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The impact of new aircraft on carbon emissions

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ABSTRACT

We examine the impact of new aircraft on total CO_2 emissions, seeking to determine whether their greater fuel efficiency may be offset by supply growth. We draw on granular global data at the aircraft–airline–route level between 2017 and 2023 and employ propensity score matching and entropy balancing to build a sample of comparable airline–route pairs operated or not by new aircraft. We then analyze how the share of new aircraft correlates with supply and carbon emissions by estimating a high-dimensional fixed effects model. Overall, we find that the adoption of new aircraft has led to a substantial increase in supply that does, in part, offset the greater fuel efficiency. However, we find evidence of heterogeneous effects depending on the type of route or geographical area analyzed. All in all, our results point to the limitations of new aircraft for reducing carbon emissions at the global level.

1. Introduction

One of the primary challenges facing aviation in the coming years will be reducing its environmental impact.[1] Flying less would constitute an effective way to reduce emissions; however, such a change in behavior entails significant economic, social, and political challenges given the well-documented relationship between air traffic volumes and economic growth. An alternative approach to tackling this dilemma between growth and the environmental implications of flying is to reduce the intensity of aircraft emissions. Yet, the technological options available to do just that are currently limited.

Applicable disruptive technologies are far from being technically feasible in the aviation sector (Graham et al., 2014). Likewise, while green hydrogen and biofuels have been identified as a promising alternative, a range of economic and technical challenges have still to be met (Winchester et al., 2015; Staples et al., 2018; Boretti, 2021; Degirmenci et al., 2023; Mayeres et al., 2023; Rupcic et al., 2023; Yusaf et al., 2024; Braun et al., 2024).

Indeed, to date, the main technological advance has been the enhanced fuel efficiency of newly built aircraft powered by conventional jet fuel (Graham et al., 2014; Abrantes et al., 2021; Bravo et al., 2022).[2] The current generation of aircraft is approximately 80 % more fuel-efficient than planes from 50 years ago (International Air Transport Association, 2023). Here, one of the greatest technological milestones of recent years – and one that has already had a significant impact on the global aviation market – has been

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[1] Aviation is responsible for approximately 3% to 6% of global CO_2 emissions (Lee et al., 2021).

[2] Small improvements in fuel consumption can also be made by retrofitting new technologies into existing aircraft (Cansino and Roman, 2017; Müller et al., 2018). Bigger planes and denser seat configurations can also reduce the fuel use per seat-km (Park and O'Kelly, 2014; Csereklyei and Stern, 2020; Lo et al., 2020).

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the launch of the new models of the two most widely flown aircraft families, i.e. the Airbus A-320 and the Boeing B737, which concentrate around 65 % of flights worldwide. Their newest versions – that is, the A-320neo and the B737 MAX – generate around 20 % fewer kg of CO_2 per seat-km than their older versions. The planes, first introduced in 2017 with a marked surge in adoption from 2021 onwards, today account for around 10.5 % of total flights.

In this paper, we examine the impact that these new aircraft are having on supply and CO_2 emissions. To do so, we draw on worldwide data from RDC aviation at the aircraft/airline/route level from 2017 to 2023 and employ propensity score matching and entropy balancing techniques to build a sample of comparable–route pairs affected and unaffected by these new aircraft in 2017. We then analyze how the share of new aircraft correlates with emission intensity, total CO_2 emissions, flights and seats by estimating a high-dimensional fixed effects (FE) model including airline-route FE, year FE and the interaction of origin/destination airport FE with year FE. We also analyze the heterogenous effects when splitting the sample by different route attributes and by the region of origin.

Given that carbon emission rates are directly proportional to fuel consumed, studies that examine the relationship between fuel costs and jet fuel consumption have much in common with the current study. Most of this literature draws on US airline data for relatively long time periods, although in some instances the level of data aggregation is at the airline/aircraft level. Yet, it is typically reported that an increase in fuel prices leads to a reduction in fuel consumption or to less demand, although there is some disagreement as to the quantitative significance of this effect (Wadud, 2014; Brueckner and Abreu, 2017, 2020; Fukui and Miyoshi, 2017; Miyoshi and Fukui, 2018; Csereklyei and Stern, 2020). Other studies focus on the strategies adopted by airlines to reduce their environmental impact as a response to higher fuel costs, including fleet replacement, lower aircraft utilization, and flying at slower speeds and with higher load factors (Wadud, 2015; Oliveira et al., 2021; Brueckner et al., 2024) while a related stream in the literature estimates pass-through rates of changes in fuel costs (Scotti and Volta, 2018; Chuang, 2020; Gayle and Lin, 2021; Pal and Mitra, 2022).

However, while previous studies consider the aggregate reaction of airlines to marginal changes in fuel costs, this study takes a different approach by focusing on the supply shock and the associated lower carbon emission rates that result from the use of new, more fuel-efficient aircraft.[3] To the best of our knowledge, evidence regarding rebound effects in the aviation sector is scarce, with the exception of Evans and Schäfer's (2013) simulation of the effect of a hypothetical improvement in aircraft efficiency. In their study, increased efficiency was shown to lead to lower prices, increased demand, and increased frequency competition, but this rebound effect is mitigated by delays due to traffic congestion.

Likewise, there is limited evidence on the environmental impact of this new generation of aircraft, which represents the most significant technological advancement in the sector in recent years. Using a dataset comprising 270 different aircraft/engine combinations from the B737 and A320 families, Grampella et al. (2017) show a statistically significant overall impact of incremental technical progress on noise, as well as on local and global pollutants. Carvalho et al. (2024) provides strong evidence of the energy efficiency (and the associated emissions efficiency) of new aircraft within the Airbus A320 family, based on operational data from Brazilian air transport in 2018.

Furthermore, two studies exploit the unexpected grounding of the B737 MAX aircraft in the US market. Divakaruni and Navarro (2024) find significant price increases attributable to the grounding which resulted in capacity restrictions and the more intensive use of less fuel-efficient aircraft. Forbes and Park (2024) find a reduction in the number of flights, which reduces emissions, but airlines also reallocate planes across their network in a way that increases emissions in some locations due to changes in the plane mix.

Other related studies have examined the role of price-based measures in incentivizing fleet renewal. De Jong (2022) and Fageda and Teixidó (2024) provide evidence that the European Union Emissions Trading System (EU ETS)—which, in practice, implies an increase in fuel costs—has encouraged the adoption of new aircraft. This finding is consistent with the theoretical predictions developed by Brueckner and Zhang (2010). In contrast, Fageda and Flores-Fillol (2025) find only modest effects from NOx-related airport charges.

The impact of new aircraft on carbon emissions is a priori unclear given that it is likely mediated by both greater fuel efficiency and potential supply growth. If new aircraft simply replace older planes, i.e. if the fleet renewal hypothesis holds, then we would expect fewer total carbon emissions (given their greater fuel efficiency) and no relevant impact on supply. If new aircraft are used more intensively than the older planes or serve as a tool for airline growth, i.e. if the supply growth hypothesis holds, then we would expect an increase in supply. Such an increase may partially, or even fully, offset the lower emission intensity; thus, the overall impact on emissions would not differ from zero and might even be positive.

Here, we report that the adoption of new aircraft has led to a substantial increase in supply that partially offsets their lower emission intensity. However, this general result conceals a high degree of heterogeneity in a sample that considers routes from around the world. Thus, while we find evidence in favor of the fleet renewal hypothesis for North America, network airlines, and shorter routes, we find clear evidence of the supply growth hypothesis for Asia and the Middle East, low-cost airlines, and longer routes.

The rest of the paper is organized as follows. Section 2 describes the data used. Section 3 outlines the empirical strategy employed and presents and explains the results. Finally, section 4 concludes.

2. Data

We utilize annual global data from RDC Aviation (Apex schedules) for the period 2017 to 2023, at the aircraft-airline-route-year level, where the route represents the airport pair. At this level, we have information on total CO_2 emissions, seats, flights, distance, the

[3] We focus on the emissions associated with the use of aircraft. However, aircraft manufacturing also generates emissions, which means while fleet renewal brings greater fuel efficiency, their manufacture is associated with higher rates of emission (Kito, 2021).

operating airline, and the aircraft model used. It is worth noting that using monthly or quarterly data would be helpful to account for seasonal variations. Unfortunately, the data available are only reported at the annual level. Note also that our data is based on non-stop flight services, so that we cannot account for competition on connecting routes. Furthermore, we cannot account for aircraft ownership structures due to the lack of information.

We also collect income per capita data from the World Bank Development Indicators at the country level. Additionally, we use supply data to construct a competition intensity indicator, namely the Herfindahl-Hirschman Index (HHI). Finally, we consider the fact that air routes may be operated by either low-cost or network carriers. We identify network airlines as those airlines that are part of one of the three global alliances (Oneworld, Star Alliance, and SkyTeam).

Our primary dataset is structured at the aircraft–route–airline–year level, where a route is defined by its origin and destination airports. For example, the dataset includes information on flights and emissions from London Heathrow to Lisbon operated by British Airways in 2018, using either an A320 or an A321 aircraft. We then aggregate this information to the route–airline–year level. In the same example, the aggregated data include the total number of flights and emissions from London Heathrow to Lisbon by British Airways in 2018. When a route–airline pair involves multiple aircraft types, as in this case, we compute weighted average values based on the share of each aircraft used on that route by the airline. This approach allows us to exploit detailed supply-side data that cover both domestic and international flights. Importantly, our main covariate of interest is the share of total flights operated with new aircraft—specifically, those from the A320neo (NEO) and B737 MAX (MAX) families.

Fig. 1 shows the share of total world flights being flown by the most popular aircraft families, that is, the A320 and B737 (see Fig. A1 for details on the number of flights operated with new aircraft). The new versions of aircraft within these families were launched in 2017, but very few flights were operated by either NEO or MAX before 2019. Moreover, MAX jets were grounded between March 2019 and November 2020 due to their involvement in two fatal accidents at the end of 2018. However, from 2021 onwards, there has been a marked increase in the number of flights operated by both NEO and MAX. Thus, in 2023, 3.6 million flights were operated by these two new aircraft, accounting for 10.6 % of all flights in the worldwide aviation market,[4] while the two families as a whole account for around 65 % of total flights given that they are dominant on short-/medium-haul routes.

Fig. 2 shows the share of new aircraft and the share of total flights flown by these aircraft by region in 2023. Most new aircraft are concentrated in North America, Europe and Asia. The figure also shows that North America, Europe and the Middle East have a higher share of new aircraft than the actual share of total flights while in the rest of the regions the share of new aircraft is lower. This indicates that the relatively richer regions have a disproportionate share of the new aircraft, which is unsurprising given the high capital costs of new aircraft mean that, on average, they are more likely to be operated by airlines from high-income countries. However, as Fig. A2 and Table A5 in the appendix show, the geographical spread of the newest aircraft is quite remarkable. Thus, we find airlines with 40 or more of these planes in their fleet in the United States (Southwest, American Airlines, United, Delta, Frontier, Alaska airlines, and Spirit airlines), China (China Southern, China Eastern, Air China, and Spring), India (Indigo and Air India), Japan (ANA and Japan airlines), Brazil (Gol and Azul), Mexico (Aeromexico and Volaris), Canada (Air Canada), the Middle East (Flynas and flydubai) and several European countries (Ryanair, Wizzair, Pegasus, Turkish airlines, easyjet, Lufthansa, British Airways, SAS, and Aeroflot).

