Carbon Regulation and Competition in European Airline Industry

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Abstract

The European Union Emissions Trading System is set to substantially increase the effective carbon price faced by airlines. To quantify the impact of this carbon regulation on the European airline industry, we estimate a two-stage model of airline competition with endogenous route entry and pricing using European data on market shares and prices. Counterfactual simulations indicate that network changes are concentrated among low-cost and regional carriers, while full-service carriers' networks remain largely unaffected. The simulations also show that the policy benefits Central and Eastern Europe, while hurting long-haul markets. Our analysis further shows that, while the carbon policy can reduce airline profits by up to 17%, it increases consumer surplus by up to 9% and reduces total distance flown—a proxy for emissions—by up to 6.6%. Thus, the tax is largely incident on airlines rather than consumers. These results suggest that carbon regulation can achieve both environmental and welfare gains in airline markets.

Keywords: Carbon Regulation, European Airline Competition, Two-stage Game

JEL Codes: L52, L62, L90

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1 Introduction

The aviation industry's growing share of EU greenhouse gas emissions presents a significant environmental challenge, as near-term technological solutions like new aircraft and Sustainable Aviation Fuels (SAFs) are not yet viable at scale. This gap between climate goals and the slow pace of innovation motivates market-based policies like the EU Emissions Trading System (EU-ETS) to drive emissions reductions. This paper investigates the competitive and network-level effects of such carbon regulations on the European airline industry, analyzing how these policies affect airline competition and endogenous route network formation. We ask: How do the distinct business models of full-service carriers (FSCs) and low-cost carriers (LCC) shape their strategic responses to rising carbon costs? How does regulation alter market structure through route entry and exit? And what are the ultimate consequences for consumer welfare and its geographic distribution across Europe?

The European market's structure is unique, shaped by factors that distinguish it sharply from its North American or Asia-Pacific counterparts. First, because of high population densities, distances between origins and destinations are shorter making indirect flights through hub and spoke systems much less attractive. These high population densities also lead to severe congestion at a large fraction of European airports. The continent hosts nearly half of the world's most congested, slot-coordinated airports (IATA) and features high aircraft utilisation rates. Second, because the European market includes more than 27 countries and was deregulated much later than the US market[1], the market remains highly fragmented despite waves of privatization and consolidation over the past 35 years. In our empirical analysis, we include 14 competing firms. Finally, while state aid to national carriers is prohibited, the FSC's in the European market are all legacy national carriers. There are legacy advantages as well as legacy fixed costs that affect their continuing network shapes and strategies. These legacies result in important asymmetries between FSCs and LLCs.

In summary, European airline networks are dominated by direct point-to-point short-haul flights rather than hub-and spoke. Price competition is intense due to competition from LCCs and due to a fragmented market structure. Overall, LCC market shares are similar to those in the US market (50% in Europe vs 40% in the US.[2])

This market structure gives rise to an intense competitive dynamic and a bifurcation of airline business models. FSCs typically operate from major, congested primary airports, leveraging grandfathered slot allocations, legacy hub cost advantages, and network economies to serve both point-to-point and international connecting traffic. In contrast, LCCs exploit

[1]The European Council adopted three packages of economic liberalisation in 1986, 1990, and 1992, resulting in "a substantially liberalised internal Community market" (Butcher, 2010)

[2]Bontemps et al. (2023).

a point-to-point model, often from smaller, secondary airports minimising operational costs. These divergent strategies create starkly different cost structures and fare strategies; LCCs leverage their operational efficiencies to offer lower base fares and unbundled services, capturing more of the price-sensitive market segment. Crucially, the point-to-point model affords LCCs greater strategic flexibility in network expansion. By serving a wider portfolio of cities, LCCs possess a combinatorially larger set of feasible new routes to enter, allowing them to rapidly redeploy aircraft to capture emerging demand in markets that may be too thin or unprofitable for the more rigid hub-and-spoke structure of an FSC. This fundamentally alters the calculus of route entry and profitability across the continent.

It is within this complex competitive environment that Europe is implementing some of the world's most stringent aviation carbon policies, which are poised to significantly affect airline operations. From 2026, airlines' free allowances of carbon emissions permits under the EU-ETS will be completely phased out. This will dramatically increase the effective carbon price for airlines. This will be compounded by the ReFuelEU (EU Renewable Fuel) mandate which will require that airlines to increase use SAFs between 2025 and 2050. Currently, SAFs are several times more expensive than conventional jet fuel and face significant production shortfalls. These cost shocks will disproportionately impact airlines based on their business models, route structures, and margins, making the interaction between environmental regulation and competition a first-order question for the industry's future.

To answer these questions, we estimate a two-stage game of airline competition. In the first stage, airlines choose their route networks and flight frequencies. In the second stage, they compete on prices. We estimate the model using a rich dataset containing detailed information on the European airline markets networks, prices,and market shares. Our counterfactual analysis simulates the impact of a carbon tax, implemented through the EU-ETS. The simulation finds a new network equilibrium using an iterative algorithm where airlines sequentially re-optimise their route choices.

Our key findings are sixfold. First, our estimates reveal stark differences in the demand and cost structures of FSCs and LCCs, particularly in the valuation of hub airports and the underlying spatial distribution of fixed costs. Second, the impacts of a carbon tax are highly asymmetric: network adjustments are concentrated amongst LCCs and smaller regional carriers, while large FSCs with valuable and congested hubs prove remarkably resilient. Third, the policy induces a significant geographic redistribution of welfare. Central and Eastern European countries benefit from intensified competition on shorter routes, while remote regions like Iceland and Norway suffer from reduced connectivity. Fourth, we find that carbon pricing reduces aggregate airline emissions as airline networks shift towards shorter routes. Fifth, we find that the tax is largely incident on airlines. Airline profits decline significantly while consumer welfare increases. Finally, we find that despite the significant reduction in airline profits, overall, carbon pricing is *total welfare-enhancing* as aggregate increases in consumer welfare and tax revenue outweigh the loss in industry profits. Thus, the policy in aggregate produces a "double dividend" reducing the environmental externality and forcing a competitive reallocation of aircraft that improves allocative efficiency in the imperfectly competitive airline market. This double dividend is not equally distributed; airlines are largely losers and consumers gain.

We contribute to the literature in two main ways. First, we build on structural models of airline competition. While most research focuses on the U.S. market, where hub-and-spoke networks are central to competition ((Berry (1992); Berry and Jia (2010); Aguirregabiria and Ho (2012); Bontemps et al. (2023); Yuan and Barwick (2024))), our analysis focuses on the European market. Existing studies of the European market that have examined specific features such as slot allocation (Marra (2024)), LCC subsidies (Bontemps et al. (2024)), or mergers (Bergantino et al. (2024)), our paper provides the first analysis of the equilibrium impacts of environmental taxation in the imperfectly competitive European airline market.

Second, we advance the literature on the economic impacts of carbon taxation. While many studies focus on the environmental efficacy of carbon pricing (Metcalf (2019); Bayer and Aklin (2020); Timilsina (2022)), we examine how such policies fundamentally reconfigure a large oligopolistic industry. Our approach is similar in spirit to that of Ryan (2012), who studied the U.S. cement industry. We adapt the core insight that environmental policy is not just a cost shock but a catalyst for changes in market structure, concentration, and welfare. This paper is the first to apply this lens to the European airline industry, quantifying the competitive fallout from its unique and stringent carbon policies.

Outline: Section 2 reviews the European airline market and our dataset. Section 3 presents the two-stage model. Section 4 discusses estimation and identification. Section 5 reports parameter estimates. Section 6 presents the counterfactual analysis of the EU-ETS. Section 7 concludes.

2 Background and Data

This section provides background on the European airline industry and describes our data sources and processing steps.

2.1 Background: European Airline Industry

The Rise of European Low-Cost Carriers: Following the deregulation of European aviation in 1992, consolidation of full-service carriers (FSCs) and entry, expansion and consolidation of low-cost carriers (LCCs) have fundamentally reshaped the continent's competitive landscape. LLCs market share have surged from just 5.3% in 2001 to approximately 35% by 2022. Table 1 shows that LCCs account for more than half of all intra-European passenger traffic. The scale of this transformation is exemplified by Ryanair, which in 2023 carried 182 million passengers—more than any single FSC in Europe (Statista). The LCC sector itself is heterogeneous, comprising two main archetypes: subsidiaries of legacy FSC groups (such as Vueling, Eurowings, and Transavia) and independent, 'pure-play' LCCs (such as Ryanair, EasyJet, and Wizz Air). It is this latter group, with its distinct business models, that has been the primary driver of market disruption.

Table 1: Market Share Conditional on Travel

	2016	**2017**	**2018**	**2019**
Low-cost	56.49%	55.97%	55.53%	56.36%
Full-service	43.51%	44.03%	44.47%	43.64%

The primary strategic difference between FSCs and LLCs lies in their network architecture. FSCs, such as British Airways at London-Heathrow, Iberia at Madrid-Barajas, or Air France at Paris-Charles de Gaulle, typically use a *Hub-and-Spoke* model to centralize operations, exploiting legacy cost advantages and economies of scale while funnelling passengers from short-haul intra-European flights into lucrative long-haul services to the rest of the world. In contrast, LCCs use a decentralized *Point-to-Point* (P2P) network, which provides greater routing flexibility by offering direct flights between a wider variety of city pairs.

The distinction is visually apparent in Figure 1, which contrasts the hub-centric network of Air France-KLM with the diffuse, web-like structure of Ryanair. While Ryanair maintains large operational bases at airports like London Stansted, these do not function as connecting hubs for transfer passengers; their strategic role is to serve large origin-destination markets, not to facilitate transfers, underscoring the airline's strict adherence to the P2P model.[3]

Second, cost structures differ markedly. FSCs incur higher per-passenger and per-flight costs, driven by higher legacy labour and fleet costs, operations at expensive hub airports, lower fleet utilisation, and premium offerings like business class and meal services. According to KPMG, the cost per available seat kilometre for LCCs (excluding fuel) is 20%–30% lower

[3]Ryanair operates de facto hubs at London Stansted and Dublin. However, these are primarily used as operational bases for aircraft and do not function as international hubs in the FSC sense. Their significance lies in serving large local markets rather than facilitating connecting traffic.

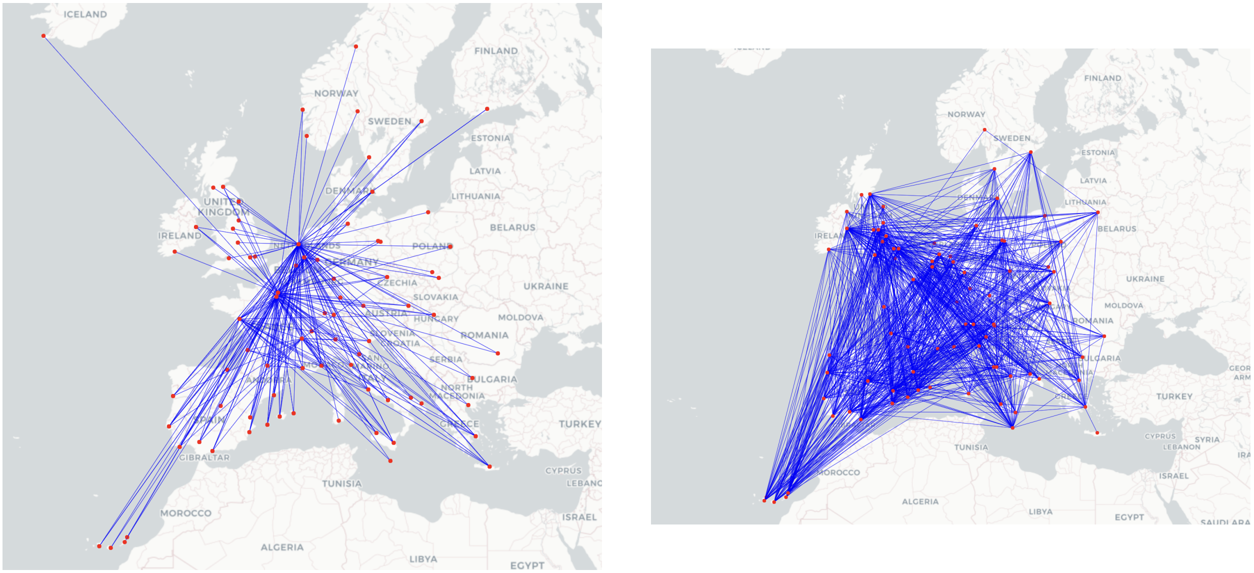

Figure 1: Route Maps of Air France-KLM (left) and Ryanair (right) in Q2 2019

than for FSCs (KPMG), granting them a substantial pricing advantage.

Third, service levels and airport selection strategies diverge. LCCs 'unbundle' their product, earning a significant portion of revenue from ancillary fees for services like baggage handling and seat selection.[4] In contrast, FSCs traditionally offer a more inclusive fare. This strategic bifurcation extends to airport choice, which is particularly notable in Europe's multi-airport metropolitan areas. FSCs typically operate from large international hubs, while LCCs favour smaller, secondary airports. London provides the clearest example across its six airports: Heathrow serves almost exclusively FSCs as the principal international hub; Gatwick accommodates both; Stansted and Luton are major LCC bases; and the City and Southend airports cater to specialised segments.[5] Although Heathrow is the most connected, its severe capacity constraints and high airport charges make it economically unattractive to the LCC business model.

