The environmental challenge in aviation: Can airport charges be part of the solution?*

Xavier Fageda† and Ricardo Flores-Fillol‡

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Abstract

Aviation is becoming a major contributor to greenhouse gas emissions and generates local pollution with harmful health effects. This paper studies the effects of airport charges by means of a theoretical setup and an empirical application. The equilibrium analysis identifies how airport charges affect fares, frequencies, and aircraft emissions. The welfare analysis concludes that frequencies are excessive when the damage caused by emissions is severe. Finally, our model explores mechanisms for revenue-neutral airports to compensate rises in emission charges by lowering non-emission charges to generate incentives for airlines to renew their fleets. The empirical analysis concludes that NOx-emission charges have a modest effect on fares and frequencies as compared to per-passenger and per-flight charges. Although only emission charges spur the use of newer aircraft, they should be much higher than their actual values to play a relevant role in contributing to a more sustainable aviation.

Keywords: pollution; aircraft; airport; airline; emission and non-emission charges

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†Department of Economic Policy, Universitat de Barcelona, Avinguda Diagonal 690, 08034 Barcelona, Spain.

‡Departament d'Economia and ECO-SOS, Universitat Rovira i Virgili, Avinguda de la Universitat 1, 43204 Reus, Spain. E-mail: ricardo.flores@urv.cat.

1 Introduction

Currently, aviation accounts for about 3% of global CO_2 emissions.[1] Taking into account its projected growth, there is no doubt it will become a major contributor to climate change in the coming years (IATA, 2022). In fact, the World Wildlife Fund describes the environmental footprint of aviation as "one of the fastest-growing sources of the greenhouse gas emissions driving global climate change" (WWF, 2023).

Air traffic also generates local externalities affecting neighborhoods surrounding airports, such as noise and polluting emissions that worsen air quality. Focusing on air pollutants, nitrogen oxides (NO_x) are within the ones producing the most harmful effects on human health (Schlenker and Walker, 2016).[2]

All in all, aviation faces nowadays a major environmental challenge, with social movements (like the so-called "flight shame") and political initiatives (like France's short-haul flight ban) that call the whole sector into question. This situation exerts a raising pressure on aviation that should look for a way to re-invent itself to remain as a valid and socially-acceptable transportation mode in the near future.

Although there are some technological innovations that could transform the sector (such as electric or hydrogen-powered aircraft), they are decades away from becoming an actual alternative to be used in commercial aircraft propulsion systems. Finally, substituting fossil jet kerosene by aviation biofuels seems really complex and extremely expensive.[3]

Looking at market-based measures to mitigate these externalities, there are two main options. The first one consists in increasing the costs for airlines and/or passengers, thereby yielding a lower supply and/or demand. Of course, an environmental-growth tradeoff arises here given the unquestionable contribution of aviation to GDP. The second one has to do with creating incentives for airlines to use newer aircraft models, which are quieter, more fuel-efficient, and produce less NO_x emissions. This paper investigates the strategic role of NO_x-related emission charges as a way to combine these two market-based measures.

[1] The climate impact of aviation extends beyond CO_2 emissions. In fact, non-CO_2 emissions at high altitudes have been found to multiply their impact, so that the overall effect of aviation in terms of CO_2-warming-equivalent emissions (based on global warming potential) is about 6% (Lee *et al.*, 2021).

[2] The effect of nitrogen oxides (NO_x) goes beyond the local dimension, as they also contribute to climate change (the same happens with sulfur oxides (SO_x)). See Grobler *et al.* (2019) for a detailed analysis.

[3] The abatement cost associated with biofuels ranges from \$46 to \$652 per metric ton of CO_2 equivalent (Winchester *et al.*, 2015). Major challenges here comprehend biofuel prices rising higher than those of jet fuel, a lack of sufficient feedstock or the need for major capital investment in bio-refining infrastructures (Staples *et al.*, 2018).

At this point, it is important to acknowledge that the effect of airport charges in mitigating NO_x emissions cannot become a conclusive solution for global emissions and climate change. Therefore, the use of emission charges cannot be a substitute for more radical technological innovations or policies that address directly CO_2 emissions like carbon taxes or emissions trading systems. However, they can behave as a useful tool to generate the right incentives leading to a more sustainable commercial aviation given the current state of technology.[4]

We first propose a theoretical model where n airlines compete on a certain city-pair market by choosing prices (i.e., airfares) and service quality (i.e., flight frequencies). The model sheds light on the effect of airport charges on equilibrium fares, flight frequencies, and emission levels (which depend on aircraft vintage, as newer aircraft are quieter and less polluting). These effects constitute the testable predictions for our empirical application. Furthermore, the model includes a welfare analysis that unveils the broad impact of aviation's environmental externality and a final section that studies the way airports can compensate rises in emission charges by reducing non-emission charges.

Our empirical application uses data from RDC Aviation over the period 2013-2022 to examine the impact of airport charges on fares and frequencies (on the short run) and share of new aircraft (on the long run) at the airline-route level. For the short-run analysis, we use the panel sample with data for every year and reduced-form supply and fare equations are estimated. In one set of regressions, the dependent variable is the number of frequencies at the airline-route level. In another set of regressions, the dependent variable is the weighted posted fare at the airline-route level. For the long-run analysis, we propose another set of regressions having as dependent variable the share of new aircraft being used.

The proposed theoretical setup builds on the model by Brueckner (2010), which generalizes the duopoly model of fare-and-frequency competition in Brueckner and Flores-Fillol (2007) to competition among n firms. Then we incorporate emissions in a similar way as Brueckner and Zhang (2010) along with the implied environmental externality.[5] The schedule delay

[4]The magnitude of airport charges is rather small (around 4% of airline operating expenses) in comparison to, for example, fuel costs. However, airlines invest non-negligible resources in trying to avoid them (ACI, 2021). In this regard, they can take action to reduce the impact of airport fees by either lobbying to achieve price controls from regulators or expediting the process to renew their fleets.

[5]The duopoly model in Brueckner and Flores-Fillol (2007) is extended by Brueckner and Girvin (2008) to incorporate noise as an airline externality and by Brueckner and Zhang (2010) to introduce airline emissions. Czerny (2015) extends the setup in Brueckner and Zhang (2010) by considering a general per-aircraft capital cost function. Shah and Brueckner (2012) depart from the analysis in Brueckner (2010) to model fare and frequency competition in freight transportation. In a diffferent setup with two countries and two airlines, Yuen

is introduced as a function decreasing with flight frequency, in line with Brueckner (2004), Brueckner and Flores-Fillol (2007 and 2020), and Bilotkach *et al.* (2010).

More precisely, the theoretical model contributes to the literature by incorporating emissions along with the implied environmental externality in a setup with n carriers à la Brueckner (2010). This is the key element that allows: *i*) modeling emission and non-emission charges that affect the equilibrium fares, flight frequencies, and emission (in Section 3), yielding testable predictions for our empirical application, *ii*) carrying out the welfare analysis (in Section 4) that yields different results depending on the magnitude of the externality, and *iii*) studying the way airports can compensate rises in emission charges by reducing non-emission charges to generate incentives for airlines to renew their fleets (in Section 5).

The empirical literature on airport charges is scarce and focuses on their determinants rather than on their effects (Van Dender, 2007; Bel and Fageda, 2010; Bilotkach *et al.*, 2012; Allroggen *et al.*, 2013, Bottasso *et al.*, 2017; Valdes and Sour, 2017; Conti *et al.*, 2019). Differently, Doi (2022) is more related to our study and develops a structural model with an application to the Japanese domestic market to analyze the effect of airport charges on fares and frequencies. He finds that per-passenger charges significantly raise fares and reduce frequencies, while per-flight (i.e., per-seat) charges decrease frequencies but do not have any significant impact on fares.

Furthermore, several empirical analyses have made use of reduced-form equations within a DiD framework to estimate the impacts of market-based measures raising airline costs. Fageda and Teixidó (2022) and Kang *et al.* (2022) focus on the effects of the EU Emissions Trading System (ETS) on frequencies and emissions, while De Jong (2022) and Fageda and Teixidó (2023) study the fleet-renewal incentives generated by this emission market. Instead, Borbely (2019), Falk and Hagsten (2019), and Bernardo *et al.* (2024) examine the impact of European flight-ticket taxes on traffic and frequencies. They all find significant effects of these market-based measures, although the magnitude of the impact differs in each study. All of them differentiate between routes affected and not affected by the policy using a dummy variable, so that they do not include airport charges as a mediating factor.

Other related works have estimated pass-through rates by focusing on fuel costs (Waddud, 2015; Scotti and Volta, 2018; Chuang, 2020; Gayle, 2021). Finally, some studies have analyzed the fall in fuel usage when fuel costs increase (Brueckner and Abreu, 2017 and 2020; Fukui and Miyoshi, 2017; Brueckner *et al.*, 2024).

Our theoretical results indicate that airlines react to a rise in either emission or non-emission charges by raising airfares and decreasing flight frequencies. Looking at the effect on airline

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and Zhang (2011) study the effects of imposing unilateral country regulations to mitigate emissions.

emissions, only emission charges have an actual impact. The welfare analysis and the study of the rate of substitution between emission and non-emission charges highlight the usefulness of emission charges to mitigate emissions and the overprovision of (polluting) flight frequencies. Furthermore, revenue-neutral airports can implement such policies in a smooth way, as they can compensate increases in emission charges by decreases in non-emission charges.

The effects of emission and non-emission charges on fares, frequencies, and airline emissions suggested by out theoretical model are confirmed and quantified empirically. Our empirical findings suggest that emission charges have a modest effect on fares and frequencies in comparison to non-emission charges. By contrast, emission charges lead to a higher use of newer aircraft while non-emission charges have no significant effects. However, the actual impact of emission charges on the share of new aircraft is small given that their current rates are very low.

These empirical results, along with our theoretical insights, suggest that there is room for further increases in emission charges, which should create further incentives for airlines to speed up their fleet-renewal strategies. This approach suggesting higher emission charges seems consistent with the current trend toward more stringent environmental standards. Although emission charges cannot become a conclusive solution for climate change, they can mitigate NO_x emissions. Therefore, given the current state of technology, emission charges can contribute to achieve a more sustainable commercial aviation. However, this would require emission charges to be much higher than they are currently.

The plan of the paper is as follows. Section 2 presents the model while Section 3 computes the equilibrium and performs a comparative-static analysis that yields testable predictions for our empirical application. Section 4 presents the welfare analysis and Section 5 studies the way airports can compensate rises in emission charges by reducing non-emission charges. Section 6 contains our empirical application that confirms and quantifies our comparative-static predictions. Finally, a brief conclusion closes the paper. Proofs of all propositions are provided in Appendix A. Additional figures and tables are provided in Appendix B (available online).

2 The model

Different to most theoretical models that are typically used in transportation economics, the analysis that follows accounts for the double competition in prices (i.e., fares) and service quality (i.e., flight frequency) that characterizes transportation markets along with the possibility to accommodate many market structures, as there are $n \geqslant 2$ firms (i.e., airlines) competing in the market. Brueckner (2010) proposes the first model encompassing the aforementioned features, generalizing the duopoly model of schedule competition (i.e., frequency competition) in Brueckner and Flores-Fillol (2007) to competition among n firms. Our model constitutes a step further in this series, as it incorporates carriers' emissions and capital cost into the analysis, along with emission and non-emission airport charges. With these elements, the model can shed light on the effect of airport charges on equilibrium fares, flight frequencies, and emission levels (which depend on aircraft vintage, as newer aircraft are less polluting).

Preferences and budget constraint. Each consumer (i.e., passenger) traveling with carrier i has a quasi-linear utility function given by

$$U\left(a_i t_i, x\right) = \ln a_i t_i + x, \tag{1}$$

and a budget constraint given by

$$x + z_i t_i = y, \tag{2}$$

where t_i denotes trips undertaken with carrier i, a_i stands for carrier i's brand loyalty, x is a composite good, z_i is the full price of travel on carrier i, and y denotes the common level of income (more details on brand loyalty and full prices are provided later on).[6] Plugging (2) into (1) and maximizing utility with respect to t_i yields the following demand for trips on carrier i:

$$t_i = \frac{1}{z_i}. \tag{3}$$

Finally, plugging (3) into (1) and (2) allows obtaining the following indirect utility function:

$$U = \ln \frac{a_i}{z_i} + y - 1. \tag{4}$$

Total demand for carrier i. An individual consumer will choose carrier i whenever $\ln \frac{a_i}{z_i} + y - 1 \geqslant \ln \frac{a_j}{z_j} + y - 1$, for all $j \neq i$. This inequality holds whenever

$$a_j \leqslant a_i z_j / z_i, \tag{5}$$

which indicates that brand loyalty to carrier i must be larger than brand loyalties to competing carriers, taking into account relative full prices. Brand loyalty, which is assumed to be exogenous and consumer-specific, follows a symmetric and uniform distribution with density

[6] Brueckner (2010) assumes Cobb-Douglas preferences. Quasi-linear preferences yield similar results and simplify some expressions.

