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Welfare Effects of Electric Aircraft Introduction in the Italian Air Transport Market: A Structural Approach

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Abstract

We measured the social welfare effects of the introduction of all-electric aircraft using data from the air transport sector in Italy. The estimation of the welfare effects was done through a structural model typical of empirical industrial organisation work, in which equilibrium is estimated through the interaction of demand (from passengers) and supply (from airlines), and its perturbation due to the introduction, in some routes where it is technologically possible, of electrically powered aircraft. This model makes it possible to estimate the social welfare effects and the relative contributions of consumer surplus and airline profits. The structural model uses data from eight years: 2014–2019 and 2022–2023. We find that, net of global environmental effects, the introduction of electric aircraft improves social welfare when the new technology reduces marginal operating costs. Given the technology currently available, the welfare effects remain limited because electric aircraft can operate only on routes with strict constraints on range and capacity. Relaxing these constraints substantially increases the potential gains but also introduces greater uncertainty, as results rely on progressively more speculative assumptions. A further contribution of this work lies in the flexibility of the proposed methodology, which can easily incorporate more accurate technological parameters as the technology evolves.

Keywords: Electric aircraft, welfare effects, structural econometric model

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1 Introduction

The issue of environmental sustainability is a central factor in the aviation industry. Although it is responsible for only a low percentage of the world's CO2 output (about 2-3%, Intergovernmental Panel on Climate Change (2014); European Environment Agency (2019); International Energy Agency (2020); World Bank (2021)), aircraft operations are highly emission-intensive, and for this reason, industry associations (e.g., International Air Transport Association 2020), airlines, and policymakers are particularly active in identifying strategies to reduce emissions. Among these, as is also the case with the endothermic internal combustion automobile sector, one possible way to reduce CO2 emissions is the introduction of electric-powered aircraft (Baumeister et al., 2020).

In fact, the design and development of electric-powered aircraft (henceforth electric aircraft) certainly lag behind electric motors in the automotive sector, but the first models are already available, and some are already in operation in certain areas (e.g., Norway) for short distances. Moreover, development projects are underway to produce several models with more seats and longer travel distances in the near future (de Vries et al., 2024).

As with any new alternative mode of transportation, electric aircraft, in addition to engineering development issues, require assessing their possible social effects. Thus, assessing the impact of electric aircraft on social welfare-both for the consumer-passenger aggregate (demand side) and for the industry as a whole (supply side)-is crucial. As highlighted in the literature review section, the few studies available are attempts either to implement a cost-benefit analysis for electric aircraft (Jussila Hammes and Johansson, 2023) or to compare electric aircraft to traditional aircraft in terms of different dimensions (e.g., costs, emissions, technical characteristics) as in Baumeister et al. (2020) and Avogadro and Redondi (2024). In particular, cost-benefit analysis is very useful for estimating the second- and third-order effects of introducing a new mode of transportation (such as the effects on employment in upstream supply sectors and in downstream sectors like tourism and the local economy). However, it has the disadvantage of relying on many ad hoc assumptions, which make it very similar to case studies and not sufficiently general for defining policy implications.

For this reason, in this paper we present an initial study that applies a structural model typical of empirical industrial organization (Berry et al., 1993; Berry, 1994) to the air transport sector to estimate the effects on consumer welfare and airline surplus of the possible introduction of full electric aircraft on some routes. By means of a counterfactual analysis that disrupts the air transport market equilibrium given by the intersection of supply and demand, for the introduction of electric aircraft on technologically feasible routes, one can quantify the welfare effects in a rigorous way. This allows measuring in monetary terms whether social welfare increases, whether this occurs for both consumers and producers, who receives the greatest benefit (or cost), and what types of airlines are responsible for any benefits. Both the results and the methodology itself can support policy decisions aimed at promoting the green transition.

One novelty of this paper is the inclusion of environmental consciousness directly in the demand estimation. While previous studies have typically relied only on the supply side - mainly because of the lack of data on consumers' environmental preferences - we explicitly model how such preferences affect air travel choices. This allows us to jointly capture demand- and supply-side adjustments in response to the technological transition toward electric aircraft. Within this extended framework, we perturb the market equilibrium and analyze how prices, market shares, profits, consumer surplus, and overall welfare evolve under alternative scenarios: a base scenario, closely related to the current technological situation of electric aircraft, which envisions the possible introduction of electric aircraft on routes with a maximum distance of 400 km and low-capacity planes (up to about 20 passenger seats); and a prospective scenario, representing what may be realized in a few years, with electric aircraft capable of operating longer distance routes and with higher capacity (up to 90 passengers).

The plan of the paper is as follows. Section 2 discusses the literature review, Section 3 presents the empirical strategy to estimate the social effects of introducing electric aircraft, Section 4 shows the data sources, the definition of the variables, and the descriptive statistics, Section 5 displays the econometric results related to the structural model of the Italian air transportation market, while Section 6 presents the counterfactual analysis that quantifies the social effects. Finally, conclusions and policy implications are drawn in Section 7.

2 Literature review

The literature relevant to this study can be broadly classified into two main categories. The first comprises articles that attempt to quantify the potential benefits and costs associated with the introduction of electric aircraft through a cost-benefit analysis (CBA) approach. The second category, while related to the first, consists of contributions that examine the distinctive features of electric aircraft, often in comparison with conventional ones.

As discussed in World Bank (2005), the focus of CBA in the transport sector is generally on the impacts on transport users, operators, and taxpayers. CBAs are typically based on a partial equilibrium approach, whereby the focus on the transport sector relies on the assumption that all economic sectors utilizing transport operate under perfect competition, with no substantial economies of scale in production. In this context, where most analyses concentrate on the primary impacts experienced by transport users, operators, and government, the total impact of the project under evaluation is typically regarded as the sum of the changes occurring at different levels. The change in consumer surplus (CS) is employed as a metric for quantifying the benefits experienced by transport users, while the change in producer surplus (PS) captures the benefits accruing to firms. In essence, producer surplus can be considered the supply-side equivalent of consumer surplus. The sum of CS and PS gives the total surplus or social welfare (SW).[1] The

[1] In cases where governmental involvement is evident, it is recommended that the change in government surplus (GS) - defined as the difference between financial inflows, typically derived from taxation, and outflows, which include expenditures such as subsidies - be incorporated into the assessment.

change in the cost of externalities completes the picture and enables an assessment of the overall impacts.[2] Although this decomposition may appear straightforward, in practice it often proves complex.