Fig. 3 shows the relationship between the average emission intensity (measured as kilograms of CO_2 per seat-km) and the average aircraft size, bearing in mind that larger aircraft are more fuel efficient. Given that CO_2 emissions are directly proportional to fuel consumption, this measure of intensity is equivalent to an indicator of fuel efficiency. Indeed, the amount of CO_2 emissions from a flight given an aircraft type and the number of kilometers flown is obtained by multiplying the kilograms of fuel consumed by 3.5 (see, for example, Eurocontrol's small emitters tool: https://www.eurocontrol.int/tool/small-emitters-tool).

NEO and MAX aircraft are the most fuel efficient and are, thus, responsible for around 20 % fewer emissions per seat-km than their older versions (see Table A1 in the appendix for further details). Only the A330neo records a similar emission intensity, but it is a widebody aircraft used on long-haul routes. Among the smaller new aircraft, the A319neo and the A220-300, has a similar emission intensity. Fig. A3 in the appendix shows that fuel costs represent around 20–30 % of an airline's total expenditure; hence, operating new fuel-efficient aircraft means an airline can make significant cost savings.[5]

The new aircraft models we examine are structurally similar to their older counterparts. The main difference lies in the engine[6]: These new engines are significantly more fuel-efficient, providing aircraft with greater range. They are also quieter—both externally and from the passengers' perspective inside the cabin. Other improvements in the new versions include a slight increase in seating capacity and speed, as well as certain enhancements to cabin comfort.

Importantly, most of the upgrades—such as winglets or sharklets—could be incorporated into enhanced versions of older models. However, the new engines are exclusive to the latest models and cannot be retrofitted onto older aircraft.

Airlines may respond to the lower operating costs enabled by the new engines in different ways. They might increase flight frequency (i.e., supply), or pass the cost savings on to passengers in the form of lower ticket prices. In turn, lower prices could stimulate demand, leading indirectly to increased supply.

Table 1 and Table A2 in the appendix present a comparison of fuel costs for the A320 and B737 aircraft families across a typical

[4] Of these flights, 1.3 million were operated using the A320neo model, 1.2 million with the B737 MAX 8, 0.94 million with the A321neo and 0.2 million with the B737 MAX 9. The market presence of the smaller A319neo and B737 MAX 7 remains marginal.

[5] Note also that new aircraft are quieter and generate fewer NOx emissions (Fageda and Flores-Fillol, 2025). For example, the A320-neo and the B737 Max-8 generate 52% fewer NOx emissions than earlier comparable models, a difference that rises to 62% in the case of the A321-neo. Furthermore, the 85-decibel maximum noise-level contour of the A320-neo is around 50% lower than that of an earlier comparable model.

[6] "NEO" stands for "New Engine Option".

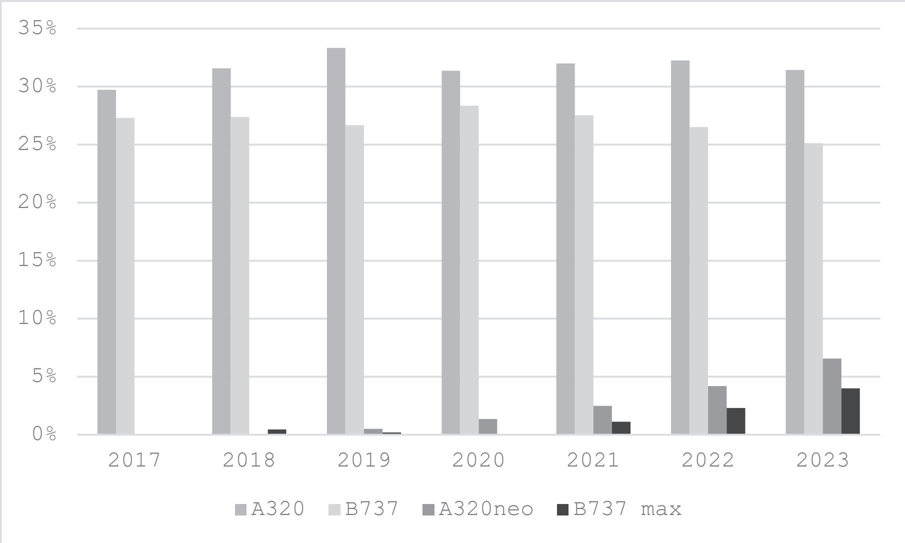

Fig. 1. Share of total flights (operated by selected aircraft families). Notes: The A320 family includes the A318, A319, A320 and A321 aircraft; the A320neo includes the A319neo, A320neo and A321neo; the B737 includes the B737-300, B737-400, B737-500, B737-600, B737-700, B737-800 and B737-900; and the B737 Max includes the B737 Max 7, B737 Max 8 and B737 Max 9.

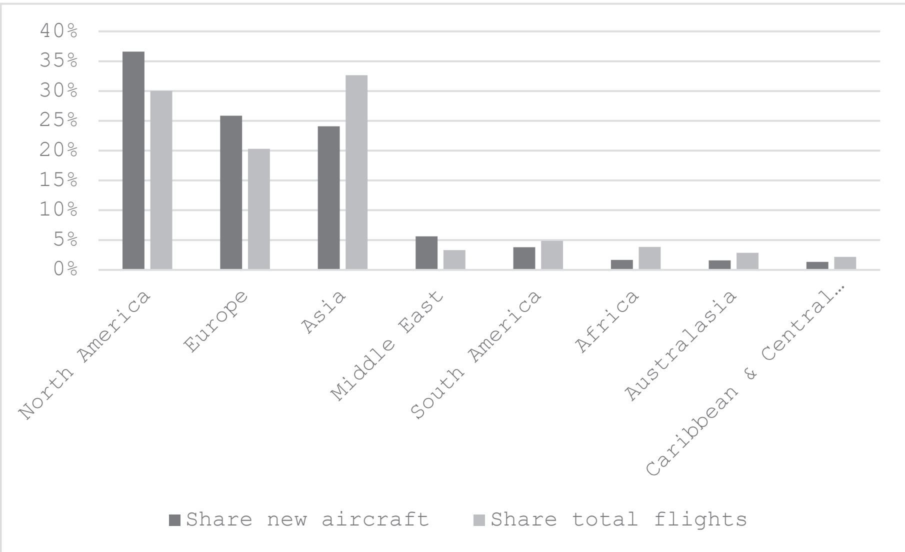

Fig. 2. Share of new aircraft and total flights by region (2023).

range of route distances. The differences between the new and older versions are substantial: cost savings per flight range from $350 to $1,330. Considering that a single aircraft can operate hundreds or even thousands of flights annually, the cumulative savings are significant. For instance, the cost per kilometer for an A320 ranges from $2.32 to $3.78, while for an A320neo it ranges from $1.91 to $3.09. These notable cost reductions are expected to drive supply growth. Moreover, the substantial investment involved in acquiring new aircraft may further incentivize their intensive use compared to less efficient models.

Note that new aircraft might affect passenger demand through improved comfort, reduced travel time, or environmental appeal. This demand response could further influence the net environmental impact. To this point, our analysis relies on detailed supply data, but we do not have demand information to explore if some demand drivers, beyond the potential lower prices that airlines may transfer to passengers' due lower costs, could also have an influence on the documented supply growth.

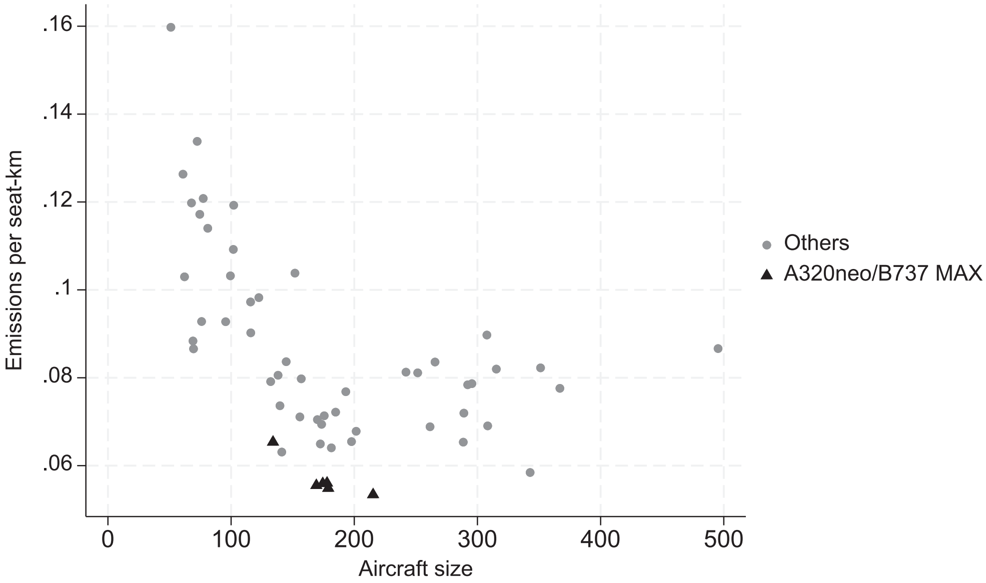

Fig. 3. Emission intensity vs. aircraft size (mean sample values).

Table 1
Cost fuel savings of new aircraft according to route distance (USD).

	500 km	1000 km	1500 km	2000 km	2500 km	3000 km
A320 vs A320neo	−345	−543	−740	−962	−1133	−1245
A321 vs A321neo	−334	−617	−900	−1082	−1205	−1328
B737-800 vs B737 MAX 8	−260	−461	−611	−678	−746	−871
B737-900 vs B737 MAX 9	−255	−333	−494	−563	−632	−701

Notes: These numbers arise from multiplying the total fuel consumption per route with the fuel costs. Fuel consumption in kilos has been obtained from the Eurocontrol Set emitter calculator (https://www.eurocontrol.int/tool/small-emitters-tool). We take the average fuel price per kg in the period 2017–2023 (0.676 USD per kilo) from the US Energy Information Administration (https://www.eia.gov/). See Table A2 for more details. Note that fuel prices in 2022 and 2023 have been 1.1 and 0.8 USD per kilo, respectively. Thus, cost savings in recent years are even higher than those reported in the table.

3. Empirical analysis

3.1. Methodology

We estimate the following equation (1) for the route-airline pair *i*, origin airport *a*, destination airport *d* and year *t*:

$$\mathrm{Y}_{it} = \alpha + \beta Share\_new\_aircraft_{it} + \lambda X_{it} + \gamma_i + \eta_t + \eta_t X \delta_a + \eta_t X \delta_d + \varepsilon_{it} \quad (1)$$

where the dependent variables (*Y*) are the emission intensity (measured by kg of CO_2 per seat-km), total CO_2 emissions and the number of flights and seats.