λ/α^n, where $\lambda > 0$ is the mass of passengers (or market size) and brand loyalty for each carrier $i = 1, 2, ..., n$ ranges between 0 and $\overline{a}_i \equiv \alpha$. Therefore, total demand for carrier i is

$$q_i = \int_{a_1=0}^{a_i z_1/z_i} \int_{a_2=0}^{a_i z_2/z_i} \cdots \int_{a_i=0}^{\alpha} \cdots \int_{a_n=0}^{a_i z_n/z_i} \underbrace{\frac{\lambda}{\alpha^n z_i}}_{t_i \frac{\lambda}{\alpha^n}} da_1 da_2 \cdots da_i \cdots da_n. \tag{6}$$

Carrying out the integration in (6) yields

$$q_i = \frac{\lambda \Pi_{j \neq i} z_j}{n z_i^n}. \tag{7}$$

Full price. The full price (or generalized cost) of travel on carrier i accounts for the monetary and non-monetary cost of a trip and is given by

$$z_i = p_i + \frac{\gamma}{f_i}, \tag{8}$$

where p_i is the airfare and f_i the frequency provided by the carrier.[7] The *schedule delay* γ/f_i stands for the non-monetary cost of a trip and is decreasing with frequency, with $\gamma > 0$ being the cost of schedule delay that converts it to a money value. This specification is in line with Brueckner (2004), Brueckner and Flores-Fillol (2007 and 2020), and Bilotkach *et al.* (2010).[8]

Cost and profit function. The supply and the demand of scheduled services are related by

$$\ell s_i f_i = q_i, \tag{9}$$

where $\ell \in [0, 1]$ denotes the (parametric) load factor and s_i stands for the number of available seats per aircraft (i.e., aircraft size), so that the passengers per flight are given by ℓs_i. Airline i's *cost per flight* equals

$$C_i = \tau_p \ell s_i + \tau_f s_i + r_f e_i s_i + \frac{\varepsilon_f s_i}{e_i} + \theta, \tag{10}$$

[7] Our stylized theoretical model does not encompass price discrimination, as it would complicate the analysis unnecessarily, taking into account the focus of the paper. See Fageda and Flores-Fillol (2023) for a model with vertically-differentiated airlines supplying different qualities (i.e., flight frequencies) at different fares.

[8] Letting T denote the time circumference of the circle and assuming that consumers are uniformly distributed around it in terms of their preferred departure time, utility depends on expected schedule delay, which is defined as the difference between the preferred and actual departure times and equals $T/4f_i$. Scheduled services operated by a carrier f_i are evenly spaced. Therefore, the schedule delay is equal to a disutility parameter $\delta > 0$ times the expected schedule delay expression, thus equaling $\delta T/4f_i = \gamma/f_i$, where $\gamma \equiv \delta T/4$.

where e_i are the emissions per seat, ε_f/e_i is the capital cost per seat (with $\varepsilon_f > 0$), $\theta > 0$ captures any cost per departure independent of emissions and aircraft payload,[9] while $\tau_p > 0$, $\tau_f > 0$, and $r_f > 0$ denote per-passenger charges, per-seat charges, and emission charges. As in Brueckner and Zhang (2010), the capital cost per seat is decreasing with emissions, as older and more-polluting aircraft are cheaper that the newer and cleaner ones.[10,11] Per-passenger charges are related to the actual volume of passengers per flight (ℓs_i), per-seat charges are related to aircraft size (s_i), and emission charges are related to emissions ($e_i s_i$).[12] Under this specification, cost per seat C_i/s_i realistically falls with aircraft size, capturing the presence of economies of traffic density (i.e., economies from operating a larger aircraft) that are unequivocal in the airline industry. Using (9) to substitute s_i, the *total cost* for airline i becomes

$$TC_i = C_i f_i = \left(\tau_p + \frac{\tau_f}{\ell} + \frac{r_f}{\ell} e_i + \frac{\varepsilon_f}{\ell}\frac{1}{e_i}\right) q_i + \theta f_i, \tag{11}$$

which, after renaming $\tau \equiv \tau_p + \frac{\tau_f}{\ell}$, $r \equiv \frac{r_f}{\ell}$, and $\varepsilon \equiv \frac{\varepsilon_f}{\ell}$, becomes

$$TC_i = \left(\tau + r e_i + \frac{\varepsilon}{e_i}\right) q_i + \theta f_i, \tag{12}$$

where τ denotes total non-emission charges (including both per-passenger and per-seat charges) expressed in per-passenger terms, r stands for emission charges expressed in per-passenger

[9] The θ term encompasses, among others, infrastructure fees (per aircraft movement), administrative fees (per route and schedule) or gate rental fees.

[10] Although the assumed functional form of the capital cost may not be representative of the precise relationship between capital costs and emissions, it captures the existing tradeoff between the two magnitudes in a simple way. In Brueckner and Zhang (2010), the capital cost function has a slightly different functional form and is given by $\frac{\beta+\varepsilon_f s_i}{e_i}$, with $\beta > 0$, where the β term does not have a straightforward interpretation. A possible drawback of the capital cost function that we propose has to do with the proportional effect of emissions, so that a 50% reduction in emissions would duplicate the capital cost per seat. An alternative formulation ruling out this proportional effect could be $\beta + \frac{\varepsilon_f s_i}{e_i}$, with $\beta > 0$. However, this specification would be tantamount to redefining our cost per departure θ and nothing else would be affected.

[11] The capital cost in our model could be more broadly interpreted as an aircraft leasing cost with a limited duration, which would allow operating a certain number of flights.

[12] Although the term $e_i s_i$ is interpreted as aircraft emissions, it could also be understood as fuel consumption (as older aircraft are less efficient and more pollutant). Similarly, r_f is interpreted as the emission charge, while it could be understood as the fuel price. However, this fuel price cannot be altered by airlines' decisions (as r_f is a parameter of the model). Therefore, our model cannot accommodate airlines' choice on fuel composition, i.e., determining the proportion between kerosene and aviation biofuels. The reason is that this choice is based on the tradeoff between emissions and fuel prices (biofuels reduce emissions but are more expensive). In any case, biofuels face major challenges (as explained in footnote 3) and represent less than 0.1% of total aviation fuel consumption.

terms and ε/e_i is the capital cost expressed in per-passenger terms. Carrier i's profits are $\pi_i = p_i q_i - TC_i$, which can be rewritten after using (12) as $\pi_i = \left(p_i - \tau - re_i - \frac{\varepsilon}{e_i}\right) q_i - \theta f_i$. Finally, using (7) and (8), this expression becomes

$$\pi_i = \frac{\left(p_i - \tau - re_i - \frac{\varepsilon}{e_i}\right) \lambda \Pi_{j \neq i} \left(p_j + \frac{\gamma}{f_j}\right)}{n \left(p_i + \frac{\gamma}{f_i}\right)^n} - \theta f_i. \tag{13}$$

Environmental externality. Aircraft emissions produce a social damage. The value of this externality is $E = \eta_f \sum_{i=1}^{n} e_i s_i f_i$, where $e_i s_i f_i$ denotes the emissions generated by an individual airline and $\eta_f > 0$ is the per-flight marginal environmental damage. Using (9) to substitute s_i, then $E = \frac{\eta_f}{\ell} \sum_{i=1}^{n} e_i q_i$, i.e.,

$$E = \eta \sum_{i=1}^{n} e_i q_i, \tag{14}$$

where $\eta \equiv \frac{\eta_f}{\ell}$ is the marginal environmental damage expressed in per-passenger terms.

3 Equilibrium analysis and comparative statics

Carrier i chooses p_i, f_i, and e_i, viewing the choices of the other $j \neq i$ competing carriers as parametric. In reality, the choice of e_i is a consequence of airline's fleet renewal strategy, as emission intensity and aircraft vintage are undoubtedly related. The first-order conditions are

$$\frac{\partial \pi_i}{\partial p_i} = \frac{\lambda \Pi_{j \neq i} \left(p_j + \frac{\gamma}{f_j}\right)}{\left(p_i + \frac{\gamma}{f_i}\right)^n} \left(\frac{1}{n} - \frac{p_i - \tau - re_i - \frac{\varepsilon}{e_i}}{p_i + \frac{\gamma}{f_i}}\right) = 0, \tag{15}$$

$$\frac{\partial \pi_i}{\partial f_i} = \frac{\left(p_i - \tau - re_i - \frac{\varepsilon}{e_i}\right) \lambda \Pi_{j \neq i} \left(p_j + \frac{\gamma}{f_j}\right)}{\left(p_i + \frac{\gamma}{f_i}\right)^{n+1}} \frac{\gamma}{f_i^2} - \theta = 0, \tag{16}$$

$$\frac{\partial \pi_i}{\partial e_i} = \frac{\lambda \Pi_{j \neq i} \left(p_j + \frac{\gamma}{f_j}\right) (\varepsilon - re_i^2)}{n \left(p_i + \frac{\gamma}{f_i}\right)^n e_i^2} = 0. \tag{17}$$

With firm symmetry, the symmetric equilibrium is the natural focus, and it is found by setting $p_i = p_j = p$, $f_i = f_j = f$, and $e_i = e_j = e$ for all i. Making this substitution, (17) yields the equilibrium emission level, i.e.,

$$e^* = \frac{\varepsilon^{1/2}}{r^{1/2}}, \tag{18}$$

where superscript $*$ denotes equilibrium values. Simplifying (15) and substituting (18) allows obtaining the equilibrium fare conditional on frequency, which equals

$$p^* = \frac{n}{n-1}\left(\tau + 2r^{1/2}\varepsilon^{1/2} + \frac{\gamma}{nf^*}\right). \tag{19}$$

Finally, plugging (18) and (19) into (16) yields the equilibrium condition for flight frequency

$$\underbrace{\frac{\lambda(n-1)}{\theta n^2} - f^*}_{L(f)^*} = \underbrace{\frac{\tau + 2r^{1/2}\varepsilon^{1/2}}{\gamma}(f^*)^2}_{Q(f)^*}. \tag{20}$$

The observation of (20) reveals that the f^* solution occurs at the intersection between a linear expression $L(f)^*$ and a quadratic expression $Q(f)^*$. Hence, the equilibrium frequency can be found graphically as shown in Figure 1.[13] Second-order conditions are satisfied and the comparative-static analysis can be done by inspecting the equilibrium conditions (18), (19), and (20), along with Figure 1.[14]

The effect of τ, r, ε, θ, n, γ, and λ on f^* can be inferred directly by looking at their influence on $L(f)^*$ and $Q(f)^*$ in Figure 1. Although the number of airlines n is viewed as parametric (which makes sense in a short-run analysis), the emission level is assumed to be its equilibrium value, as it is easier for airlines to undertake fleet adjustments having implications in their emissions than observing relevant changes in the market structure on certain route (further discussion on the case in with airlines cannot adjust their emissions provided below).

Proposition 1 *The equilibrium frequency varies with respect to the parameters as follows:*

$$\frac{\partial f^*}{\partial \tau} < 0,\ \frac{\partial f^*}{\partial r} < 0,\ \frac{\partial f^*}{\partial \varepsilon} < 0,\ \frac{\partial f^*}{\partial \theta} < 0,\ \frac{\partial f^*}{\partial n} < 0,\ \frac{\partial f^*}{\partial \gamma} > 0,\ \textit{and}\ \frac{\partial f^*}{\partial \lambda} > 0.$$

The reduction of the equilibrium frequency is a natural reaction to higher costs (τ, r, ε, and θ) or the presence of more competitors (n). Intuitively, carriers increase flight frequency in response to either a rise in the disutility of schedule delay or a market expansion (γ and λ).

Deriving fare impacts requires to take into account the *direct effect* on p^* looking at (19) while holding f^* fixed, along with the *indirect effect* on p^* through f^* looking at (20) and the way f^* enters into the equilibrium fare equation (19).

[13] $L(f)^*$ and $Q(f)^*$ are simply the two parts in which the equilibrium condition for flight frequency (20) can be separated. This disaggregation allows plotting the equilibrium condition (see Figure 1), which facilitates considerably the comparative-statics exercise that follows.

[14] Simple computations allow showing that $\partial^2\pi_i/\partial p_i^2 < 0$, $\partial^2\pi_i/\partial f_i^2 < 0$, and $\partial^2\pi_i/\partial e_i^2 < 0$. The conditions $\partial^2\pi_i/\partial p_i \partial e_i$ and $\partial^2\pi_i/\partial f_i \partial e_i$ are equal to 0 for the equilibrium e (see (18)). Finally, $\partial^2\pi_i/\partial f_i \partial p_i$ also equals 0 at the solution given by (18), (19), and (20), thereby ensuring the negativity of the Hessian determinant.

Proposition 2 *The equilibrium fare varies with respect to the parameters as follows:*

$$\frac{\partial p^*}{\partial \tau} > 0,\ \frac{\partial p^*}{\partial r} > 0,\ \frac{\partial p^*}{\partial \varepsilon} > 0,\ \frac{\partial p^*}{\partial \theta} > 0,\ \frac{\partial p^*}{\partial n} < 0,\ \frac{\partial p^*}{\partial \gamma} > 0,\ \textit{and}\ \frac{\partial p^*}{\partial \lambda} < 0.$$

Quite naturally, higher costs (τ, r, ε, and θ) are passed through in a higher fare. The negative effect on p^* of an increase in the number of competitors in the market (n) is also natural and expected. As passengers become more sensitive to schedule delay (γ), higher equilibrium frequencies come together with a rise in equilibrium prices. Finally, the negative effect of market size (λ) on the equilibrium fare has to do with the aforementioned presence of economies of traffic density (i.e., economies from operating a larger aircraft) that translate into lower operating costs, which are passed through in a lower fare.

The effects of r and ε on e^* can be ascertained from the inspection of (18) and are summarized in the proposition that follows.

Proposition 3 *The equilibrium emissions vary with respect to emission charges and capital cost as follows:*

$$\frac{\partial e^*}{\partial r} < 0\ \textit{and}\ \frac{\partial e^*}{\partial \varepsilon} > 0.$$

Higher emission charges r spur the use of newer aircraft, which are less polluting. Instead, a higher capital cost ε generates incentives either to acquire used and more-polluting aircraft or to extend the lifespan of existing aircraft (slowing down any fleet renewal).