Slot Constraints in European Airports: Europe has many of the world's most congested airports, with major hubs like London Heathrow operating at or near full capacity for decades. Expanding this infrastructure is notoriously difficult, often blocked by regulatory constraints, political opposition, and financial challenges. As a result, airline operations are managed by a rigid system of "slots"—the right to use a runway for a specific takeoff or landing. The allocation of these slots is critical, as Europe is home to nearly half of the

[4]While FSCs increasingly adopt similar pricing practices, they are still generally perceived as offering higher service quality. See: Daily Telegraph.

[5]London City mainly serves business routes (e.g., London–Paris or London–Frankfurt), while Southend is dominated by charter airlines.

world's IATA Level-3 airports, where demand for flights consistently exceeds capacity.[6]

European aviation policymakers have long debated the allocation of scarce airport slots. The current system, established in 1993, relies on "grandfathering," allowing an airline to retain its historical slots if it uses them at least 80% of the time in a season ((European Union)). This "use it or lose it" rule gives established national carriers a powerful advantage, letting them control valuable slot portfolios. The value of these slots has created perverse incentives, such as running near-empty "ghost flights" during periods of low demand simply to meet usage rules and avoid losing the asset.[7]

Table 2 shows that passengers flying with full-service carriers are far more likely to travel through slot-controlled airports than their low-cost counterparts. In our model, we will explore precisely how these airport characteristics shape airline revenues, costs, and network expansion strategies for each carrier type.

Table 2: Share of routes including at least one slot-controlled airport

	2016	**2017**	**2018**	**2019**
Low-cost	15.42%	14.30%	14.54%	15.08%
Full-service	32.91%	33.15%	32.48%	31.96%

Hubs, Airline, and Slot Constraints: The European airline industry has gone through waves of consolidation over the past 35 years. Table 3 lists the current parent airline groups, their associated operating carriers, and designated hub airports, using the industry-standard IATA codes. Airlines are aggregated at the parent company level. For instance, 'IAG' represents the International Airlines Group (IAG) which includes British Airways (BA, the UK's flag carrier), Iberia (Spain's flag carrier), Aer Lingus (Ireland's flag carrier), and the low-cost subsidiary Vueling. IAG's hubs include the hubs of its carriers: London Heathrow (LHR), Madrid-Barajas (MAD) and Dublin (DUB). Carriers within the same parent group typically coordinate operations through code-sharing and provision of complementary routes. All major hub airports used by FSCs are slot-controlled airports; all 18 are designated as Level 3 congested under the IATA system.

Aircraft Utilisation: Aircraft utilisation directly limits an airline's ability to adjust flight frequencies. There are two important features of the 2019 market. First, European carriers operated with high levels of fleet efficiency, meaning most aircraft were already near full operational capacity, leaving little slack to increase total network frequency without

[6]IATA classifies airports into three categories: Level-1 airports have no significant congestion; Level-2 airports may require coordination; Level-3 airports consistently face demand that exceeds available capacity. This system is widely used to measure airport congestion.

[7]This phenomenon was widely reported during the pandemic. See: Forbes.

Table 3: Full service carriers

Parent	Subsidiary airlines	Hubs
IAG	British Airways, Iberia, Aer Lingus, Vueling	LHR, MAD, DUB, BCN, FCO
AF-KLM	Air France, KLM, Transavia	CDG, AMS
LH	Lufthansa, Austria Airline Swiss, Brussels Airline, Eurowings	FRA, MUC, ZRH VIE, BRU
SAS	Scandinavian Airlines	CPH, ARN, OSL
AY	Finnair	HEL
A3	Aegean Airlines	ATH
LO	LOT Polish Airlines	WAW

Note: Hub airports represent the central hubs for all airlines under the same parent company.

expanding fleets.[8] Second, the continent's airlines were not undergoing significant fleet expansion during this period. Given the long lead times for aircraft orders—typically three to five years—rapid capacity growth was not feasible, and no large-scale orders were pending delivery. The high utilisation motivates a key feature of our modelling assumptions: to enter a new route, an airline must reallocate an existing aircraft from another route within its existing network.

2.2 Data

Our data comes from Sabre Market Intelligence (Sabre), a global distribution system that provides travel reservation and pricing tools for many of Europe's largest airlines, including IAG Group, Air France-KLM Group, Lufthansa Group, EasyJet, and Wizz Air. Because this system is actively used by airlines for fare optimisation, it offers highly accurate, itinerary-level pricing information. Our data contains information for 2016 to 2022. We focus our analysis on the most recent pre-covid year, 2019.

The raw Sabre data are organised at the itinerary or route level, defined as a specific airline's service between an origin and destination airport. Each observation includes key characteristics such as average airfare (price), flight frequency, travel time, and passenger volume, aggregated to the quarterly frequency. We choose the top 100 airports by passenger volume and make two key processing decisions. First, given that only 6% of European passengers in our sample travel on connecting flights, we restrict our analysis to the direct flight market. Second, because airlines typically operate return services with nearly identical prices and frequencies, we aggregate directional itineraries into a non-directional route as in Yuan and Barwick (2024) and Bontemps et al. (2023). Finally, we supplement the Sabre data with: (1) metropolitan population data from Eurostat (European Union), which we use

[8] See the report from Eurocontrol

to construct our market size variable, (2) airport-to-airport surface distances obtained via the Google Distance Matrix API.

Table 4 presents summary statistics. The industry is dominated by 14 parent airline groups, with the six largest being the three primary FSCs (IAG, Air France-KLM, and Lufthansa Group) and the three primary LLCs (Ryanair, EasyJet, and Wizz Air). These six account for 87% of all intra-European passenger traffic. We observer 11,292 itineraries or routes in total with 4,039 being monopoly routes and the remaining majority featuring multi-firm competition. The important role of hubs is also evident, with nearly 22% of all itineraries involving a flight to or from a designated hub airport. A typical route in our sample has an average fare of approximately \$86, a frequency of roughly one flight per day, and a travel distance of about 1,400 kilometres (a flight duration of just under two hours). In total, the routes in our 2019 sample served over 350 million passengers.

Table 4: Summary statistics

(a) Sizes:		**(c) Demand and cost**	**Mean**	**St.Dev**
# firms	14	fare (100 USD)	0.86	0.57
# itineraries	11292	frequency (daily)	0.95	1.74
# markets	7025	distance (1,000 km)	1.38	0.73
# hub itineraries	2432	market size (1 million)	2.82	2.01
# monopoly itineraries	4039	product shares	1.48%	2.40%
# city pairs	2003			
# passengers (1 million)	354			
# quarters	4			
(b) Market shares		**(d) Market level statistics**	**Mean**	**St.Dev**
BA	0.16	# products	2.07	1.11
AF	0.09			
LH	0.12			
FR (Ryanair, LLC)	0.25			
U2 (Easyjet, LLC)	0.21			
W6 (Wizz Air, LLC)	0.04			
Other	0.13			

Hub itineraries are defined as those where at least one of the origin or destination airports is classified as a hub airport. Market shares in panel (b) exclude outside options, such as individuals choosing not to travel or opting for alternative modes of transportation. Fares are calculated as the average fare across all tickets for a specific itinerary.

Table 5 reports key summary statistics for each airline's hub cities and their characteristics. While LCCs do not operate formal hubs in the traditional sense, we identify the two most connected cities in each LCC's network for comparative purposes. Panels (a) and (b) reveal that FSCs maintain far greater connectivity from their hubs and operate at significantly higher frequencies, particularly on dense business routes. For instance, Lufthansa Group (LH) operates approximately 40 daily flights between its hubs in Munich and Düsseldorf, while IAG operates 35 between Madrid and Barcelona. This contrast is starkly illustrated in Panels (c) and (d), which measure network concentration. Nearly 70% of Air France–KLM's entire route network touches its hubs in Paris or Amsterdam, a clear empirical signature of a Hub-and-Spoke model. In contrast, LCCs exhibit much lower concentration levels, with their routes more evenly distributed across a wide range of cities, reflecting their decentralised Point-to-Point strategy.[9]

Table 5: Hub airport summary statistics

Airlines	Top Hub	Hub Index	Freq	Second Hub	Hub Index	Freq
(a) Full service:						
IAG	Madrid	60	2.3	London	56	2.6
AF-KLM	Amsterdam	73	2.1	Paris	52	1.9
LH	Frankfurt	66	3.0	Munich	64	4.0
(b) Low Cost:						
FR	Dublin	61	0.9	London	56	1.2
U2	London	61	1.8	Geneva	51	0.7
W6	Budapest	37	0.4	Bucharest	27	0.4
Airlines	Top Hub	Concentration		Second Hub	Concentration	
(c) Full service:						
IAG	Madrid	14%		London	25%	
AF-KLM	Amsterdam	36%		Paris	37%	
LH	Frankfurt	19%		Munich	18%	
(d) Low Cost:						
FR	Dublin	7%		London	7%	
U2	London	12%		Geneva	9%	
W6	Budapest	18%		Bucharest	14%	

Note: The table presents key summary statistics for each airline's hub cities. The Hub Index represents the total number of cities served by the hub, indicating its level of connectivity. Freq refers to the average frequency of all itineraries to/from a specific hub. Concentration refers to the proportion of itineraries to/from this hub city relative to the total number of itineraries.

Table 6 shows that around 43% of all markets are served by more than one airline group. It also shows that the average fare of monopoly markets is higher than that of more competitive markets. Also, the standard deviation of fares in monopoly markets is also higher. Table 7 shows that FSCs operate, on average, nearly two times as many routes involving a hub as LCCs. Table 8 presents the average quarterly change in the number of routes per parent airline. FSCs alter their portfolio of hub-related routes in response to seasonal demand more than LCCs, particularly during the peak summer quarter (Q2).

[9] Wizz Air shows a relatively high concentration rate, primarily because it operated a much smaller network in 2019 compared to the other airlines. This is also reflected in its smaller market share. Since then, Wizz Air has expanded significantly, and its hub concentration is now closer to that of Ryanair and EasyJet.

Table 6: Market Competition and Fare Statistics by Number of Parents

Number of Parents	1	2	3	4	5
Frequency	15,315	8,290	2,490	561	49
Percentage	57.35%	31.04%	9.32%	2.10%	0.18%
Average Fare	1.163	1.073	1.038	1.117	1.113
Std. Dev	0.578	0.456	0.365	0.374	0.426

Total Markets: 26,705; Mean Parents: 1.57; Median: 1.00

Table 7: Average Number of Routes with at Least One Hub per Parent Airline

	2016	2017	2018	2019
Low-cost	201	214	233	239
Full-service	383	384	392	389

Table 8: Average Quarterly Change in Routes per Parent by Quarter

		Q1	Q2	Q3	Q4
All Routes	Low-cost	−13.9	44.0	10.8	−27.9
	Full-service	−9.9	26.3	8.3	−21.7
At least one Hub	Low-cost	−1.3	5.4	2.0	−4.0
	Full-service	−5.0	12.0	3.4	−9.4

Figure 2 shows the passenger share, revenue share, and frequency share for each parent airline. While LCCs like Ryanair (FR) and EasyJet (U2) have the largest passenger shares, FSCs such as IAG (BA) and Lufthansa Group (LH) have the highest revenue and frequency shares, reflecting their focus on premium services and dense schedules.

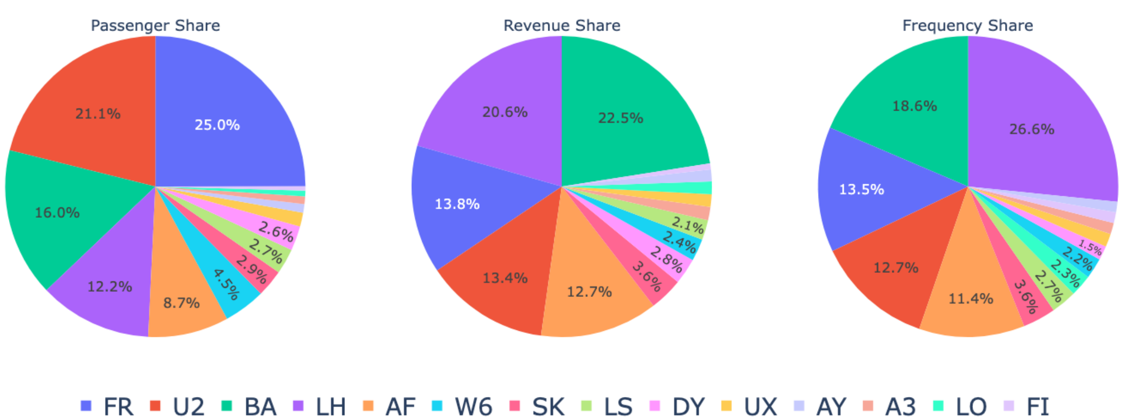

Figure 2: Market Share Analysis

Figure 3 shows a network analysis. The network size is the total number of airports served by each airline. A larger network size implies a broader set of feasible route alternatives. The three largest full-service airlines (AF, BA, LH) and the three largest low-cost carriers (FR, U2, W6) exhibit the largest network sizes. The network density is defined as the ratio of observed routes to total possible routes. We also report the number of observed routes against the number of possible routes. Full-service carriers show lower connectivity across their served cities, reflecting their hub-and-spoke business model. Low-cost carriers have higher network density percentages. The network efficiency, defined as the average number of unique routes per airport, measures how intensively each served airport is used. Low-cost carriers again score higher on this metric: for example, Ryanair (FR) operates on average more than ten unique routes per airport it serves, whereas Air France (AF) averages fewer than three.

