091 (0.270)
Constant	4.671 *** (0.001)		2.143 *** (0.796)	5.861 *** (0.000)		6.387 *** (2.051)
Observations	14,016	14,016	14,016	14,784	14,784	14,784
Route-specific dummies	Included	Included	Included	Included	Included	Included
R ²	0.925	0.667	0.933	0.901	0.586	0.876
Adjusted R ²	0.924	0.665	0.933	0.901	0.584	0.875
Residual Std. Error	0.112 (df = 13,938)			0.142 (df = 14,702)		
F Statistic		10,393.920 ***	176,237.200 ***		6486.890 ***	93,498.880 ***

Note: ** $p < 0.05$; *** $p < 0.01$; the robust standard errors are displayed below the coefficients.

In panel A, the results of the air passenger flows are displayed. Again, the findings suggest that the number of flights, GDP per capita, population, and LCCs are positively related to air passenger flows. While the size of the coefficient on flights, GDP per capita, and LCCs is similar for both short-haul and medium-haul routes, the size of the coefficient on population is much larger for medium-haul routes than on short-haul routes. This may be because airports and airlines serving cities with smaller populations do not operate as many longer distance flights, and passengers from smaller cities connect via the larger cities for longer flights.

The results of the flight frequency estimation are presented in panel B. The coefficients are all of the same sign observed in the first estimation, but when the sample is separated between short-haul and medium-haul flights, clear differences emerge. The coefficient on aircraft size is much larger for medium-haul routes than short-haul routes. While it is clear that flight frequency and aircraft choice are influential with respect to the operating effectiveness of airlines, our results demonstrate a stronger relationship between these two variables for longer flights. One explanation for this may be the difference in the crew costs because pilots and crew operating larger aircraft are paid more than those operating smaller aircraft. By catering for changes in demand on longer routes by adjusting flight frequency and reducing aircraft size, the savings to the airline are greater. When we consider the price of jet fuel, we again find that the effect is larger on medium-haul routes. The cost of fuel

greatly affects the profitability of airlines, and it is easy for airlines to adjust flight frequency in response and as longer flights consume more jet fuel, reducing flight frequency on longer routes will lead to greater savings.

Our results so far show that the important influential factors for determining air passenger flows are flights, population, GDP per capita, and LCCs, while the important influential factors for determining flight frequency are aircraft size, the price of jet fuel, competition, and distance. We next consider how these results influence carbon emissions. Airline operations are complex and require the balancing of conflicting objectives to operate at profit-maximising levels and, to cater for growing demand, airlines can choose to increase flight frequency or to increase aircraft size. There appear to be higher returns to flight frequency in terms of operating effectiveness, with the main reasoning for increasing flight frequency being that it reduces passengers' schedule delay. Therefore, the optimal strategy for airlines seems to be to increase flight frequency and reduce aircraft size to accommodate changes in passenger flows. We now explore whether this strategy will have negative environmental consequences by examining whether the factors that influence flight frequency at the route level also influence the level of CO₂ emissions. In our analysis, we consider total CO₂ emissions on each route and CO₂ emissions per available seat kilometre, which is a measure of emission efficiency, on each route. The results are presented in Table 5 and show that most of the explanatory variables are statistically significant in determining both total carbon emissions and emission efficiency.

Table 5. Regression results for CO₂ emissions at the route level.

	Dependent Variables: lnCO _{2it}		Dependent Variables: lnCO _{2ASKit}	
	(1) <i>Pooled-OLS</i>	(2) <i>RE</i>	(3) <i>Pooled-OLS</i>	(4) <i>RE</i>
lnFlights _{it}	0.108 *** (0.024)	0.172 *** (0.021)	0.108 *** (0.024)	0.172 *** (0.021)
lnPax _{it}	0.134 *** (0.023)	0.048 ** (0.023)	0.134 *** (0.023)	0.048 ** (0.023)
lnAsize _{it}	0.078 * (0.046)	0.022 (0.040)	−0.922 *** (0.046)	−0.978 *** (0.040)
lnHICP _{it}	0.036 *** (0.012)	−0.072 *** (0.017)	0.036 *** (0.012)	−0.072 *** (0.017)
lnJetfuel _t	−0.038 *** (0.006)	−0.054 *** (0.016)	−0.038 *** (0.006)	−0.054 *** (0.016)
lnHHI _{it}	0.025 (0.021)	0.030 * (0.018)	0.025 (0.021)	0.030 * (0.018)
lnKM _{it}	0.781 *** (0.010)	0.772 *** (0.009)	−0.219 *** (0.010)	−0.228 *** (0.009)
ETS _t	0.016 *** (0.005)	0.043 *** (0.014)	0.016 *** (0.005)	0.043 *** (0.014)
Constant	3.168 *** (0.408)	4.560 *** (0.456)	10.076 *** (0.408)	11.468 *** (0.456)
Observations	18,000	18,000	18,000	18,000
Route-specific dummies	Included	Included	Included	Included
R ²	0.982	0.985	0.988	0.990
Adjusted R ²	0.982	0.985	0.988	0.990
F Statistic (df = 156; 17,843)	6388.768 ***	1,178,921.000 ***	9285.141 ***	1,746,014.000 ***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; the robust standard errors are displayed below the coefficients.