Regarding electric aircraft, to our knowledge, there is only one contribution in the literature that explicitly applies a cost-benefit analysis: Jussila Hammes and Johansson (2023). Consistent with the aforementioned framework, the authors estimate changes in consumer and producer surplus by simultaneously estimating demand and supply equations. Their approach is based on the assumptions and models used by the Swedish Transport Administration in its analyses of transport infrastructure investments. The core idea of the paper is to compare benefits and costs against a status quo scenario to evaluate whether route electrification is socially desirable. The authors focus primarily on emissions, calculating CO2 and CO2-equivalent savings - taking into account high-altitude effects - as a measure of the societal benefits from electric aircraft, and thus as an indication of how much public investment in airport infrastructure could be justified. Their results indicate that electric aircraft will only become a commercially viable option on many routes in the future. Furthermore, they propose the implementation of research and development subsidies for advancing electric aircraft and battery technologies.

The second group of studies related to our work includes those that analyze the characteristics of electric aircraft in comparison with conventional ones. Current contributions are relatively unanimous in identifying the Heart Aerospace ES-19 as the reference model for first-generation electric aircraft, featuring 19 seats and a 400 km range. Several sources also cite the Eviation Alice, an aircraft with 9 seats and an 800 km range. Other references include the Heart Aerospace ES-30, which offers 30 seats and a 400 km range, although this latter model has recently undergone a redesign and is now configured as a hybrid aircraft.

Baumeister et al. (2020) focus on the potential for reducing emissions through the use of first-generation electric aircraft in Finland. The authors compare carbon dioxide equivalent (CO2-eq) emissions and door-to-door travel times on 47 routes, relative to existing aircraft and other transport modes, and find that replacing conventional aircraft would reduce both CO2-eq emissions and travel times.

Avogadro and Redondi (2024) present a cost model for comparing the operating costs of first-generation electric aircraft with those of their conventional counterparts on regional routes. They find that, on average, electric aircraft have higher costs than traditional ones, although this discrepancy narrows when comparing the 19-seat electric aircraft (ES-19) with the Beechcraft 1900. In one of their scenarios - where aircraft prices and maintenance costs are reduced - the operating costs of electric aircraft could be up to 5% lower. Overall, the authors conclude that electric aircraft will penetrate markets to a significant extent only after substantial technological advancements, and that their contribution to the industry's net-zero transition appears limited,

[2] If data are available, such changes can be compared with investment costs. However, the current version of the paper focuses on CS and PS. Emissions are considered only insofar as they affect air transport demand (and thus consumer surplus), while the global benefits from their reduction following the introduction of electric aircraft are not taken into account.

especially for first-generation models.

In another study, FAIR (2022) compare the same models on several Finnish routes. Their findings indicate a potential reduction in cost per passenger of about 5% by switching from traditional to electric aircraft, a figure that rises to 27% when only operating costs are considered.

Overall, the literature agrees on the nascent state of this technology (see, for example, Dominković et al. (2018); Gnadt et al. (2019); Caset et al. (2018); Baumeister et al. (2020)). This reflects the still-limited understanding of the technology, its potential, and the associated costs (Avogadro and Redondi, 2024). We also faced similar challenges in this respect, which led us to construct different scenarios based on alternative assumptions, as discussed in the following sections.

3 Empirical strategy

In this section we present the empirical strategy used to estimate the social welfare impacts of all-electric aircraft. The approach relies on the estimation of a structural model of the air transport sector to recover equilibrium prices and quantities, followed by counterfactual simulations of the introduction of electric aircraft on selected routes in order to quantify the resulting changes in consumer surplus and airline profits.

3.1 Structural model of the airline industry

We develop a structural model of demand and supply following the recent literature on differentiated product markets (Berry, 1994; Berry and Jia, 2010), considering passengers flying from an Italian origin airport to another Italian airport as destination. The model jointly describes demand and supply, i.e., the behavior of all airlines providing connections among Italian airports.

3.1.1 Demand model

Demand is modeled using a nested logit specification (McFadden, 1977). Let m denote a market, defined as an origin–destination airport pair.[3] In each market, a representative consumer chooses between flying from the origin to the available destinations or selecting the outside option, i.e., traveling by another mode or not traveling at all. Accordingly, the nested logit model features two nests: one including all flying options and one corresponding to the outside alternative. This structure ensures that if one flying product disappears, substitution to another flying option is more likely than substitution to the outside good.

Each product $j \in \mathcal{J}_m$ in market m corresponds to a flight operated by a given airline, possibly direct or with one connection. The product is characterized by a vector of observed characteristics

[3] A more general definition of a market in air transport is the city pair, which bundles together all airports serving the same metropolitan area. For Italy, for instance, the city of Milan includes three airports: Milan Malpensa (MXP), Milan Linate (LIN), and Milan Bergamo (BGY). However, such cases are relatively limited. Therefore, as is typical in structural work (e.g., Berry and Jia (2010)), we adopt the more restrictive airport-pair definition of a market.