The main explanatory variable is *share_new_aircraft*, which is the share of total flights flown by NEO and MAX aircraft at the airline-route level. Given that these new aircraft are more fuel efficient than older versions, we expect a negative effect of this variable when emission intensity is the dependent variable.

The effect of the *share_new_aircraft* variable, however, is less clear when we consider either supply or total emissions as dependent variables. Here, two hypotheses might be formulated: the fleet renewal hypothesis and the supply growth hypothesis.

An increase in the share of new aircraft might be explained simply by fleet renewal. In this case, the *share_new_aircraft* variable should not have any relevant impact on the number of flights flown, but it would lead to fewer emissions because of the greater fuel efficiency of the new aircraft. This hypothesis would also be consistent with a slight increase in the number of seats if older and smaller aircraft are replaced with larger planes.

Alternatively, airlines might use their newer aircraft more intensively than their older planes due to their higher capital costs and greater fuel efficiency, or they might opt to use them to support an airline expansion plan. Furthermore, lower fuel costs may translate into lower prices, thereby stimulating both demand and supply. If these effects are relevant, we would expect a positive effect of the *share_new_aircraft* variable when the dependent variables are the number of either flights or seats. These potential rebound effects might imply a partial, or even total, offsetting of the greater fuel efficiency achieved, so that the actual impact of new aircraft on total

CO_2 emissions would be non-statistically different from zero or even positive.

As covariates (X_{it}), we consider different route attributes: distance, the mean income of the origin and destination countries, the share of flights operated by network airlines, and the Hirschman-Herfindahl Index (HHI) as an indicator of competition intensity on a given route. The equation also includes multiple fixed effects (FE) to control for unobservable factors. ε_{ikjt} is the error term.

We may expect higher supply and emissions (but lower emissions intensity) on routes connecting wealthier endpoints, due to higher demand and greater financial resources available to invest in newer aircraft. Similarly, network airlines may operate at higher frequencies (and therefore generate higher emissions) because business travelers are more sensitive to schedule delay costs.

Furthermore, airlines may compete either on prices or on quantities. In regressions where emissions intensity is the dependent variable, we expect a positive coefficient for the HHI variable, as weaker price competition may disincentivize the use of more fuel-efficient and cost-effective aircraft. In regressions where supply or total emissions are the dependent variables, we may expect a negative coefficient for the HHI variable, since quantity competition may lead to increased frequencies.

Results for the distance variable should be interpreted with caution. Most of its effect is already captured by the route-airline fixed effects. Therefore, this variable only reflects minor differences within each route-airline pair, such as those caused by variations in flight paths.

We consider route-airline FE (γ_i) and year FE (η_t). Furthermore, we include the interaction between airport and year FE at both the origin and destination levels (δ_a, δ_d). In practice, this entails adding thousands of dummy variables in the regressions—approximately 33,000 dummies capturing airline-route FE, 7 for year FE, and around 17,500 for airport-year FE.

This rich set of fixed effects allows us to control for time-invariant unobservable factors at the route-airline level. Given the relatively short time period analyzed, this includes, for example, cost differences across airlines, business, migration or tourism links that drive route demand, the population size of cities where airports are located, and common time shocks such as the business cycle or the COVID-19 pandemic. We also control for time-varying unobservable factors at the origin and destination airports, including demand and cost shocks, or airport capacity shocks.

In this context, the overall explanatory power of all regressions is very high, with R^2 values always exceeding 80 %. The inclusion of this comprehensive set of fixed effects is crucial to our analysis, as we rely on worldwide data but have access to a limited set of observable variables.

These multiple fixed effects help control for unobservable shocks that may influence both supply decisions and emissions. However, they do not allow us to identify the specific impact of such shocks. An alternative strategy to address unobserved heterogeneity would be to implement an instrumental variables (IV) approach, but identifying a valid instrument that affects supply choices without simultaneously influencing emissions is particularly challenging.

Note that all continuous variables with positive values are expressed in logs so that the coefficients can be interpreted as elasticities and the influence of outliers reduced. To address the heteroskedasticity and autocorrelation impacting standards errors, we include robust standard errors clustered by route–airline pairs.

For routes to be considered comparable, we focus on route-airline pairs that were operated using an aircraft from one of the two most popular aircraft families in 2017 (i.e. the A320 and the B737). However, even with this restricted sample and the inclusion of a rich set of fixed effects, our estimates may be biased since new aircraft might be used on routes with specific characteristics.

Tables 2 and 3 present the descriptive statistics of the variables used in the empirical analysis, along with their correlation matrix. For all variables, sample variability is high, as the standard deviation exceeds the mean. A representative route operates approximately five flights per week, generating around 4,000 tons of CO_2. The average distance is about 1,700 km, and the intensity of competition is relatively high, with an HHI of approximately 0.30. On average, network airlines account for roughly 30 % of flights. The correlations among the explanatory variables included in the analysis are generally low, with values below 20 %. The main exception, as expected, concerns the correlation between the outcome variables—flights, seats, and total emissions—which are strongly correlated. It is also worth noting that the estimated variance inflation factor (VIF) is low for all covariates, with values below 2 in all regressions, indicating no serious multicollinearity issues.

Table A3 in the appendix shows the results of a regression in which the dependent variable is *share_new_aircraft*, and the explanatory variables include the same route attributes as those considered in equation (1): namely, distance, mean income of origin and destination countries, a dummy for network airlines, and the HHI index. Additionally, we include a dummy for routes affected by an emissions trading scheme (i.e. routes within the European Economic Area, and domestic routes in South Korea and New Zealand, although these last two represent a marginal number of observations). The regression is run using the pseudo-maximum likelihood estimation because the dependent variable contains many zero values. The results show that new aircraft are more likely to be used by network airlines, and on longer and on more competitive routes. Furthermore, they are more likely to be used on routes with richer endpoints and routes affected by an emissions trading system (ETS), which are also routes with relatively rich endpoints.[7]

To eliminate bias related to observable heterogeneity (i.e., new aircraft are more likely to be used on longer routes connecting wealthier endpoints), we implement two strategies. First, we apply propensity score matching (PSM) to construct a sample with comparable treated and control observations (Rosenbaum and Rubin, 1983). In this analysis, paired observations have similar covariate levels (i.e., distance, income, and share of network airlines) in the first year of the period considered. Additionally, we include the total number of flights in the PSM procedure. First, we first estimate the probability of being affected by a new aircraft, conditional on the pre-existing characteristics that differ between groups. Second, we match observations in both groups (affected and not affected

[7] The results of this analysis are in line with findings from previous studies (De Jong, 2022; Fageda and Flores-Fillol, 2025).

Table 2
Descriptive statistics of the variables used in the empirical analysis.

Variable	Mean	Std. dev.	Minimum value	Maximum value
Emissions per seat-km (CO_2 kgs per route-airline-year)	0.0698	0.0756	0.0188	0.2543
Flights (total per route-airline-year	259.50	465.77	13	11,337
Seats (total per route-airline-year)	43,965.95	79,622.59	380	1,972,638
Emissions (total CO_2 tonnes per route-airline-year)	3,965.965	6,884.517	220.603	182,744.7
Share_new_aircraft (Percentage of flights operated by NEO/MAX)	0.0506	0.1874	0	1
Income (mean annual values of the origin and destination countries)	28,274.84	21,234.24	345	107,470
Share network (Percentage flights operated by airlines integrated in alliances)	0.3055	0.3824	0	1
Distance (number of kms of the route)	1,694.3	1,059.194	26.03	17,764.63
HHI	0.3055	0.3824	0.0977	1

Table 3
Correlation matrix of the variables used in the empirical analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Emissions per seat-km (1)	1								
Flights (2)	0.01	1							
Seats (3)	0.01	0.99	1						
Emissions (4)	−0.01	0.83	0.83	1					
Share_new_aircraft (5)	−0.04	−0.001	0.001	0.02	1				
Income (6)	−0.02	0.07	0.06	0.11	0.10	1			
Share network (7)	0.02	0.18	0.16	0.20	0.01	0.03	1		
Distance (8)	−0.14	−0.16	−0.15	0.09	0.15	0.11	−0.03	1	
HHI (9)	0.01	−0.18	−0.19	−0.19	0.001	0.15	−0.06	0.03	1

by a new aircraft) using the nearest neighbor algorithm. Then, we re-estimate equation (1) using the reduced matched sample.

To ensure comparability, we also use the complementary strategy of entropy balancing (EB) (Hainmueller, 2012), which reweighs the sample units so that the first and second moments of the relevant covariates match exactly those observed in the treated group. However, a limitation of this technique is that time-varying airport-year fixed effects at the origin and destination cannot be included. For this reason, our preferred technique is PSM. We estimate the model using the matched sample and the high-dimensional fixed effects method; however, this means that we are unable to apply weights, which is necessary for EB in the regressions.

Table 4 and Fig. 4 show the standardized difference in means between treated route–airline pairs and control route-airline pairs before and after applying PSM and EB in 2017, considering as inputs the total number of flights, income, share of network airlines and distance. Treated route-airline pairs are those with new aircraft in at least one year of the period considered, whereas control routes-airline pairs are those with no new aircraft in the whole of the period considered. In the unmatched sample, treated route-airlines have 67 % more flights than control route-airlines. The bias in the unmatched sample is 26 %, 19 % and 11 % for the variables of income, share of network airlines and distance, respectively. When we apply PSM, the bias is reduced substantially, falling below 6 % in all cases; when we apply EB, the bias is zero as this technique imposes no differences between treated and control route-airline pairs. Thus, the matched and reweighted samples correct the potential bias due to differences in the observable factors between the treated and control route-airline pairs before the introduction of the new aircraft.

PSM constructs a reduced matched sample in which treated observations are paired with control observations that have similar values for the covariates. In practice, the matched sample includes only control observations that closely resemble at least one treated observation in terms of covariate values.

In this context, the unmatched sample comprises 17,867 treated route-airline pairs and 51,060 control route-airline pairs. After matching, the sample includes 17,866 treated route-airline pairs and an equal number of matched control route-airline pairs (17,866).

In the case of EB, the number of effective observations may decrease because the method assigns greater weights to some observations while down-weighting or even excluding others to achieve covariate balance. Since this method uses weights rather than discarding observations directly, it does not provide specific counts for treated and control units, although the underlying logic is similar to that of PSM.

It is also worth noting that the sample is slightly reduced when including origin-year and destination-year fixed effects, as these additional fixed effects absorb all the variability in some route-airline pairs with very few observations.

3.2. Main results

We report the results of the different regressions run, considering emission intensity, both the number of flights and seats, and total CO_2 emissions as dependent variables. In each of the following tables, column (1) shows the results for the full sample. Column (2) reports the results of the regressions of the re-weighted sample after applying EB, while the regressions in column (3–5) consider the matched sample after applying PSM. Column (4) shows the results of the regression that includes airport-year fixed effects. Finally, column (5) indicates the results of the same regression as in (4) but excluding the years hit hardest by the Covid-19 pandemic (2020 and 2021). We report the results of various regressions by means of a robustness check and the baseline regression is reported in

Table 4
Mean differences between treated and control airline-routes in 2017.