In case airlines cannot alter their emissions undertaking fleet renewal strategies in the short run (i.e., $e = \overline{e}$), the effects of τ, r, ε, θ, n, γ, and λ on f^* and p^* remain as indicated in Propositions 1 and 2. In this situation, the effects of exogenous changes in $\overline{e}$ on f^* and p^* depend on the actual value of $\overline{e}$.[15]

[15] With $e = \overline{e}$, (19) and (20) become $p^* = \frac{n}{n-1}\left(\tau + r\overline{e} + \frac{\varepsilon}{\overline{e}} + \frac{\gamma}{nf^*}\right)$ and $\frac{\lambda(n-1)}{\theta n^2} - f^* = \frac{\tau + r\overline{e} + \frac{\varepsilon}{\overline{e}}}{\gamma}(f^*)^2$. Although airlines cannot renew their fleets under $e = \overline{e}$, exogenous changes in e can be analyzed. There is a threshold for $\overline{e}$, which coincides with its equilibrium value provided in (18), that determines its overall effect on f^* and p^*. More precisely, $\partial f^*/\partial \overline{e} < 0$ and $\partial p^*/\partial \overline{e} > 0$ for $\overline{e} > e^*$, while $\partial f^*/\partial \overline{e} > 0$ and $\partial p^*/\partial \overline{e} < 0$ for $\overline{e} < e^*$. This result shows greater advantages for emission mitigations when aircraft fleets are old and polluting (so that $\overline{e} > e^*$), given that newer and cleaner aircraft would boost service quality while decreasing fares.

4 Welfare analysis

The welfare analysis follows the local approach suggested in Brueckner (2010), given that it is not possible to define an explicit objective function for the planner. Determining the socially-optimal emission levels, fares, and flight frequencies requires analyzing their effect on carriers and consumers, along with their environmental impact. The material that follows is structured in two steps. First, holding n fixed, it explores the effect of changes of p, f, and e on airline profits, consumer utility, and environmental externality. Second, it relates these changes to determine the socially-optimal p, f, and e.

4.1 Airline profits, consumer utility, and environmental externality

Changes in airline profits. With symmetric carriers, an airline's profit (see (13)) is given by $\pi = \lambda \frac{p-\tau-re-\frac{\varepsilon}{e}}{n\left(p+\frac{\gamma}{f}\right)} - \theta f$, so that overall industry profits become

$$n\pi = \lambda \frac{p-\tau-re-\frac{\varepsilon}{e}}{p+\frac{\gamma}{f}} - n\theta f. \tag{21}$$

Therefore, changes in p, f, and e yield the following effects on profits:

$$\frac{\partial n\pi}{\partial p} = \frac{\lambda}{p+\frac{\gamma}{f}} - \lambda \frac{p-\tau-re-\frac{\varepsilon}{e}}{\left(p+\frac{\gamma}{f}\right)^2} > 0, \tag{22}$$

$$\frac{\partial n\pi}{\partial f} = \lambda \frac{\left(p-\tau-re-\frac{\varepsilon}{e}\right)\frac{\gamma}{f^2}}{\left(p+\frac{\gamma}{f}\right)^2} - n\theta \lesseqgtr 0, \tag{23}$$

$$\frac{\partial n\pi}{\partial e} = \lambda \frac{\frac{\varepsilon}{e^2} - r}{p+\frac{\gamma}{f}} > 0 \text{ for } e < e^*, \tag{24}$$

so that a coordinated fare increase in the industry would boost aggregate profits, while the ultimate effect of a coordinated frequency increase depends on parameter values. The effect emissions on profits hinges on the value of such emissions. More precisely, airlines are interested in increasing emissions as long as their level is below its equilibrium value (see (18)).

Changes in consumer utility. The indirect utility in (4), after eliminating carrier's subscripts can be rewritten as

$$U = \ln \frac{a}{z} + y - 1, \tag{25}$$

so that the environmental externality does not enter directly in consumers' utility, although it affects social welfare in a way that is specified later on.[16] For an individual consumer, the

[16] Many models dealing with externalities use social welfare functions that are equal to consumer surplus plus firms' profits minus the externality damage (see, for instance, Brueckner and Girvin, 2008).

utility decline in \$ associated to a higher z can be written as

$$\partial y/\partial z = \frac{\partial U/\partial z}{\partial U/\partial y} = -\frac{1}{z}, \tag{26}$$

which is tantamount to the negative value of the demand for trips on a certain carrier $-t$ (see (3)). Therefore, the overall utility loss caused by a rise in z is

$$\lambda \partial y/\partial z = -\frac{\lambda}{z}. \tag{27}$$

Consequently, the changes in utility associated to an increase in either p or f are, respectively

$$\lambda \underbrace{\frac{\partial y}{\partial z}}_{-\frac{\lambda}{p+\frac{\gamma}{f}}} \underbrace{\frac{\partial z}{\partial p}}_{1} = -\frac{\lambda}{p+\frac{\gamma}{f}} < 0, \tag{28}$$

$$\lambda \underbrace{\frac{\partial y}{\partial z}}_{-\frac{\lambda}{p+\frac{\gamma}{f}}} \underbrace{\frac{\partial z}{\partial f}}_{-\frac{\gamma}{f^2}} = \frac{\lambda \frac{\gamma}{f^2}}{p+\frac{\gamma}{f}} > 0, \tag{29}$$

where the full price is expressed in terms of p and f. Naturally, a rise in p translates into a higher full price and, therefore, utility falls. Instead, an increase in f pushes down the full price and represents a utility gain.

Changes in the environmental externality. For symmetric carriers, the externality in (14) equals $E = \eta neq$. Given that $q = \frac{\lambda}{nz}$ under symmetry (see (7)), the value of the externality is

$$E = \frac{\lambda \eta e}{z} = \frac{\lambda \eta e}{p+\frac{\gamma}{f}}. \tag{30}$$

Hence, changes in p, f, and e yield the following effects on the environmental externality:

$$\frac{\partial E}{\partial p} = -\frac{\lambda \eta e}{\left(p+\frac{\gamma}{f}\right)^2} < 0, \tag{31}$$

$$\frac{\partial E}{\partial f} = \frac{\lambda \eta e \frac{\gamma}{f^2}}{\left(p+\frac{\gamma}{f}\right)^2} > 0, \tag{32}$$

$$\frac{\partial E}{\partial e} = \frac{\lambda \eta}{p+\frac{\gamma}{f}} > 0, \tag{33}$$

showing that higher prices would help mitigating pollution while the use of older aircraft (i.e., higher e) or a more intensive use of the existing fleet (i.e., higher f) would aggravate the environmental damage.

4.2 The social optimum

To properly study the changes in p, f, and e, it is important to identify the *agents* (i.e., airlines, consumers, and environmental externality) affected in each of the cases. First, airlines' decisions on e obviously affect the environmental externality (see (30)) but do not affect consumers, as explained above (see (25)). Second, airlines' decisions on p and f affect both: i) consumers, because p and f determine the full price z that enters in their utility function (see (25)), and ii) the environmental externality, which also depends on the full price z (see (30)).

At the social optimum, a profit gain to the n carriers derived from a rise in emissions e should just compensate its environmental damage, i.e.,

$$\frac{\partial n\pi}{\partial e} - \frac{\partial E}{\partial e} = 0 \tag{34}$$

Plugging (24) and (33) into (34) yields

$$e^{SO} = \frac{\varepsilon^{1/2}}{(r+\eta)^{1/2}}, \tag{35}$$

where superscript SO denotes socially-optimal values. The comparison between (18) and (35) reveals a natural result: the excess of emissions is proportional to their marginal environmental damage, so that $e^* > e^{SO}$ for $\eta > 0$ while $e^* = e^{SO}$ for $\eta = 0$. This result confirms that, at the social optimum with $\eta > 0$, airlines would gain from increasing their emissions, i.e., $\partial n\pi/\partial e > 0$ for $e = e^{SO} < e^*$ (see (24)).

Looking at fares, the profit gain to the carriers derived from a rise in p and the mitigation of the externality (environmental gain) should just cancel consumers' utility loss, i.e.,

$$\frac{\partial n\pi}{\partial p} + \lambda \frac{\partial y}{\partial z}\frac{\partial z}{\partial p} - \frac{\partial E}{\partial p} = 0. \tag{36}$$

Substituting (22), (28), and (31) into (36) yields $p^{SO} = \tau + (r+\eta)\, e^{SO} + \frac{\varepsilon}{e^{SO}}$. Then the socially-optimal fare is obtained using (35):

$$p^{SO} = \tau + 2\,(r+\eta)^{1/2}\,\varepsilon^{1/2}. \tag{37}$$

In the absence of an externality, the socially-optimal fare equals the marginal cost and lies below its equilibrium level (i.e., $p^* > p^{SO}$ for $\eta = 0$). Instead, a sufficiently large environmental damage reverses this result, meaning that the externality needs to be internalized (i.e., passed through in a higher fare) to prevent from environmental degradation (i.e., $p^* < p^{SO}$ for $\eta >> 0$).

The socially-optimal frequency is obtained in a similar manner, so that the utility gain as f varies should cancel the aggravated externality (i.e., environmental damage), while accounting for the changes in airlines' profits , i.e.,

$$\frac{\partial n\pi}{\partial f}+\lambda\frac{\partial y}{\partial z}\frac{\partial z}{\partial f}-\frac{\partial E}{\partial f}=0 \tag{38}$$

Making use of (23), (29), (32), (35), and (37), the expression in (38) yields

$$\underbrace{\frac{\lambda}{\theta n}-f^{SO}}_{L(f)^{SO}}=\underbrace{\frac{\tau+2\left(r+\eta\right)^{1/2}\varepsilon^{1/2}}{\gamma}\left(f^{SO}\right)^{2}}_{Q(f)^{SO}}. \tag{39}$$

Similarly to the equilibrium analysis, the inspection of (39) reveals that the socially-optimal frequency occurs at the intersection between a linear and a quadratic expression ($L\left(f\right)^{SO}$ and $Q\left(f\right)^{SO}$). The comparison of (20) and (39) allows reaching some interesting conclusions.

Looking at the linear expressions (which do not depend on η), $L\left(f\right)^{*}<L\left(f\right)^{SO}$ emerges. Then the analysis departs from the case where there is no environmental externality ($\eta=0$), so that $Q\left(f\right)|_{\eta=0}^{*}=Q\left(f\right)|_{\eta=0}^{SO}$, which allows concluding that there is an underprovision of frequency in equilibrium $f^{*}<f^{SO}$, as depicted in Figure 2 (points **A** and **B**).

The result is different when aircraft emissions cause a non-negligible social damage, i.e., $\eta>0$. At this point, a threshold value for the marginal environmental damage $\widetilde{\eta}$ can be established, so that $f^{*}<f^{SO}$ for $\eta<\widetilde{\eta}$, $f^{*}=f^{SO}$ for $\eta=\widetilde{\eta}$, and $f^{*}>f^{SO}$ for $\eta>\widetilde{\eta}$. Therefore, the underprovision result remains as long as the environmental damage caused by the externality is low, while there is an overprovision of flight frequency when the externality is severe. This last scenario seems the more realistic one and is represented in Figure 2 (points **A** and **C**).[17] The proposition below summarizes the results obtained in this welfare analysis.

Proposition 4 *The comparison of the equilibrium and the social-optimum values for p, f, and e yields the following results.*
i) When there is no environmental externality, there is no inefficiency associated to emissions, fares are too high, and there is an underprovision of flight frequency, i.e., $e^{*}=e^{SO}$, $p^{*}>p^{SO}$, and $f^{*}<f^{SO}$ for $\eta=0$.
ii) Instead, when aircraft emissions cause severe social damage, emissions are too high, fares too low, and there is an overprovision of flight frequency, i.e., $e^{*}>e^{SO}$, $p^{*}<p^{SO}$, and $f^{*}>f^{SO}$ for $\eta>\widetilde{\eta}>>0$.

Departing from the realistic case described in Proposition 4 and depicted in Figure 2 (points **A** and **C**), an optimal emission tax t could be designed to alter carriers' behavior in equilibrium

[17] In a study focusing on the Japanese domestic market, Doi *et al.* (2023) conclude that there is an underprovision of flight frequency and that optimal airport charges should be negative (i.e., subsidies).

and achieve the efficient frequency. This tax would be tantamount to an accrued emission charge $r_t = r + t$ and would raise $Q(f)^*$ in Figure 2, so as to achieve the efficient flight frequency $f^* = f^{SO}$. This situation is illustrated in Figure 2 (points **D** and **C**).

The equilibrium quadratic function after the implementation of the optimal tax would become $Q(f)^*_t = \frac{\tau+2(r+t)^{1/2}\varepsilon^{1/2}}{\gamma}(f^*)^2$ and this tax would be smaller than the environmental damage $0 < t < \eta$.[18] This result is encapsulated in the corollary that follows.

Corollary 1 *When aircraft emissions cause severe social damage ($\eta > \widetilde{\eta} >> 0$) and there is an overprovision of frequency, an optimal emission tax could be designed to achieve the efficient frequency.*

5 Airport choices

Emission charges are usually designed to be revenue-neutral, in the sense that they should not increase airports' overall revenues (Scheelhaase, 2010).[19] Under these circumstances, an eventual rise of emission charges r should be compensated by a fall in non-emission charges τ. As a consequence, raising emission charges should be better accepted by airlines operating at the airport and, at the same time, create incentives to spur the use of newer and less polluting aircraft. Departing from this reality, this section explores the rate of substitution between these two charges. Assuming that charges are the sole source of revenues for airports and normalizing any other costs to zero,[20] an airport profit function reduces to

$$\Pi = \tau \sum\nolimits_{i=1}^{n} q_i + r \sum\nolimits_{i=1}^{n} e_i q_i. \tag{40}$$

In a symmetric equilibrium, using $q^* = \frac{\lambda}{nz^*}$ (see (7)) and replacing e^* by its equilibrium

[18] After the implementation of the optimal tax, emissions would remain inefficiently high $e^*_t = \frac{\varepsilon^{1/2}}{(r+t)^{1/2}} > e^{SO} = \frac{\varepsilon^{1/2}}{(r+\eta)^{1/2}}$. Although levying a tax for the value of the externality $t = \eta$ would achieve efficient emissions $e^*_t = e^{SO}$, it would not be optimal in terms of frequency as it would recover the underprovision result, i.e., $f^* < f^{SO}$ for $Q(f)^*_t = Q(f)|^{SO}_{\eta > \widetilde{\eta}}$ with $t = \eta$ (as the intercept of $L(f)^{SO}$ exceeds the intercept of $L(f)^*$).