X_{jm}, a price p_{jm}, and unobserved characteristics ξ_{jm}. Observed characteristics include variables such as distance, origin, and destination, while ξ_{jm} captures features such as advance purchase conditions or refund policies. The indirect utility for consumer i from product j is:

$$u_{ijm} = X_{jm}^{\top}\beta - \alpha p_{jm} + \xi_{jm} + \varepsilon_{ijm}(\lambda), \tag{1}$$

where ε_{ijm} follows a Generalized Extreme Value distribution generating the standard nested logit market shares (Cardell, 1997). The mean utility of the outside option is normalized to zero. The utility of the outside good is:

$$u_{i0m} = \varepsilon_{i0m}. \tag{2}$$

Conditional on choosing a flying product, the share of consumers who select product j in market m is:

$$\frac{e^{(X_{jm}\beta - \alpha p_{jm} + \xi_{jm})/\lambda}}{D_m^{\lambda}}, \tag{3}$$

where

$$D_m^{\lambda} = \sum_{k=1}^{J} e^{(X_{km}\beta - \alpha p_{km} + \xi_{km})/\lambda}. \tag{4}$$

The share of consumers choosing any air transport option is:

$$s_m(X_m, p_m, \xi_m, \theta_d) = \frac{D_m^{\lambda}}{1 + D_m^{\lambda}}, \tag{5}$$

where $\theta_d = (\beta, \alpha, \lambda)$ is the vector of demand parameters. The overall market share of product j in market m is then:

$$s_{jm}(X_m, p_m, \xi_m, \theta_d) = \frac{e^{(X_{jm}\beta - \alpha p_{jm} + \xi_{jm})/\lambda}}{D_m^{\lambda}} s_m(X_m, p_m, \xi_m, \theta_d). \tag{6}$$

Under these assumptions, Berry (1994) show that:

$$\ln\left(\frac{s_{jm}}{s_{0m}}\right) = X_{jm}\beta - \alpha p_{jm} + \sigma \ln s_{j|m} + \xi_{jm}, \tag{7}$$

where:

$$\begin{aligned} s_{jm} &= \frac{\#\,\text{pax from } m \text{ choosing } j}{\text{origin population of } m}, \\ s_{0m} &= \frac{(\text{population of } m) - (\#\,\text{pax from } m \text{ flying to Italy})}{\text{origin population of } m}, \\ s_{j|m} &= \frac{\#\,\text{pax from } m \text{ choosing } j}{\#\,\text{pax of } m}. \end{aligned} \tag{8}$$

3.1.2 Identification

The product-level unobservable ξ_{jm} captures missing attributes such as ticket flexibility, departure time, or destination events, which are correlated with price. For example, refundable tickets are usually more expensive. To obtain unbiased estimates, we therefore use instrumental variables. Following the empirical IO literature (Berry et al., 1993; Berry, 1994), we exploit (a) cost-side variables, (b) competitors' characteristics, and (c) lagged or cross-market variables when available. The construction of the instruments is detailed in the empirical section.

3.1.3 Supply

Airlines in each market m compete *à la* Bertrand with horizontally differentiated products. Assuming market independence, airline a's profit in market m is:

$$\pi_m^a = \sum_{j=1}^{J^a} (p_{jm}^a - mc_{jm}^a) q_{jm}^a = \sum_{j=1}^{J^a} (p_{jm}^a - mc_{jm}^a) s_{jm}^a M_m, \tag{9}$$

where M_m is the market size (origin population). First-order conditions (FOCs) are:

$$s_{jm}^a + \sum_{h=1}^{J^a} (p_{hm}^a - mc_{hm}^a) \frac{\partial s_{hm}^a}{\partial p_{jm}^a} = 0, \tag{10}$$

which in matrix form can be written as:

$$mc^a = p^a + (s^a)^{-1} \frac{\partial s^a}{\partial p^a}.$$

3.1.4 Estimation

We jointly estimate the demand and supply parameters using the Generalized Method of Moments (GMM). On the demand side, we invert the market share equations (Berry, 1994) to obtain:

$$\xi_{jm} = \log\left(\frac{s_{jm}}{s_{0m}}\right) - \left(X_{jm}^\top \beta + \alpha p_{jm} + \sigma \ln \frac{s_{jm}}{1 - s_{0m}}\right). \tag{11}$$

Since p_{jm} and $\ln \frac{s_{jm}}{1-s_{0m}}$ are endogenous, we use instruments Z_{kjm} ($k = 1, \ldots, K$) satisfying:

$$E\left(\xi_{jm} Z_{kjm}\right) = 0, \quad k = 1, \ldots, K. \tag{12}$$

On the supply side, marginal cost is modeled as:

$$mc_{jm} = W_{jm}^\top \psi + \zeta_{jm}, \tag{13}$$

where W_{jm} is a vector of observed cost shifters and ζ_{jm} a cost shock. The associated moments are:

$$E\left(\zeta_{jm} w_{l,jm}\right) = 0, \quad l = 1, \ldots, L. \tag{14}$$

The system of $K + L$ moment equations jointly identifies θ_d and ψ, with the optimal weighting matrix computed from the first-step residuals.

3.1.5 *Counterfactual analysis*

The introduction of electric aircraft alters the equilibrium of the air transport market by modifying the marginal costs of certain products. The counterfactual equilibrium is determined by iterating between the pricing condition (10) and the market share equations until convergence, i.e., until the change in prices between iterations becomes negligible.

We simulate two main scenarios:

- Base scenario: electric aircraft with 21 seats and 400 km range. The marginal cost of LCC products adopting electric aircraft is reduced progressively from 0 to –10%, in 1% steps.
- Prospective scenario: electric aircraft with 90 seats and 800 km range. The marginal cost varies from –10% to +10%, also in 1% steps, reflecting potential future technological and operational outcomes.

For each of these cases, we compute the resulting equilibrium prices, market shares, consumer surplus, and airline profits. Social welfare is obtained as the sum of total consumer surplus and total producer surplus. We also analyze key oligopolistic mechanisms, including the *pass-through* rate - the proportion of marginal cost changes transmitted to final prices. A pass-through equal to 1 implies full transmission of cost changes, while values below (above) 1 indicate partial (more-than-proportional) transmission. The magnitude of pass-through depends on market concentration, typically increasing with stronger market power. Finally, we distinguish the welfare effects by business model, assessing whether low-cost carriers (LCCs) or full-service carriers (FSCs) predominantly adopt electric aircraft and thus drive the overall welfare impact. These results form the basis for the policy discussion in the following sections.