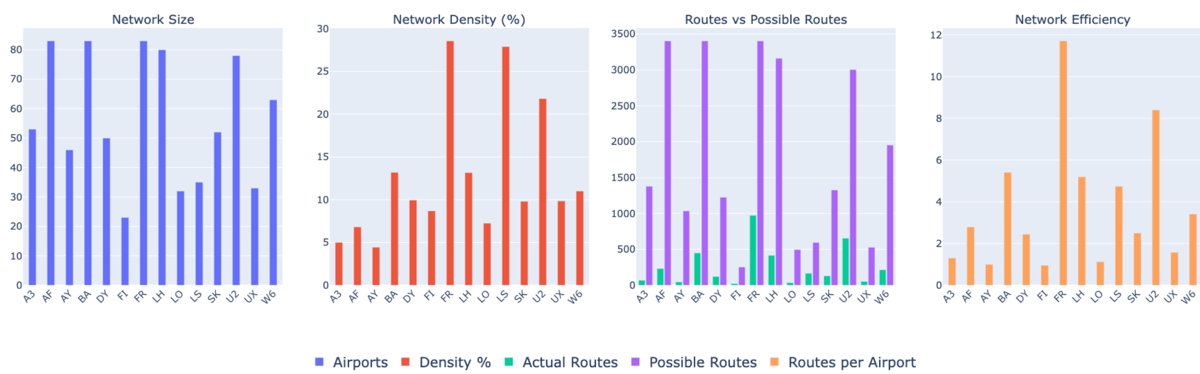

Figure 3: Network Analysis

3 Model

This section introduces a static two-stage model of airlines' entry, flight frequency, and pricing decisions. In the first stage, airlines simultaneously decide routes to enter and flight frequency, thereby shaping the overall flight network. In the second stage, airlines compete on prices to attract customers.

Let $g \in \mathcal{G}$ be an airline group in the intra-European[10] aviation industry, where airlines are defined at the parent group level. A market $m \in \mathcal{M}$ is defined by a non-directional city-pair $c, d \in \mathcal{C}$ where $\mathcal{C}$ is the set of cities.[11] We restrict our analysis to direct flights

[10]Flights to and from Armenia, Azerbaijan, Georgia, Belarus, Moldova, Serbia, Ukraine, Russia, and Turkey are excluded due to their non-compliance with current European aviation policy.

[11]The definition of a market as a city-pair follows Berry (1992); Aguirregabiria and Ho (2012); Yuan and Barwick (2024).

only, which comprise around 94% of air travel in Europe. A product j is defined to be an airline g offering flights between airports $a, b \in \mathcal{A}$ where $\mathcal{A}$ is the set of airports. That is, each j corresponds to a unique (g, a, b). Furthermore, let $j = 0$ denote the outside option of not flying. Let $\mathcal{J}_{gm}$ be the set of products chosen by airline g in stage one of the two stage game. In equilibrium, the set of products available in market m is the outside option $j = 0$ plus $\mathcal{J}_m = \left\{ \bigcup_g \mathcal{J}_{gm} \right\}$. That is, it is the outside option plus the set of products chosen by airlines in stage one. We omit the time subscript t for simplicity, unless otherwise specified and denote the number of products in market m with $J_m = |\mathcal{J}_m|$.

Airline choices and consideration set: Each airline's choices include route network $\mathbf{N}_g$, flight frequencies $\mathbf{F}_g$, and prices $\mathbf{P}_g$ in all routes. The route network $\mathbf{N}_g$ is represented by a vector where element $\mathbf{N}_{g,ab} = 1$ if airline g enters the route between airport a and airport b, and $\mathbf{N}_{g,ab} = 0$ otherwise. We assume that in the short run, an airline can only operate flights in cities in which we observe it operating in Berry (1992). We also assume that if an airline is not operating in a slot controlled airport in 2019, it cannot enter that airport in the short run. Furthermore, an airline can only enter its hub airport in a city unless it is already operating in both its hub and a secondary airport. Finally, an airline can only enter a market that is served by at least one airline. These constraints capture the fact that expanding services in directions outside the support of the observed route network entails greater costs. We assume these greater costs are sufficiently large that such entry is not feasible in our estimation nor in our counterfactual simulation. Let r be a non-directional route defined by a pair of airports (a, b) and $\mathbf{R}_g$ be the set of all feasible routes for airline g.

3.1 Second Stage: Pricing

In the second stage, given route networks and flight frequencies, airlines compete in prices. They simultaneously set prices for all products in each market to maximise profits under complete information.

Demand: The demand model is a discrete-choice model following Berry and Jia (2010) and Yuan and Barwick (2024). For a product j in market m, the utility of consumer i is given by:

$$U_{ijm} = \begin{cases} -\alpha p_{jm} + x_{jm}\beta + \xi_{jm} + \nu_{im}(\lambda) + \lambda\varepsilon_{ijm} & \text{if } j \in \mathcal{J}_m \\ \nu_{im}(\lambda) + \lambda\varepsilon_{ijm} & \text{if } j = 0 \end{cases}$$

where x_{jm} is a vector of product characteristics, p_{jm} is the product price, ξ_{jm} is the unobserved (to researchers) product characteristic, $\nu_{im}(\lambda)$ is the "nested-logit" shock, ε_{ijm} is the i.i.d extreme value type I utility shock, α is the price coefficient, β is the vector of utility parameters, and $\lambda \in (0, 1)$ is the nesting parameter. Let $\theta_d = (\alpha, \beta, \lambda)$ denote the vector of demand parameters.

The product characteristics x_{jm} include distance, distance squared, airline, major hub airport, city, seasonal fixed effects, and the logarithm of flight frequency. Distance terms affect substitution to the outside option. Higher frequency offers consumers more travel options and greater flexibility. Third, we include airline-airport fixed effects for selected major hub airports and their respective national carriers. This fixed effect is important because major European hubs serve not only intra-European passengers but also a substantial volume of intercontinental transfer passengers who fall outside the scope of our analysis.[12] We include this additional fixed effect to control for the influence of intercontinental layover traffic on observed demand patterns at major hub airports.

The model implies that the market share for product j in market m is:

$$s_{jm}(\mathbf{p}_m, \mathbf{x}_m, \boldsymbol{\xi}_m; \theta_d) = \underbrace{\frac{(\sum_{k\in\mathcal{J}_m} \exp((x_{km}\beta - \alpha p_{km} + \xi_{km})/\lambda))^\lambda}{1 + (\sum_{k\in\mathcal{J}_m} \exp((x_{km}\beta - \alpha p_{km} + \xi_{km})/\lambda))^\lambda}}_{\text{Probability of flying}} \times \underbrace{\frac{\exp((x_{jm}\beta - \alpha p_{jm} + \xi_{jm})/\lambda)}{\sum_{k\in\mathcal{J}_m} \exp((x_{km}\beta - \alpha p_{km} + \xi_{km})/\lambda)}}_{\text{Conditional probability of choosing } j}$$

where $\mathbf{p}_m = (p_{km} : k \in \mathcal{J}_m)$, $\mathbf{x}_m = (x_{km} : k \in \mathcal{J}_m)$, and $\boldsymbol{\xi}_m = (\xi_{km} : k \in \mathcal{J}_m)$.

Supply: Airlines simultaneously set prices in each market to maximise profits:

$$\sum_{m\in\mathcal{M}} \sum_{j\in\mathcal{J}_{gm}} (p_{jm} - \mathrm{MC}_{jm}) \cdot s_{jm}(\mathbf{p}_m, \mathbf{x}_m, \boldsymbol{\xi}_m; \theta_d) \cdot \mathrm{MS}_m \quad \forall g$$

where MC_{jm} is the marginal cost of product j in market m and MS_m is the market size defined as the geometric mean of the populations of the two endpoint cities. Let $\mathbf{O}_m$ be the ownership matrix for market m where element (j, k) equals 1 if the same firm owns both products j and k. The Bertrand-Nash F.O.C.s for profit maximisation yield:

$$\mathrm{MC}_m = \mathbf{p}_m + (\mathbf{O}_m \odot \frac{\partial s_m}{\partial p_m})^{-1} s_m$$

where MC_m is a $J_m \times 1$ vector of marginal costs for all products in market m, and $\odot$ denotes the element-wise product.

[12] Specifically, international transfer passengers travelling on a single itinerary with a short layover are not captured in our dataset and are excluded from the demand estimation. However, some travellers choose to extend their stopover to visit the hub city itself. In such cases, the intra-European leg of the journey is included in our demand sample.

The marginal cost function is specified as:

$$\mathrm{MC}_{jm} = w_{jm}\theta_s + \omega_{jm}$$

where w_{jm} is a vector of observable cost shifters, ω_{jm} is an unobserved cost shock, and θ_s is the vector of marginal cost parameters. We include various product characteristics in w_{jm}, such as distance, distance squared, log of flight frequency, airline, city, airport, and seasonal fixed effects.

3.2 First Stage: Entry and Frequency

In the first stage, airlines simultaneously determine their route networks and choose flight frequencies. Airlines incur fixed costs for each active route. For airline g, offering flight network $\mathbf{N}_g$ and flight frequency $\mathbf{F}_g$, we assume that the total fixed cost is:

$$\mathrm{FC}_g(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc}) = \sum_{j \in \mathbf{R}_g} N_{gj} \cdot (z_j(f_{gj})\theta_{fc} + \kappa_{gj})$$

where $z_j(f_j)$ is a vector of observable route characteristics including market size and frequency times distance, κ_j is an unobserved route specific fixed cost shock, and θ_{fc} is a vector of fixed cost parameters.$\boldsymbol{\kappa}_g$ is the vector of all route-specific shocks for airline g. Fuel costs are a fixed cost of operating a route and are proportional to frequency times distance.

We assume that, firms choose their route networks in stage on before the second stage shocks, ξ_{jm} and ω_{jm} are realised.[13] Let $(\mathbf{N}, \mathbf{F}, \mathbf{X}, \mathbf{W})$ be the networks, frequencies, product characteristics, and marginal cost shocks of all airlines in all markets. Then, for each airline g, expected second stage profits can be written:

$$\Pi_{2g}(\mathbf{N}, \mathbf{F}, \mathbf{X}, \mathbf{W}; \theta_d, \theta_c) =$$
$$\mathbb{E}_{\boldsymbol{\xi},\boldsymbol{\omega}}\left[\sum_{m \in \mathcal{M}} \sum_{j \in \mathcal{J}_{gm}} (p_{jm} - \mathrm{MC}_{jm}) \cdot s_{jm}(\mathbf{p}_m, \mathbf{x}_m, \boldsymbol{\xi}_m; \theta_d) \cdot \mathrm{MS}_m\right].$$

In this expression, $\mathbf{p}_m$ is the equilibrium price vector that arises in the stage two in market m after the demand and cost shocks $(\boldsymbol{\xi}_m, \boldsymbol{\omega}_m)$ are realised. The expectation is taken over all unobserved demand and cost shocks in all markets. We assume that the demand and cost shocks are independent across markets and products and are identically distributed for each airline. Furthermore, we assume airlines know the distributions of these shocks when

[13]Prior work, including Aguirregabiria and Ho (2012), Sweeting (2013), Eizenberg (2014), and Yuan and Barwick (2024), make an analogous assumption.

making entry and frequency decisions.

We assume that airlines have complete information about all competitors entry cost shocks and simultaneously choose route networks and flight frequencies $(\mathbf{N}_g, \mathbf{F}_g)$ to maximise expected profits net of fixed costs:

$$\Pi_{2g}(\mathbf{N}, \mathbf{F}, \mathbf{X}, \mathbf{W}; \theta_d, \theta_c) - \text{FC}_g(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc})$$

3.3 Equilibrium

The equilibrium of this two-stage game is a subgame perfect pure strategy Nash equilibrium. Airlines solve the second-stage pricing game given the route networks and flight frequencies chosen in the first stage. The equilibrium consists of networks, frequencies, and prices: $\{\mathbf{N}^*, \mathbf{F}^*, \mathbf{P}^*\}$. The existence and uniqueness of equilibrium in the second-stage pricing game are established by Nocke and Schutz (2018) for multi-product nested logit models. However, equilibrium in the first-stage game is not guaranteed to exist, as noted by Bontemps et al. (2023) and Yuan and Barwick (2024). We assume the existence of a first-stage equilibrium, but we do not assume the uniqueness and allow for multiple equilibria.

4 Identification and Estimation Strategies

The identification of demand and cost parameters is straightforward. The identification of the nesting parameter λ follows Berry and Jia (2010). This section focuses on the identification and estimation of the linear fixed-cost parameters θ_{fc} and we omit the demand and marginal cost parameters for brevity.

4.1 Construction of Moment Inequalities

To ease notation, we suppress dependence on $(\mathbf{X}, \mathbf{W}, \theta_c, \theta_d)$ and on the competitors' strategies and unobserved fixed cost shocks.