[19] As explained in Subsection 6.1, NO_x emission charges are implemented as revenue-neutral in all the airports included in our sample, except Barcelona and Norwegian airports.

[20] This section considers a unique airport, abstracting from any network considerations that fall out of the scope of the analysis. Furthermore, this section is now introduced as an extension of the previous analysis. The airport is assumed to be a passive player, as it does not optimally choose charges. Therefore, airport choices are not modeled in the equilibrium analysis in Section 3 and, consistently, the airport is not introduced it in the welfare analysis in Section 4.

level in (18), the expression (40) becomes

$$\Pi = \frac{\lambda}{z^*}\left(\tau + r^{1/2}\varepsilon^{1/2}\right), \tag{41}$$

where the equilibrium full price $z^* = p^* + \frac{\gamma}{f^*}$ depends on the parameters of the model. Given that $\frac{\partial f^*}{\partial \tau} < 0$, $\frac{\partial f^*}{\partial r} < 0$, $\frac{\partial p^*}{\partial \tau} > 0$, and $\frac{\partial p^*}{\partial r} > 0$ (see Propositions 1 and 2), then $\frac{\partial z^*}{\partial \tau} > 0$ and $\frac{\partial z^*}{\partial r} > 0$ follow directly and stand for the pass-through rates of τ and r to full prices.

Assumption 1 *Emission charges are sufficiently low, so that $r < \varepsilon$.*

Looking at the equilibrium condition (20), it is easy to ascertain that $\left|\frac{\partial f^*}{\partial r}\right| > \left|\frac{\partial f^*}{\partial \tau}\right|$ for $r < \varepsilon$. Similarly, the inspection of the equilibrium condition (19) reveals that $\frac{\partial p^*}{\partial r} > \frac{\partial p^*}{\partial \tau}$ for $r < \varepsilon$ when holding f^* fixed.[21] Therefore, under Assumption 1, the effect of emission charges on full prices exceeds that of non-emission charges, so that $\frac{\partial z^*}{\partial r} > \frac{\partial z^*}{\partial \tau} > 0$. From an economic viewpoint, this assumption does not seem to be stringent as environmental charges are relatively low. In fact, this is fully confirmed empirically in Subsection 6.3.

For revenue-neutral airports, the rate of substitution between charges is

$$\frac{\partial r}{\partial \tau} = -\frac{\partial \Pi/\partial \tau}{\partial \Pi/\partial r} = -\frac{z^* - \frac{\partial z^*}{\partial \tau}\left(\tau + r^{1/2}\varepsilon^{1/2}\right)}{\frac{\varepsilon^{1/2}}{2r^{1/2}}z^* - \frac{\partial z^*}{\partial r}\left(\tau + r^{1/2}\varepsilon^{1/2}\right)} < 0, \tag{42}$$

where $\partial\Pi/\partial\tau > 0$ and $\partial\Pi/\partial r > 0$ are assumed to hold, which means that an increase in charges (either τ or r) raises airport profits in spite of the fact that traffic falls (because charges are passed through in a higher full price).[22] For a given increase in emission charges, the analysis that follows studies the condition allowing for a higher decrease in non-emission charges. This situation occurs whenever $\left|\frac{\partial r}{\partial \tau}\right| < 1$, which is tantamount to

$$\Lambda \equiv \frac{\varepsilon^{1/2}}{2r^{1/2}} - \triangle\varphi\left(\tau + r^{1/2}\varepsilon^{1/2}\right) > 1, \tag{43}$$

where $\triangle\varphi \equiv \varphi_{z^*,r} - \varphi_{z^*,\tau}$ denotes the semi-elasticity gap, with $\varphi_{z^*,r} = \frac{\partial z^*}{\partial r}/z^*$ and $\varphi_{z^*,\tau} = \frac{\partial z^*}{\partial \tau}/z^*$ being the pass-through semi-elasticities with respect to τ and r, respectively. Therefore, $\triangle\varphi$ captures the relative pass-through rate between emission charges r and non-emission charges τ. Under Assumption 1, $\triangle\varphi > 0$ (given that $\frac{\partial z^*}{\partial r} > \frac{\partial z^*}{\partial \tau}$) and $\partial\Lambda/\partial\triangle\varphi < 0$. Therefore, the following proposition can be formulated.

[21] From (20), it follows that $\frac{\partial Q(f)^*}{\partial r} = \frac{\varepsilon^{1/2}}{r^{1/2}}\frac{(f^*)^2}{\gamma}$ and $\frac{\partial Q(f)^*}{\partial \tau} = \frac{(f^*)^2}{\gamma}$, so that $\frac{\partial Q(f)^*}{\partial r} > \frac{\partial Q(f)^*}{\partial \tau}$ for $r < \varepsilon$. In this case, an increase in r raises the height of $Q(f)^*$ more than an increase in τ and, therefore, yields a more pronounced reduction in the equilibrium f^*, i.e., $\left|\frac{\partial f^*}{\partial r}\right| > \left|\frac{\partial f^*}{\partial \tau}\right|$. From (19), it follows that, holding f^* fixed, $\frac{\partial p^*}{\partial r} = \frac{\varepsilon^{1/2}}{r^{1/2}}\frac{n}{n-1}$ and $\frac{\partial p^*}{\partial \tau} = \frac{n}{n-1}$, so that $\frac{\partial p^*}{\partial r} > \frac{\partial p^*}{\partial \tau}$ for $r < \varepsilon$.

[22] In fact, the inspection of (42) reveals that $\partial\Pi/\partial\tau > 0$ and $\partial\Pi/\partial r > 0$ require both pass-through rates $\partial z^*/\partial\tau$ and $\partial z^*/\partial r$ not to be very high.

Proposition 5 *Under Assumption* 1*, the lower the pass-through rate of emission charges* r *as compared to the pass-through rate of non-emission charges* τ*, the more a revenue-neutral airport can reduce* τ *to compensate for an increase in* r*. In this situation, the airport would obtain the same revenue and the airlines would pay the same overall charges. Furthermore, the airport would generate incentives for airlines to renew their fleet by adopting newer and cleaner aircraft.*

Although both emission and non-emission charges represent a source of income for airports and a cost for airlines and passengers (because charges are passed through in a higher full price), the effect of these two instruments does not need to be the same. As the relative effect of emission versus non-emission charges on prices becomes lower, modest increases in r are more likely to have a high impact in airport's revenues. In this situation, a revenue-neutral airport would compensate by lowering τ more than proportionally.

Two caveats are needed at this point. The first one has to do with the fact that this result holds as long as r is bounded from above, as determined in Assumption 1. In fact, as emission charges increase over time and airlines adopt cleaner aircraft technologies, the condition in Assumption 1 is expected to bind and, eventually, reverse. Second, airlines are asymmetric in reality and make use of different aircraft technologies. In such a situation, airlines having older fleets would be net losers in this zero-sum game.

6 Empirical application

Using the available data, this section focuses on airport charges, distinguishing between emission charges and non-emission charges. Emission charges (r_f) are NO_x-related while non-emission charges comprise per-passenger charges (τ_p) and per-seat charges (τ_f). The main goal of this empirical application is to examine the impact of airport charges on frequencies and fares (short run) and the share of new aircraft (long run) at the airline-route level by estimating reduced-form equations and adding different fixed effects (airline-route and year).

We first describe the dataset. Then we explain the adopted empirical strategy and report the obtained results, connecting them with the comparative-static predictions from our theoretical model (see Propositions 1, 2, and 3).

6.1 Data

RDC Aviation provides different types of data that are useful for our purposes. Our sample is based on routes from European airports (European Economic Area, the UK, and Switzerland) to Europe and the rest of the world. Data are available over the period 2013-2022 for airport charges and flight frequencies, while fare data are available for the period 2015-2022. Frequency data are complete, in the sense that they include all flights with air services. Instead, fare data are based on the information collected by RDC Aviation for many (but not all) routes from European airports. Although data for fares and frequencies are monthly, they are collapsed at the year level because airport charges typically change on an annual basis. All regressions use samples with thousands of route-airline pairs, which is the unit of observation of our analysis, thereby covering a high proportion of traffic of the European market.

Airport charges. We use detailed data on airport charges, both for 139 European airports with more than one million passengers per year and for 90 large non-European airports. These data are based on a representative flight for short- and long-haul routes: an A320 flight for short-haul routes and an A350 flight for long-haul routes, under the assumption of a 80% load factor for both types of routes and a 25% share of connecting passengers for long-haul routes.[23] There is information on NO_x-related emission charges (r_f) and on non-emission charges that comprise per-passenger charges (τ_p) and per-seat charges (τ_f).[24,25] The chargeable item of per-passenger charges (τ_p) is the passenger. They take different values depending on whether the destination is domestic or international and incorporate discounts for connecting passengers. The chargeable item of per-seat charges (τ_f) is the flight. They take different values according to aircraft weight. Finally, NO_x-related emission charges (r_f) are based on aircraft type. These emission charges have been imposed: *i*) in the main airports of Switzerland (1997), Sweden (1998), and Germany (2008) and also *ii*) in Copenhagen (2010), the two main airports of London (2004) and Amsterdam (2022). In all these cases, emission charges are designed to be implemented as revenue-neutral for airports (Scheelhaase, 2010), in the sense that they should not increase airport revenues. Therefore, airports need to compensate these

[23] Therefore, routes operated with regional aircraft are excluded from the analysis.

[24] Since 2012, flights within Europe are affected by the EU Emissions Trading System (ETS). Although the EU ETS could be considered as a type of emission charge (given that it raises airlines' cost of fuel), its design and implementation has different features because it is not set on an airport basis and affects all intra-European routes. Therefore, we decided to use it as a control in our empirical analysis.

[25] *Flight ticket taxes* are per-passenger charges even though, sometimes, they are designed with environmental purposes. They have been imposed in several European airports, being the most recent examples Austria and Germany (2011), Norway (2016), Sweden (2018), and Portugal and The Netherlands (2021).

new emission charges by decreasing other non-emission charges (i.e., per-passenger and/or per-seat charges).[26] Summary statistics on airport charges are provided in Appendix B (Figures A1-A5 and Tables A1-A2).

Supply. There is information at the airline-route level for flights departing from European airports. The data comprises frequencies, seats, distance, and aircraft type. The availability of data on route distance and aircraft type allows computing fuel consumption, CO_2 emissions (using the Eurocontrol's Small Emitter Tool $-$ SET), and NO_x emissions. Interestingly, these data also allow obtaining information on aircraft vintage. Aircraft introduced after 2010 are considered as *new aircraft* in the subsequent analysis.[27]

Fares. There is information on posted fares on routes departing from European airports. More precisely, these data include mean posted fares corresponding to bookings made three months, one month, and one week before the flight departure. Weighted fares are also available, where weights are based on the number of registered bookings in each of the aforementioned periods. This weighted measure is the one being used in our regressions. Finally, it should be noted that our fare variable refers to an economy fare class charged to one-way trips. These one-way fares are computed as the mean between the fares for both directions.

Controls. Population at the urban level of origin and destination airports is considered (data from United Nations). Additionally, per capita income at the country level of origin and destination airports is also considered (data from World Bank). There are also data on fuel costs (data from RDC Aviation). CO_2 costs are also included (data from the International Carbon Action Partnership) given that flights within the European Economic Area (EEA) are affected by the EU Emission Trading System (EU ETS) since 2012. Finally, we include a dummy variable for monopoly routes.

6.2 Empirical strategy

Given that data are available for several periods (years), we can study the impacts on fares and frequencies of emission and non-emission charges on the short-run along with the effect of emission charges on aircraft vintage (or emissions intensity) on the long-run.

More precisely, the comparative statics from our theoretical model in Propositions 1 and 2 predict that higher airport charges, either non-emission or emission charges, should lead to

[26] However, there are a few non-neutral emission charges such as the ones charged by the airport of Barcelona (2014) and the ones levied on domestic flights within Norway (2007).

[27] *New narrowbody aircraft* include A220, A320-neo, and B737-MAX families. *New widebody aircraft* include A330-neo, A350, A380, B747-8, and B787 families.

an increase of fares (i.e., $\partial p^*/\partial \tau > 0$ and $\partial p^*/\partial r > 0$) and a decrease of frequencies (i.e., $\partial f^*/\partial \tau < 0$ and $\partial f^*/\partial r < 0$). Similarly, Proposition 3 suggests that non-emission charges do not have any impact on aircraft vintage, whereas emission charges should spur the use of newer aircraft that are associated with lower emissions (i.e., $\partial e^*/\partial \tau = 0$ and $\partial e^*/\partial r < 0$).

For the short-run analysis, we use the panel sample with data for every year and reduced-form supply and fare equations are estimated. In one set of regressions, the dependent variable is the number of frequencies at the airline-route level. In another set of regressions, the dependent variable is the weighted posted fare at the airline-route level. For the long-run analysis, we propose another set of regressions having as dependent variable the share of new aircraft being used.[28] To examine these long-run effects, data are collapsed using mean values for the entire period at the airline-route level.

Therefore, the following equations for the route-airline pair i in year t are estimated:

$$log(Y_{it}) = \alpha + \beta_1 log\,(non\text{-}emission_{it}) + \beta_2 emission_{it} + \psi X_{it} + \rho_i + \phi_t + \epsilon_{it}, \tag{44}$$

$$share\_new_i = \alpha + \beta_1 non\text{-}emission_i + \beta_2 emission_i + \psi X_i + \epsilon_i, \tag{45}$$

where the dependent variables (Y_{it}) in equation (44) are the logarithms of fares and frequencies, and the dependent variable in equation (45) is the share of new aircraft (from 0 to 1). The *non-emission* variable comprises all non-emission charges (i.e., both per-passenger and per-seat charges) expressed in per-seat terms. The *emission* variable includes charges based on aircraft's NO_x emissions, expressed in per-seat terms (i.e., the per-seat cost of NO_x). Note that all continuous variables without zero values are expressed in logarithms. Given that many airports do not apply NO_x-emission charges and that airlines may not use new aircraft, the *emission* and *share_new* variables are not transformed in logarithms. Both *non-emission* and *emission* are built considering the mean values at both endpoints of the route. It must be mentioned that the emission variable is the per-seat cost of NO_x for the regression using (44), while it is the NO_x charge itself for the regression using (45) because the use of newer aircraft may reduce airlines' NO_x-related costs.[29]

As suggested before, noise charges could also be considered as another type of emission charges. However, the available data on noise charges only contains information on differences

[28] As defined in footnote 27.