4 Data

This section describes the data sources, the variables used in the structural model, and the main descriptive statistics. Data on demand and supply in the air transportation sector come from OAG Traffic Analyser (TA) and OAG Schedule Analyser (SA). Information on variations in CO2 emissions is taken from the OAG Emissions dataset.[4]

OAG Schedule Analyser provides daily information on all commercial flights worldwide by airline, including aircraft capacity (in seats), flight duration, and distance. Economic data, that is those required to estimate demand and supply, are obtained from OAG Traffic Analyser. In these datasets, a flight represents a connection that can be direct or include one or more stops at a gateway airport (G). Hence, a flight is defined as a link between an origin airport (O) and a destination airport (D). A direct connection is denoted as O-D, and an indirect one as O-G-D. The same connection may be offered by several airlines. Thus, in the analysis a flight is a connection operated by an airline. TA provides monthly data on prices and quantities

[4] See `https://www.oag.com/`.

sold (actual bookings), including both tickets sold by travel agents and those purchased directly online. Information on tickets sold through travel agents is sourced from Global Distribution Systems (GDS), while data on online sales come from companies specialized in web-only data. We consider only the discount economy booking class.[5]

The dataset covers monthly data from 2014 to 2019 and from 2022 to 2023. The years 2020 and 2021 are excluded due to the impact of the COVID-19 pandemic. Overall, we have eight years of data, corresponding to 96 monthly observations.

The OAG Emission dataset links the quantity of fuel burnt and the CO2 produced to each flight. When these data are unavailable, we rely on the Eurocontrol Small Emitter Tool as an alternative source.

As already explained in Section 3.1.1, a market is defined by an origin-destination airport pair, which varies over time within each year. Therefore, a single market is defined by all products in a given origin-destination pair for a specific month and year. A market is thus an (origin-destination-month-year) combination. Table 1 reports descriptive statistics at the market level, including 370 markets.

Variable	Mean	Std dev.
No. of products per market	1.57	0.61
No. of airlines per market	1.42	0.5
No. of direct passengers	5,161	6,880
No. of connecting passengers	199	227
No. of FSC passengers	1,780	4,114
No. of LCC passengers	3,580	5,214
s_{0mt}	0.993	0.0095
pop_{mt}	1,428,642	1,201,905
No. of markets	370	57
No. of city pair	316	47
No. of gateways (per market)	1.1	0.2

Table 1: Market-level descriptive statistics

Each market includes between one and two products on average (1.57), and a similar number of competing airlines (1.42). The mean number of passengers on direct flights (5,161) is much higher than on connecting flights (199). Italian passengers mainly travel with LCCs: the average number of LCC passengers is 3,580, compared to 1,780 for FSCs. Relative to the origin city population, the share of air travelers is low-just below 1%-while the outside option share exceeds 99%. The average population of the origin city (the province where the airport is located) is around 1.5 million. There are 316 airport pairs.

The econometric specification of the nested logit model is:

[5]Fares are calculated in US dollars and do not include fees for seat allocation, baggage, or priority boarding. They also exclude payments for on-board food and beverages, as well as taxes, airport fees, and surcharges(Dresner et al. (2021)).

$$\log\left(\frac{s_{jm}}{s_{0m}}\right) = X_{jm}\beta + \alpha p_{jm} + \sigma \ln s_{jm|w} + \xi_{ijm} \tag{15}$$

Observable characteristics include $DIRECT$, a dummy equal to 1 if the flight is direct; $DIST$, the flight distance (in kilometers); CO_2, the amount of carbon dioxide (in kilograms) emitted by the flight; HSR, a dummy equal to 1 if a high-speed rail connection exists between the origin and destination; and LCC, a dummy equal to 1 if the airline is a low-cost carrier. We include fixed effects for airline, month, year, origin airport, and destination airport. The estimated equation is therefore:

$$\begin{aligned}\log\left(\frac{s_{jm}}{s_{0m}}\right) &= \beta_1 DIRECT_{jm} + \beta_2 DIST_{jm} + \beta_3 CO_{2,jm} + \beta_4 HSR_{jm} + \beta_5 LCC_{jm} \\ &\quad + \alpha p_{jm} + \sigma \ln s_{jm|w} + \mu_a + \gamma_{\text{month}} + \eta_{\text{year}} + \vartheta_O + \lambda_D + \epsilon_{jm} \end{aligned} \tag{16}$$

where ϵ_{jm} is the error term including the unobserved component ξ_{ijm}. To identify the coefficients α and σ of the endogenous variables p_{jm} and $\ln s_{jm|w}$, we follow related structural work (e.g., Bontemps et al. (2024); Berry and Jia (2010)) and employ standard cost- and supply-based instrumental variables. The exclusion restriction relies on the fuel cost per aircraft seat ($fuelcostseat$), the number of competing products in the market ($competprod$), and the number of competing direct products ($directcompetprod$).

	Unweighted		Weighted on pax(jmt)	
Variable	*Mean*	*Std dev.*	*Mean*	*Std dev.*
Observed characteristics				
P (Price (US \$))	82.72	49.33	57.58	35.34
Passengers	3,410	5,147		
s_{jm}	0.004	0.006	0.0095	0.0106
$s_{jm\|g}$	0.636	0.387	0.773	0.275
$DIRECT$	0.579	0.494	0.963	0.189
$DIST$	746.636	242.308	448.397	310.907
LCC	0.406	0.491	0.668	0.471
HSR	0.066	0.2480		
$CO2(kg)$	248.74	256.52		
Ryanair	0.222	0.416	0.438	0.496
easyJet	0.043	0.202	0.113	0.316
Ita Airways	0.545	0.498	0.294	0.455
oneworld	0.059	0.236	0.052	0.222
Star alliance	0.095	0.293	0.064	0.245
Sky team	0.557	0.497	0.306	0.461
Instruments				
$fuelcostseat$	28.42	8.61	28.58	8.44
$competprod$	1.966	0.960		
$directcompetprod$	0.164	0.337		
Observations	54,175			

Table 2: Product-level descriptive statistics

Table 2 reports descriptive statistics of the variables included in the nested logit model. The mean price is about 83 US\$, but when weighted by passengers it falls to 58 US\$, suggesting that denser routes have lower prices. The mean number of passengers per product is 3,410, and the average market share is below 0.01%. Within the nest, the average share of flying products is much higher (64% unweighted, 77% weighted). Direct flights represent 58% of all flights, but 96% when weighted by passengers, confirming that the main routes are served directly. The average distance is 747 km unweighted and 448 km weighted. LCCs account for 67% of weighted passengers. *Ita Airways* has the largest unweighted share (55%), while *Ryanair* reaches 44% when weighted. *SkyTeam* dominates among alliances with 56%, mainly due to *Ita Airways*. The average fuel cost per seat is 28 US\$, and markets show around two competing products on average, with only 0.16 offering direct flights. This indicates that most competition occurs on connecting flights. The total number of observations used in the structural model is 54,175.[6]

Figure 1 illustrates the price evolution over time. FSCs generally charge higher fares than LCCs. Prices for connecting flights are consistently higher than for direct ones.