Let $\Pi_{1g}(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc}) := \Pi_{2g}(\mathbf{N}_g, \mathbf{F}_g) - \text{FC}_g(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc})$ denote airline g's profit conditional on its own actions, its competitors actions, and all other state variables. Assuming observed choices $(\mathbf{N}_g^*, \mathbf{F}_g^*)$ maximise profits, for any alternative actions $(\mathbf{N}_g^a, \mathbf{F}_g^a)$, we have:

$$\Pi_{1g}(\mathbf{A}_g^*, \mathbf{f}_g^*, \boldsymbol{\kappa}_g; \theta_{fc}) - \Pi_{1g}(\mathbf{N}_g^a, \mathbf{F}_g^a, \boldsymbol{\kappa}_g; \theta_{fc}) = \Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc}) + \Delta_g^a(\boldsymbol{\kappa}_g) \geq 0$$

where $\Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc})$ is the difference in profit unrelated to fixed cost shocks and

$\Delta_g^a(\boldsymbol{\kappa}_g)$ is the difference in fixed cost shocks between the observed and alternative networks. Under the linear fixed cost specification, we have:

$$\Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc}) = \Pi_{2g}(\mathbf{N}_g^*, \mathbf{F}_g^*) - \Pi_{2g}(\mathbf{N}_g^a, \mathbf{F}_g^a) - \sum_{j \in \mathbf{R}_g} (z_j^*(f_j^*) N_{gj}^* - z_j^a(f_j^a) N_{gj}^a)\theta_{fc}$$

where $z_j^*(f_j^*)$ and $z_j^a(f_j^a)$ denote the observable route characteristics under the optimal and alternative stage one choices.

We use a vector of non-negative instruments Y that are correlated with changes in profits but uncorrelated with the fixed cost shocks difference to construct the moment inequalities. We have K instruments available and for each instrument Y_k:

$$\mathbb{E}[Y_k \cdot \Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc})] + \underbrace{\mathbb{E}[Y_k \cdot \Delta_g^a(\boldsymbol{\kappa}_g)]}_{=0} \leq 0$$

Then we construct sample moment inequalities to estimate the fixed cost coefficients θ_{fc} following Pakes et al. (2015):

$$\frac{1}{N^a} \sum_{\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a} Y_k \cdot \Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc}) \leq 0 \quad \forall k = 1, ...K$$

where N^a is the number of feasible alternative route networks for airline g.

4.2 Estimation Strategy

Exploring all possible alternative route networks is computationally infeasible because the number of $(\mathbf{N}_g^a, \mathbf{F}_g^a)$ combinations grows exponentially with the number of routes in airline g's network and the number of feasible frequencies for each route. To address this challenge, we consider only a subset of alternative route networks and frequencies.

Alternative Route Network and Frequency: Following Yuan and Barwick (2024) and Bontemps et al. (2023), we consider only single-market deviations. Specifically, if an airline is active in a market, we consider two alternative scenarios: (1) exiting the market while keeping all other routes and frequencies unchanged; and (2) redeploying the same frequency to an alternative route in which the airline is not currently active, while keeping all other routes and frequencies unchanged.

Moment Inequalities under Single-Market Deviations: As we focus on single-market deviations, and only consider direct flights, the demand and pricing conditions in all other markets remain unchanged. Recall that $\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*) = \Pi_{2g}(\mathbf{N}_g^*, \mathbf{F}_g^*) - \mathrm{FC}_g(\mathbf{N}_g^*, \mathbf{F}_g^*)$ is the sum of expected profits net of fixed costs for all routes j^* in the network $\mathbf{N}_g^*$. Let

$(\pi_{1g}(j^*), \pi_{2g}(j^*), \mathrm{fc}(j^*))$ be the components of those profits and costs accruing from route j^*. Then the inequalities arising from single-market deviations can be written:

$$\begin{aligned}\Delta\pi_{1g}(j^*, j^a; \theta_{fc}) =& \pi_{2g}(j^*) - \pi_{2g}(j^a) - (z^*_{j^*} - z^a_{j^a})\theta_{fc} - \kappa_{gj^*} + \kappa_{gj^a} \geq 0 \quad \forall j^* \in \mathbf{N}^*_g, j^a \in \mathbf{R}_g \\ \pi_{2g}(j^*, 0) =& \pi_{1g}(j^*, 0) - \kappa_{j^*} \geq 0 \quad \forall j^* \in \mathbf{N}^*_g\end{aligned}$$

where the second inequality considers deviations that remove planes from service.

Identification: The identification of θ_{fc} relies on the differences in attributes between observed and alternative routes. Any attribute that does not vary across routes—such as a constant term or a full-service airline dummy—cannot be identified through these inequalities. To simulate the counterfactual, we will impose a distributional assumption on the fixed cost shocks.

Table 9 presents the attributes and expected profits of observed and alternative routes by airline. For the Frequency×Distance measure, full-service airlines (FSCs) consistently operate longer routes than low-cost carriers (LCCs) in both observed and alternative networks. This pattern reflects the distinct business models of the two groups. Hub-and-spoke networks naturally link longer city-pairs to one or more hubs, whereas point-to-point strategies favour shorter sectors to maximise daily aircraft utilisation—a hallmark of the European low-cost model.[14]

The percentage change between observed and alternative networks shows that FSCs' alternative routes have higher Frequency×Distance values than their current operations. Because alternative frequencies are the same as the observed frequency, the increase comes from longer average distances. Among LCCs, the picture is more heterogeneous. EasyJet, often described as a "hybrid" or semi-full-service carrier, displays a pattern similar to the FSCs, consistent with its strategy of operating both dense leisure city-pairs and key primary airports. Ryanair's Frequency×Distance shows almost no difference between observed and alternative routes. This is intuitive because Ryanair already operates the most extensive network in Europe, serving nearly every major city-pair of economic relevance, so potential alternatives offer similar distances and therefore limited scope for reallocation. Wizz Air, headquartered in Budapest and heavily focused on Eastern Europe, shows a positive difference (alternative routes shorter on average). Many of its feasible redeployments link medium-sized cities in Central and Eastern Europe, because the largest Eastern European markets are already present in its current network. Several regional carriers, such as Finnair and Icelandair, exhibit very high Frequency×Distance values, reflecting the remote

[14]EUROCONTROL's *Data Snapshots* document the higher average stage length of full-service carriers and the shorter, more numerous sectors flown by European LCCs.

Table 9: Route's attributes and Expected Profits for Observed and Alternative Network

Airline	**Frequency $\times$ Distance**			**Market Size (millions)**			**Expected Variable Profit ($ 1000)**			**Obs. (in 1000)**
	Observed	**Alt.**	**Diff (%)**	**Observed**	**Alt.**	**Diff (%)**	**Observed**	**Alt.**	**Diff (%)**	
Full-Service Airlines										
BA (British Airways)	1,483	2,042	-37.7	3.258	2.622	+19.5	901.2	813.1	+9.8	2,051
AF (Air France)	1,504	2,315	-53.9	3.489	2.587	+25.9	1,090.7	337.3	+69.1	1,386
LH (Lufthansa)	1,613	3,020	-87.3	3.329	2.636	+20.8	603.4	778.5	-29.0	2,127
Low-Cost Airlines										
FR (Ryanair)	611	617	-1.1	2.620	2.944	-12.4	474.7	431.4	+9.1	2,559
U2 (easyJet)	749	1,028	-37.2	2.641	2.748	-4.0	761.2	809.7	-6.4	2,487
W6 (Wizz Air)	479	442	+7.6	2.252	3.160	-40.3	375.0	363.7	+3.0	763
Regional Airlines										
A3 (Aegean)	765	571	+25.4	3.020	3.480	-15.2	213.2	244.6	-14.7	242
AY (Finnair)	1,314	1,099	+16.3	2.026	3.486	-72.0	410.3	686.2	-67.2	136
SK (SAS)	842	1,209	-43.7	2.284	3.456	-51.3	518.5	704.6	-35.9	331
LO (LOT Polish)	1,649	1,737	-5.3	3.230	4.088	-26.6	287.2	403.5	-40.5	60
UX (Air Europa)	971	1,231	-26.8	3.601	4.004	-11.2	506.7	626.8	-23.7	51
DY (Norwegian)	438	661	-50.8	1.798	3.050	-69.7	529.3	668.0	-26.2	237
FI (Icelandair)	3,706	1,595	+57.0	0.937	4.501	-380.2	421.1	684.1	-62.5	21
LS (Jet2)	1,320	827	+37.3	1.956	3.325	-70.0	408.9	417.0	-2.0	124
Market Average	1,072	1,546	-44.2	2.896	2.822	+2.6	679.5	624.5	+8.1	12,578

Notes: Frequency $\times$ Distance measured in daily flights $\times$ km. Market size represents quarterly geometric mean of the population at two endpoints in millions. Alt. denotes alternative routes. Diff (%) shows percentage change from observed to alternative values. Obs. denotes the count of pairs between one observed route and one alternative route in thousands. Full-service airlines comprise legacy carriers, while regional airlines include smaller carriers serving specific markets.

geographic position of their hubs (Helsinki and Reykjavik) and the long sectors required to connect them to the rest of Europe.

FSCs also tend to serve markets with larger populations than LCCs. The difference terms show that FSCs' alternative routes generally connect *smaller* endpoint populations than their observed routes. This is natural because most large European city-pairs are already covered in their current networks, so remaining alternatives involve thinner markets. In contrast, all LCCs have alternative routes with *larger* market size than the observed routes. This reflects their tactical avoidance of certain large markets in the observed network—often to avoid higher landing fees, congestion charges, or labour costs at primary airports—and their focus on secondary airports around major metropolitan areas.[15]

Expected variable profits from second-stage price competition also differ by business model. FSCs earn higher expected profits than LCCs on both observed and alternative routes, reflecting their ability to command price premia through brand reputation, business-class demand, and hub connectivity. The differences between observed and alternative profits are larger for FSCs than for LCCs, a result of strong hub effects. Most of the profitable hub routes for FSCs are already included in their current networks; alternative routes are therefore more likely to be non-hub markets where network economies are weaker and price competition is stronger. This large gap supports our decision to allow hub and non-hub routes within the same full-service airline to follow different distributions of fixed-cost shocks. Among LCCs, profit differences are modest, consistent with already optimised point-to-point schedules and intense fare competition on thick leisure markets. All regional carriers show higher expected profits for alternative routes. Their continued operation of current networks is likely sustained by substantial subsidies and public-service obligations, which reduce the private incentive to redeploy capacity even when profitable alternatives exist.[16]

Large full-service and low-cost carriers have far more observations than regional airlines. On the one hand, this richer data generates greater variation for the moment-inequality estimation. On the other hand, it allows us to estimate the fixed-cost distribution separately for each of the six largest European airlines—a level of flexibility that is rarely achievable in the existing literature.

[15] For example, Ryanair often uses airports such as Charleroi for Brussels and Beauvais for Paris, allowing it to tap large catchment areas while avoiding the high costs of main hubs.

[16] Regional carriers in Europe frequently receive national or EU subsidies, particularly on thin peripheral routes; see European Commission reports on Public Service Obligation (PSO) routes. It is worth noting, however, that large legacy carriers such as Air France also receive state support, especially during crises.

5 Estimation Results

This section presents the estimation results for the demand, marginal cost, and fixed cost components of our model.

5.1 Demand Estimation

Table 10 reports the demand-estimation results for the core parameters and selected fixed effects. We use two types of instruments: (i) the number of products offered in each market, and (ii) the average fare of routes with similar distances[17] The first-stage F-statistic for price is 172.55, and the heteroskedasticity-robust F-statistic is 91.16, indicating strong instrument relevance.

Table 10: Demand Estimation Results: Core Parameters and Selected Fixed Effects

Variable	**Coefficient**		**Variable**	**Coefficient**	
Core Demand Parameters			*Airport FE*		
Price ($100)	−5.426	(0.515)	Amsterdam Schiphol	−0.580	(0.082)
Log Frequency	1.217	(0.037)	Frankfurt Airport	−0.621	(0.105)
Distance (1,000 km)	0.325	(0.163)	Madrid-Barajas	−1.554	(0.118)
Distance^2	0.145	(0.033)	Barcelona-El Prat	−1.701	(0.103)
Nesting Parameter	0.885	(0.054)	Vienna International	−0.742	(0.058)
Q2	0.533	(0.084)			
Q3	0.181	(0.065)	*City FE*		
Q4	−0.018	(0.063)	London/Southend/Cambridge	−1.100	(0.160)
			Paris/Pontoise	−1.309	(0.145)
Airline FE			Amsterdam/Rotterdam	−0.580	(0.082)
British Airways	3.449	(0.401)	Dusseldorf/Dortmund/Cologne	−0.608	(0.194)
Air France	1.663	(0.236)	Rome	−1.412	(0.107)
Lufthansa	3.585	(0.452)	Madrid	−1.554	(0.118)
Ryanair	−0.094	(0.053)			
Wizz Air	−0.263	(0.089)	*Airline-Airport FE*		
			Air France at Paris CDG	1.987	(0.323)
			Air France at Amsterdam Schiphol	1.951	(0.358)
			British Airways at London Heathrow	0.633	(0.417)
			Lufthansa at Frankfurt Airport	−0.037	(0.259)

Notes: Standard errors in parentheses.

The estimated nesting parameter is 0.885 and is significant. In the nested-logit framework, this parameter captures the correlation in unobserved utility among products within the same nest. Here all airline itineraries form one nest and the outside option forms the other. A value close to one indicates strong substitution among airline products and substantial correlation in their unobserved components (for example, common shocks such as weather or macro-demand factors).

[17] Routes with distances between 99% and 101% of the current route.