The results show that the number of passengers and number of flights are positively associated with CO₂ emissions, suggesting that more passengers and more flights lead to greater total CO₂ emissions and greater carbon inefficiencies. The contribution to carbon inefficiencies may be because increased air traffic leads to increased congestion, both on the ground and in the air, the latter of which may lead to sub-optimal flight paths. Consistent with Lo et al. [16], we find that route distance increases total CO₂ emissions but decreases CO₂ emissions per available seat kilometre. The greater emissions efficiency observed in relation to distance is likely due to a combination of factors such as the take-off phase being more carbon-intensive than the cruising segment of the flight and the tendency to utilise

less fuel-efficient aircraft on regional and shorter flights [55]. We further find that aircraft size and CO₂ emissions per available seat kilometre are negatively related, indicating that larger aircraft generate lower CO₂ per ASK [16]. The coefficient on the price of jet fuel is negative and significant in all regressions, indicating that higher fuel prices lead to lower emissions. This result is as we would expect but is in contrast to the findings of Lo et al. [16] who, in a study confined to four regional Italian airports, find that fuel price is a positive determinant of total CO₂ emissions.

Our results have important implications for airlines. We identified the main determinants of passenger demand and flight frequency. In response to increases in air passenger demand, we find that firms tend to favour increasing flight frequency while reducing aircraft size. However, this choice with regards to flight frequency and aircraft size have negative environmental consequences, supporting the observation that “large aircraft have lower environmental per passenger km costs” [56]. If airlines wish to reduce emissions, they could amend the way in which they cater for changes in passenger flows by increasing aircraft size (increasing carbon efficiency) as opposed to increasing flight frequency (decreasing carbon efficiency).

5. Concluding Remarks

In this study, we examine the main factors that influence air passenger flows and flight frequency and how the decisions airlines make to optimise operations may have negative environmental consequences. Confining our analysis to the European market, we identify the determinants of air passenger flows and flight frequency on 150 intra-Europe air routes by applying Fixed-Effects and Random-Effects models with instrumental variables, and employ clustering analysis to identify differences between the markets short-haul and medium-haul routes. We subsequently implement log-linear modelling to investigate whether the most significant determinants of air passenger flows influence aviation-related carbon emissions. Our results demonstrate that the significant factors that influence the operational planning decisions of an airline often lead to carbon inefficiencies. For example, we find that while reducing aircraft size may increase operational efficiency, it is a driver of carbon inefficiency.

Our findings give insights into the challenges that airlines will face with the introduction of CORSIA as we demonstrate that the pursuit of current strategies to adapt to changes in passenger flows lead to an increase in carbon emissions and considerable inefficiencies. While aircraft have become greener and more efficient in recent years, these efficiency gains will be outstripped by the increase in demand for air travel. As a result, achieving the level of CO₂ emissions mandated by CORSIA cannot be achieved by airlines relying on efficiency improvements alone. To avoid large-scale policy costs, we suggest ways in which airlines can adjust their response to changes in passenger demand that have lower environmental consequences.