[6]Fuel cost source: IATA Jet Fuel Price Monitor. Population data: Istat.

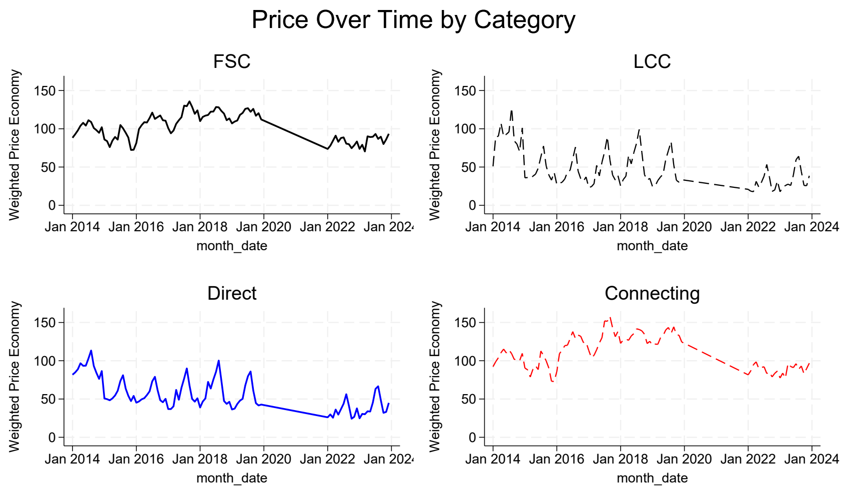

Figure 1: Price dynamics in Italian air transport markets

Figure 2 shows the price distribution. LCC flights are concentrated at lower price levels, and direct flights also display lower dispersion.

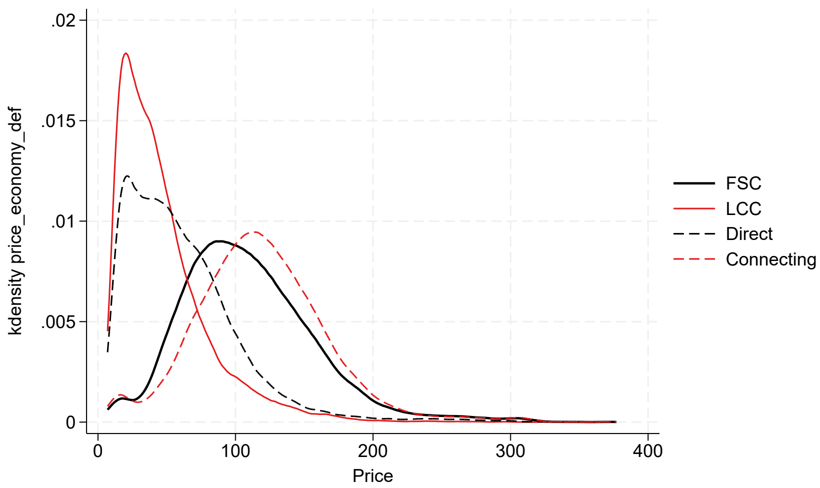

Figure 2: Price distribution by airline model and flight type

On the supply side, the marginal cost of production depends linearly on product characteristics:

$$mc_{jm} = W_{jm}^{\top}\psi + \zeta_{jm}, \tag{17}$$

where W_{jm} is a $L \times 1$ vector of observed characteristics $w_{l,jm}$, $l = 1, \ldots, L$, and ζ_{jm} is a marginal cost shock. Observable characteristics include $DIRECT$, a dummy equal to 1 if the flight is direct, and $FUELCOST$. The estimated equation is:

$$mc_{jm} = \chi_1 DIRECT_{jm} + \chi_2 FUELCOST_{jm} + \mu_a + \eta_{year} + \vartheta_O + \lambda_D + \varepsilon_{jm} \tag{18}$$

5 Estimates from the econometric structural model

This Section presents and discusses the parameter estimates of the demand and supply equations.

5.1 Estimates of the demand parameters

The left panel of Table 3 reports the estimated coefficients of the regressors in the demand equation (16), jointly estimated with the marginal cost equation (18) using the optimal two-step GMM procedure. Standard errors are reported in parentheses together with significance levels.

Table 3: Econometric estimates from structural model

Demand model		Supply model	
	Dependent variable: $\log s_{jmt}$		Dependent variable: mc_{jmt}
Independent variables	Coefficient	Independent variables	Coefficient
P_{jmt}	-0.0421^{***}	$DIRECT_{jmt}$	-32.2810^{***}
	(0.0033)		(0.5035)
$\log s_{jmt\|g}$	0.3603^{***}	$FUELCOST_{jmt}$	0.7711^{***}
	(0.0225)		(0.0677)
$DIRECT_{jmt}$	0.3342^{***}		
	(0.1336)		
$DIST_{jmt}$	0.0003^{***}		
	(0.0001)		
$CO2_{jmt}$	-0.0001^{***}		
	(0.0000)		
HSR	-0.9128^{***}		
	(0.0452)		
LCC	-1.0320^{***}		
	(0.1049)		
Observations	54,175	Observations	54,175
Adj. R^2		Adj. R^2	0.47
Airline FEs	✓	Airline FEs	✓
Month FEs	✓		
Year FEs	✓	Year FEs	✓
Origin FEs	✓	Origin FEs	✓
Destination FEs	✓	Destination FEs	✓

Robust standard errors in parentheses.
Legend: *** = 1% significance level, ** = 5% significance level, * = 10% significance level.