We convert the estimated coefficients into willingness-to-pay (WTP) measures.[18] On average, consumers are willing to pay about \$22.4 for a one-unit increase in the log of daily flight frequency, reflecting the high value passengers place on schedule convenience. The linear and quadratic distance terms are both positive and significant at the 5% level. Evaluated at the sample mean distance of roughly 1,000 km, consumers marginal WTP is $\frac{0.325+2\times0.145\times1}{|-5.426|} \times 100 \approx \$8.6$. Seasonal preferences are also evident. Relative to the baseline quarter (Q1), consumers value spring (Q2) flights about \$9.8 more and summer (Q3) flights about \$3.3 more, while winter (Q4) shows no significant difference. Carrier and hub effects are also obvious. Full-service airlines receive sizable premia: consumers are willing to pay roughly \$32.7 more to fly with the Air France-KLM Group than with Ryanair on the same route. Air France-KLM also enjoys strong hub advantages: itineraries involving CDG or AMS are valued about \$36 higher than competing services on identical markets. Overall, the WTP estimates highlight the key drivers of consumer choice in European short-haul aviation: a high value on frequency, a non-linear premium for longer distances, pronounced seasonal patterns, and significant brand and hub advantages.

Table 11 reports the summary statistics for the own- and cross-price elasticities implied by the estimated demand parameters. The average own-price elasticity is -4.49, which is close to the estimate reported in Bontemps et al. (2023) (-3.78) and notably more elastic than the values from the two-consumer-type model in Berry and Jia (2010). Elasticities of this magnitude are consistent with evidence from the airline industry, where empirical studies of European short-haul markets typically find own-price elasticities ranging between -3 and -5 for leisure-dominated routes. Such values indicate that passengers are quite sensitive to fare changes: a 1% increase in price leads, on average, to roughly a 4.5% decrease in demand. This high responsiveness reflects the availability of close substitutes—both between airlines on the same city pair and across alternative modes of transport. The cross-price elasticities, while smaller in absolute value, confirm significant substitution across carriers operating in the same market, reinforcing the interpretation of a highly competitive environment.

European air travelers are generally more price sensitive, as documented in both empirical studies and industry reports (see for example, IATA Report.) This heightened sensitivity reflects the greater presence of low-cost carriers, denser and more competitive point-to-point networks, and, on average, lower income levels across Europe. In contrast, the estimated cross-price elasticities are mostly positive, consistent with standard substitution patterns among competing airline products and confirming that passengers readily switch to rival

[18] WTP is calculated as the ratio of the coefficient of interest to the absolute value of the price coefficient. It measures how much more consumers are willing to pay for a one-unit change in a product characteristic, holding utility constant.

carriers when relative fares change.

Table 11: Summary Statistics for Price Elasticities

	5th Percentile	**95th Percentile**	**Mean**	**Variance**
Own-Price Elasticity	−9.96	−1.03	−4.49	9.21
Cross-Price Elasticity	0.03	1.64	0.68	0.32

5.2 Marginal Cost Estimation

Table 12 reports the marginal cost estimates and summary statistics for markup and marginal costs. The average marginal cost per passenger is \$67.6, roughly 30% lower than comparable U.S. estimates such as those in Yuan and Barwick (2024), who report mean marginal costs around \$95 per passenger for similar short-haul markets. This difference is in line with broad industry evidence. European carriers consistently report lower unit operating costs than their U.S. counterparts. For example, IATA cost benchmarking shows that European short-haul airlines have cost per available seat kilometre (CASK) roughly 20-35% below that of major U.S. legacy carriers over the past decade, largely because of a higher share of low-cost carriers, denser route networks, and more efficient aircraft utilisation.[19] Low-cost carriers such as Ryanair and Wizz Air routinely report CASK levels less than half of those of U.S. full-service carriers, and their presence drives average European unit costs downward even for network airlines.

The average route distance in our sample is 1,407 kilometres (about 875 miles), which implies a unit cost of roughly \$0.05 per kilometre or \$0.08 per mile. These figures closely match international benchmarks: Berry and Jia (2010) report about \$0.06 per mile for U.S. domestic flights, while Yuan and Barwick (2024) find around \$0.08 per mile. IATA cost data for European short-haul operations similarly cluster in the \$0.05-\$0.09 per mile range once adjusted for fuel prices and exchange rates, reinforcing the plausibility of our estimates.

The implied markup is also sizeable. The average markup is \$17.9, corresponding to an average percentage markup of 35.2% and an average per-route profit of roughly \$0.56 million. These figures are broadly consistent with European airline financial statements and with the 25-35% margin estimates commonly reported for competitive U.S. domestic routes. Higher airport charges and slot constraints in Europe may also sustain slightly higher margins even in markets served by multiple carriers.

[19] See IATA Annual Review and InterVISTAS (2015) *Estimating Air Travel Demand Elasticities*, which report CASK figures for major world regions.

Table 12: Marginal Cost Estimation Results: Core Parameters and Selected Fixed Effects

Variable	**Coefficient**		**Variable**	**Coefficient**	
Core Cost Parameters			*Airport FE*		
Distance (1,000 km)	0.098	(0.020)	Frankfurt Airport	0.099	(0.011)
Distance^2	0.024	(0.006)	Paris CDG	0.217	(0.026)
Frequency	0.064	(0.005)	London Heathrow	0.175	(0.027)
Q2	0.090	(0.010)	Amsterdam Schiphol	0.117	(0.010)
Q3	0.021	(0.010)			
Q4	−0.006	(0.010)	*City FE*		
			London/Southend/Cambridge	0.150	(0.017)
Airline FE			Paris/Pontoise	0.041	(0.022)
Air France	0.608	(0.019)	Amsterdam/Rotterdam (Randstad)	0.117	(0.01)
British Airways	0.744	(0.016)	Frankfurt/Mannheim	0.099	(0.011)
Lufthansa	0.831	(0.018)	Dusseldorf/Dortmund/Cologne	0.243	(0.022)
Ryanair	0.020	(0.013)			
Wizz Air	−0.044	(0.022)			
Summary Statistics					
Average Marginal Cost	\$67.6				
Average Markup	\$17.9				
Average Percentage Markup	35.2%				
Average Profit	\$560,586				

Notes: Standard errors in parentheses.

The cost coefficients reveal clear economic patterns. Both distance and distance^2 are positive and significant, implying that marginal cost rises at an increasing rate with route length. This convexity reflects the growing cost of fuel, crew time, and maintenance over longer legs and is consistent with engineering cost studies for narrow-body fleets. The coefficient on frequency is also positive, in contrast to many U.S. studies where frequency often lowers marginal cost by spreading fixed expenses across more departures. In Europe, two factors likely drive this difference. First, European carriers operate with consistently high load factors—often above 85%—leaving little unused capacity to absorb additional flights. Second, high-frequency services are typically short-haul "city-hopper" routes (e.g., London-Amsterdam or Madrid-Barcelona) where airlines deploy smaller regional jets with higher per-seat operating costs.[20]

As expected, full-service carriers face higher marginal costs than low-cost airlines, and operating from large hub airports (e.g., FRA, CDG, LHR) is also associated with higher costs. These patterns mirror industry evidence on cost heterogeneity: full-service airlines incur higher labour and service costs, while congested hubs impose higher landing fees and turnaround expenses. The recovered marginal-cost distribution, together with realis-

[20]For example, British Airways frequently operates Embraer 190s from London City Airport to destinations such as Dublin and Amsterdam, which raises per-passenger marginal costs relative to larger narrow-body aircraft.

tic markups and distance-cost relationships, supports the internal consistency of our model and aligns well with both academic estimates and industry cost benchmarks for European short-haul aviation.

5.3 Linear Fixed Cost Estimation

Table 13 reports the fixed cost estimation results. The instrument Y_k includes dummy variables indicating whether a market's exogenous characteristic (e.g., size or population) falls within the k-th evenly-spaced cell. Fewer instruments lead to a wider estimate set. However, overloading the number of instruments can result in an empty estimate set. We increase the number of instruments until an empty set is reached. Then, we report the most precise estimate set.

Table 13: Entry Cost Estimation (in $100s)

IV Count		Frequency × Distance		Market Size	
Diff. Ineq.	**Obs. Ineq.**	**Lower**	**Upper**	**Lower**	**Upper**
20	10	770	1,743	445	834
	20	770	1,657	445	834
	30	770	1,657	445	834
30	10	1,086	1,417	433	654
	20	1,086	1,417	433	654
	30	1,086	1,387	433	654
40	10	Empty Set		Empty Set	
	20	Empty Set		Empty Set	
	30	Empty Set		Empty Set	

Notes: Each coefficient is set-identified using moment inequalities. "Diff. Ineq." refers to difference-based moment inequalities requiring the observed route to have the highest expected profit among alternatives. "Obs. Ineq." refers to moment inequalities requiring observed routes to have non-negative profits. Both sets use Market Size and Distance as instruments, with counts shown in the first two columns. Frequency × Distance measured in daily flights × thousands of kilometers. Market size is the geometric mean of endpoint populations in millions.

The estimation results show that, at the sample averages (Distance = 1,350 km; Market size = 2.896 million), the implied *per-flight* linear component of the fixed cost (distance term + market-size term) evaluates to the midpoint value[21] of approximately $3,602.89.

[21]Computation (units: USD per flight; coefficients reported in the table are in $100s):

$$\text{Distance part} = \frac{(1086 + 1387)}{2} \times 100 \div 90 \times 1.350 = 1236.5 \times 100 \div 90 \times 1.350 \approx 1{,}854.80,$$

$$\text{Market size part} = \frac{(433 + 654)}{2} \times 100 \div 90 \times 2.896 = 543.5 \times 100 \div 90 \times 2.896 \approx 1{,}748.09,$$

$$\text{Total (Distance + Market)} \approx 1{,}854.80 + 1{,}748.09 \approx \$\mathbf{3{,}602.89}.$$

We clarify the economic interpretation of the \$3.6k fixed-cost component through three key considerations, contextualised within European airline industry benchmarks.

First, the \$3.6k figure is not the total "per-flight" operating cost reported in airline financial statements. Instead, it represents the specific component of fixed costs that scales linearly with distance and market size within our econometric specification. Industry-standard cost metrics typically reported on a per-flight basis—such as fuel allocated by available seat-kilometres (ASK), variable handling fees, or aircraft turnaround costs—are captured both within our marginal-cost and fixed cost estimates.

Second, industry benchmarking employs standardised metrics such as CASK (cost per available seat-kilometre). European carriers exhibit substantial variation: ultra-low-cost carriers report CASK values of 3.2-4.2 US cents, while full-service carriers exceed 10 US cents (CAPA, 2025; Wizz Air H1 FY24). Since CASK declines systematically with stage length, converting to per-flight equivalents requires aircraft-specific adjustments. For narrowbody aircraft typical of European short-haul operations, industry sources report operating costs of \$2,900-\$3,200 per block hour for A320/B737 aircraft (OPShots, 2015; Simple Flying, 2024), suggesting a 1.5-hour flight at 1,300km incurs approximately \$4,350-\$4,800 in total costs. Within this context, our \$3.6k estimate represents a reasonable fixed-cost component, accounting for roughly 75-80% of total per-flight costs.

Third, our fixed cost shock does not have mean zero, which implies that a portion of the true per-flight fixed cost could be partially absorbed into the intercept term. Specifically, total per-flight fixed cost comprises three components: (i) the linear term computed here (\$3.6k), (ii) the intercept (mean of the fixed cost shock), and (iii) the route-specific idiosyncratic shock. Therefore, actual per-flight fixed costs (linear component + intercept + shock) will exceed \$3.6k in many cases. Industry evidence confirms substantial variation in total costs: European low-cost carriers report per-passenger costs ranging from €40 for Ryanair to €79 for easyJet (excluding fuel), while legacy carriers like IAG and Lufthansa operate at €159-164 per passenger (The Flight Club, 2025). With typical load factors of 85-90% on 150-180 seat aircraft, this translates to per-flight costs varying from approximately \$5,100 to \$25,000 across different business models (EUROCONTROL, 2024), supporting our framework where fixed costs include both the linear component and additional stochastic elements.

6 Counterfactual Experiment on Carbon Policy

Carbon taxation has emerged as a pivotal policy instrument in the European aviation industry, with significant implications for airline operational costs and route economics. The current regulatory framework centres on the EU Emissions Trading System (EU ETS), which has experienced substantial price volatility and structural reforms in recent years. According to the International Emissions Trading Association, the average EU ETS carbon price is expected to rise from €84.4 per tonne during 2022-2025 to almost €100 per tonne during 2026-2030 (Statista). Critically, the system's application to aviation has been significantly strengthened, with 25% fewer free allowances allocated to aircraft operators in 2024, and complete removal of free allocation scheduled for 2026 (European Commission). This regulatory tightening ensures that airlines will face substantially higher carbon costs in the immediate future.

International organisations project even more dramatic carbon price escalations over the coming decades. Advanced modelling by Enerdata indicates that EU ETS prices will progressively increase after 2030, reaching around €130/tCO2 in 2040, before rapidly escalating to exceed €500/tCO2 by 2044 (Enerdata). These projections, spanning from approximately \$100 to \$500 per tonne over the next two decades, translate to substantial operational cost increases for airlines. For typical narrow-body aircraft operating intra-European routes, these carbon prices correspond to additional costs ranging from approximately \$1 to \$5 per kilometre flown, depending on fuel efficiency and carbon content assumptions.

Concurrent with carbon pricing pressures, the aviation industry faces mounting fuel cost challenges through two primary mechanisms. First, conventional aviation fuel supplies are increasingly constrained by environmental regulations and policy frameworks designed to reduce fossil fuel dependency. Second, mandatory sustainable aviation fuel (SAF) adoption requirements impose substantial cost premiums on airlines. Current market data indicates that SAF costs between two to seven times more than traditional jet fuel, while EASA's 2024 assessment shows conventional aviation fuel priced at €734 per tonne compared to aviation biofuels at €2,085 per tonne. Industry projections suggest that SAF prices will remain two to three times higher than conventional jet fuel until 2030 (World Economic Forum), creating persistent upward pressure on airline fuel costs beyond carbon taxation effects.