	Unmatched			Matched-PSM			Matched-EB		
	Treated (N = 17,867)	Control (N = 51,060)	% bias	Treated (N = 17,866)	Control (N = 17,866)	% bias	Treated	Control	% bias
ln(flights)	5.4189	4.3036	66.9	5.4187	5.3242	5.7	5.4189	5.4176	0.1
ln(income)	9.9852	9.736	26.5	9.9851	9.9374	5.1	9.9852	9.9851	0.0
Share network	0.3712	0.2989	18.6	0.3712	0.3668	1.1	0.3712	0.3712	0.0
ln(distance)	7.282	7.203	11.4	7.282	7.2723	1.4	7.282	7.2819	0.0

Notes: The table shows the percentage standardized differences between treated and control airline-routes in 2017, considering the unmatched sample, the sample after applying propensity score matching (PSM) and the reweighted sample after applying entropy balancing (EB). The differences between treated and control airline-routes regarding the HHI variable is less than 2% in the unmatched and matched samples.

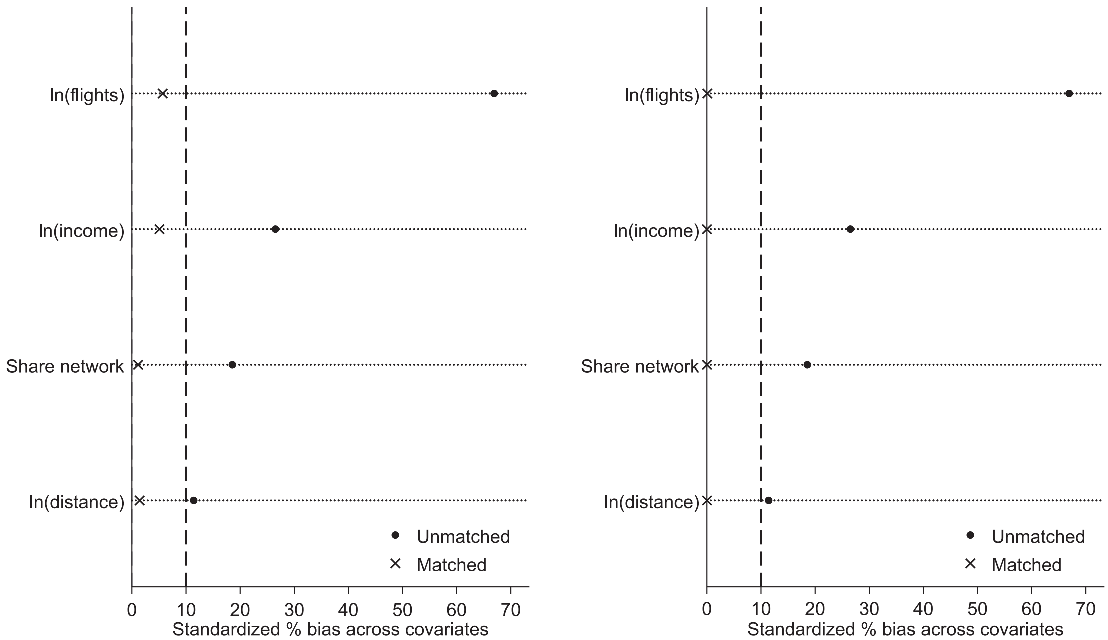

Fig. 4. Standardized mean difference for covariates on treated and control routes before and after propensity score matching and entropy balancing. Notes: The graph plots the percentage standardized differences between treated and control airline-routes in 2017. In the left panel, x indicates balancing with PSM (Rosembaum et al., 1983) and the dots without balancing. In the right panel, x indicates balancing with EB (Hainmueller, 2012) and the dots without balancing. The dashed grey vertical lines mark the 10 % difference, below which differences in means are considered negligible.

column (4).

In all regressions, the overall explanatory power of the model is very high. This, however, is unsurprising given that the high-dimensional fixed effects regression means adding thousands of dummies in each regression. Controlling for all these unobservable factors makes the results for variables with high-time variability – the case, for example, of *share_new_aircraft* – more reliable. The effect of covariates with low-time variability – the case, for example, of distance – may be captured by the fixed effects.

Table 5 shows the results when the dependent variable is emission intensity. Consistent with the descriptive evidence, the elasticity of the *share_new_aircraft* variable is around −0.20. Route–airline pairs that are fully operated with new aircraft produce around 20 % fewer emissions per seat-km than route–airline pairs operated with older planes. This result holds for all regressions. Furthermore, longer routes that link richer endpoints and routes operated by a higher share of network airlines both have fewer emissions per seat-km. No clear effects are found for the HHI variable.

Tables 6 and 7 show the results of regressions when the dependent variables are the total number of flights and seats, respectively. The estimated elasticity of the *share_new_aircraft* variable when the dependent variable is the number of flights is around 0.5 to 0.11, the latter outcome corresponding to the preferred regressions that include the full set of fixed effects after applying PSM. The estimated elasticities when the dependent variable is the number of seats are higher, ranging from 0.10 to 0.18 (0.16 corresponding to the preferred regression). The difference in these two sets of results may reflect the fact that these new aircraft are bigger than their older versions and, hence, have more seats. Thus, the introduction of new aircraft has led to a substantial increase in supply. Route–airline pairs that are fully operated with new aircraft have around 11 and 16 % more flights and seats, respectively, than those route–airline

Table 5
Emission intensity regressions.

	(1)	(2)	(3)	(4)	(5)
Share_new_aircraft	−0.196***	−0.206***	−0.206***	−0.207***	−0.208***
	(0.000953)	(0.00130)	(0.00120)	(0.00133)	(0.00141)
ln(distance)	−0.208	1.123	1.145	−1.031***	−1.063***
	(0.540)	(1.262)	(1.201)	(0.0502)	(0.0517)
ln(income)	−0.0198***	−0.0194***	−0.0213***	−0.0216**	−0.00622
	(0.00231)	(0.00327)	(0.00339)	(0.0110)	(0.0118)
HHI	0.00189**	0.00354***	0.00264*	−0.00210	−0.00127
	(0.000852)	(0.00132)	(0.00143)	(0.00136)	(0.00143)
Share_network_airlines	−0.000646	−0.00337**	−0.00341**	−0.00294**	−0.00244
	(0.00102)	(0.00158)	(0.00159)	(0.00139)	(0.00162)
Observations	489,565	337,588	204,592	199,951	147,492
R-squared	0.963	0.959	0.958	0.971	0.973
Sample	All	Matched-EB	Matched-PSM	Matched-PSM	Matched-PSM
Period	All	All	All	All	2020 & 2021 excluded
Route-airline FE (#)	YES (112,236)	YES	YES	YES	YES
		(68,830)	(34,155)	(33,507)	(33,452)
Year FE (#)	YES (7)	YES (7)	YES (7)	YES (7)	YES (5)
Origin Airport & Year FE (#)	NO	NO	NO	YES (8,904)	YES (6,459)
Destination Airport & Year FE (#)	NO	NO	NO	YES (8,854)	YES (6,418)

Note: This table shows the coefficients of the linear estimation where the outcome variable is CO_2 emissions per seat-km. We show in parenthesis the number of coefficients associated to each type of fixed effect (FE). Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Flight frequency regressions.

	(1)	(2)	(3)	(4)	(5)
Share_new_aircraft	0.0495***	0.0664***	0.0647***	0.111***	0.0968***
	(0.0139)	(0.0189)	(0.0172)	(0.0212)	(0.0241)
ln(distance)	0.658*	2.966***	2.136*	0.505	−3.824***
	(0.361)	(1.000)	(1.289)	(1.416)	(1.263)
ln(income)	0.505***	0.780***	0.796***	1.193***	1.510***
	(0.0407)	(0.0633)	(0.0566)	(0.240)	(0.263)
HHI	−1.174***	−0.975***	−0.990***	−0.660***	−0.619***
	(0.0175)	(0.0291)	(0.0281)	(0.0264)	(0.0306)
Share_network_airlines	0.281***	0.540***	0.541***	0.443***	0.456***
	(0.0229)	(0.0421)	(0.0402)	(0.0389)	(0.0451)
Observations	489,565	337,588	204,592	199,951	147,492
R-squared	0.816	0.816	0.811	0.863	0.871
Sample	All	Matched-EB	Matched-PSM	Matched-PSM	Matched-PSM
Period	All	All	All	All	2020 & 2021 excluded
Route-airline FE (#)	YES (112,236)	YES	YES	YES	YES
		(68,830)	(34,155)	(33,507)	(33,452)
Year FE (#)	YES (7)	YES (7)	YES (7)	YES (7)	YES (5)
Origin Airport & Year FE (#)	NO	NO	NO	YES (8,904)	YES (6,459)
Destination Airport & Year FE (#)	NO	NO	NO	YES (8,854)	YES (6,418)

Note: This table shows the coefficients of the linear estimation where the outcome variable is flight frequency. We show in parenthesis the number of coefficients associated to each type of fixed effect (FE). Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

pairs operated with older planes. Interestingly, the results are similar regardless of whether we apply PSM or EB to produce a comparable sample.

As expected, supply is higher on routes that connect richer endpoints and on routes where the intensity of competition is higher. Supply is also higher on routes dominated by network airlines. Outcomes for the distance variable are inconclusive.

Finally, Table 8 shows the results of regressions when the dependent variable is total CO_2 emissions. The *share_new_aircraft* variable is negative and statistically significant, indicating that routes with a higher share of new aircraft are responsible for fewer emissions. The estimated elasticity ranges between −0.05 and −0.09. Thus, the increase in supply partially offsets the lower emission intensity of new aircraft. If, however, the number of seat-km offered were kept constant, the reduction in emissions would be around 20 %, but our results report this reduction to be only 5 % (or 9 %, at most, depending on the regression taken into consideration).

3.3. Additional results

Table 9 presents additional robustness checks. Note that we focus here on the main outcome variable, total emissions, in order to

Table 7
Seats regressions.

	(1)	(2)	(3)	(4)	(5)
Share_new_aircraft	0.102***	0.122***	0.121***	0.161***	0.144***
	(0.0139)	(0.0189)	(0.0172)	(0.0213)	(0.0243)
ln(distance)	0.671*	2.972***	2.174*	0.572	−3.696***
	(0.359)	(1.004)	(1.295)	(1.420)	(1.276)
ln(income)	0.524***	0.808***	0.823***	1.253***	1.558***
	(0.0407)	(0.0635)	(0.0568)	(0.241)	(0.264)
HHI	−1.181***	−0.987***	−1.001***	−0.659***	−0.619***
	(0.0175)	(0.0291)	(0.0281)	(0.0264)	(0.0306)
Share_network_airlines	0.285***	0.547***	0.547***	0.443***	0.453***
	(0.0229)	(0.0423)	(0.0403)	(0.0390)	(0.0452)
Observations	489,565	337,588	204,592	199,951	147,492
R-squared	0.814	0.814	0.809	0.861	0.869
Sample	All	Matched-EB	Matched-PSM	Matched-PSM	Matched-PSM
Period	All	All	All	All	2020 & 2021 excluded
Route-airline FE (#)	YES (112,236)	YES	YES	YES	YES
		(68,830)	(34,155)	(33,507)	(33,452)
Year FE (#)	YES (7)	YES (7)	YES (7)	YES (7)	YES (5)
Origin Airport & Year FE (#)	NO	NO	NO	YES (8,904)	YES (6,459)
Destination Airport & Year FE (#)	NO	NO	NO	YES (8,854)	YES (6,418)

Note: This table shows the coefficients of the linear estimation where the outcome variable is total number of seats. We show in parenthesis the number of coefficients associated to each type of fixed effect (FE). Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
CO_2 emission regressions.