The estimated coefficients of the demand regression in Table 3 have the expected signs and are statistically significant. The price coefficient is negative (-0.04), while the nesting parameter σ, associated with the variable $log(s_{jmt|g})$, lies between 0 and 1, confirming that there is substitution between the outside option and the air travel nest. As expected, passengers show a preference for direct flights: the coefficient of $DIRECT$ is positive (0.33). On average, a passenger is willing to pay about 8 US$ more to fly directly between origin and destination, obtained as the ratio between the $DIRECT$ and price coefficients. The coefficients of $CO2$, HSR, and LCC are negative and significant, indicating that passengers prefer less polluting flights, value the absence of a high-speed rail alternative, and appreciate higher service quality.

5.1.1 *Price elasticities, marginal costs and markups*

The demand estimates allow us to compute price elasticities, reported in Table 4. We calculate the elasticity for each product and then take the market-level average, that is, for each airport pair and month. The average own-price elasticity is -4.31 (standard deviation 2.88). These estimates are slightly lower in magnitude than those found in previous studies.[7] A possible explanation for the lower elasticity in our results is that the Italian domestic market is characterized by relatively short distances and limited modal competition. Only a few city pairs are connected by high-speed rail, the main exception being the Milan-Rome route. The mean cross-price elasticity is 1.44 (standard deviation 1.15).

Table 4: Italian air transport: own and cross price elasticities

	Mean	S.D.
Own price elasticity	-4.31	2.88
Cross price elasticity	1.44	1.15

Marginal costs are obtained by solving equation (13) using the demand parameter estimates. From these, we calculate markups and compare them with observed prices for the full sample and subsamples of LCCs, FSCs, direct, and connecting flights, as reported in Table 5. The average ticket price is 83 US$, lower for LCCs (46 US$) and higher for FSCs (108 US$). Direct flights average 57 US$, while connecting flights average 118 US$. The estimated marginal cost is about 62 US$, lower for LCCs (25 US$) and higher for FSCs (87 US$). The average markup is 21 US$, with both LCCs and FSCs around 22-25 US$. Markups are similar across direct (22 US$) and connecting (20 US$) flights.

Table 5: Italian aviation mark-ups and marginal costs estimates, market averages (US $)

	Price	Mark-up	Marginal Cost
All flights	83	21	62
LCCs	46	22	25
FSCs	108	25	87
Direct	57	22	35
Connecting	118	20	98

5.2 *Estimates of the supply parameters*

The right panel of Table 3 reports the estimated coefficients for the components of marginal cost. As expected, direct flights have lower marginal costs: the coefficient of $DIRECT$ is -32.28

[7] Berry and Jia (2010) report elasticities for leisure travelers of -6.55 in 2006; Ciliberto and Williams (2014) find similar values (-6.1) for 2006-2008, both using nested logit models with two traveler types. Bontemps et al. (2022), in a model without consumer heterogeneity, estimate aggregate elasticities of -4.16 in 2011 and -3.49 in 2016. All these studies are based on US data, while evidence for Europe is more limited. Brons et al. (2002) provide reduced-form estimates for an earlier period when the European market was less mature and LCCs were marginal. Bontemps et al. (2024) estimate a structural model with European data and find an elasticity of -7.28.

and statistically significant. The coefficient of $FUELCOST$ is positive (0.77) and significant, confirming that higher fuel costs increase marginal costs.

6 Counterfactual analysis

This Section presents the counterfactual analysis, which simulates a new market equilibrium following the introduction of electric aircraft (EA). The equilibrium arises from two simultaneous perturbations. On the demand side, the adoption of EA, characterised by net-zero emissions, is expected to increase market shares for products using the new technology. On the supply side, the operating cost structure changes, leading to variations in marginal costs. These two effects interact: changes in marginal costs influence the prices of airlines operating EA, which in turn trigger reactions from competitors in the same markets. The feedback loop continues until market shares and prices converge to a new equilibrium.

As explained in Section 3.1.5, the simulation framework assumes a one-to-one replacement of traditional aircraft with EA and considers two technological scenarios. In the baseline scenario, EA are introduced only on short routes (up to 400 kilometres) with a maximum of 21 passengers, and marginal costs vary within a range between -10 and 0 percent. In the prospective scenario, technological progress allows EA to operate flights of up to 800 kilometres and 90 passengers, with marginal cost variations ranging from -10 to +10 percent. These scenarios provide a stylised yet realistic representation of the current and potential diffusion of EA in short-haul markets.

The results show a marked increase in the number of EA flights when moving from the baseline to the enhanced-technology scenario. In the baseline, only 76 products (0.14 percent of the 54,175 flights in the sample) operate EA. In the prospective scenario, the number rises to 6,973, corresponding to 13 percent of total flights. Given that the dataset covers eight years, this translates into about ten EA flights per year in the baseline and 872 per year in the prospective scenario. Most adoptions occur among full-service carriers (FSCs): in the baseline, 100 percent of EA flights are operated by FSCs, while in the prospective scenario low-cost carriers (LCCs) introduce EA on 1,661 flights (more than 200 per year) but still account for only 24 percent of total adoptions. This pattern suggests that, although LCCs hold large market shares in European and Italian markets, their cost-minimisation strategies and focus on dense, high-demand routes make them less likely to adopt EA, which are more suited to short, thin routes. Conversely, FSCs appear to be the natural early adopters, particularly on peripheral and low-density connections such as those between Sicily and Pantelleria. This distinction has policy implications: FSCs could represent the main target of subsidies supporting the adoption of low-emission technologies, while stronger incentives may be required to induce LCCs to invest in EA.

Prices evolve consistently with marginal cost changes. When marginal costs decrease, prices fall; when they increase, prices rise. In the baseline scenario, a 5 percent reduction in marginal costs reduces average prices by USD 0.002. In the prospective scenario, a 10 percent variation in marginal costs (either positive or negative) produces an average price change of about USD

0.77. The effects are stronger in markets where EA are introduced, as cost reductions translate more directly into price adjustments.