While global policy on aviation emissions has been inconsistent to date, the implementation of CORSIA from 2021 seeks to comprehensively combat the negative environmental consequences of airlines, and our findings have numerous implications for policymakers. First, the forthcoming CORSIA is largely silent with respect to aircraft size, and we find, consistent with Lo et al. [16], that aircraft size can reduce CO₂ emissions and improve CO₂ efficiency. Therefore, providing incentives to airlines to cater for increases in demand by increasing aircraft size should have positive environmental consequences. Also, our finding that carbon inefficiencies are more of a concern on shorter routes can also inform policy. Shorter routes tend to be served by older, less efficient aircraft, so incentives to retrofit these fleets is an option to policymakers. We find that airlines respond to the increasing price of jet fuel by reducing flight frequency, and the price of jet fuel is a negative determinant of CO₂ emissions on a route. Hence, policymakers can incentivise airlines to seek alternatives to jet fuel by taxing jet fuel at a higher rate to achieve emission reductions.

Our analysis has some shortcomings, mainly related to data availability. First, due to the lack of available data regarding route-specific airfare, we follow previous scholars and

use a nationwide proxy. While airfare is an important determinant of both demand for air travel and flight frequency, we find our proxy necessitates that any results obtained in our analysis regarding its importance should be evaluated cautiously, and hence, this study remains reticent as to the impact of airfare. Second, our analysis focuses on passenger transport and ignores the environmental consequences of cargo transport. However, as air passenger travel emits four times the amount of CO₂ as freight, we are confident in the robustness of our results.

Comprehensive policy to govern aviation related emissions will lead to difficulties for airlines who will need to develop a framework that maximises operations allowing them to cater for increases in demand while also ensuring policy compliance. We identify the most influential factors that determine demand and flight frequency at the route level, and which of these factors also contribute to carbon (in)efficiencies. While our research is informative for airlines as to how the decisions they make to optimise operations can negatively impact the environment, airlines are not homogeneous. Hence, future research could focus on identifying the main sources of the CO₂ airlines individually generate, thereby allowing each airline to minimise emissions at the lowest cost to them.

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Data Availability Statement: Following the journals Guide for Authors, we wish to specify that the data that supports the findings of this study are openly available in the following URLs: Eurostat: <https://ec.europa.eu/eurostat/data/database> (accessed on 29 June 2021), EUROCONTROL: <https://ansperformance.eu/data/> (accessed on 29 June 2021), OECD: <https://stats.oecd.org/> (accessed on 29 June 2021), U.S. EIA: <https://www.eia.gov/> (accessed on 29 June 2021). Otherwise, the data from CIRIUM require a subscription and are not publicly available. We cannot share the data that were collected from this database.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. List of Air Routes in Europe

Table A1. The list of 150 air routes for 15 European countries.

ID	Route	ID	Route	ID	Route	ID	Route	ID	Route
1	VIE-FRA	31	CPH-OSL	61	HEL-ARN	91	FCO-CTA	121	LIS-MAD
2	VIE-ZRH	32	CPH-ARN	62	HEL-CPH	92	FCO-PMO	122	LIS-ORY
3	VIE-CDG	33	CPH-LHR	63	HEL-LHR	93	FCO-CDG	123	LIS-LHR
4	VIE-DUS	34	CPH-AMS	64	HEL-AMS	94	FCO-MAD	124	LIS-OPO
5	VIE-TXL	35	CPH-CDG	65	HEL-FRA	95	FCO-LHR	125	LIS-BCN
6	VIE-AMS	36	CPH-HEL	66	HEL-CDG	96	FCO-BCN	126	LIS-AMS
7	VIE-HAM	37	CPH-FRA	67	HEL-MUC	97	FCO-AMS	127	LIS-CDG
8	VIE-MUC	38	CPH-BRU	68	HEL-OSL	98	FCO-CAG	128	LIS-BRU
9	VIE-FCO	39	CPH-ZRH	69	HEL-KUO	99	FCO-TRN	129	LIS-GVA
10	VIE-CPH	40	CPH-MUC	70	HEL-AGP	100	FCO-FRA	130	LIS-MUC
11	BRU-MAD	41	ATH-SKG	71	CDG-FCO	101	AMS-LHR	131	ARN-CPH
12	BRU-BCN	42	ATH-HER	72	CDG-AMS	102	AMS-BCN	132	ARN-OSL
13	BRU-LHR	43	ATH-CDG	73	CDG-BCN	103	AMS-CDG	133	ARN-HEL
14	BRU-FCO	44	ATH-FCO	74	CDG-MAD	104	AMS-MAD	134	ARN-LLA
15	BRU-LIS	45	ATH-RHO	75	CDG-FRA	105	AMS-FCO	135	ARN-LHR
16	BRU-FRA	46	ATH-AMS	76	CDG-NCE	106	AMS-CPH	136	ARN-GOT

Table A1. Cont.