	(1)	(2)	(3)	(4)	(5)
Share_new_aircraft	−0.0943***	−0.0842***	−0.0850***	−0.0457**	−0.0640***
	(0.0139)	(0.0189)	(0.0172)	(0.0213)	(0.0242)
ln(distance)	1.464**	5.095***	4.319**	0.541	−3.759***
	(0.662)	(1.267)	(1.835)	(1.409)	(1.262)
ln(income)	0.504***	0.788***	0.802***	1.231***	1.551***
	(0.0408)	(0.0636)	(0.0569)	(0.240)	(0.263)
HHI	−1.179***	−0.983***	−0.998***	−0.661***	−0.620***
	(0.0175)	(0.0291)	(0.0281)	(0.0264)	(0.0306)
Share_network_airlines	0.284***	0.543***	0.543***	0.440***	0.451***
	(0.0229)	(0.0422)	(0.0403)	(0.0389)	(0.0452)
Observations	489,565	337,588	204,592	199,951	147,492
R-squared	0.814	0.806	0.802	0.856	0.864
Sample	All	Matched-EB	Matched-PSM	Matched-PSM	Matched-PSM
Period	All	All	All	All	2020 & 2021 excluded
Route-airline FE (#)	YES (112,236)	YES	YES	YES	YES
		(68,830)	(34,155)	(33,507)	(33,452)
Year FE (#)	YES (7)	YES (7)	YES (7)	YES (7)	YES (5)
Origin Airport & Year FE (#)	NO	NO	NO	YES (8,904)	YES (6,459)
Destination Airport & Year FE (#)	NO	NO	NO	YES (8,854)	YES (6,418)

Note: This table shows the coefficients of the linear estimation where the outcome variable is total CO_2 emissions. We show in parenthesis the number of coefficients associated to each type of fixed effect (FE). Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

minimize the number of tables embedded in the text. For the sake of clarity, we only report the results of the main explanatory variable of the analysis, *share_new_aircraft*.

In column (1), we consider only the share of new aircraft variable along with route-airline fixed effects (FE) as covariates. Columns (2) through (5) progressively add more covariates: control variables (column 2), year FE (column 3), origin/destination-year FE (column 4, which corresponds to the baseline regression), and airline-year FE (column 5). This approach helps us assess the potential influence of covariates on the results for the main variable of interest. Moreover, the airline-year FE accounts for potential effects related to changes in the airline's financial health during the period studied.

Column (6) excludes the years 2019 and 2020 to assess the impact of the unexpected grounding of the B737 MAX aircraft, which occurred from March 2019 to November 2020.

Finally, columns (7) and (8) show results using different specifications of propensity score matching. Column (7) includes only the covariates, while column (8) uses only total flights as the predictor of treatment probability.

Across all regressions, the impact of new aircraft on total emissions ranges from approximately −5% to −10 %. This effect is slightly larger when origin/destination and year FE are not included, and when the propensity score matching excludes flights.

Table 9
CO_2 emission regressions (robustness checks).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share_new_aircraft	−0.0968***	−0.0873***	−0.0850***	−0.0457**	−0.0434**	−0.0416**	−0.0828***	−0.0581***
	(0.0162)	(0.0183)	(0.0172)	(0.0213)	(0.0198)	(0.0201)	(0.0213)	(0.0211)
Observations	204,592	204,592	204,592	199,951	199,774	141,263	188,716	199,052
R-squared	0.751	0.760	0.802	0.856	0.874	0.857	0.868	0.859
Sample	Matched-PSM	Matched-PSM	Matched-PSM	Matched-PSM	Matched-PSM	Matched-PSM	Matched-PSM (covariates)	Matched3-PSM (flights)
Period	All	All	All	All	All	No 2019 & 2020	All	All
Route-Airline FE	YES	YES	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	YES	YES	YES	YES	YES
Year FE	NO	NO	YES	YES	YES	YES	YES	YES
Origin Airport & Year FE	NO	NO	NO	YES	YES	YES	YES	YES
Destination Airport & Year FE	NO	NO	NO	YES	YES	YES	YES	YES
Airline & Year FE	NO	NO	NO	NO	YES	NO	NO	NO

Note: This table shows the coefficients of the linear estimation where the outcome variable is total CO_2 emissions. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fig. 5 shows the estimated coefficients for each year in the period under analysis for the outcome variables (emissions intensity, number of flights, number of seats, and total emissions). These results are based on regressions using the matched sample, with route–airline FE and year FE.

The figures reveal a greater use of more fuel-efficient aircraft during the years most affected by the COVID-19 pandemic, namely 2020 and 2021. As expected, both emissions and supply levels dropped sharply during those years. Overall, the figures suggest that the lower the level of supply, the higher the relative use of the more efficient aircraft.

While the immediate effects of the COVID-19 pandemic on the aviation industry are well documented—particularly the sharp drop in demand leading to capacity reductions and price cuts—the long-term effects are still unfolding. There is emerging evidence that the recovery has been slower for business travel compared to leisure travel (Borsati and Fageda, 2024; Cristea and Miromanova, 2025). If

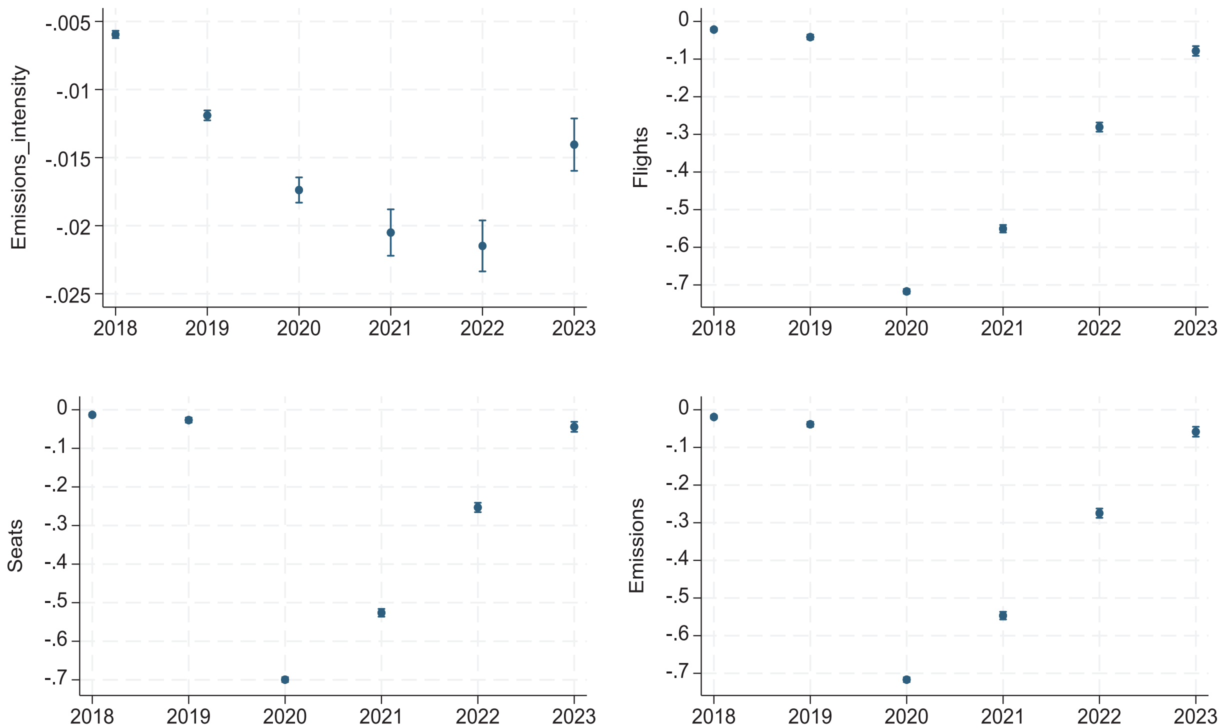

Fig. 5. Estimated year FE coefficients. Note: This table shows the estimated coefficients associated to each year of the considered period for the four outcome variables (emissions intensity, flights, seats and total emissions). The regressions used the matched sample, all controls and route-airline and year FE. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the post-pandemic aviation landscape is characterized by a greater share of leisure passengers—who tend to be more cost-sensitive—this could incentivize airlines to adopt newer, more fuel-efficient aircraft.

However, financial difficulties faced by some airlines in the aftermath of the pandemic may also hinder such investments. Therefore, the long-term impact of the pandemic on the relationship between new aircraft adoption and emissions remains uncertain.

We analyze the case where decarbonization benefits of new aircraft may be potentially higher, given that it involves the most popular models and a significant reduction in fuel consumption compared to older versions. However, even in this case, the benefits appear to be limited. Table A1 in the appendix provides detailed information on the most efficient aircraft in our sample, including their first year of introduction. We differentiate between larger and smaller aircraft.

Airbus and Boeing have primarily focused on new versions of larger aircraft. Regarding aircraft with fewer than 150 seats, the only new models (defined as those introduced after 2010) in the 100–140 seat range are the A220, Embraer 195/190-E2, and A319neo. All of these have operated a limited number of flights, possibly because they were recently introduced or because they are less competitive compared to older versions. For aircraft with fewer than 100 seats, the only new models are the ARJ21-700 and the SSJ 100–95, both with a small market presence.

Within this context, we have explored the hypothesis of limited decarbonization benefits from new small aircraft by running additional regressions focusing on smaller aircraft and short-haul routes. The regressions for smaller aircraft include those with fewer than 150 seats; focusing solely on aircraft with fewer than 100 seats is not meaningful due to the limited market presence of only two new models. The regressions for short-haul routes include routes shorter than 1000 km, considering that small aircraft are generally used on such routes. Note that the short-haul route regressions include all aircraft types, not just the popular families analyzed in the main analysis.

Table A4 in the appendix shows the results of these additional regressions. The results for the small aircraft sample show a smaller reduction in emissions intensity than those found in the NEO/MAX regressions. Furthermore, we find evidence of a rebound effect, where new models are replacing older, smaller models. Regarding the regressions using the short-haul route subsample, we do not find evidence of a reduction in emissions because modest improvements in emissions intensity are offset by significant supply growth. Thus, we provide evidence of modest or even negligible decarbonization benefits when focusing on small aircraft.