Given these converging cost pressures from both carbon pricing mechanisms and fuel supply constraints, we implement five counterfactual scenarios that increase the Frequency $\times$ Distance coefficient by 1,000, 2,000, 3,000, 4,000, and 5,000 respectively. This experiment captures the combined effects of escalating carbon taxation and higher fuel prices within a range of \$1-5 per additional kilometre flown. The lower bound reflects current EU ETS price levels with modest SAF adoption, while the upper bound corresponds to high carbon price scenarios with extensive SAF mandates.

Airline competition also plays a crucial role in route network choices. While the increased coefficients incentivise airlines to favour shorter routes, the change in route network affects all airlines' expected variable profits.

In Section 5.3 we estimated bounds on fixed costs and did not make any assumptions about the distribution of fixed costs other than independence across products. To simulate counterfactuals, we use an additional assumption on the distribution of fixed costs, assuming these are drawn from a parametric distribution consistent with the bounds estimated in Section 5.3. Section 6.1 discusses estimation of the fixed cost distribution under this additional assumption. The counterfactual equilibrium concept and algorithm are described in Section 6.2. Section 6.3 presents the counterfactual results.

6.1 Fixed Cost Distribution Estimation

As noted above, we assume that fixed costs are independent across products. In addition, we classify routes into T types and assume that for each route j of type τ_j fixed costs are normally distributed:

$$\kappa_j \sim \mathcal{N}(\mu(\tau_j), \sigma^2(\tau_j)).$$

The mean is the average fixed entry cost for routes of type τ_j. We define route types as follows: routes offered by the three largest full-service airlines (BA, AF, LH) including hub airports, these same airlines' routes excluding hub airports, routes offered by the three largest LLCs (FR, U2, W6), and routes offered by a pooled group of smaller airlines including and excluding hubs. This specification captures differences in entry costs across FSCs and LLCs and across hub and non-hub airports. There are 11 route types in total.

In Section 4.2, the single market deviation implies the following two set of inequalities: for any airline g, observed product j^*, and alternative product j', we have:

$$\begin{aligned}
&\pi_{2g}(j^*) - \pi_{2g}(j^a) - (z_{j^*} - z_{j'})\theta_{fc} - \kappa_{j^*} + \kappa_{j'} \geq 0 \quad \forall j^* \in \mathbf{N}_g^*, j' \in \mathcal{J}_{\text{alt}} \\
&\pi_{2g}(j^*) - z_{j^*}\theta_{fc} - \kappa_{j^*} \geq 0 \quad \forall j^* \in \mathbf{N}_g^*
\end{aligned}$$

where $\mathcal{J}_{\text{alt}}$ is the set of feasible alternative routes for the observed route j^*.

The marginal likelihood of observing route j^* is given by:

$$\int_{-\infty}^{\pi_{2g}(j^*)} \prod_{j' \in \mathcal{J}_{\text{alt}}} \Phi\left(\frac{\pi_{2g}(j^*) - \pi_{2g}(j') - \kappa_{j^*} + \mu(\tau_{j'})}{\sigma(\tau_{j'})}\right) \phi\left(\frac{\kappa_{j^*}}{\sigma(\tau_{j^*})}\right) \frac{1}{\sigma(\tau_{j^*})} d\kappa_{j^*}$$

and the partial log-likelihood function for all observed routes is:

$$\sum_{j^*} \log \int_{-\infty}^{\pi_{2gj}(j^*)} \prod_{j' \in \mathcal{J}_{\mathrm{alt}}} \Phi\left(\frac{\pi_{2g}(j^*) - \pi_{2g}(j') - \kappa_{j^*} + \mu(\tau_{j'})}{\sigma(\tau_{gj'})}\right) \phi\left(\frac{\kappa_{j^*}}{\sigma(\tau_{j^*})}\right) \frac{1}{\sigma(\tau_{gj^*})} d\kappa_{j^*}$$

Table 14 reports the estimation results for the lower bound, middle point, and upper bound of the linear fixed-cost parameter estimates. They yield similar estimates for the mean and standard deviation of the fixed cost shock distributions across all airline groups. Hub routes for all full-service airlines exhibit negative mean fixed, while all non-hub routes and routes operated by low-cost carriers demonstrate consistently positive means.

Table 14: Distribution for Fixed Cost Shocks by Airlines and Hub Status

		Lower Bound		Middle Point		Upper Bound	
Airline	Route Type	μ	σ	μ	σ	μ	σ
Full-Service Airlines							
Air France	Non-hub	3.59	3.82	3.69	3.87	3.94	3.99
	Hub	−3.61	4.17	−3.72	4.19	−3.97	4.26
British Airways	Non-hub	5.08	4.99	5.08	5.00	5.08	5.04
	Hub	−2.97	4.22	−2.97	4.27	−2.97	4.36
Lufthansa	Non-hub	5.53	4.22	5.53	4.24	1.66	4.39
	Hub	−3.16	4.99	−3.16	5.03	−7.47	5.08
Low-Cost Airlines							
Ryanair	All routes	2.87	3.61	2.87	3.62	2.87	3.67
easyJet	All routes	8.18	7.20	8.18	7.17	8.18	7.13
Wizz Air	All routes	5.07	2.61	5.07	2.61	5.07	2.64
Pooled (Other Airlines)							
Pooled	Non-hub	5.64	3.67	6.11	3.72	5.61	3.70
	Hub	−10.22	2.12	−10.05	2.15	−10.53	2.19

Notes: The means and standard deviations are in $\$10^5$. Each column block corresponds to lower bound, middle point, and upper bound of the linear fixed-cost parameter estimates.

The negative hub route's mean indicates the lower fixed entry costs for these routes, which can be explained by established industry knowledge and practices. First, European full-service airlines frequently benefit from extensive government incentive schemes and subsidies, which fundamentally differs from the competitive landscape faced by major US carriers. Many European airlines remain government-owned or receive substantial state support. Research by Transport & Environment reveals that the aviation sector receives €26.4 billion of indirect subsidies annually through tax breaks on VAT (€13.6 billion) and fuel tax exemptions (€10.7 billion) (Transport & Environment). This contrasts sharply with the operational environment of the major US carriers, which operate as privately-owned entities with limited government support. The European model of state involvement creates implicit incentives for maintaining certain routes that serve broader economic or political objectives beyond pure commercial viability. Second, the fundamental purpose of many hub routes operated by major full-service airlines in Europe is to facilitate international transfer passengers connecting to or from long-haul flights (Centreforaviation.com). Evaluating these routes in isolation, considering only point-to-point demand, would rarely demonstrate profitability. The network effects and connecting passenger flows create substantial value that is not captured in simple route-level analysis.

Ryanair's fixed entry cost is the lowest in the sample, a result consistent with its ultra-low-cost operational model. In contrast, easyJet's higher entry costs reflect a significant strategic divergence. Unlike Ryanair's exclusive focus on secondary airports, easyJet deliberately operates from primary airports at considerably higher costs, positioning itself to compete directly with full-service airlines at their traditional hub airports (Industry Report). This strategic choice necessitates substantially higher entry costs as easyJet must overcome the established advantages of incumbent full-service carriers while operating in more expensive airport environments. The airline's emphasis on higher frequency services and premium airport access creates natural barriers to entry that require substantial initial investment to establish competitive viability.

Our estimates of fixed entry costs align closely with established industry benchmarks. For instance, the estimated entry cost for British Airways on an average non-hub route approximates \$0.5 million per quarter, translating to nearly \$2 million annually. Industry reports indicate that route establishment costs typically range between \$1.5-3 million annually for full-service carriers on medium-haul European routes (IATA Airline Profitability Report). These estimates encompass not only direct operational costs but also substantial fixed investments required for viable route operations, including airport slot acquisition (exceeding \$500,000 for premium European airports), ground handling arrangements, marketing expenditure, and regulatory compliance costs.

6.2 Counterfactual Simulation Algorithm

As discussed in Section 4.2, solving an equilibrium for the entire network is computationally feasible. We restrict airlines' action space to single-market deviations.

Simulation Algorithm: We fix the set of feasible routes for each airline throughout the counterfactual simulation. If a city is served by an airline, it is likely that this airline will maintain some presence in this city, even if it exits the city in later counterfactual iterations. For each quarter, we rank markets based on total revenues, and airlines in a market based on their revenues.[22]

Then, we begin with the market with the highest total revenue. For each airline in that market, starting from the airline with the highest revenue, we evaluate whether redeploying its aircraft (frequency) to an alternative route would yield a higher expected net profit. If an airline finds a more profitable alternative route, it deviates accordingly. In addition, if the expected net profit of the current route is negative, the airline exits the market. After all airlines in the market have been evaluated and potential deviations executed, we proceed to the next market in the revenue ranking and repeat the process. After a market has been processed, the rankings of airlines in subsequent markets are updated if an airline has entered that market. The ranking of markets are updated after all markets have been visited. This continues until all markets have been visited. This ordering mimics real-world behaviour, as airlines typically prioritise larger markets over smaller ones and are likely to make decisions for larger markets first. Also, larger airlines in a market are likely established incumbents, while other smaller airlines are likely followers.

Drawing Fixed Cost Shock: We need to draw fixed cost shocks to ensure the observed route network satisfies the single-market deviation constraints. Our dataset contains 64,661 Quarter-Airline-Route combinations. We first draw $\hat{\kappa}_{j'}$ for all alternative routes. Then, $\hat{\kappa}_{j^*}$ is drawn from the truncated normal distribution with the following upper bound:

$$\hat{\kappa}_{j^*} \leq \min_{j' \in \mathcal{J}_{\text{alt}}} \{\pi_{2g}(j^*) - \pi_{2g}(j') - (z_{j^*} - z_{j'})\theta_{fc} - \hat{\kappa}_{j'}\}$$

Note that all variables depend on f_j^* which is held fixed.

6.3 Counterfactual Results

We simulate counterfactuals separately for 4 quarters, 5 carbon prices, and 3 linear fixed-cost parameter estimates (lower bound, middle point, and upper bound). In all cases, the algorithm converged, with convergence occurring on average around 5 iterations. Table 15 presents the counterfactual results by airline type.

Total Routes denotes the total number of unique routes in our sample. Unsurprisingly, the summer peak season (Q2, Q3) features substantially more routes than the winter off-peak season (Q1, Q4). Low-cost carriers contribute the majority of unique routes, followed by full-service airlines and regional carriers. This distribution reflects the European aviation market structure, where low-cost carriers have significantly expanded their route networks following liberalisation.

[22] For the counterfactual simulation, we use the same 36 draws of ξ and ω as in the estimation of linear fixed cost parameters.

Table 15: Network Analysis Results - All Carbon Scenarios

Metric	Low				Medium				High				VHigh				UHigh			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Total Routes																				
All	2406	2868	2978	2523	2406	2868	2978	2523	2406	2868	2978	2523	2406	2868	2978	2523	2406	2868	2978	2523
Full Service	730	863	909	771	730	863	909	771	730	863	909	771	730	863	909	771	730	863	909	771
Low Cost	1276	1481	1520	1336	1276	1481	1520	1336	1276	1481	1520	1336	1276	1481	1520	1336	1276	1481	1520	1336
Regional	400	524	549	416	400	524	549	416	400	524	549	416	400	524	549	416	400	524	549	416
Total Deviations																				
All	86	100	40	84	120	150	60	100	136	176	62	116	166	194	86	144	176	222	110	188
Full Service	26	26	8	18	32	38	12	22	36	38	12	24	42	40	16	36	44	54	28	46
Low Cost	16	20	8	24	24	28	10	26	30	32	12	30	34	38	18	28	40	46	20	38
Regional	44	54	24	42	64	84	38	52	70	106	38	62	90	116	52	80	92	122	62	104
Exit Number																				
All	28	7	15	16	32	10	15	17	33	10	15	18	37	29	15	20	51	38	17	28
Full Service	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Low Cost	28	7	15	16	30	7	15	16	29	7	15	16	27	7	15	16	29	7	15	16
Regional	0	0	0	0	2	3	0	1	4	3	0	2	10	22	0	4	22	31	2	10
Total Markets																				
All	1548	1811	1867	1615	1548	1811	1867	1615	1548	1811	1867	1615	1548	1811	1867	1615	1548	1811	1867	1615
Full Service	659	783	828	702	660	787	829	704	661	786	829	706	662	787	829	708	663	790	830	708
Low Cost	1084	1258	1279	1126	1085	1263	1279	1126	1086	1264	1279	1128	1088	1265	1281	1128	1089	1266	1281	1132
Regional	363	466	484	381	370	473	488	385	373	478	491	389	377	490	496	396	376	491	497	403
Changed Markets																				
All	91	80	45	69	121	115	59	90	136	137	65	103	162	168	81	125	178	194	95	163
Full Service	23	24	8	15	29	35	11	19	34	35	11	22	39	35	14	34	42	49	25	44
Low Cost	43	26	22	37	51	34	24	41	54	37	26	45	55	41	32	42	62	47	34	52
Regional	39	47	18	36	59	72	30	46	67	90	34	58	90	121	47	74	101	134	55	104
Affected Routes																				
All	213	183	95	154	277	268	125	208	312	323	140	236	375	372	175	282	401	433	202	365
Full Service	29	28	6	15	37	35	10	16	39	40	10	17	47	38	13	34	52	54	24	43
Low Cost	49	27	23	36	60	34	25	44	64	39	27	47	62	41	36	43	69	47	39	52
Regional	37	42	17	32	51	63	26	41	58	81	29	51	85	99	41	61	96	113	49	86
Total Iterations																				
Counts	3	3	2	3	5	4	3	3	4	3	3	3	4	13	4	3	4	6	4	3

Total Deviations measures the reallocation of aircraft to different routes by exiting current markets and entering new ones. The number of deviations increases monotonically with carbon cost intensity—from 40 under low carbon costs to 222 under ultra-high costs in peak season. while deviations represent approximately 3–7% of total routes, their impact extends far beyond this percentage, as discussed below. Crucially, the burden falls disproportionately on regional carriers, who can account for over 120 deviations compared to just 8–54 for larger airlines. This fragility stems from regional airlines' longer average route lengths and thinner profit margins. In contrast, full-service carriers benefit from hub economies of scale and established market positions, while low-cost carriers operate higher-frequency, shorter-haul routes that are less carbon-intensive per passenger-kilometre.