[29] Total NO_x charges associated to a flight depend on the charge rate and the taxable base, which is given by the NO_x grams emitted by the aircraft. The *fare* and *frequency* regressions consider the total NO_x charge divided by the number of aircraft seats. The *share_new* regressions just consider the charge rate because the NO_x grams and the number of seats depend on the type of aircraft being used.

between aircraft models A320 and A320-neo for year 2022. Furthermore, airports set different noise categories with complex rate systems. In spite of these data limitations, we can provide an estimation accounting for the influence of noise charges on aircraft vintage on the long-run. More precisely, we estimate a different specification of equation (45) that incorporates an interaction variable between a dummy for airports applying noise-differentiated runway charges ($noise$ variable) and the NO_x-emission charges variable ($emission$ variable).

The uninteracted term for the $emission$ variable shows the effect when noise charges are not applied. The sum of the uninteracted term of emission charges and the interaction term with noise charges shows the effect of NO_x-emission charges when noise charges are also applied. Thus, a positive effect of the interaction term would indicate that the impact of NO_x-emission charges on the share of new aircraft is higher when noise charges are simultaneously applied.

X is a set of control variables at the route level, including population and income (demand shifters) at both endpoints of the route, fuel and CO_2 costs (cost shifters), and a dummy for monopoly routes. Furthermore, route-airline fixed effects (ρ_i) and year fixed effects (ϕ_t) are also incorporated in the regressions having fares and frequencies as dependent variables (route-airline fixed effects capture the effect of time-invariant variables such as route distance). To examine the long-term effects of non-emission and emission charges when the dependent variable is the share of new aircraft, data are collapsed using mean values for the entire period. In this case, the controls also include route distance and the Herfindahl-Hirschman concentration Index (HHI) instead of the dummy for monopoly routes. In all regressions, standard errors are robust to heteroscedasticity and clustered at the route level.

All regressions consider both the entire sample and different subsamples. First, we use a subsample of routes within the EEA that allows considering a more homogeneous group of routes. Second, we focus on a subsample excluding 2020 from the analysis, given that the aviation market was severely hit by the pandemic, which could distort the identification of the effects related to airport charges. Finally, we consider a subsample that excludes routes having London Heathrow (LHR) as an endpoint. The reason is that this airport could be seen as an outlier, given that it applies both NO_x-emission charges and noise charges substantially higher than the rest of airports. Therefore, this subsample allows examining whether the obtained effects for the entire sample are driven or not by this airport.

Table 1 shows the descriptive statistics of the variables used in the empirical analysis considering subsamples mentioned before. Furthermore, we also provide the descriptive statistics for a subsample of routes with positive NOx-emission charges to show a precise measure of the relative level of these charges respect to non-emission charges.[30] All variables have enough variability, as they show a relatively high standard deviation in relation to the mean. Looking at the mean values per year, one-way fares charged by airlines at the route level range from EUR 85 to EUR 110, and the frequency goes from 329 to 348 flights (i.e., less than one daily flight). The values of non-emission and emission airport charges are around EUR 24 and EUR 0.06 per seat, respectively. These values increase to EUR 27 and EUR 0.18 when focusing on the subsample of routes with positive emission charges. Thus, emission charges are very low as compared to non-emission charges. Finally, the mean share of new aircraft is around 3%-7%, being slightly higher for the subsample of routes with positive emission charges. This table also reports the correlation values between the *non-emission* and *emission* variables for the different subsamples. The positive correlation between the two variables is in the range 0.15-0.30. To make sure that multicollinearity is not an issue, the tables that report results from regressions provide the variance inflation factors (VIF) of the *non-emission* and *emission* variables, which allow estimating the correlation between each of these variables and the rest of variables included in the analysis.

Table 2 provides information on the number of observations referring to routes that link airports depending on whether they apply or not emission charges. This table also shows the mean and standard deviation of the *emission* variable for routes that link airports applying these charges. Observations with emission charges represent 34% of the entire sample for $fare$ regressions, 37% for $frequency$ regressions, and 40% for $share\_new$ regressions. Thus, the numbers in this table show that there is a high proportion of routes affected by emission charges. Furthermore, the standard deviation in relation to the mean is high, even when restricting the attention to observations referring to routes that link airports applying emission charges.

6.3 Results

The material that follows shows our main empirical findings on the effect of airport charges on fares and frequencies (short term) and on aircraft vintage (long-run).

[30] Appendix *B* provides detailed descriptive information on emission and non-emission charges applied at European airports. It also provides information related to new aircraft.

6.3.1 Short-run: Effects on fares and flight frequencies

Table 3 shows the results of the fare regressions.[31] The coefficients of the main variables in our analysis, *non-emission* and *emission*, are positive and statistically significant. They are clearly below one, which suggests a relatively modest elasticity. A 1% increase in *non-emission* leads to about a 0.2 increase in fares in all regressions. The effect of emission charges is much lower. A EUR 1 increase in *emission* leads to a fare increase in the range 0.16-0.27. In terms of elasticities, a 1% increase in *emission* leads to about a 0.009 increase in fares. All in all, these empirical results confirm our theoretical predictions in Proposition 2 (i.e., $\partial p^*/\partial \tau > 0$ and $\partial p^*/\partial r > 0$). Furthermore, the lower elasticity associated to emission charges is fully consistent with our theoretical finding in Proposition 5 suggesting that $\frac{\partial z^*}{\partial \tau} > \frac{\partial z^*}{\partial r} > 0$, under Assumption 1 (which also implies a positive semi-elasticity gap $\triangle\varphi \equiv \varphi_{z^*,\tau} - \varphi_{z^*,r} > 0$).

Some caution is needed in the interpretation of these results. Price discrimination and yield management strategies that characterize airline pricing must be taken into account. Intertemporal price dispersion can be analyzed with our data given that we have data for mean posted fares corresponding to bookings made three months, one month, and one week before the flight departure. The results of these regressions are almost the same as those obtained when using average weighted fares (see Table A3 in Appendix *B*). Furthermore, some additional regressions (that have been carried out as robustness checks) have not found remarkable differences between network and low-cost airlines, between monopoly and non-monopoly routes, or between routes according to traffic size (see Table A4 in Appendix *B*).

Table 4 shows the results of the frequency regressions. As observed in fare regressions, the R^2 is high and VIFs are very low. As expected, higher non-emission and emission charges lead to lower flight frequencies given that the coefficients of *non-emission* and *emission* are negative and statistically significant. A 1% increase in *non-emission* leads to a $0.07 - 0.08$ decrease in flight frequencies. As in the case of fares, the effect of emission charges is lower: a EUR 1 increase in *emission* leads to about 0.22-0.37 decrease in frequencies. In terms of elasticities, a 1% increase in *emission* leads to a 0.01 decrease in frequencies, regardless the subsample being used. All in all, these empirical results confirm our theoretical predictions in

[31] Fare and frequency regressions include route-airline fixed effects that allow controlling for all unobservable factors that are time-invariant. In practice, this implies to add thousands of dummies in each regression, which explain the high R^2. Since the fixed effects model controls for all the factors that are constant over time and that cannot be observed, the results for the variables that vary over time are more reliable. Note also that the VIFs that quantify the relationship between charges (*non-emission* and *emission* variables) and the rest of explanatory variables are very low, meaning that multicollinearity is not an issue.

Proposition 1 (i.e., $\partial f^*/\partial\tau < 0$ and $\partial f^*/\partial r < 0$).

Table 5 shows the results of regressions that make a distinction between the two main types of non-emission charges: per-passenger charges (the chargeable item is the passenger) and per-seat charges (the chargeable item is the flight).[32] Interestingly, per-passenger charges (τ_p) lead to higher fares and per-seat charges (τ_f) lead to lower frequencies, regardless the subsample being used. However, per-passenger charges only have significant effects on frequencies when considering the subsample for within-EEA routes. These results suggest that per-passenger charges have a clearer effect on fares than on flight frequencies, while per-seat charges have a clearer effect on flight frequencies than on fares. Comparing the results reported in this table with those of the previous regressions reveals that the positive effect of NO_x-emission charges on prices is particularly low as compared to passenger charges. On the other hand, the negative effect of NO_x-emission charges on frequencies is relatively low as compared to per-seat charges.

6.4 Long-run: Effects on aircraft vintage

Table 6 shows the results of regressions where the dependent variable is the share of new aircraft. As mentioned before, data are collapsed using mean values for the entire period to capture the long-term effects of *non-emission* and *emission*. As expected, non-emission have no relevant impact on the share of new aircraft. In fact, the coefficient of the *non-emission* variable is not statistically significant, except in the regression that excludes routes having LHR as an endpoint (although the size of this coefficient is very small, i.e., 10 times smaller than that of the *emission* variable). Instead, higher emission charges are associated to an increase in the use of newer aircraft, given that the coefficient of the *emission* variable is positive and statistically significant in all regressions. More precisely, a EUR 1 increase in emission charges leads to an increase of 0.005 in the share of new aircraft. At the margins, the impact of emission charges on the share of new aircraft is small but still remarkable. Note that the mean values of the *share_new* variable are very low because the most popular new aircraft (A320-neo and B737-MAX families) were not introduced in the market until 2019. Furthermore, NO_x-emission charges are generally low. Thus, emission charges may speed up the presence in the market of such new aircraft models. However, those incentives would only be relevant if emissions charges were much higher than their actual values (which are very low).

[32] In these regressions, per-passenger charges are expressed as total charges per passenger.

While our results suggest that emission charges may have (modestly) contributed to a faster fleet-renewal process, some caveats must be mentioned. First, the increased use of newer aircraft could be also a function of fleet-renewal strategies (old aircraft leave the fleet for economic reasons). Airlines have incentives to renew their fleets given the lower fuel consumption, lower noise-related charges, and lower CO_2 costs (in the case of intra-EEA flights) associated to the newer aircraft. Second, part of the effect that we find could also be related to changes in the use of the current fleet (i.e., using the newest aircraft at airports imposing emission charges and the oldest aircraft at airports that do not impose emission charges).

It may be the case that airlines use their newest aircraft in premium city-pair markets that, in turn, involve airports applying environmental charges intensively. To deal with this potential challenge in the identification of the effect of emission charges, Table 7 provides the results of several robustness checks. First, we consider a subsample for routes having a hub airport as one of the endpoints (either origin or destination), given that premium city-pair markets are usually served by flights from/to hub airports.[33] Second, we restrict even more the sample to interhub routes where both the origin and destination are hub airports. Furthermore, we apply a propensity score matching procedure and reestimate equation (45). Following Rosenbaum and Rubin (1983), we first estimate the probability of being affected by emission charges, conditional on the preexisting characteristics that differ between groups (population, income, and distance), to obtain a propensity score for each observation. In a second step, we match the observations in both groups (either affected or not by emission charges) with respect to the propensity score, using the first nearest neighbor algorithm. This algorithm matches those observations affected by emission charges with the control observations that have the closest propensity score. Then we drop all the observations without common support and reestimate equation (45) using the reduced matched sample. With this technique, we produce a matched sample having similar values of the covariates (income, population, and distance) for routes affected and non-affected by emission charges. This allows eliminating potential confounders such as, for example, income differences between routes affected and non-affected by emission charges.

We also run a regression that applies weights according to the number of flights in the route, so that routes having more flights receive a higher weight in the estimation. Finally, we also apply the matching procedure using the total number of flights as determinant of the probability of being affected by emission charges. Results remain similar to those found in

[33]Hub airports are the main connection nodes for network carriers. In our analysis, network carriers are identified as those airlines integrated in a global airline alliance (Oneworld, Star Alliance, and SkyTeam).

regressions reported in Table 6.

Furthermore, the effect of NO_x-emission charges is expected to be higher when accounting for noise charges given that several airports imposing NO_x charges also apply differentiated runway charges according to noise emissions. Table 8 provides suggestive evidence in this line. We include a dummy variable for those airports applying noise-differentiated runway charges ($noise$ variable) that we interact with the NO_x-emission charges variable ($emission$ variable). The results of this regression suggest that the incentives to use newer aircraft are particularly effective on those airports that apply both NO_x and noise charges. However, the interpretation of these results needs to be done with some caution, given the high correlation between the uninteracted emission variable and the interaction term.

All in all, we can conclude that non-emission charges do not have any impact on aircraft vintage, whereas emission charges modestly spur the use of newer aircraft that are associated with lower emissions, as predicted by our theoretical model in Proposition 3 (i.e., $\partial e^*/\partial \tau = 0$ and $\partial e^*/\partial r < 0$). The incentives generated by emission charges leading to a faster fleet renewal depend on the amount of these emission charges, which are (currently) low. However, our empirical results provide suggestive evidence of the mechanisms explored in the comparative-static analysis of our theoretical analysis.

7 Concluding remarks

Undoubtedly, there is a growing pressure on air transportation to provide more sustainable services. Airports are key players in this matter, as they can make use of emission charges to design incentives for airlines to undertake fleet renewal strategies, acknowledging that newer aircraft are associated with lower emissions.

This analysis examines, both theoretically and empirically, the impact of airport charges on fares and frequencies (on the short run) and airline emissions (on the long run). Our theoretical results indicate that airlines react to a rise in either emission or non-emission charges by raising airfares and decreasing flight frequencies. Looking at the effect on airline emissions (i.e., aircraft vintage, as newer aircraft are cleaner), only emission charges have an actual impact. These theoretical predictions are confirmed and quantified empirically, although the impact of emission charges on the share of new aircraft is small.