3.4. Heterogeneous effects

Our analysis of the full sample provides more evidence supporting the supply growth hypothesis than supporting fleet renewal. However, these results may well mask the considerable degree of heterogeneity that might be expected in an analysis based on data gathered from around the world. Tables 10 and 11 replicate the previous analyses taking into consideration two different types of heterogeneity: in Table 10, we analyze the differences between subsamples when using the same control variables as earlier; in Table 11, we consider subsamples based on the route's region of origin. Note that the outcomes in these tables only show the results of the preferred regression, which considers the full set of fixed effects after applying PSM. We do not report the results when the dependent variable is emission intensity as they remain very similar regardless of the subsample considered. For the sake of clarity, we only report the results of the main explanatory variable of the analysis, *share_new_aircraft*.

In what follows, a route is defined as either high or low in terms of income, distance, and share of network airlines if it has values higher or lower than those of the mean sample. Thus, columns (1) and (2) in Table 6 consider subsamples based on high- and low-income routes, respectively; the subsamples in columns (3) and (4) refer to routes with high and low shares of network airlines, respectively; columns (5) and (6) to monopoly and oligopoly routes, respectively; and finally, columns (7) and (8) to longer and shorter routes.

Our results for high-income routes are in line with those reported previously. Routes with a higher share of new aircraft are responsible for an increase in supply of about 0.08 in terms of number of flights and 0.13 in terms of number of seats. This partially offsets their greater fuel efficiency, reducing emissions by just −0.08. The increase in supply is higher on low-income routes with estimated elasticities of 0.12 for flights and 0.17 for seats. Here, supply growth completely offsets the lower emission intensity, so that the net effect on total CO_2 emissions is not statistically different from zero. It should be noted, in this regard, that richer countries are likely to be more mature markets with less growth potential; furthermore, airlines operating in high-income countries usually have older fleets so that renewal may play a more significant role.[8] Differences in price-demand elasticities could also help explain this result, considering that new aircraft entail lower fuel costs, which may ultimately translate into lower ticket prices. If price-demand elasticities are higher in low-income countries, then the potential price reductions associated with new aircraft could lead to a stronger stimulus to demand—and consequently to supply—in those countries.

Fleet age and a lower proportion of price-sensitive passengers may also help explain the differences observed on routes with a higher share of network airlines, given that these carriers typically operate older fleets and serve a larger proportion of business passengers. A higher share of new aircraft does not lead to an increase in flight frequency when we consider only routes where network airlines are dominant. However, it does result in an increase in the number of seats, with an estimated elasticity of 0.10. This can be explained by the replacement of both older and smaller versions of the popular aircraft families. Overall, the net effect on total CO_2

[8] According to data from airfleet.net website (accessed in October 2024 so that the purchase of new aircraft in the period 2017–2023 are included), the mean fleet age of the largest US and European network airlines is between 13 and 16 years, while it is around 10–12 years for the largest low-cost. In contrast, the mean fleet age of the largest airlines (either network or low-cost) in other leading markets, including Brazil, China, Mexico, India, Indonesia and Turkey, is 10 years or less. See Table A5 for more details.

Table 10
Regressions with subsamples (covariates).

	(1) ln flights)	(2) ln(flights)	(3) ln(flights)	(4) ln(flights)	(5) ln(flights)	(6) ln(flights)	(7) ln(flights)	(8) ln(flights)
Share_new_aircraft	0.0803***	0.125***	0.0463	0.154***	−0.0230	0.168***	0.183***	0.0378
	(0.0258)	(0.0429)	(0.0324)	(0.0288)	(0.0452)	(0.0251)	(0.0263)	(0.0402)
	(1) ln(seats)	**(2) ln(seats)**	**(3) ln(seats)**	**(4) ln(seats)**	**(5) ln(seats)**	**(6) ln(seats)**	**(7) ln(seats)**	**(8) ln(seats)**
Share_new_aircraft	0.130***	0.174***	0.101***	0.201***	0.0473	0.215***	0.228***	0.101**
	(0.0258)	(0.0431)	(0.0326)	(0.0290)	(0.0453)	(0.0253)	(0.0265)	(0.0402)
	(1) ln (emissions)	**(2) ln (emissions)**	**(3) ln(emissions)**	**(4) ln(emissions)**	**(5) ln (emissions)**	**(6) ln (emissions)**	**(7) ln (emissions)**	**(8) ln (emissions)**
Share_new_aircraft	−0.0822***	−0.0216	−0.117***	0.00273	−0.164***	0.00784	0.0185	−0.105***
	(0.0258)	(0.0429)	(0.0326)	(0.0288)	(0.0452)	(0.0252)	(0.0264)	(0.0401)
Observations	122,602	74,230	84,869	108,436	55,604	135,524	93,023	102,765
Sample	High-income	Low-income	High share network	Low share network	Monopoly	Oligopoly	Longer	Shorter

Note: This table shows the coefficients of the linear estimation using different outcome variables. All regressions include as covariates distance, income, share of network airlines, HHI and year FE, route–airline FE, and origin and destination airport FE interacted with year FE. The sample used is the matched sample after applying propensity score matching. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11
Regressions with subsamples (regions).

	(1) ln(flights)	(2) ln(flights)	(3) ln(flights)	(4) ln(flights)	(5) ln(flights)	(6) ln(flights)	(7) ln(flights)	(8) ln(flights)
Share new aircraft	0.00245	0.146*	0.0762**	0.161	0.285***	0.295***	0.144**	−0.0753
	(0.0393)	(0.0857)	(0.0367)	(0.122)	(0.0530)	(0.0920)	(0.0707)	(0.123)
	(1) ln(seats)	**(2) ln(seats)**	**(3) ln(seats)**	**(4) ln(seats)**	**(5) ln(seats)**	**(6) ln(seats)**	**(7) ln(seats)**	**(8) ln(seats)**
Share new aircraft	0.0510	0.183**	0.130***	0.168	0.351***	0.344***	0.176**	−0.0633
	(0.0395)	(0.0854)	(0.0369)	(0.121)	(0.0533)	(0.0928)	(0.0750)	(0.124)
	(1) ln (emissions)	**(2) ln (emissions)**	**(3) ln(emissions)**	**(4) ln (emissions)**	**(5) ln (emissions)**	**(6) ln (emissions)**	**(7) ln (emissions)**	**(8) ln (emissions)**
Share new aircraft	−0.177***	−0.0205	−0.0719**	−0.0224	0.150***	0.142	0.00858	−0.241*
	(0.0394)	(0.0862)	(0.0367)	(0.121)	(0.0530)	(0.0928)	(0.0747)	(0.124)
Observations	43,252	9,853	65,182	5,583	58,079	7,457	3,311	5,372
Sample	North America	Rest of America	European Economic Area	Rest of Europe	Asia	Middle East	Oceania	Africa

Note: This table shows the coefficients of the linear estimation using different outcome variables. All regressions include as covariates distance, income, share of network airlines, HHI and year FE, route–airline FE, and origin and destination airport FE interacted with year FE. The sample used is the matched sample after applying propensity score matching. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

emissions is −12 %. In contrast, a higher share of new aircraft implies a notable increase in supply on routes where low-cost airlines are dominant, both in terms of flights and seats (with estimated elasticities of 0.15 and 0.20, respectively) so that the net effect on CO_2 emissions is not statistically different from zero. This result supports the hypothesis that network airlines are mainly using the new aircraft for fleet renewal and that low-cost airlines use them for supply growth. In this regard, our analysis focuses on aircraft that are primarily used on short- and medium-haul routes where low-cost airlines in most countries are gaining market share.

When considering the subsample of monopoly routes, our results provide clear evidence in support of the fleet renewal hypothesis, given that a higher share of new aircraft does not lead to greater supply and the net effect of CO_2 emissions is −16 % (relatively like what we would expect in terms of emission intensity reduction). In contrast, when considering just the oligopoly routes, our analysis finds support for the supply growth hypothesis, given that the marked increase in supply fully offsets the emission intensity reduction. This does not necessarily mean that competition is harmful, just that the growth potential is higher on routes operated by several airlines.

Finally, an increase in the share of new aircraft leads to a marked increase in supply on longer routes (ie; routes with more than 1700 kms) with no significant effect in terms of total CO_2 emissions. In contrast, a higher share of new aircraft does not increase the number of flights on shorter routes (ie; routes with less than 1700 kms), although it does increase the number of seats (with an estimated elasticity of 0.10). This again can be explained by the replacement of older, smaller versions of the popular aircraft families considered. The net effect in terms of total CO_2 emissions is −10 %. Note that fuel costs have a greater weight over total costs on longer routes as we shown in Table 1; thus, the cost savings from greater fuel efficiency may play a major role on these latter routes.

Table 11 shows the regression results for subsamples based on the region of origin. In the case of the North America subsample, we find evidence that supports the fleet renewal hypothesis. For this region, a higher share of new aircraft does not lead to an increase in supply, either in terms of the number of flights or seats. Hence, the reduction in emissions is around −17 %, which is like the figure we would expect from the fall in emission intensity. In the case of the European Economic Area, the results are the same as those found for the full sample: an increase in the share of new aircraft leads to an increase in the number of flights and seats (with estimated elasticities of 0.7 and 0.13, respectively) that partially offsets the reduction in emission intensity (net effect on total carbon emissions of −7%). A potential explanation for the differences between the US and the European Economic Area is that the fleet of European airlines was younger than that of their US counterparts before the introduction of the new aircraft models (De Jong, 2022; Brueckner et al., 2024). This difference is likely attributable to the incentives for fleet renewal associated with the EU ETS.

In the case of the Asia subsample, we find evidence in support of the supply growth hypothesis. An increase in the share of new aircraft leads to a marked increase in supply both in terms of the number of flights and seats (with estimated elasticities of 0.28 and 0.30, respectively). Indeed, such a high increase in supply accounts for the increase in total CO_2 emissions. Similar trends are noted for the Middle East, although the statistical effect on total CO_2 is more imprecise, probably due to the low number of observations.

The greater rebound effect in Asia compared to Europe—and especially the United States—may be related to the different levels of maturity and development between the two types of markets. Liberalization in the United States and Europe, along with the subsequent consolidation of hub-and-spoke networks and the emergence of low-cost carriers, took place decades ago. In contrast, these changes have occurred more recently in many Asian countries and, in several cases, are still an emerging phenomenon. Among other things, this may help explain, as mentioned earlier, why the average age of aircraft fleets is lower for Asian airlines.

Moreover, the prospects and potential for air traffic growth are greater in Asia, as are, on average, the growth expectations for both the economy and the population. According to RDC data for 2023, the United States and the European Economic Area account for 23 % of aviation-related emissions, while representing only 4.7 % and 7.3 % of the global population, respectively. In contrast, for example, China and India account for 11.7 % and 3.2 % of emissions, while together accounting for nearly 40 % of the global population.