Exit Number captures routes where airlines withdraw completely rather than redeploying aircraft. Pure exits increase substantially with carbon costs, rising from as few as 7 to as many as 51 under extreme scenarios. Remarkably, exits concentrate almost exclusively amongst low-cost carriers, with only scattered exits by regional carriers and virtually none by full-service airlines across all scenarios. This pattern reflects the thin operating margins inherent to the low-cost business model, as evidenced by the lower expected variable profits shown in Table 9. The near-complete absence of full-service carrier exits underscores the powerful role of hub networks and sunk investments in maintaining route viability even under extreme carbon pricing—a finding consistent with evidence that full-service airlines exhibit greater route persistence due to network effects and slot constraints at major airports.

Total Markets refers to unique city pairs served in our sample. *Changed Markets* denotes city pairs experiencing altered market structure between counterfactual and observed networks, where market structure encompasses all product offerings governing competitive dynamics. Regional airlines again show the greatest sensitivity: under ultra-high carbon costs, approximately 25–27% of regional airline markets experience structural changes, compared to less than 10% for full-service and low-cost carriers. This disparity reflects regional carriers' focus on thinner routes with fewer competitors, where the exit or entry of even a single airline fundamentally alters market conditions.

Affected Routes quantifies all routes in the observed network experiencing market structure changes. Revenue and profit or those routes change despite unchanged exogenous attributes through competitive spillovers. Notably, the affected routes can reach 10–20% of the total network—substantially exceeding the direct impact measured by total deviations alone. This multiplier effect demonstrates that carbon pricing's competitive consequences extend well beyond the routes directly restructured. Unlike previous metrics, affected routes distribute more evenly across airline types relative to their network sizes, suggesting that competitive interdependencies propagate throughout the network regardless of the type of airlines.

In summary, carbon pricing triggers cascading effects throughout the European aviation network, with regional carriers bearing disproportionate adjustment costs while full-service carriers demonstrate remarkable resilience. Crucially, the true economic impact extends far beyond the routes directly restructured: competitive spillovers affect a substantial portion of the network, with up to 433 routes experiencing altered profit conditions in peak season under ultra-high carbon costs. This multiplier effect—where market structure changes propagate throughout interconnected city-pair markets—highlights the critical importance of general equilibrium considerations in transport policy evaluation. Analyses focusing solely on direct route adjustments would severely underestimate the policy's full economic consequences.

How do ticket prices, passenger numbers, and airlines' net profits adjust when an additional carbon cost is imposed and the route network is re-optimised? Addressing these questions clarifies which types of routes shift for different airline groups and sets up the welfare analysis that follows. Table 16 reports the results for Q2, which we highlight because the Q2 network is the largest and therefore most informative; the other quarters display very similar patterns.

We report average fares separately for routes that are *common* to both the baseline and counterfactual networks and for routes that appear only in one network (i.e., *non-common* routes that are either newly added or dropped). Average fares on common routes remain stable across scenarios because the underlying market structure on those links—such as the set of active competitors and their relative positions—changes little, so second-stage pricing incentives are largely preserved. In contrast, for non-common routes, the pattern depends on airline type. For large full-service and low-cost carriers, the routes that are discontinued or replaced tend to have below-average fares, which suggests that re-optimisation targets links where competition is stronger and price premia are limited—often because the routes do not connect hubs or major cities and hence cannot sustain higher markups. For small regional carriers, however, the deviated (dropped) routes typically have higher average fares; these links are frequently (near-)monopoly services connecting remote, long-distance pairs that are relatively costly to operate under higher carbon prices and that face thinner demand.

The mechanism linking carbon costs to fares operates through the network rather than directly through prices in our two-stage framework. In the second stage, pricing depends on the contemporaneous competitive structure of the realised network, not directly on costs. Consequently, higher carbon costs influence fares by altering which routes are profitable to operate, which then changes competitive intensity on the resulting network. This implies that higher carbon costs do not mechanically translate into higher pass-through to prices or lower total passenger numbers. Empirically, across counterfactuals, newly chosen routes

Table 16: Q2 Combined Analysis - Fares, Passengers, and Net Profits

Metric	Airline	Baseline	Low			Medium			High			VHigh			UHigh		
		Total	Common	Only BL	Only CF	Common	Only BL	Only CF	Common	Only BL	Only CF	Common	Only BL	Only CF	Common	Only BL	Only CF
Fares	All Airlines	0.92	0.92	1.10	1.03	0.92	1.11	1.03	0.91	1.12	0.99	0.91	1.13	0.99	0.91	1.14	1.00
	Full Service	1.35	1.35	1.31	1.24	1.35	1.30	1.25	1.35	1.31	1.19	1.35	1.31	1.26	1.35	1.32	1.23
	Low Cost	0.59	0.59	0.48	0.59	0.59	0.52	0.54	0.59	0.50	0.52	0.59	0.56	0.53	0.59	0.59	0.56
	Regional	1.15	1.15	1.36	1.10	1.15	1.29	1.09	1.14	1.30	1.07	1.14	1.27	1.05	1.14	1.25	1.05
		BL	**Total**	**Comm**	**Non**	**Total**	**Comm**	**Non**	**Total**	**Comm**	**Non**	**Total**	**Comm**	**Non**	**Total**	**Comm**	**Non**
Passengers	All Airlines	100.8	106.1	3.7	1.6	108.2	3.7	3.8	109.1	3.8	4.5	108.7	3.6	4.3	109.2	3.4	5.1
	% Change		**(+5.3%)**			**(+7.4%)**			**(+8.2%)**			**(+7.9%)**			**(+8.4%)**		
	Full Service	38.8	40.2	3.1	-1.7	40.2	3.1	-1.6	40.3	3.0	-1.5	40.1	2.9	-1.7	40.8	2.7	-0.7
	% Change		**(+3.6%)**			**(+3.7%)**			**(+3.8%)**			**(+3.3%)**			**(+5.1%)**		
	Low Cost	49.0	50.3	0.5	0.9	51.1	0.5	1.7	51.2	0.6	1.6	51.4	0.5	2.0	51.3	0.5	1.8
	% Change		**(+2.7%)**			**(+4.4%)**			**(+4.5%)**			**(+5.0%)**			**(+4.8%)**		
	Regional	13.0	15.6	0.2	2.4	16.9	0.2	3.7	17.6	0.2	4.4	17.2	0.2	4.0	17.1	0.1	4.0
	% Change		**(+19.9%)**			**(+30.1%)**			**(+35.5%)**			**(+32.2%)**			**(+31.5%)**		
Net Profit	All Airlines	88.9	85.8	-2.0	-1.1	82.7	-4.6	-1.6	79.8	-7.1	-2.0	77.0	-9.6	-2.3	73.8	-11.9	-3.2
	% Change		**(-3.5%)**			**(-7.0%)**			**(-10.3%)**			**(-13.4%)**			**(-17.0%)**		
	Full Service	33.2	32.0	-0.8	-0.5	30.6	-2.0	-0.7	29.2	-3.3	-0.7	27.9	-4.6	-0.7	26.4	-5.6	-1.2
	% Change		**(-3.8%)**			**(-8.1%)**			**(-12.1%)**			**(-15.9%)**			**(-20.4%)**		
	Low Cost	44.5	43.3	-0.9	-0.3	42.3	-1.8	-0.4	41.3	-2.7	-0.5	40.3	-3.6	-0.5	39.3	-4.5	-0.7
	% Change		**(-2.6%)**			**(-5.0%)**			**(-7.2%)**			**(-9.4%)**			**(-11.8%)**		
	Regional	11.2	10.5	-0.3	-0.3	9.9	-0.7	-0.6	9.3	-1.1	-0.8	8.8	-1.4	-1.1	8.1	-1.7	-1.4
	% Change		**(-5.9%)**			**(-11.8%)**			**(-17.3%)**			**(-21.6%)**			**(-27.4%)**		

Notes: Fares: Common = Routes in both baseline and counterfactual; Only BL/CF = Routes only in baseline/counterfactual. Passengers (millions) and Net Profit (10^8 USD: BL = Baseline; Comm = Common route difference; Non = Non-common route difference. % = change from baseline.

exhibit higher average fares than common routes, but this difference does not necessarily grow monotonically with the level of the carbon cost. As carbon costs rise, some previously optimal links become unprofitable and exit; this selection margin widens the gap between the average fares of old and new routes, which is precisely what we observe.

Passenger volumes can increase relative to the baseline even when carbon costs are higher, because fares on common routes are nearly unchanged while the re-optimised network may attract additional demand on newly added links. In our results, total passenger numbers rise in all scenarios. For large carriers, the aggregate change is modest, reflecting the fact that their core, high-capacity networks remain largely intact. For regional airlines, the proportional increase is more pronounced, because their newly selected routes feature substantially lower average fares relative to the routes they discontinue, which stimulates demand. A decomposition confirms that most of the passenger growth for regional carriers originates from non-common (i.e., newly operated) routes.

Higher passenger numbers and nearly stable fares do not guarantee higher net profits, because fixed and carbon-related costs also increase. In the baseline, we estimate total net profits across all airlines at approximately $8.89 billion (USD). This magnitude aligns extremely well with industry evidence for 2019, which places European airlines' net profits at roughly €7 billion (Eurocontrol Industry Monitor June 2019) and is consistent with IATA's regional benchmarks (IATA Airline Industry Economic Performance June 2019).[23] Across counterfactuals, net profits decline for all airline groups and the losses increase with the carbon cost, as expected. Full-service and regional carriers experience the largest reductions, which is consistent with their longer average stage lengths—implying higher carbon exposure per link—and with the relatively lower average fares on the routes they select after re-optimisation.

In Table 17, we report the change in airlines' net profit (producer surplus), consumer surplus, and the carbon-related revenues paid by airlines—either to government in the form of a carbon tax or to fuel suppliers via higher prices for sustainable fuels. We then present the combined change in producer and consumer surplus, followed by the total welfare change obtained by adding carbon revenues to these surplus components. For completeness, we also report the change in daily flown distance, which provides a transparent proxy for daily carbon savings: flying fewer total kilometres implies lower emissions, holding aircraft technology and load factors fixed.

The results display several patterns. Net profit losses become more severe as the carbon cost rises, reflecting higher per-kilometre operating costs and re-optimisation away from

[23]Differences stem from currency units (USD vs. EUR), data vintages, coverage definitions, and the fact that our aggregates are model-based.

Table 17: Q2 Welfare Analysis - Net Profit Changes, Consumer Surplus, Carbon Revenue, and Flight Distance

Metric	Baseline	Low			Medium			High			VHigh			UHigh		
	Total	Total	Comm	Non	Total	Comm	Non	Total	Comm	Non	Total	Comm	Non	Total	Comm	Non
Net Profit	88.9	-3.1	-2.0	-1.1	-6.2	-4.6	-1.6	-9.2	-7.1	-2.0	-11.9	-9.6	-2.3	-15.1	-11.9	-3.2
% Change		**(-3.5%)**			**(-7.0%)**			**(-10.3%)**			**(-13.4%)**			**(-17.0%)**		
Consumer Surplus	19.4	+0.97	+1.12	-0.15	+1.44	+1.61	-0.17	+1.60	+1.63	-0.03	+1.53	+1.61	-0.09	+1.74	+1.94	-0.19
% Change		**(+5.0%)**			**(+7.4%)**			**(+8.2%)**			**(+7.9%)**			**(+9.0%)**		
Surplus Change	–	-2.13	-0.88	-1.25	-4.76	-2.99	-1.77	-7.60	-5.47	-2.03	-10.37	-7.99	-2.39	-13.36	-9.96	-3.39
Carbon Revenue	–	3.11	–	–	6.18	–	–	9.21	–	–	12.08	–	–	14.84	–	–
Total Welfare Change	–	+0.98	–	–	+1.42	–	–	+1.61	–	–	+1.71	–	–	+1.48	–	–
Daily Flight Distance Δ	2,863.0	-29.0	–	–	-65.8	–	–	-91.8	–	–	-140.5	–	–	-188.7	–	–
% Change		**(-1.0%)**			**(-2.3%)**			**(-3.2%)**			**(-4.9%)**			**(-6.6%)**		

Notes: Net Profit and Consumer Surplus in 10^8 USD; Flight Distance in 10^3 km. Comm = Common route changes; Non = Non-common route changes (entry/exit effects). Surplus Change = Net Profit change + Consumer Surplus change. Carbon Revenue = $[(1.25 + \text{increment}) \times \text{FD\_counterfactual} - 1.25 \times \text{FD\_baseline}] \times 100/90 / 10^3$, where increment is 1, 2, 3, 4, 5 for Low, Medium, High, VHigh, UHigh scenarios. Total Welfare Change = Surplus Change + Carbon Revenue. Flight Distance Δ shows FD_delta (counterfactual minus baseline). % = percentage change from baseline.

previously profitable links. By contrast, consumer surplus increases in all scenarios, because newly entered routes tend to exhibit lower fares and attract additional passengers, consistent with the demand and pricing movements documented in Table 16. On balance, the combined consumer-producer surplus becomes more negative at higher carbon cost levels, largely because growing profit shortfalls outweigh consumer gains.