The welfare analysis in Section 4 and the study of the rate of substitution between emission and non-emission charges is in Section 5 highlight the usefulness of emission charges to mitigate emissions and the overprovision of (polluting) flight frequencies. Furthermore, revenue-neutral airports can implement such policies in a smooth way, as they can compensate increases in emission charges by decreases in non-emission charges.

All in all, our empirical findings show that emission charges have a modest effect on fares and frequencies as compared to non-emission charges. The effect of NO_x-emission charges on prices is very low as compared to per passenger charges. On the other hand, the negative effect of NO_x-emission charges on frequencies is relatively low as compared to per seat charges. By contrast, only emission charges have significant effects (albeit small) on the share of newest aircraft. Thus, emission charges may speed up the presence in the market of such new aircraft models. However, those incentives would only be relevant if emissions charges were much higher than their actual values (which are very low).

These empirical results along with our theoretical insights suggest that there is room for further increases in emission charges, which should create further incentives for airlines to speed up their fleet-renewal strategies. This approach suggesting higher emission charges seems consistent with the current social demand for more stringent environmental standards.

Using non-emission charges to compensate the airlines for increases in emission charges may be a useful mechanism to implement a smooth transition toward newer, quieter, and more fuel-efficient aircraft. New and disruptive technological innovations (such as electric or hydrogen-powered aircraft) will surely be the future of aviation but, as the technology develops sufficiently to apply successfully these advancements to commercial aircraft propulsion systems, market-based measures can be efficient and effective. However, even if there was an ambitious implementation of airport emission charges, other complementary measures aimed at increasing fuel costs could be needed as fuel costs represent a much higher share of overall airline costs than airport charges.

This discussion about airport charges recalls the debate on measures to mitigate externalities (i.e., pollution and congestion) associated to private transportation in urban areas. For instance, London's congestion toll is combined with a low emission zone that works as a price-based measure imposing an additional fee to vehicles that do not meet emission standards.[34] Although there are many differences between road and air transportation, the evidence from both transportation modes highlights the potential of vintage-specific charges.

[34]See Barahona *et al.* (2020), Bernardo *et al.* (2021), and Fageda *et al.* (2022) for a complete analysis on the effectiveness and acceptability of congestion tolls and low emission zones in urban areas.

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Figures and Tables

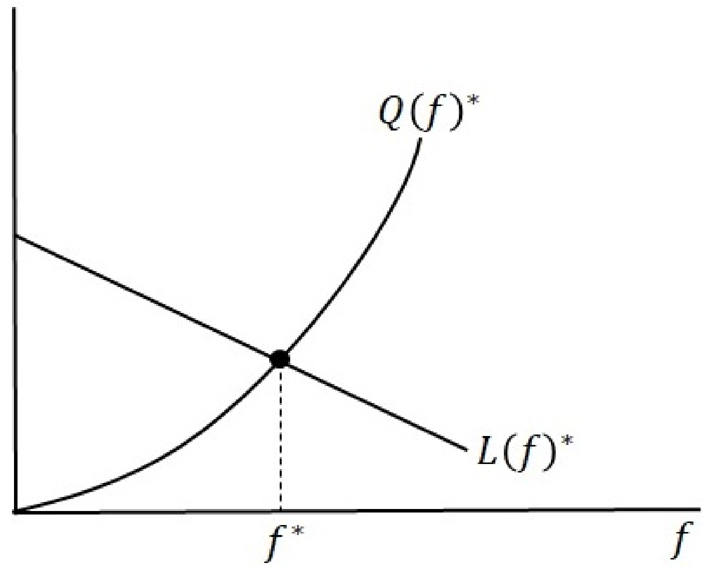


Figure 1: The equilibrium flight frequency

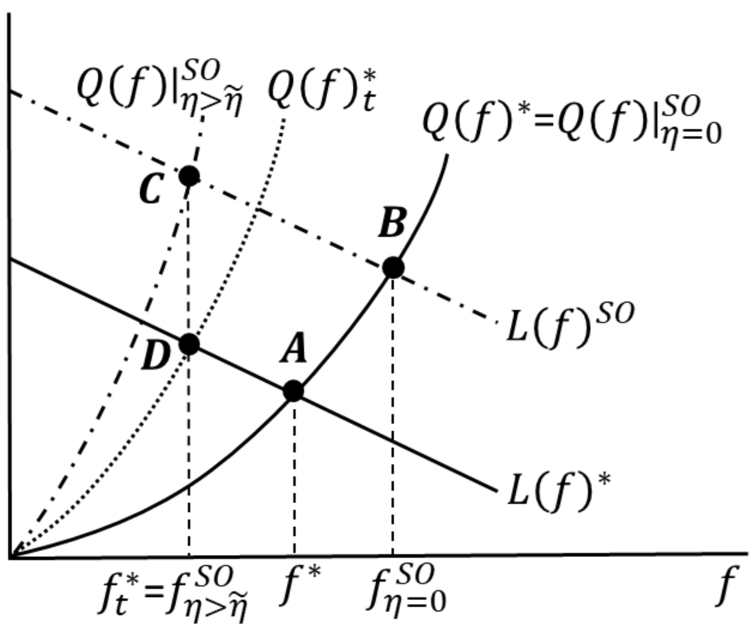


Figure 2: Underprovision for $\eta = 0$ and overprovision for $\eta > \widetilde{\eta}$

Table 1. Descriptive statistics of main variables

	Panel A: Fare and frequency regressions				
	All	**Within EEA**	**2020 excluded**	**LHR excluded**	**Emission > 0**
fare (EUR)	108.73 (125.45) *n=53,589*	85.04 (46.09) *n=47,234*	109.97 (126.83) *n=47,964*	104.55 (112.95) *n=52,458*	135.25 (152.76) *n=18,378*
frequency (flights)	348.52 (484.57) *n=95,469*	348.44 (511.31) *n=77,032*	359.96 (497.47) *n=88,294*	329.42 (456.21) *n=92,137*	451.64 (593.75) *n=35350*
non-emission (EUR)	24.82 (7.96) *n=95,459*	24.23 (7.41) *n=77,022*	24.75 (7.93) *n=88,284*	24.29 (7.43) *n=92,127*	27.79 (8.18) *n=35340*
emission (EUR)	0.06 (0.24) *n=95,469*	0.05 (0.22) *n=77,032*	0.06 (0.25) *n=88,294*	0.04 (0.07) *n=92,137*	0.18 (0.38) *n=35350*
per-seat charges (EUR)	7.77 (3.70) *n=95,459*	7.63 (3.74) *n=77,022*	7.76 (3.74) *n=88,284*	7.60 (3.56) *n=92,127*	8.14 (3.62) *n=35340*
per-passenger charges (EUR)	22.25 (8.51) *n=95,469*	21.86 (8.18) *n=77,032*	22.19 (8.49) *n=88,294*	21.85 (8.22) *n=92,137*	24.45 (8.30) *n=35350*
Correlation ***non-emission*** / ***emission***	0.24	0.18	0.23	0.19	0.23
	Panel B: Aircraft vintage regressions				
	All	**Within EEA**	**2020 excluded**	**LHR excluded**	**Emission > 0**
share_new (proportion over 1)	0.05 (0.18) *n=19,786*	0.03 (0.14) *n=16,235*	0.05 (0.18) *n=19,671*	0.05 (0.18) *n=19,291*	0.07 (0.19) *n=7,989*
non-emission (EUR)	24.52 (7.54) *n=19,780*	23.95 (6.94) *n=16,229*	24.52 (7.53) *n=19,665*	24.13 (7.14) *n=19,285*	26.82 (7.49) *n=7,983*
emission (EUR)	1.63 (3.28) *n=19,786*	1.51 (3.00) *n=16,235*	1.63 (3.28) *n=19,671*	1.21 (1.77) *n=19,291*	4.05 (4.10) *n=7,989*
Correlation ***non-emission*** / ***emission***	0.33	0.31	0.33	0.15	0.36

Notes: This table reports mean values for the considered subsamples (standard deviation in parentheses). Notation: *n* denotes number of observations. Correlation values between the variables of non-emission and emission charges for the considered subsamples are also provided. Sample sizes vary because some of the independent variables have few missing values (or zero values that get dropped with the log transformation). Emission, non-emission, and per-seat charges are expressed in per-seat terms, while per-passenger charges are expressed in per-passenger terms.

Table 2. Distribution of the *emission* variable (observations with positive and zero values)

Regressions	**Number of observations with values = 0**	**Number of observations with values > 0**	**Mean (standard deviation) Observations with values > 0**
fare	35,211	18,378	0.16 (0.24)
frequency	60,119	35,350	0.18 (0.38)
share_new	11,797	7,989	4.05 (4.10)

Note: Data refer to the entire sample.

Table 3. Fare regressions

VARIABLES	(1) ***log(fare)***	(2) ***log(fare)***	(3) ***log(fare)***	(4) ***log(fare)***
log(non-emission)	0.207***	0.213***	0.249***	0.204***
	(0.0227)	(0.0239)	(0.0234)	(0.0233)
emission	0.163***	0.204***	0.170***	0.279***
	(0.0213)	(0.0377)	(0.0220)	(0.0528)
emission (elasticity)	0.009***	0.009***	0.009***	0.010***
	(0.0012)	(0.0017)	(0.0012)	(0.0020)
Observations	53,553	47,224	47,930	52,422
Route-airline pairs	13,374	11,585	13,254	13,021
Years	8	8	7	8
R-squared	0.943	0.913	0.946	0.939
VIF (*non-emission)*	1.24	1.17	1.24	1.19
VIF (*emission)*	1.15	1.15	1.14	1.14
Sample	all	within EEA	2020 excluded	LHR excluded

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the logarithm of fares. Controls: fuel costs, CO_2 costs, population, income, dummy for monopoly routes, route-airline and year fixed effects. For *emission*, the table reports both the coefficient $\partial \log(fare)\,/\partial emission$ and the elasticity $\partial \log(fare)\,/\,\partial \log(emission)$, using the *margins* command of Stata. VIF refers to the estimated variance inflation factor.

Table 4. Frequency regressions

log(non-emission)	-0.0756***	-0.0889***	-0.0811***	-0.0809***
	(0.0149)	(0.0162)	(0.0147)	(0.0148)
emission	-0.227***	-0.298***	-0.222***	-0.364***
	(0.0324)	(0.0940)	(0.0330)	(0.0691)
Emission (elasticity)	-0.015***	-0.015***	-0.014***	-0.015***
	(0.0021)	(0.0049)	(0.0021)	(0.0028)
Observations	95,206	76,813	88,042	91,874
Route-airline pairs	19,647	16,123	19,532	19,152
Years	10	10	9	10
R-squared	0.894	0.900	0.901	0.890
VIF (*non-emission*)	1.22	1.13	1.22	1.18
VIF (*emission*)	1.20	1.45	1.20	1.15
Sample	all	within EEA	2020 excluded	LHR excluded

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the logarithm of frequencies. Controls: fuel costs, CO_2 costs, population, income, dummy for monopoly routes, route-airline and year fixed effects. For *emission*, the table reports both the coefficient $\partial \log(frequency)\,/\partial emission$ and the elasticity $\partial \log(frequency)\,/\,\partial \log(emission)$, using the *margins* command of Stata. VIF refers to the estimated variance inflation factor.

Table 5. Fare and frequency regressions (charges per passenger, charges per seat)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(fare)	***log(fare)***	***log(fare)***	***log(fare)***	***log(frequency)***	***log(frequency)***	***log(frequency)***	***log(frequency)***
log(per-seat charges)	-0.0139	1.96e-05	0.00418	-0.0174	-0.0429***	-0.0464***	-0.0393***	-0.0465***
	(0.0140)	(0.0145)	(0.0153)	(0.0145)	(0.00879)	(0.00937)	(0.00848)	(0.00881)
log(per-passenger charges)	0.184***	0.181***	0.205***	0.185***	-0.00333	-0.0423*	-0.0242	-0.00906
	(0.0182)	(0.0194)	(0.0178)	(0.0190)	(0.0215)	(0.0255)	(0.0217)	(0.0217)
Observations	53,553	47,224	47,930	52,422	95,206	76,813	88,042	91,874
Route-airline pairs	13,374	11,585	13,254	13,021	19,647	16,123	19,532	19,152
Years	8	8	7	8	10	10	9	10
R-squared	0.943	0.913	0.946	0.939	0.894	0.900	0.901	0.890
Sample	all	within EEA	2020 excluded	LHR excluded	all	within EEA	2020 excluded	LHR excluded

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). Columns 1-4 report results considering the logarithm of fares as dependent variable and columns 5-8 report results considering the logarithm of frequencies as dependent variable. Controls: fuel costs, CO_2 costs, population, income, dummy for monopoly routes, route-airline and year fixed effects.

Table 6. Aircraft vintage regressions

non-emission	0.000138 (0.000215)	1.60e-05 (0.000190)	0.000183 (0.000216)	0.000493 (0.000419)
emission	0.00561*** (0.000625)	0.00520*** (0.000636)	0.00534*** (0.000651)	0.00449*** (0.000951)
Observations	19,780	16,229	19,665	19,285
Route-airline pairs	19,780	16,229	19,665	19,285
Years	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)
R-squared	0.093	0.015	0.088	0.076
VIF (*non-emission*)	1.28	1.19	1.28	1.17
VIF (*emission*)	1.17	1.16	1.17	1.11
Sample	all	within EEA	2020 excluded	LHR excluded

Notes: Standard errors in parenthesis (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), 10% (*). The dependent variable is the share of new aircraft. Controls: distance, HHI, population, income. Data are collapsed using mean values for the considered period.