Interestingly, in the case of Africa, the higher capital costs of new aircraft could explain the outcomes reported. While the estimates are imprecise due to the low number of observations, an increase in the share of new aircraft leads to fewer flights and seats and, hence, to a substantial decrease in CO_2 emissions. For the other regions (rest of America, rest of Europe, Oceania), the increase in supply fully offsets the lower emission intensity so that the net effect in terms of total CO_2 emissions is not statistically different from zero.

Regional differences could also be related to the varying degrees of passenger sensitivity to price changes. As mentioned earlier, the most significant change brought by new aircraft is the use of more efficient engines, which leads to lower fuel costs—one of the main operating expenses for airlines. We can expect that these lower costs will be passed on, to some extent, in the form of lower ticket prices for passengers. Therefore, it is possible that in regions where passengers are more price-sensitive, the rebound effect becomes more significant, potentially offsetting—partially or even fully—the lower emissions intensity of the new aircraft.

4. Conclusion

In this paper, we have examined the impact of the newest versions of the most popular aircraft families on total CO_2 emissions, testing the hypothesis that the effects of their greater fuel efficiency may be offset by the growth in supply.

When considering the full sample, we find that these new aircraft have indeed led to a notable increase in supply that offsets, in part, their lower emission intensity. Route–airline pairs that are fully operated using new aircraft have around 11 and 16 % more flights and seats, respectively, than those route–airline pairs operated with older planes; however, at the same time, these former routes are responsible for around 5 % fewer total CO_2 emissions. This result has two interpretations: on the one hand, new aircraft allow passengers to fly more air miles while emitting fewer CO_2 emissions; but, on the other hand, the increase in supply their adoption entails places limits on the overall reduction in emissions expected from this technological advance.

Yet, when considering different segments of the sample, this outcome does not always hold. For example, on routes from North America (primarily from the United States), we find evidence in support of the fleet renewal hypothesis, while evidence for the European Economic Area is less clear, reflecting perhaps the role that the emissions market in Europe might have played in accelerating fleet renewal in the years prior to the arrival of the new aircraft. Whatever the motives, the routes operated with these new aircraft have significantly lower CO_2 emissions both in the US and in the EU. It should also be stressed that North America and Europe have a higher share of new aircraft in relation to the share of total flights flown by these aircraft. Additionally, when considering just network airlines, our results support the hypothesis that this sector is using the new aircraft primarily to support fleet renewal. Furthermore, when focusing on shorter routes, new aircraft do not have any relevant supply effects, considering that such routes are usually dominated by network airlines.

In contrast, on routes from Asia and the Middle East (and less markedly so on routes from the rest of America, the rest of Europe and Oceania), we find clear evidence of the supply growth hypothesis. Moreover, in the case of low-cost airlines and longer routes, our results also provide evidence for this same hypothesis.

This being the case, new aircraft are only contributing to the containment of carbon emissions in the richer, more mature markets, while enabling network airlines – with old fleets and declining market shares – to generate fewer emissions. However, in parallel, new aircraft appear to be contributing to supply increases in growing markets and in low-cost airlines.

Despite the clear progress that new versions of typical aircraft families represent over earlier models, our results highlight their limitations in reducing global carbon emissions. These improvements primarily affect wealthier countries and network airlines. However, it is important to mention that our analysis focuses on short-term effects, as the study period spans only seven years and includes years significantly affected by the COVID-19 pandemic. This is a relatively short time frame during which the adoption of new aircraft is still in progress. While the short-term effects appear modest, the long-term impact of new aircraft on emissions remains uncertain.

It is also worth noting that our analysis focuses on a scenario where decarbonization benefits of new aircraft are expected to be relatively high, given that it involves the most popular models and significant reductions in fuel consumption compared to older versions. Even so, the observed benefits are limited. In fact, technological innovation in the sector has mainly targeted larger aircraft, while the decarbonization potential of new small aircraft is even more constrained.

It appears that a truly sustainable aviation sector will not be achieved until disruptive technologies become fully viable. Given the limited technological options currently available, reducing carbon emissions may require a combination of strategies: containing traffic growth and incentivizing fleet renewal. In this context, price-based measures—such as cap-and-trade systems or carbon/fuel taxes—could offer a cost-effective way to mitigate the potential rebound effects associated with newer aircraft. These mechanisms, by effectively increasing fuel costs, encourage airlines to choose the most suitable response based on their cost structure and demand: reducing supply, trading emissions allowances, paying taxes, or investing in more efficient aircraft. Capacity restrictions could also curb rebound effects, though they offer less flexibility than price-based measures, which allow airlines to respond according to their individual circumstances.

CRediT authorship contribution statement

Valeria Bernardo: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Xavier Fageda:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix A

Table A1
Characteristics of the most efficient large aircraft (appendix).

Aircraft	Family	Emissions per seat-km	Million flights	Mean distance	Aircraft size	Year of introduction
A321neo	A320neo	0.053	1.7	1954	215	2017
B737 MAX 8	B737 MAX	0.055	2.2	2001	179	2017
B737 MAX 7	B737 MAX	0.056	0.04	1058	169	2023
A320neo	A320neo	0.056	2.6	1680	174	2016
B737 MAX 9	B737 MAX	0.056	0.4	2201	178	2017
A330-900	A330neo	0.058	0.1	5130	343	2018
B737-800 Winglets	Boeing 737 Next Generation	0.064	16	1806	181	1998
A320 Winglets	Airbus A320 Family	0.065	4.5	1566	172	1988
B787-9	Boeing 787	0.065	2	5377	289	2012
A321 Winglets	Airbus A320 Family	0.065	1.8	2023	198	2018
A321	Airbus A320 Family	0.068	13	1690	202	1994
B787-8	Boeing 787	0.069	1.3	4958	262	2011

(*continued on next page*)

Table A1 (*continued*)

Aircraft	Family	Emissions per seat-km	Million flights	Mean distance	Aircraft size	Year of introduction
A350-900	Airbus A350 Family	0.069	1.1	5441	308	2015
B737-800	Boeing 737 Next Generation	0.069	24	1659	173	1998
A320	Airbus A320 Family	0.070	41	1558	170	1988
B737-500 Winglets	Boeing 737 Classic	0.071	0.5	1365	156	1990
B737-900 Winglets	Boeing 737 Next Generation	0.071	0.9	2051	176	2000
B737-900	Boeing 737 Next Generation	0.072	3.5	1784	185	2000
B757	Boeing 757	0.077	0.7	2558	193	1983
B777-300	Boeing 777	0.078	0.6	4676	367	1997
A330-300	Airbus A330 Family	0.079	3.5	3693	295	1994

Note: We consider aircraft with at least 150 seats.

Table A1
Characteristics of the most efficient small aircraft (appendix).

Aircraft	Family	Emissions per seat-km	Million flights	Mean distance	Aircraft size	Year of introduction
A220-300	CSeries	0.063	0.7	1469	141	2016
A319neo	A320neo	0.065	0.01	1237	134	2019
A220-100	CSeries	0.066	0.33	1514	138	2016
ERJ-195-E2	Embraer E-Jets	0.067	0.18	1303	133	2021
B737-700 Winglets	Boeing 737 Next Generation	0.074	7.1	1676	140	1998
B737-700	Boeing 737 Next Generation	0.079	1.8	1499	132	1998
A319	Airbus A320 Family	0.081	11	1427	138	1996
ARJ21-700	COMAC	0.083	0.21	872	86	2016
ERJ-190-E2	Embraer E-Jets	0.083	0.08	1019	109	2018
B737-300	Boeing 737 Classic	0.084	0.68	1390	144	1984
B737-600	Boeing 737 Next Generation	0.085	0.26	1423	133	1997
ATR 72-600/200	ATR	0.087	7	474	69	1986
B717-200	Boeing 717	0.090	1.50	977	115	1999
SSJ 100-95	Sukhoi	0.093	0.66	1553	95	2011
DHC 8-Q400	De Havilland Dash	0.093	4.20	654	76	1999
A318	Airbus A320 family	0.095	0.31	987	122	2003
ERJ-195	Embraer E-Jets	0.097	1.70	1044	115	2006
B737-500	Boeing 737 Classic	0.098	0.83	1133	122	1984
ATR 42	ATR	0.103	2.10	442	62	1995
CRJ-1000	CRJ	0.103	0.55	849	99	1992
DHC 8-Q300	De Havilland Dash	0.105	1.00	476	50	1989
ERJ-190	Embraer E-Jets	0.109	4.80	1107	101	2005
CRJ-900	CRJ	0.114	4.90	901	81	2003
ERJ-175	Embraer E-Jets	0.117	6.80	1082	77	2003

Note: We consider aircraft with less than 150 seats.

Table A2
Fuel consumption and fuels costs (aircraft of A320 and B737 families).

		Route distance					
Aircraft		500 km	1000 km	1500 km	2000 km	2500 km	3000 km
A320	**Fuel consumption (kgs)**	2793	4260	5727	7230	8772	10,315
	Fuel costs (USD)	1888	2880	3871	4887	5930	6973
	Fuel costs per km (USD)	3.78	2.88	2.58	2.44	2.37	2.32
A320neo	**Fuel consumption (kgs)**	2282	3457	4632	5807	7096	8474
	Fuel costs (USD)	1543	2337	3131	3926	4797	5728
	Fuel costs per km (USD)	3.09	2.34	2.09	1.96	1.92	1.91
A321	**Fuel consumption (kgs)**	3124	4890	6655	8418	10,166	11,913
	Fuel costs (USD)	2112	3306	4499	5691	6872	8053
	Fuel costs per km (USD)	4.22	3.31	3.00	2.85	2.75	2.68
A321neo	**Fuel consumption (kgs)**	2630	3977	5324	6818	8383	9948
	Fuel costs (USD)	1778	2688	3599	4609	5667	6725
	Fuel costs per km (USD)	3.56	2.69	2.40	2.30	2.27	2.24
B737-800	**Fuel consumption (kgs)**	2635	4142	5610	7078	8547	10,101
	Fuel costs (USD)	1781	2800	3792	4785	5778	6828
	Fuel costs per km (USD)	3.56	2.80	2.53	2.39	2.31	2.28
B737 MAX 8	**Fuel consumption (kgs)**	2250	3460	4706	6075	7443	8812
	Fuel costs (USD)	1521	2339	3181	4107	5031	5957
	Fuel costs per km (USD)	3.04	2.34	2.12	2.05	2.01	1.99
B737-900	**Fuel consumption (kgs)**	2890	4358	5988	7619	9250	10,880

(*continued on next page*)

Table A2 (*continued*)

Aircraft		Route distance 500 km	1000 km	1500 km	2000 km	2500 km	3000 km
	Fuel costs (USD)	1954	2946	4048	5150	6253	7355
	Fuel costs per km (USD)	3.91	2.95	2.70	2.58	2.50	2.45
B737 MAX 9	**Fuel consumption (kgs)**	2513	3865	5257	6786	8315	9843
	Fuel costs (USD)	1699	2613	3554	4587	5621	6654
	Fuel costs per km (USD)	3.40	2.61	2.37	2.29	2.25	2.22

Notes: These numbers arise from multiplying the total fuel consumption per route with the fuel costs. Fuel consumption in kilos has been obtained from the Eurocontrol Set emitter calculator (https://www.eurocontrol.int/tool/small-emitters-tool). We take the average fuel price per kg in the period 2017–2023 (0.676 USD per kilo) from the US Energy Information Administration (https://www.eia.gov/).