The relationship between changes in marginal costs and prices is summarized by the pass-through distribution in Figure 3. Pass-through is computed as the ratio of the change in price to the change in marginal cost.

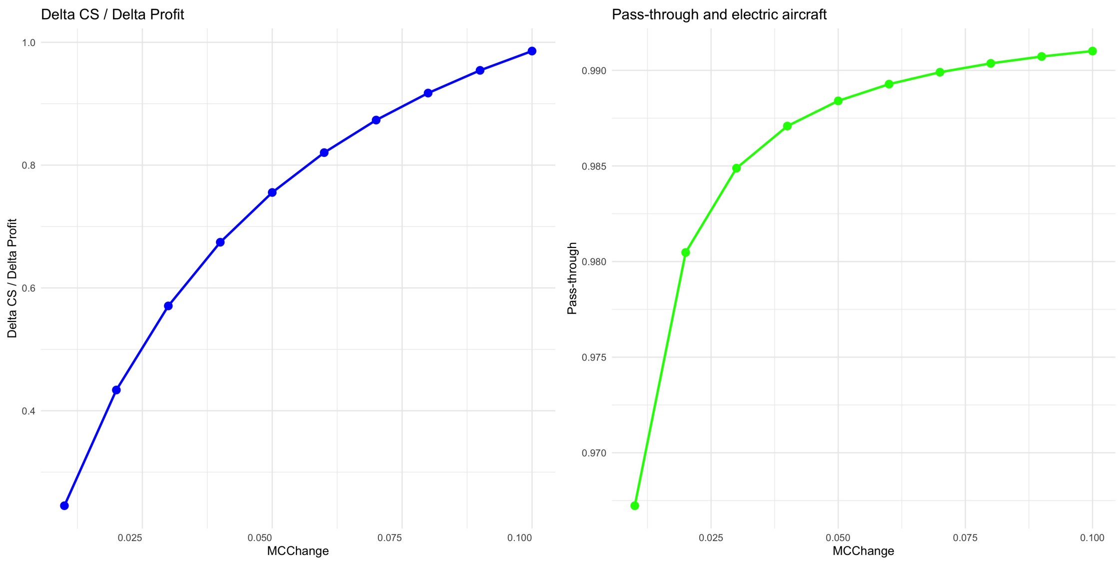

Figure 3: MC to price pass-through in baseline scenario

A value equal to one indicates that the full change in marginal costs is transmitted to prices, while values below or above one reflect partial or excessive pass-through. In the baseline scenario, when marginal costs are reduced by 10 percent, the pass-through is about 0.99, meaning that airlines internalise around 1 percent of cost variations and pass the remaining 99 percent on to consumers. In the prospective scenario, the pass-through exceeds one by about 12 percent, suggesting that prices adjust more than proportionally to cost changes.

The welfare implications of EA adoption are shown in Figures 4 and 5.

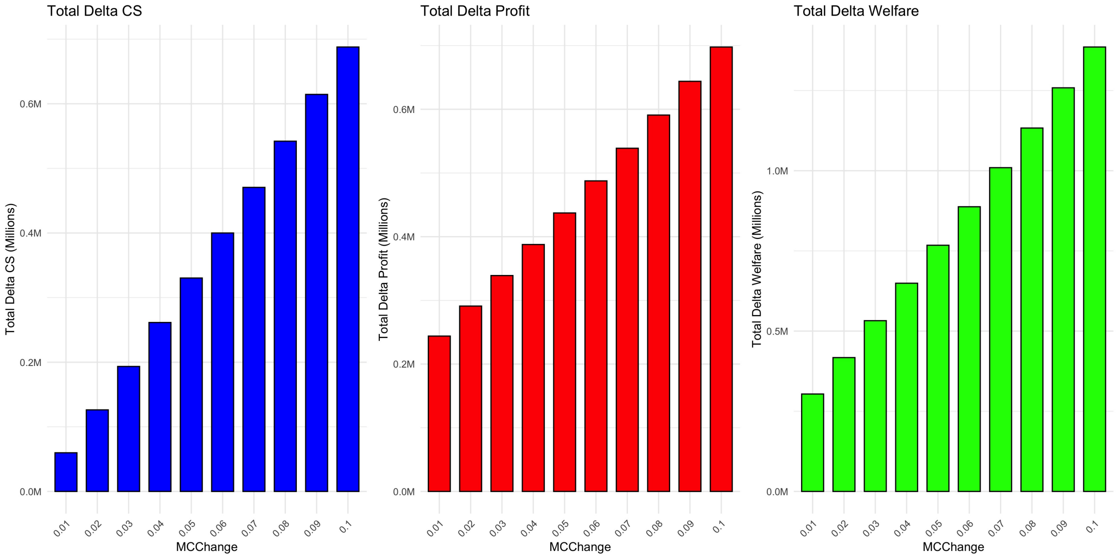

Figure 4: Welfare in baseline scenario

Figure 4 and Figure 5 report changes in consumer surplus (CS), producer surplus (π), and total welfare (W). As expected, lower marginal costs increase aggregate profits, and higher costs reduce them. In the baseline scenario, a 5 percent reduction in marginal costs raises aggregate profits by about USD 0.8 million, while a 10 percent reduction roughly doubles that value.