Table 7. Aircraft vintage regressions: Robustness to sample

non-emission	-0.000627* (0.000360)	-0.00425*** (0.000808)	0.000127 (0.000237)	0.000140 (0.000256)	0.000470* (0.000243)
emission	0.00552*** (0.000716)	0.00632*** (0.00124)	0.00629*** (0.000633)	0.00539*** (0.000605)	0.00551*** (0.000649)
Observations	10,234	2,548	15,972	19,780	15,970
Route-airline pairs	10,234	2,548	15,972	19,780	15,970
Years	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)
R-squared	0.116	0.146	0.119	0.133	0.104
VIF (*non-emission*)	1.35	1.58	1.22	1.49	1.29
VIF (*emission*)	1.18	1.25	1.14	1.43	1.22
Sample	hubs	interhub	matched-covariates	all-weighted by flights	matched-flights

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the share of new aircraft Controls: distance, HHI, population, and income. Data collapsed using mean values for the considered period.

Table 8. Aircraft vintage regressions with noise-differentiated runway charges

non-emission	0.000121 (0.000215)	-1.92e-05 (0.000190)	0.000162 (0.000216)	0.000482** (0.000219)
emission	0.00233 (0.00175)	-0.00129 (0.00141)	0.00153 (0.00175)	0.00139 (0.00177)
emission X noise	0.00334* (0.00174)	0.00667*** (0.00142)	0.00387** (0.00173)	0.00340* (0.00180)
Test [*emission+emission X noise*]=0	81.39***	69.96***	68.34***	23.58***
Observations	19,780	16,229	19,665	19,285
Route-airline pairs	19,780	16,229	19,665	19,285
Years	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)	1 (mean values 2013-2022)
R-squared	0.094	0.016	0.089	0.076
VIF (*non-emission*)	1.28	1.19	1.29	1.17
VIF (*emission*)	21.40	19.99	21.84	6.29
Sample	all	within EEA	2020 excluded	LHR excluded

Notes: Standard errors in parenthesis (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the share of new aircraft. Controls: distance, HHI, population, and income. Data collapsed using mean values for the considered period. We report the coefficients of the airport charges variables and the significance test of the sum of the coefficients for *emission*+(*emissions X noise*) variables.

A Appendix: Proofs

Proof of Proposition 1.

▶ An increase in non-emission charges τ, emission charges r or capital cost ε raises the height of $Q(f)^*$, leading to a decrease in f^*.

▶ Similarly, a rise in the cost per-departure θ or the number of competitors n shifts the intercept of $L(f)^*$ downward, leading to a fall in f^*.

▶ A higher cost of schedule delay γ reduces the height of $Q(f)^*$ and a rise in market size λ shifts the intercept of $L(f)^*$ upward, leading to a higher f^*. ■

Proof of Proposition 2.

▶ Given that θ and λ are absent from (19) and that this expression shows a negative relationship between f^* and p^*, then $\partial p^*/\partial\theta > 0$ and $\partial p^*/\partial\lambda < 0$.

▶ Looking now at the effect of the effect of τ, r or ε, it can be observed that the *direct effect* and the *indirect effect* go in the same direction, so that $\partial p^*/\partial\tau > 0$, $\partial p^*/\partial r > 0$, and $\partial p^*/\partial\varepsilon > 0$.

▶ Finally, the sign of $\partial p^*/\partial\gamma$ and $\partial p^*/\partial n$ is not obvious, as it requires to compute $\partial f^*/\partial\gamma$ and $\partial f^*/\partial n$ and account for the indirect effect of γ and n on p^* through f^*. Following this procedure (details provided below), it can be shown that $\partial p^*/\partial\gamma > 0$ and $\partial p^*/\partial n < 0$.

Computation of $\partial p^*/\partial\gamma$. First, we need to define

$$\Omega = Q(f)^* - L(f)^* = \frac{\tau + 2r^{1/2}\varepsilon^{1/2}}{\gamma}(f^*)^2 - \frac{\lambda(n-1)}{\theta n^2} + f^* = 0, \tag{A1}$$

so that

$$\frac{\partial f^*}{\partial\gamma} = -\frac{\partial\Omega/\partial\gamma}{\partial\Omega/\partial f^*} = \frac{(f^*)^2\left(\tau + 2r^{1/2}\varepsilon^{1/2}\right)}{\gamma\left[2f^*\left(\tau + 2r^{1/2}\varepsilon^{1/2}\right) + \gamma\right]}. \tag{A2}$$

Looking now at (19) and computing $\partial p^*/\partial\gamma$ yields

$$\frac{\partial p^*}{\partial\gamma} = \frac{1}{(n-1)f^*}\left(1 - \frac{\gamma}{f^*}\frac{\partial f^*}{\partial\gamma}\right). \tag{A3}$$

Finally, plugging (A2) into (A3) yields

$$\frac{\partial p^*}{\partial\gamma} = \frac{1}{(n-1)f^*}\left(1 - \underbrace{\frac{f^*\left(\tau + 2r^{1/2}\varepsilon^{1/2}\right)}{2f^*\left(\tau + 2r^{1/2}\varepsilon^{1/2}\right) + \gamma}}_{<1}\right) > 0. \tag{A4}$$

Computation of $\partial p^*/\partial n$. Using (A1) again, we can compute

$$\frac{\partial f^*}{\partial n}=-\frac{\partial\Omega/\partial n}{\partial\Omega/\partial f^*}=-\frac{\lambda\gamma\left(n-2\right)}{\theta n^3\left[2f^*\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)+\gamma\right]}. \tag{A5}$$

Looking now at (19) and computing $\partial p^*/\partial n$ yields

$$\frac{\partial p^*}{\partial n}=\frac{1}{\left(f^*\right)^2\left(n-1\right)^2}\left[-\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)\left(f^*\right)^2-\gamma f^*-\frac{\partial f^*}{\partial n}\gamma\left(n-1\right)\right], \tag{A6}$$

Plugging (A5) into (A6) yields

$$\frac{\partial p^*}{\partial n}=\frac{1}{\left(f^*\right)^2\left(n-1\right)^2}\left[-\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)\left(f^*\right)^2-\gamma f^*+\frac{\lambda\gamma^2\left(n-2\right)\left(n-1\right)}{\theta n^3\left[2f^*\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)+\gamma\right]}\right]. \tag{A7}$$

From (A1), we have that $\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)\left(f^*\right)^2+\gamma f^*=\frac{(n-1)\lambda\gamma}{\theta n^2}$. Using this expression in (A7) yields

$$\frac{\partial p^*}{\partial n}=-\frac{\lambda\gamma}{\left(f^*\right)^2\theta n^2\left(n-1\right)}\left[1-\underbrace{\frac{n\gamma-2\gamma}{n\gamma+2nf^*\left(\tau+2r^{1/2}\varepsilon^{1/2}\right)}}_{<1}\right]<0. \tag{A8}$$

■

Proof of Proposition 3.

Straightforward. ■

Proof of Proposition 4.

► Proposition 4i): case $\eta=0$. After noting that the intercept of $L\left(f\right)^{SO}$ exceeds the intercept of $L\left(f\right)^*$ for any value of η, we observe that the height of both $Q\left(f\right)^{SO}$ and $Q\left(f\right)^*$ coincides for $\eta=0$. Therefore, $f^*<f^{SO}$ as depicted in Figure 2. On the one hand, the inspection of expressions (19) and (37) reveal that $p^*>p^{SO}$ for $\eta=0$. On the other hand, the inspection of expressions (18) and (35) reveal that $e^*=e^{SO}$ for $\eta=0$.

► Proposition 4ii): case $\eta>\widetilde{\eta}>>0$. Given that η affects the height of $Q\left(f\right)^{SO}$, it follows that $f^*<f^{SO}$ for $\eta<\widetilde{\eta}$, then $f^*=f^{SO}$ for $\eta=\widetilde{\eta}$, and $f^*>f^{SO}$ for $\eta>\widetilde{\eta}$. On the one hand, the inspection of expressions (19) and (37) reveal that $p^*<p^{SO}$ for $\eta>>0$. On the other hand, the inspection of expressions (18) and (35) reveal that $e^*>e^{SO}$ for $\eta>0$. ■

Proof of Corollary 1.

Straightforward. ■

Proof of Proposition 5.

Under Assumption 1, the lower the semi-elasticity gap $\triangle\varphi$ (i.e., the lower the pass-through with respect to r as compared to the pass-through with respect to τ) the more likely for the condition $\Lambda > 1$ in (43) to be observed given that $\partial\Lambda/\partial\triangle\varphi < 0$. Consequently, the more likely for the condition $\left|\frac{\partial r}{\partial \tau}\right| < 1$ to be observed. ■

B Appendix: Additional figures and tables (online)

Figures A1 and A2 show mean values of non-emission charges aggregated at the country level and expressed in terms of total charges per seat. Figure A1 focuses on European and neighboring countries, while Figure A2 shows the situation in other countries (which are long-haul destinations for European travelers). Those charges in countries belonging to the EEA range from EUR 10 to EUR 40. Furthermore, charges in Canada, Hong-Kong, South Africa, and the United States are in line with the most expensive countries in Europe, while charges at many other long-haul destinations for European travelers are lower as compared with the European average.

Figure A3 shows NO_x-related emission charges at European airports. These charges range between EUR 3 and EUR 5 in most airports, although they are about EUR 9 in Swedish airports and Munich. The case of London Heathrow is peculiar, as emission charges reach EUR 35.

Figure A4 shows the share that each aircraft family has in our sample for the first and last year of the considered period. Interestingly, there is a remarkable increase in the share of new aircraft, which are used in almost 12% of total flights in 2022, even though the A320-neo and B737-MAX families did not have a relevant presence in the market before 2019.

Table A1 shows the emission intensity of selected aircraft in terms of per-seat NO_x, per-seat-km CO_2, and noise categories. It can be observed that newer aircraft are quieter, more fuel-efficient, and generate less NO_x emissions. More precisely, the A320-neo and the B737-MAX-8 generate 52% less NO_x emissions than the previous comparable models, being this difference 62% for the A321-neo. Shifting attention to widebody aircraft, the B787-8 and the A330-neo mitigate NO_x emissions in relation to previous comparable models by 30% and 24%, respectively. Following the ICAO's aircraft-noise categories (used in several airports), we also observe that differences in terms of aircraft *quietness* levels are also remarkable.[35]

Table A2 shows the difference in per-flight NO_x-emission charges between an A320 and an A320-neo to have an idea about the cost gap for airlines of renewing narrowbody aircraft. This difference ranges from EUR 131 in London Heathrow to around EUR 30 in Swedish airports and Munich, and EUR 10-19 for the rest of airports.

At this point, it should be acknowledged that most of these airports also apply noise charges which, in practice, increase the difference between the two models. Following the ICAO's

[35] For example, the 85-decibel maximum noise-level contour of A320-neo is around 50% lower than the previous comparable model.

aircraft-noise categories, the A320 is in the category "chapter 14 high" whereas the A320-neo is in the category "chapter 14 super-low" (as can be seen in Table A1). The comparison of runway charges paid by a A320 flight and a A320-neo flight is interesting because the A320-neo is two tons heavier but much quieter. Therefore, the A320-neo flight supports higher weight charges but lower noise charges. Figure A5 shows the airports in which runway charges for A320 flights are higher than for a A320-neo flights, meaning that noise charges more than compensate weight charges.

As in the case of NO_x-emission charges, London Heathrow is by far the airport establishing the highest noise charges. The cases of Amsterdam, Lisbon, Brussels, and several airports in France, Germany and Sweden are also worth to mention. For the rest of airports in our sample, runway charges are higher for A320-neo flights, as this aircraft model is heavier.[36]

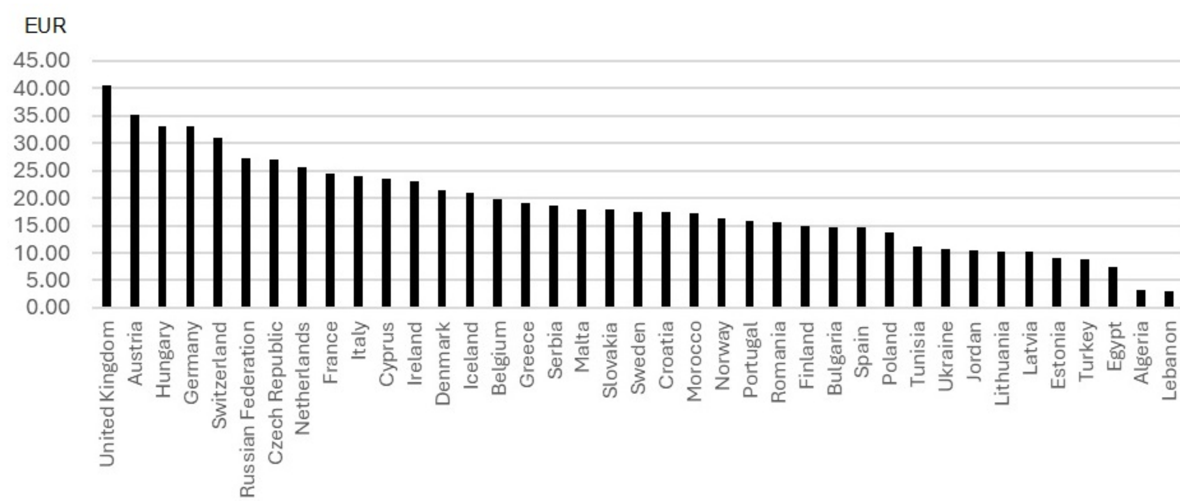


Figure A1: Total non-emission charges per country in European area (per-seat)

[36]Formally, many other airports apply some type of differentiation in terms of aircraft quietness. However, aircraft weight ultimately determines most of the runway charge. This is, for example, the case of Spanish and Italian airports.