Table A3
Share new aircraft regressions.

	(1)
ln(distance)	0.671***
	(0.0158)
ln(income)	0.157***
	(0.00969)
Network airlines	0.168***
	(0.0151)
HHI	−0.0780***
	(0.0243)
ETS	0.161***
	(0.0193)
	(0.142)
Observations	540,424
Pseudo-R2	0.181
Sample	All

Note: This table shows the coefficients of the pseudo-maximum likelihood estimation using as outcome variable the share of new aircraft. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4
Regressions with small aircraft and short-haul routes.

	(1) ln (emissions-intensity)	**(2) ln (flights)**	**(3) ln (seats)**	**(4) ln (emissions)**	**(1) ln (emissions-intensity)**	**(2) ln (flights)**	**(3) ln (seats)**	**(4) ln (emissions)**
Share_new_aircraft	−0.132***	0.0245	0.156***	−0.0663**	−0.103***	0.155***	0.217***	0.0387
	(0.00699)	(0.0274)	(0.0286)	(0.0272)	(0.00520)	(0.0261)	(0.0279)	(0.0277)
Observations	61,929	61,929	61,929	61,929	61,929	61,929	61,929	61,929
R-squared	0.969	0.932	0.930	0.931	0.969	0.932	0.930	0.931
Sample	Small aircraft	Small aircraft	Small aircraft	Small aircraft	Short-haul routes	Short-haul routes	Short-haul routes	Short-haul routes

Note: This table shows the coefficients of the linear estimation using different outcome variables. All regressions include as covariates distance, income, share of network airlines, HHI and year FE, route–airline FE, and origin and destination airport FE interacted with year FE. The sample used is the matched sample after applying propensity score matching. Small aircraft are aircraft with less than 150 seats. Short-haul routes are routes with less than 1,000 kms. Robust standard errors (in parentheses) clustered at the route level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0$.

Table A5
Airline's fleet characteristics.

Airline	Country	Fleet_size	Mean age	# NEO	# MAX
Southwest Airlines	United States	824	11.7		241
American Airlines	United States	971	13.4	80	62
United Airlines	United States	972	16.2	15	188
Ryanair	Ireland	318	10.6		113
China Southern Airlines	China	650	9.8	106	32
Delta Air Lines	United States	972	15.2	64	

(*continued on next page*)

Table A5 (*continued*)

Airline	Country	Fleet_size	Mean age	# NEO	# MAX
China Eastern Airlines	China	643	9.2	109	3
IndiGo	India	342	10.6	238	
easyJet	United Kingdom	183	10.3	55	
Air China	China	490	9.6	58	23
Lufthansa	Germany	273	13.3	39	
Alaska Airlines	United States	239	10.1		76
JetBlue	United States	283	12.3	29	
Gol	Brazil	125	10.5		48
Aeroflot	Russia	164	8.1	7	35
Turkish Airlines	Turkey	348	8.8	34	25
Spirit Airlines	United States	198	6.2	96	
Avianca	Colombia	126	8.7	37	
British Airways	United Kingdom	252	13.5	41	
Lion Air	Indonesia	79	11.2		3
SAS	Sweden	91	8.5	46	
LATAM Airlines Chile	Chile	113	11.2	4	
Air France	France	228	13.1		2
Shenzhen Airlines	China	193	10.1	24	11
Sichuan Airlines	China	191	9	38	
ANA	Japan	208	10.1	23	39
Volaris	Mexico	105	6.2	48	
XiamenAir	China	169	9.2	16	17
Vueling	Spain	127	10.3	19	
AirAsia	Malaysia	89	9.7	26	
Shandong Airlines	China	136	10.3	11	
Pegasus	Turkey	112	4.4	97	9
Wizz Air	Hungary	87	6.2	28	1
Virgin Australia	Australia	93	11.9		9
WestJet	Canada	132	25.4		34
Frontier Airlines	United States	152	4.4	123	
Eurowings	Germany	94	12	12	
Alitalia	Italy	99	7.8	26	
Saudia	Saudi Arabia	158	9,2	7	
Air Canada	Canada	200	11.6		40
Hainan Airlines	China	217	9.4	1	17
Iberia	Span	91	9.6	17	
Jetstar Airways	Australia	83	10.9	16	
Qantas	Australia	124	15		
S7 Airlines	Russia	87	12.1	15	
Air India	India	138	9	51	
Copa Airlines	Panama	100	9.5		33
Aeromexico	Mexico	112	6.9		56
Juneyao Airlines	China	95	7	29	
Japan Airlines	Japan	145	11.5		42
Norwegian Air Shuttle	Norway	45	9.5		6
KLM	France	112	14.1	2	
Cebu Pacific Air	Philippines	80	5.7	30	
flydubai	UAE	88	5		59
Garuda Indonesia	Indonesia	60	11.4		
Thai AirAsia	Thailand	59	10.2		14
VietJet Air	Vietnam	75	7.2		14
TAP Air Portugal	Portugal	83	9.3	37	
Jeju Air	Korea	41	14.3		2
Shanghai Airlines	China	87	9.3		15
Batik Air	Indonesia	66	9.4		
Vietnam Airlines	Vietnam	84	8.9		1
SpiceJet	India	21	11.9		
Air Arabia	UAE	47	8.9	6	
Flynas	Saudi Arabia	61	3.4	51	
Spring Airlines	China	128	7.6	50	
Malaysia Airlines	Malaysia	77	11		4
Aerolineas Argentinas	Argentina	83	11.1		11
Skymark Airlines	Japan	29	12.3		
Aer Lingus	Ireland	56	13.2	14	
Air New Zealand	New Zealand	106	10	15	
Lucky Air	China	51	8.5	6	3
Austrian	Austria	69	17.4	4	
Ural Airlines	Russia	49	14.4	11	
Brussels Airlines	Belgium	46	16.7		5
EgyptAir	Egypt	69	9.9	8	

(*continued on next page*)

Table A5 (*continued*)

Airline	Country	Fleet_size	Mean age	# NEO	# MAX
Qatar Airways	Qatar	260	8.8		9
SWISS	Switzerland	82	10.6		5
SunExpress	Turkey	76	10.3		18

Notes: Airlines with the highest number of total flights in our sample. They are ordered from most to least flights. Network airlines are marked in bold. Data obtained from airfleet.net website (accessed in October 2024).

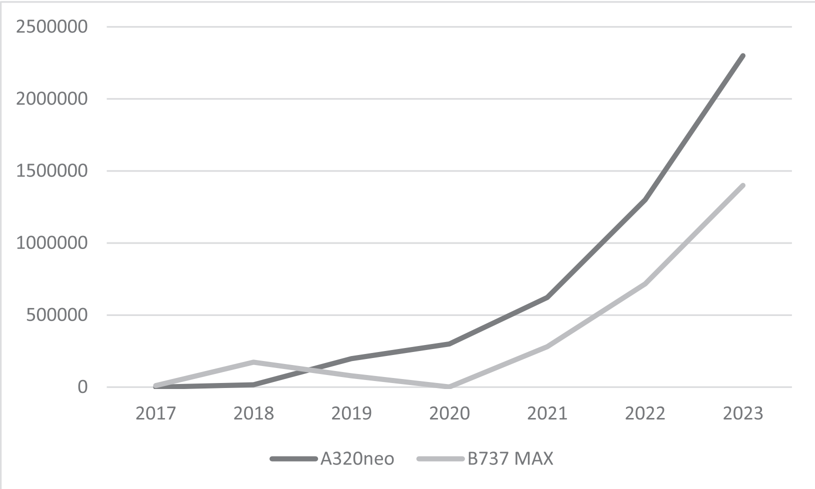

Fig. A1. Number of flights per year (new aircraft families)

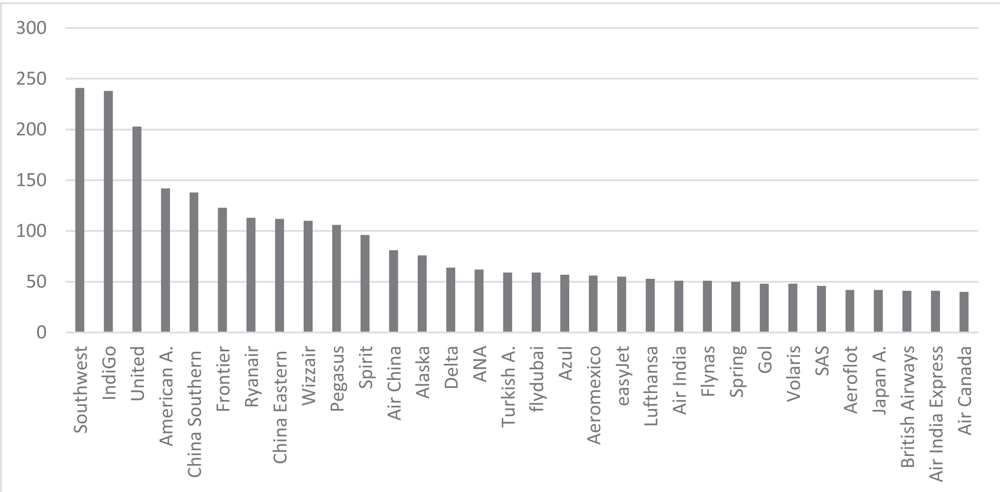

Fig. A2. Number of new aircraft by selected airlines

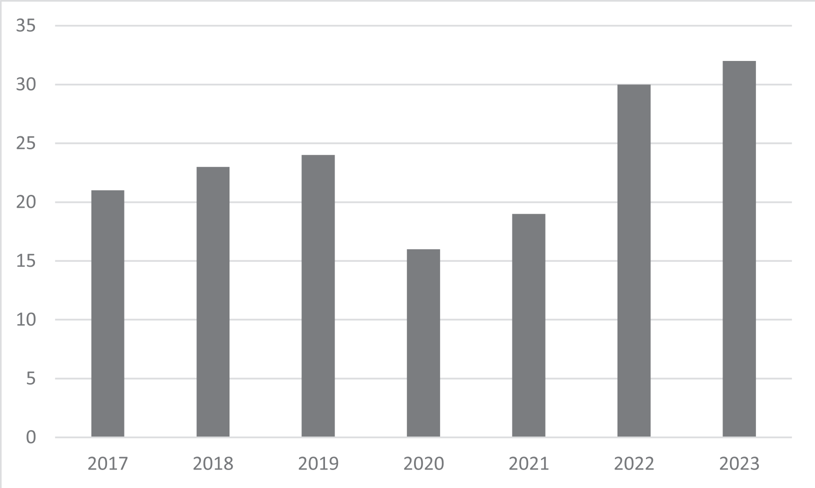

Fig. A3. Share fuel costs over total expenses of airlines worldwide

Source: Statista.

Data availability

The authors do not have permission to share data.

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