ID	Route	ID	Route	ID	Route	ID	Route	ID	Route
17	BRU-GVA	47	ATH-FRA	77	CDG-MUC	107	AMS-LGW	137	ARN-AMS
18	BRU-CPH	48	ATH-CHQ	78	CDG-TLS	108	AMS-MAN	138	ARN-MMX
19	BRU-VIE	49	ATH-MUC	79	CDG-VIE	109	AMS-ZRH	139	ARN-UME
20	BRU-AGP	50	ATH-ZRH	80	CDG-ZRH	110	AMS-FRA	140	ARN-FRA
21	FRA-TXL	51	BCN-MAD	81	DUB-LHR	111	OSL-TRD	141	LHR-DUB
22	FRA-LHR	52	BCN-PMI	82	DUB-LGW	112	OSL-BGO	142	LHR-AMS
23	FRA-HAM	53	BCN-AMS	83	DUB-STN	113	OSL-SVG	143	LHR-FRA
24	FRA-MUC	54	BCN-CDG	84	DUB-MAN	114	OSL-CPH	144	LHR-CDG
25	FRA-VIE	55	MAD-LHR	85	DUB-BHX	115	OSL-ARN	145	LHR-EDI
26	FRA-CDG	56	MAD-PMI	86	DUB-AMS	116	OSL-TOS	146	LHR-MAD
27	FRA-MAD	57	MAD-ORY	87	DUB-CDG	117	OSL-LHR	147	LHR-MUC
28	FRA-AMS	58	MAD-FCO	88	DUB-AGP	118	OSL-AMS	148	LHR-GLA
29	TXL-ZRH	59	MAD-LIS	89	DUB-FRA	119	OSL-FRA	149	LHR-ZRH
30	TXL-VIE	60	MAD-CDG	90	DUB-EDI	120	OSL-HEL	150	LHR-FCO

Note: Each route presents by ICAO airport code.

Appendix B. Definitions of Research Variables

Table A2. Definitions of variables.

Variables	Notation	Definitions
Number of departure passengers	Pax	This parameter shows the total number of air passengers carried by the air transport routes from the departure (origin) airport, broken down by country and month.
Number of departure flights	Flights	The parameter represents the total number of air passenger flights from the departure airport on the air route.
Average aircraft size	Asize	The average aircraft size on the air transport route, calculated by dividing the passenger seats available on the route by the number of air passenger flights on the route.
Population of origin (departure) city	Population	The total population of the origin city of the air route, broken down by country and year. Here, we use the annual population to the monthly data, assuming that the population of the city remains largely unchanged within the year.
GDP per capita	GDPPC	An economic indicator to describe the economic conditions of the origin city.
HICP by air transport	HICP	HICP by air transport is the consumer price index of passenger transport by air, which as a proxy measures the change over time of the prices of air passenger transport services purchased by households in Europe, broken down by country and month.
Herfindahl-Hirschman Index	HHI	This parameter commonly used to account for the market concentration. In our study, we use the ratio of the number of total seats provided by individual airlines to the number of total seats of the route to calculate the market share (MS) of airlines on that route. HHI is calculated as $HHI_{it} = MS_{1it}^2 + MS_{2it}^2 + \dots$
Number of LCCs	LCCs	The number of LCCs accounts for the number of Low-cost carriers provide service on each route for each month. This information is hand collected from Cirium database and it is a time-varying parameters.
Jet fuel price	Jetfuel	The jet fuel price is collected by the U.S. Gulf Coast Kerosene-Type Jet Fuel Spot Price FOB, which is the monthly price in U.S. dollars per gallon.
Distance	Distance	This parameter measures the distance of each air route in kilometres, which is the distance between airport pairs.
International flights	International	This information categorises the air route as either a domestic routes or an international route. This variable is a dummy variable that takes the value one if the route is domestic and zero otherwise.
CO ₂ emission per route	CO ₂	Total amount of CO ₂ emissions in ktonne of a particular route <i>i</i> in month <i>t</i> .
Total available seat kilometres per route	ASK	This parameter measures the total available seat kilometres of each air route, it is calculated as the total seats multiply by route distance.
Total distance of total flights per route	KM	This parameter is calculated as the total number of flights multiply by the route distance.
EU ETS included aviation	ETS	This information records when the aviation sector has been included the EU ETS.

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