Carbon revenues are constructed from the change in total frequency-distance cost in each counterfactual relative to the baseline. Two forces operate simultaneously. First, the per-kilometre charge increases with the carbon price (or the renewable-fuel premium). Second, total frequency-distance adjusts as airlines enter and exit routes in response to profitability. As the per-kilometre cost rises, the revenue component increases mechanically, while network adjustments can either amplify or partially offset this depending on how total operated distance responds.

The most consequential finding concerns total welfare, defined as the sum of the surplus changes and carbon revenues. Once carbon revenues are included, the net welfare effect becomes positive rather than negative. Intuitively, the carbon charge reduces distortions on two margins. It prices the externality directly (the Pigouvian channel) and, through network re-optimisation, can temper mark-ups on links with pronounced market power—improving allocative efficiency even before counting the environmental benefits of lower emissions. This mechanism is consistent with established results on corrective taxation and the "double-dividend" discussion in environmental economics, where revenue recycling and competitive reallocation can yield welfare gains in already distorted markets. In the European airline context—where many routes are effectively monopolies or duopolies—this channel is particularly salient. The policy implication is that, provided the raised revenues are used productively (for example, to reduce other distortionary charges or to support efficiency-enhancing infrastructure), carbon pricing can deliver broad social gains in addition to its primary environmental objectives.

Finally, the overall impact of the carbon policy is distributed unevenly across European countries. Figure 4, Figure 5, and Figure 6 report the percentage changes in consumer surplus, airlines' net profits, and total welfare by country in Q2 under the UHigh counterfactual. To attribute route-level changes to countries, we weight each route's contribution by the population shares of its origin and destination cities and then aggregate to the country level. For cities that straddle national boundaries (e.g., Copenhagen/Malmö or Vienna/Bratislava), we split each measure evenly across the two affected countries to avoid double counting.[24]

[24]This allocation preserves country aggregates while remaining neutral with respect to cross-border functional city regions.

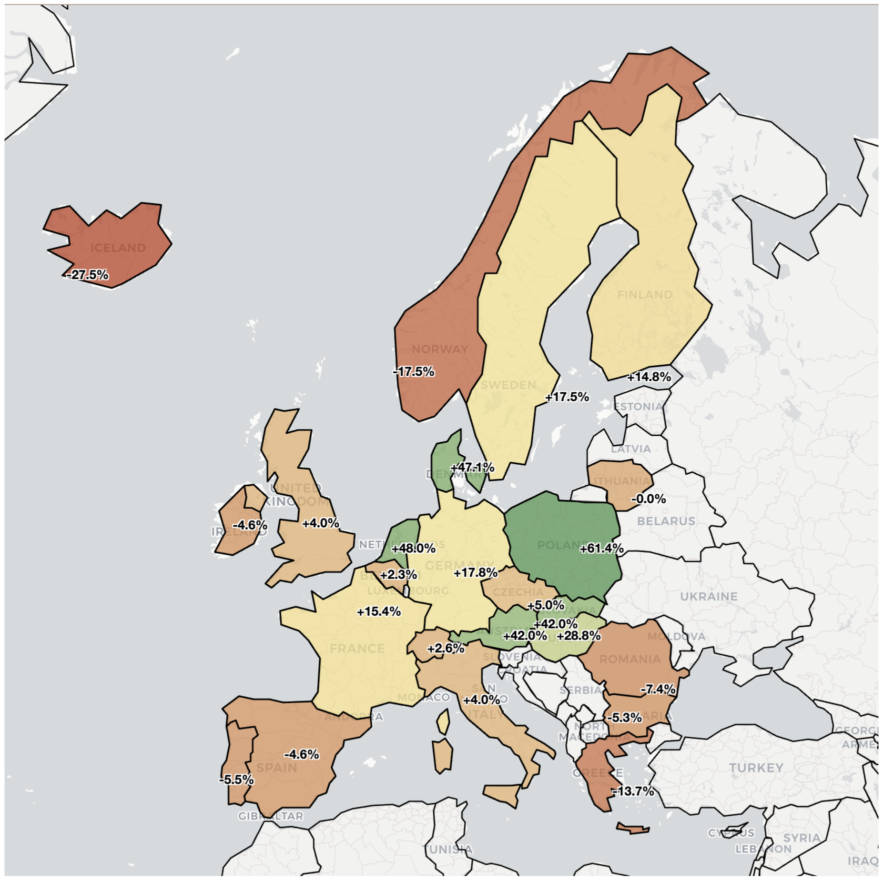

Figure 4: Change of Consumer Surplus by Countries (Q2, UHigh)

Consumer surplus increases most strongly, in percentage terms, in several Central and Eastern European countries such as Poland, Slovakia, and Hungary. Two forces account for this pattern. First, many of the newly entered routes under the carbon constraint are relatively short-haul links within the region, which typically sustain lower average fares and attract higher passenger volumes once the network is re-optimised. Second, these countries offer dense catchment areas with multiple viable secondary airports, expanding entry options and intensifying competition on newly operated links. By contrast, peripheral and island geographies such as Iceland, Norway, Greece, and Portugal experience declines in consumer surplus. Longer stage lengths in these regions raise carbon-related costs per flight, and the re-optimised network is more likely to cancel or deviate from thin, long-haul leisure routes; both the reduction in available links and the higher average fares on surviving routes depress passenger volumes. These directional effects are consistent with industry evidence that carbon exposure scales with distance and that periphery markets rely disproportionately on long sectors with limited substitution options.[25]

[25]For background, see industry discussions of distance-related carbon cost exposure and the resilience of

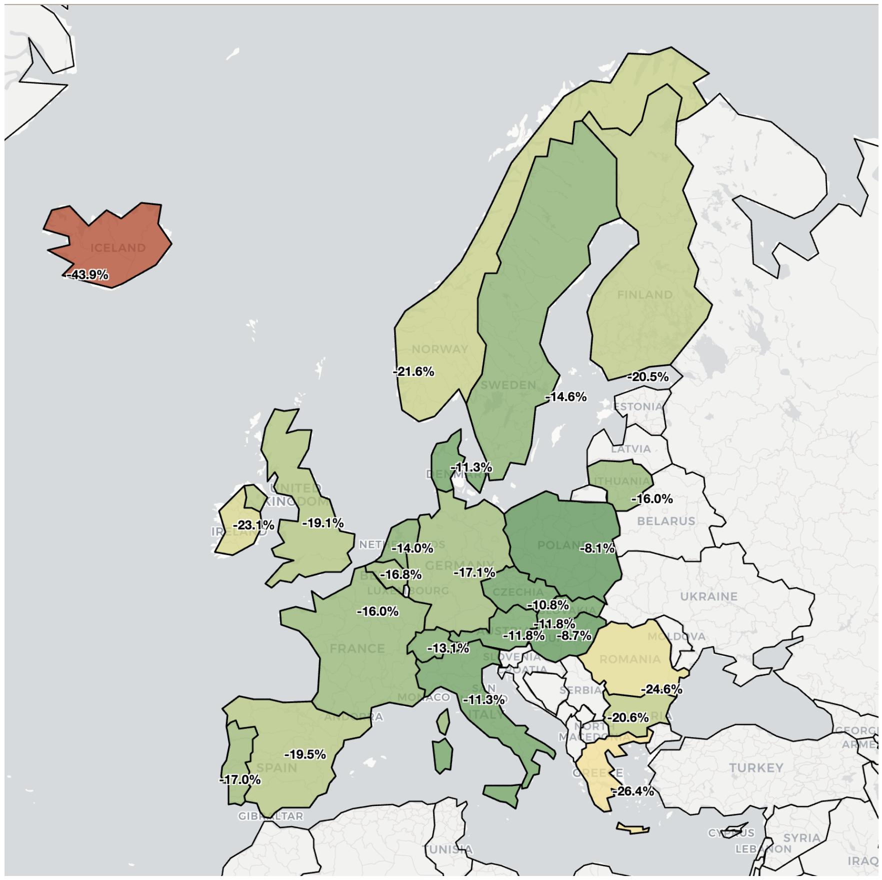

Figure 5: Change of Net Profit by Countries (Q2, UHigh)

Net profit changes in Figure 5 follow a similar geography. Peripheral countries see the largest percentage drops, reflecting both higher incremental carbon costs on longer average stage lengths and a greater incidence of route exits, which remove positive-contribution links from the portfolio. In Central and Eastern Europe, the declines are more muted because newly entered, demand-rich short-haul routes can offset part of the cost increase, and the shorter sectors imply a smaller per-flight carbon cost uplift. This asymmetry aligns with pre-existing carrier network strategies: ultra- and low-cost carriers have concentrated growth in Central/Eastern Europe using short-haul, high-frequency networks and secondary airports, while full-service and regional operators disproportionately serve longer or thinner markets where the fixed and carbon-related cost burden is harder to dilute.

short-haul, multi-airport networks in Europe in 2019–2023 reporting (e.g., EUROCONTROL network and market monitors; IATA regional outlooks).

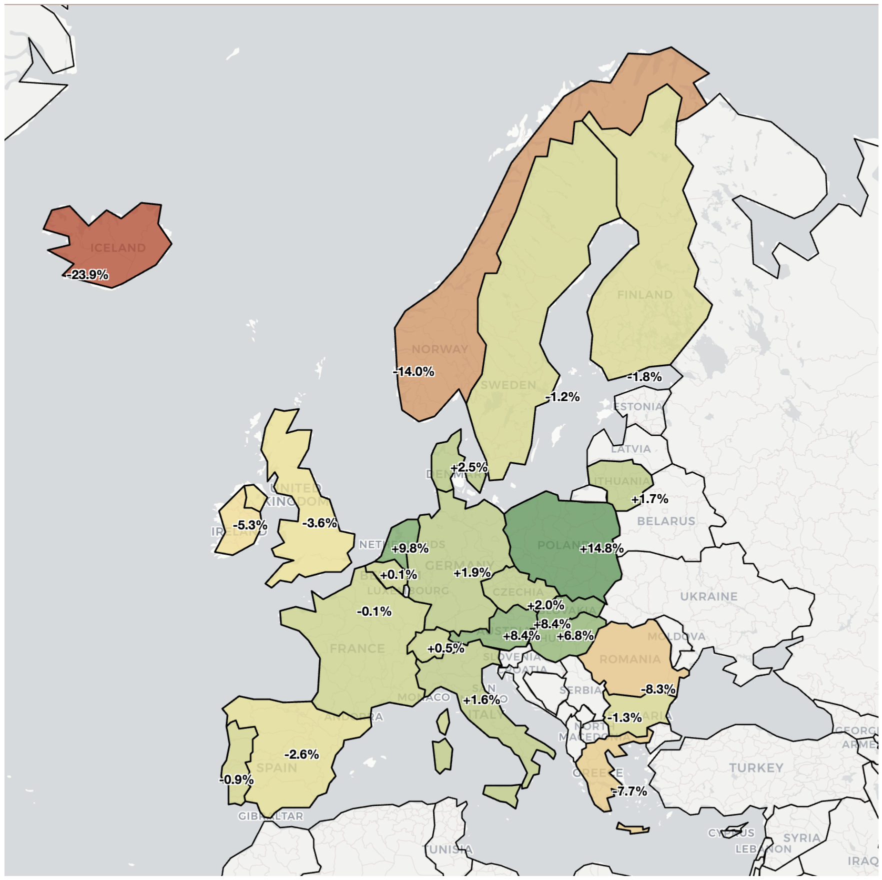

Figure 6: Change of Total Welfare by Countries (Q2, UHigh)

Total welfare changes mirror the joint behaviour of consumer surplus and producer surplus. Central and Eastern European countries emerge as net beneficiaries under the UHigh policy; for example, Poland records a projected total welfare gain of about 14.8%. In contrast, remote areas such as Iceland and Norway experience the largest welfare losses, driven by reduced network connectivity and higher average travel costs on retained routes. For countries hosting large hub airports—such as the UK, France, and Germany—aggregate welfare changes are comparatively small. Hub networks tend to preserve core trunk routes even under higher operating costs, which stabilises both prices and volumes on the common network segment; as a result, the national aggregates move little despite rebalancing at the margin across thinner spokes. Overall, these patterns are consistent with the notion that carbon pricing reshapes the extensive margin of route choice more forcefully in peripheral, long-haul-dominated markets than in central, short-haul-dense systems.

7 Conclusion

This paper quantifies the impacts of carbon regulation on the European airline industry. Our analysis reveals that network changes are concentrated among low-cost and regional carriers, while full-service carriers' networks remain largely unaffected. The policy also triggers a geographic redistribution of welfare, benefiting Central and Eastern Europe at the expense of long-haul markets. Despite reducing airline profits by up to 17%, the regulation enhances consumer surplus by up to 9% and cuts total distance flown by up to 6.6%. These findings suggest that carbon regulation can achieve a "double dividend," yielding both environmental and social welfare gains.

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