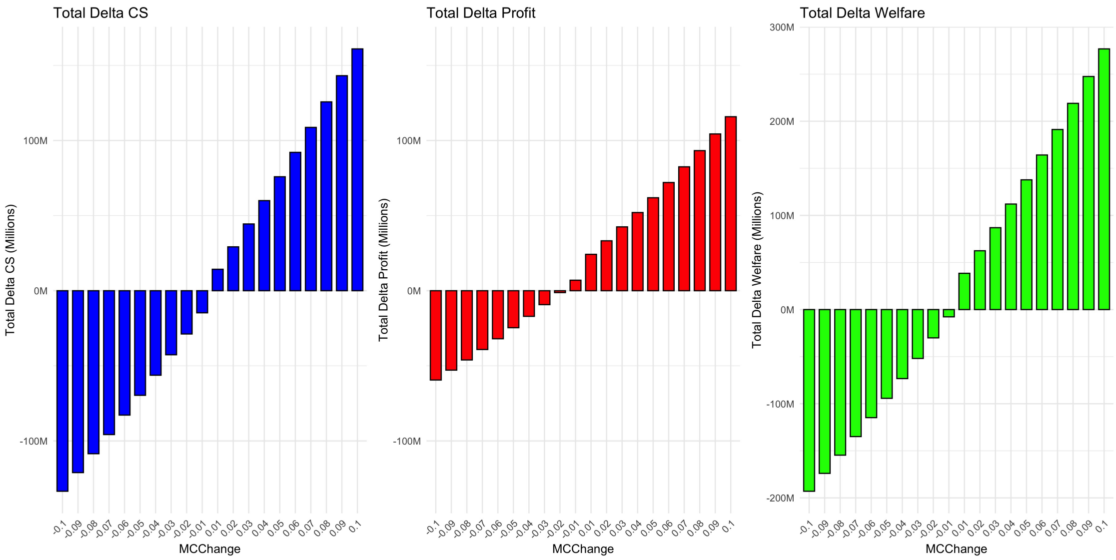

Figure 5: Welfare in prospective scenario

As shown in Figure 5, in the prospective scenario a 10 percent increase in marginal costs reduces profits by about USD 66 million, while a 10 percent decrease increases them by about USD 110 million. Consumer surplus follows the same pattern but with larger magnitudes: in the baseline scenario, CS increases by USD 0.3 million for a 5 percent cost reduction and by USD 0.7 million for a 10 percent reduction. In the prospective scenario, CS decreases by USD 90 million and USD 120 million for cost increases of 5 and 10 percent, respectively, and increases by USD 95 million and USD 160 million when costs fall by the same percentages.

Overall, total welfare increases between about USD 300 thousands in the least favourable baseline case and USD 280 million in the most favourable prospective case (with $\Delta mc = -10\%$). Conversely, when marginal costs rise, total welfare declines between USD 8 million and USD 193 million. Dividing these aggregate welfare changes by the number of products yields per-flight variations between about USD 7 and USD 5,900 per month. When only EA flights are considered, welfare gains are substantially higher, ranging from USD 6,200 per month in the least favourable case to USD 273,675 in the most favourable one.

Finally, decomposing welfare effects between airlines and consumers shows that, under current market conditions, most gains (and losses when costs increase) accrue to airlines. Roughly two-thirds of total welfare variations are captured by producers, while consumers account for the remaining third. Hence, in the absence of structural changes in market competition, the introduction of EA primarily benefits airlines, with more modest gains for passengers.

7 Conclusions

In this paper, we measured the social welfare effects of the introduction of all-electric aircraft. The focus is on the effect intra-industry i.e., on passengers and airlines. We presented the results of empirical work using data from the air transport sector in Italy. The estimation of the welfare effects was done through a structural model typical of empirical industrial organisation work (Berry et al., 1993; Berry, 1994; Berry and Jia, 2010), in which equilibrium is estimated through the interaction of demand (from passengers) and supply (from airlines), and its perturbation due to the introduction, in some routes where it is technologically possible, of all-electrically powered aircraft. This model makes it possible to estimate the social welfare effects and the weight on it of consumer surplus and airline profits. The structural model uses data from 8 years, 2014 to 2019 and 2022–2023.

The results show that social welfare increases only if the introduction of electric aircraft leads to a reduction in marginal costs (MC). When the new technology does not decrease MC, or if it increases it, the potential environmental benefits and demand effects are not sufficient to offset the higher operating costs. Therefore, the net-zero effect on demand does not compensate for a possible increase in MC, leading to an overall decrease in social welfare.

In scenarios where marginal costs decrease, social welfare gains are positive, ranging from about USD 300 thousand in the least favourable baseline case to USD 280 million in the most favourable prospective case (with a 10% reduction in marginal costs). Conversely, when marginal costs increase, total welfare declines, with losses between USD 8 million and USD 193 million. Dividing these aggregate effects by the number of products yields per-product welfare variations between roughly USD 7 and USD 5,900 per month. When considering only the products served by electric aircraft, the welfare gains are substantially larger, ranging from about USD 6,200 per month in the least favourable case to USD 273,675 in the most favourable scenario.

The distribution of social benefits between airlines and consumers also depends on the magnitude and direction of the change in MC. When social welfare increases, airlines capture almost two-thirds of the total benefits, while passengers receive the remaining one-third. This highlights that the welfare impact of electrification is not only a matter of aggregate gain but also of how these gains are shared among market participants.

From a policy perspective, these findings imply that electric aircraft should only be incentivised if they are expected to reduce operating costs, similar to the rationale for electric vehicles in road transport (Palmer et al., 2018). Moreover, Full-Service Carriers (FSCs) play a particularly important role in the adoption of new technology. Due to their operation on both high- and low-demand routes, FSCs are more likely to adopt electric aircraft earlier than Low-Cost Carriers (LCCs). Policy measures should therefore recognise this difference: FSCs should be prioritised or rewarded in adoption subsidies, while LCCs may require larger incentives to make adoption economically viable.

In conclusion, the social welfare effects of electric aircraft adoption are positive only when the new technology delivers meaningful reductions in marginal operating costs. The distribution of gains between consumers and airlines, the limited compensatory role of demand responses, and the predominant involvement of full-service carriers in early adoption all indicate that carefully crafted policies will be crucial to ensure that this transition supports both economic and environmental objectives.

With currently available technology, the welfare impact remains modest, as electric aircraft can operate only on routes constrained by limited range and capacity. While easing these constraints could unlock substantially larger benefits, doing so inevitably introduces greater uncertainty, since the results rely on assumptions that become progressively more speculative. Nonetheless, an additional value of this work lies in the flexibility of the proposed methodology, which can readily incorporate more accurate technological parameters as electric aircraft mature.

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