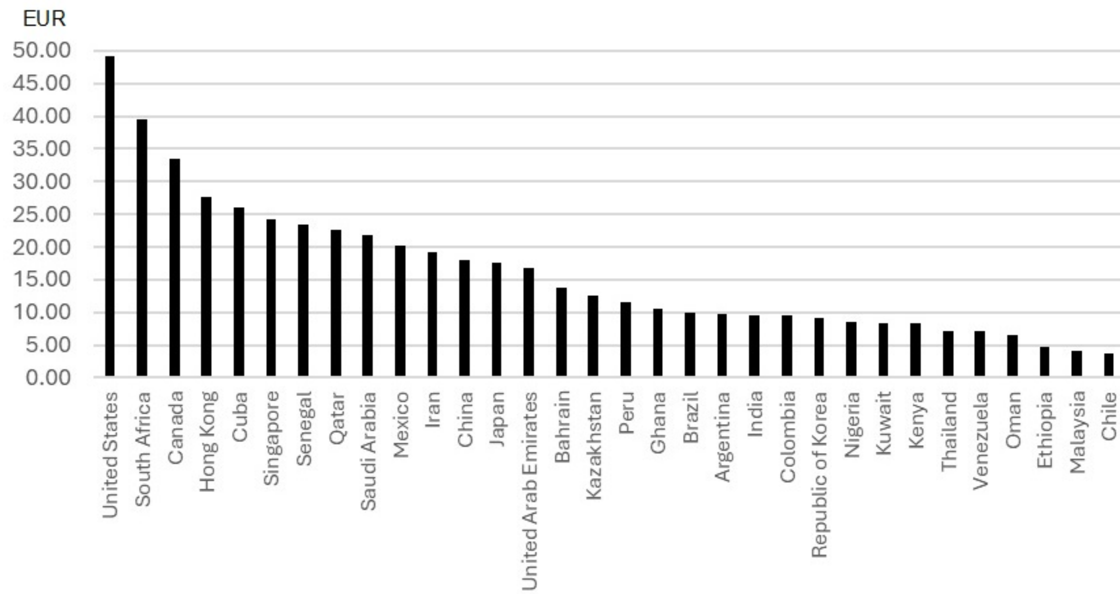
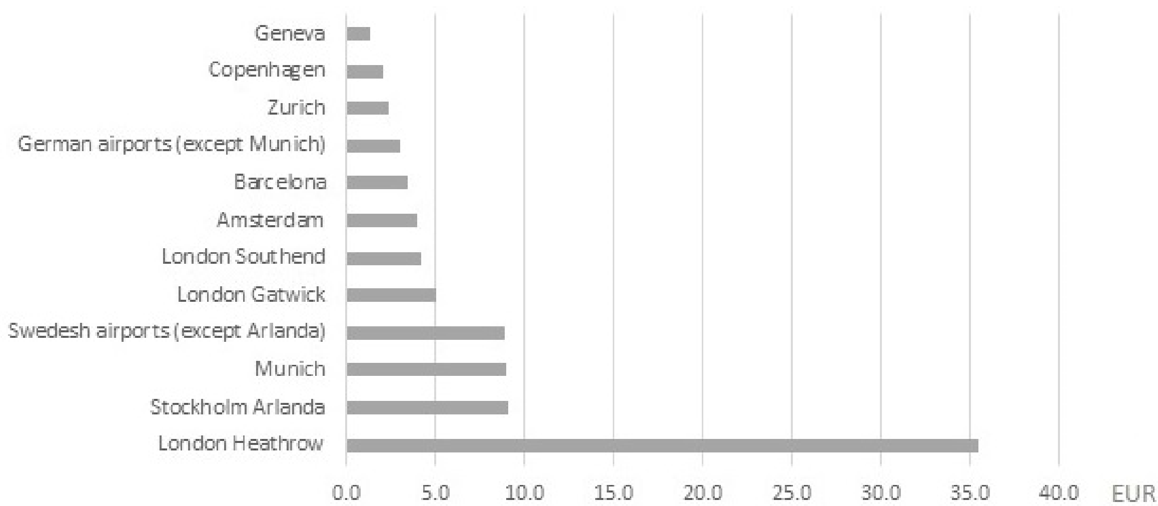


Figure A2: Total non-emission charges per country outside Europe (per-seat)



Note: The total cost per flight is computed as $charge\ x\ TB$, where TB denotes Taxable Base, which is computed as $TB = \#engines \frac{NOx(in\ grams\ per\ engine)}{1000}$. German airports include Berlin, Bremen, Cologne-Bonn, Düsseldorf, Frankfurt, Hamburg, Hannover, Münster, Nuremberg, and Stuttgart. Swedish airports include Gothenburg, Malmoe, and Stockholm Bromma.

Figure A3: Emission charges in European airports (2022)

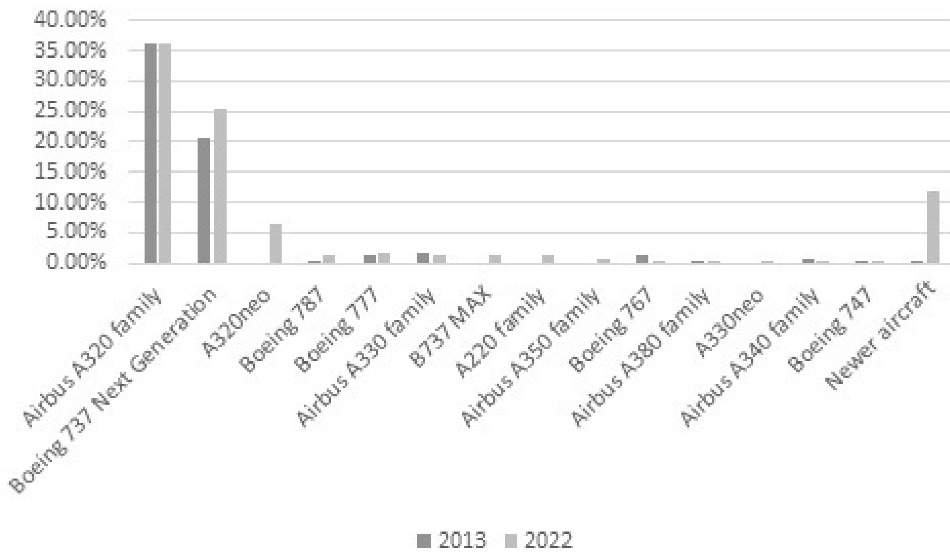


Figure A4: Share of aircraft types (per family)

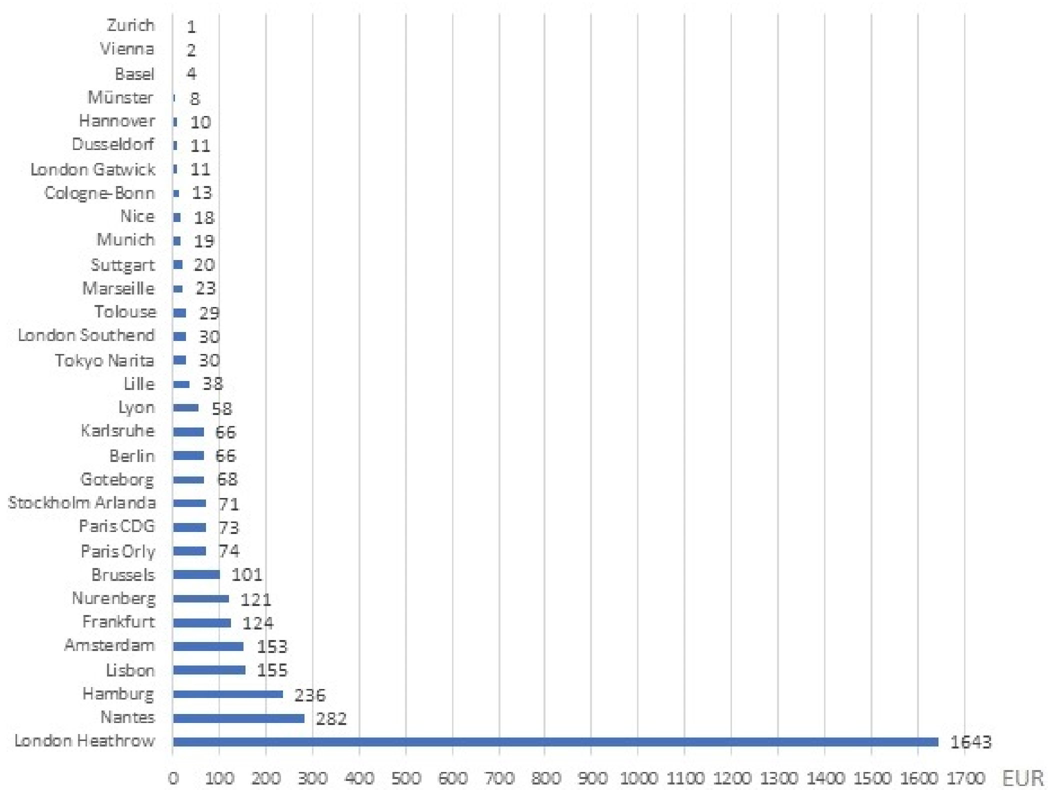


Figure A5: Higher runway charges for A320 as compared to A320-neo (2022)

Table A1. Emission intensity of selected aircraft

Aircraft	Seats	NO_X per seat (grams per engine during the LTO cycle)	ICAO noise category	Mean CO_2 emissions (kg per seat-km)	Year introduction	Type
A220-100	100	41	chapter 14 super-low	0.110	2016	narrow
B737-600	101	45	chapter 4 base	0.099	1997	narrow
B737-700	108	42	chapter 4 high	0.087	1997	narrow
A318	118	28	chapter 14 base	0.110	1995	narrow
A319	124	30	chapter 14 high	0.091	1995	narrow
A319-neo	124	29	chapter 14 super-low	NA	2017	narrow
A320	153	35	chapter 14 high	0.075	1987	narrow
A320-neo	153	23	chapter 14 super-low	0.060	2016	narrow
B737-800	161	38	chapter 4 high	0.070	1997	narrow
B737-900	175	35	chapter 4 high	0.071	1997	narrow
B737-MAX 8	175	23	chapter 14 low	0.056	2017	narrow
A321	182	48	chapter 4 high	0.073	1993	narrow
B737-MAX 9	192	21	chapter 14 super-low	0.060	2017	narrow
A321-neo	195	18	chapter 14 super-low	0.054	2016	narrow
A330-200	211	93	chapter 14 high	0.090	1994	wide
B787-8	242	35	chapter 14 super-low	0.077	2011	wide
B767-400	246	50	chapter 14 high	0.086	2000	wide
A330-300	248	79	chapter 14 high	0.087	1994	wide
A330-800-neo	252	60	chapter 14 high	0.082	2018	wide
B787-9	280	31	chapter 14 super-low	0.078	2011	wide
A340-600	303	53	chapter 14 low	0.108	2002	wide
A350-900	315	53	chapter 14 super-low	0.080	2013	wide
B777-300ER	332	105	chapter 14 high	0.102	2004	wide
B777-300	356	74	chapter 14 high	0.116	1998	wide
B747-8	362	30	chapter 4 high	NA	2012	wide
B747-400	369	29	chapter 4 high	0.111	1989	wide
A380-800	560	30	chapter 14 super-low	0.098	2007	wide

Note: Noise categories range from noisier (chapter 4 high) to quieter (chapter 14 super-low).

Table A2. Per-flight NO_X charges in 2022 (A320 vs. A320-neo)

Airport	A320	A320-neo
London Heathrow	381	251
Stockholm Arlanda	98	65
Munich	98	64
Swedish airports (except Arlanda)	95	62
London Gatwick	55	36
London Southend	45	30
Amsterdam	43	28
Barcelona	38	25
German airports (except Munich)	35	23
Zurich	26	17
Copenhagen	22	15
Geneva	15	10

Table A3. Fare regressions (booking period)

VARIABLES	(1) *log(fare 3 months)*	(2) *log(fare 1 month)*	(3) *log(fare 1 week)*
log(non-emission)	0.224***	0.187***	0.193***
	(0.0206)	(0.0236)	(0.0289)
emission	0.133***	0.187***	0.213***
	(0.0193)	(0.0226)	(0.0276)
emission (elasticity)	0.007***	0.010***	0.011***
	(0.0010)	(0.0012)	(0.0015)
Observations	53,553	53,553	53,553
Route-airline pairs	13,374	13,374	13,374
Years	8	8	8
R-squared	0.944	0.936	0.904

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the logarithm of fares for bookings made three months (column 1), one month (column 2) and one week (column 3) before departure. Controls: fuel costs, CO_2 costs, population, income, dummy for monopoly routes, route-airline and year fixed effects. For *emission*, the table reports both the coefficient $\partial \log(fare) / \partial emission$ and the elasticity $\partial \log(fare) / \partial \log(emission)$, using the *margins* command of Stata. All regressions consider the entire sample.

Table A4. Fare regressions: Robustness to sample

log(non-emission)	0.202***	0.198***	0.225***	0.177***	0.176***	0.235***
	(0.0472)	(0.0232)	(0.0295)	(0.0343)	(0.0399)	(0.0260)
emission	0.196***	0.113	0.167***	0.156***	0.211***	0.148***
	(0.0252)	(0.0710)	(0.0375)	(0.0284)	(0.0288)	(0.0366)
emission (elasticity)	0.025***	0.003	0.006***	0.011***	0.020***	0.006***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	13,694	39,701	25,344	28,209	13,116	40,188
R-squared	0.939	0.909	0.951	0.942	0.950	0.948
Sample	network airlines	low-cost airlines	monopoly routes	competitive routes	>1 daily flight	<1 daily flight

Notes: Standard errors in parentheses (robust to heteroscedasticity and clustered at the route level). Statistical significance at 1% (***), 5% (**), and 10% (*). The dependent variable is the logarithm of fares. Controls: fuel costs, CO_2 costs, population, income, dummy for monopoly routes, route-airline and year fixed effects. For *emission*, the table reports both the coefficient $\partial \log(fare) / \partial emission$ and the elasticity $\partial \log(fare) / \partial \log(emission)$, using the *margins* command of Stata.