Carbon Regulation and Competition in the 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 reveal that the impacts of carbon pricing are highly asymmetric across carrier types and market segments: network contraction is most severe for regional carriers, whose flight frequencies decline by up to 73%, while low-cost carriers' networks remain comparatively resilient. The simulations also show that the policy redistributes welfare geographically, with consumer surplus in medium- and long-haul markets declining by up to 86%, compared with up to 45% in short-haul markets. We find that the tax burden falls predominantly on airlines, whose profits decline by 12–56% across scenarios, while carbon tax revenue of \$0.7–2.3 billion and a social value of avoided CO_2 emissions of \$0.37–1.09 billion partially offset the welfare losses. These results demonstrate that carbon regulation can achieve meaningful environmental gains in airline markets, though at significant cost to industry profits and consumer welfare.

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. Near-term technological solutions—including new-generation aircraft and Sustainable Aviation Fuels (SAFs)—are not yet viable at scale, and efficiency gains have historically been outpaced by rapid demand growth. This gap between climate ambitions and the slow pace of technological adoption motivates market-based policies such as the EU Emissions Trading System (EU ETS) to drive emissions reductions. This paper investigates the competitive and network-level effects of carbon regulation on the European airline industry, analysing how these policies reshape airline competition and endogenous route network formation. We ask three questions. How do the distinct business models of full-service carriers (FSCs) and low-cost carriers (LCCs) shape their strategic responses to rising carbon costs? How does regulation alter market structure through route entry and exit? And what are the consequences for consumer welfare and its geographic distribution across Europe?

The European market's structure is distinctive, shaped by features that set it apart from its North American or Asia-Pacific counterparts. First, high population densities and short inter-city distances make indirect flights through hub-and-spoke systems far less attractive than in the United States, where connecting traffic is central to competition. 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 slot-coordinated airports (EUROCONTROL and FAA Air Traffic Organization [2024]) and features high aircraft utilisation rates. Second, because the European market spans more than 27 countries and was deregulated much later than the US market,[1] it remains highly fragmented despite waves of privatisation and consolidation over the past 35 years; our empirical analysis includes 14 competing airline groups. Finally, while state aid to national carriers is formally prohibited, Europe's FSCs are all legacy national carriers (also known as "flag" carriers) that retain significant advantages—including grandfathered slot allocations and dense hub networks—as well as legacy cost structures that continue to shape their network strategies. These legacies create important asymmetries between FSCs and LCCs.

In summary, European airline networks are dominated by direct, point-to-point short-haul flights rather than hub-and-spoke connections. Price competition is intense due to the presence of LCCs and a fragmented market structure. LCC market shares are comparable to those in the US (approximately 50% in Europe versus 40% in the US; Bontemps et al.

[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].

[2023]).

This market structure gives rise to an intense competitive dynamic and a bifurcation of 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 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 the price-sensitive market segment. Crucially, the point-to-point model affords LCCs greater strategic flexibility in network adjustment. 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. From 2026, airlines' free carbon emission allowances under the EU ETS will be completely phased out, dramatically increasing the effective carbon price (European Commission [2024]). This will be compounded by the ReFuelEU mandate, which requires airlines to increase SAF usage between 2025 and 2050. Currently, SAFs cost several times more than conventional jet fuel and face significant production shortfalls (European Union Aviation Safety Agency [2024]). These cost shocks will disproportionately affect 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 European airline networks, prices, and market shares. Our counterfactual analysis simulates the impact of increasingly stringent carbon taxation, implemented through the EU ETS. The simulation finds new network equilibria using an iterative algorithm in which airlines sequentially re-optimise their route choices in response to higher distance-related costs.

Our key findings are as follows. 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 spatial distribution of route entry costs. Second, the impacts of carbon pricing are highly asymmetric: network contraction is concentrated among LCCs and smaller regional carriers, while FSCs with valuable hub slots prove remarkably resilient. Third, the policy induces a geographic redistribution of welfare: medium- and long-haul markets—connecting peripheral regions such as Iceland and Norway to the European core—are far more severely affected than short-haul markets that dominate Central and Eastern European connectivity. Fourth, we find that the tax burden falls predominantly on airlines, while carbon tax revenue and the social value of avoided CO_2 emissions—which grows with the stringency of the carbon price as airline networks shift toward shorter, less emission-intensive routes—partially offset the aggregate welfare loss. Fifth, market concentration effects are economically small, suggesting that even aggressive carbon pricing reshapes airline networks without fundamentally altering the competitive structure of European aviation markets.

We contribute to the literature in two main ways. First, we build on structural models of airline competition and market entry. While most research focuses on the US market, where hub-and-spoke networks and connecting traffic are central to competition (Berry [1990, 1992], Berry and Jia [2010], Ciliberto and Tamer [2009], Aguirregabiria and Ho [2012], Ciliberto et al. [2021], Bontemps et al. [2023], Yuan and Barwick [2024]), our analysis focuses on the European market. Existing studies of the European market have examined specific features such as slot allocation (Marra [2024], Bauer [2025]), LCC subsidies (Bontemps et al. [2025]), or mergers (Bergantino et al. [2024]). Our paper provides the first structural analysis of how environmental taxation reshapes equilibrium outcomes in the imperfectly competitive European airline market, accounting for endogenous network adjustment.

Second, we advance the literature on the economic impacts of carbon regulation. While many studies focus on the environmental efficacy of carbon pricing (Metcalf [2019], Bayer and Aklin [2020], Colmer et al. [2025], Timilsina [2022]), we examine how such policies fundamentally reconfigure a large oligopolistic industry. Our approach is most closely related to Ryan [2012] and Fowlie et al. [2016], who study the US cement industry, and to Fowlie [2009], who analyses emissions leakage under imperfect competition. We adapt their core insight—that environmental policy is not merely a cost shock but a catalyst for changes in market structure, concentration, and welfare—to the European airline industry. Our setting offers two distinctive features relative to this prior work: the treatment variable is route-specific (varying with distance flown), which generates heterogeneous cost shocks across the network; and the regulated firms' production locations (i.e., route networks) are themselves endogenous choice variables, creating a network restructuring channel largely absent in manufacturing contexts.

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: EU Emissions Trading System

The EU Emissions Trading System (EU ETS) is a European-wide cap-and-trade programme that establishes a price for the right to emit carbon dioxide (CO_2). Introduced in 2005, it is the world's first and largest market-based climate policy.[2] The system operates by imposing a cap on aggregate CO_2 emissions from regulated installations across thirty-one countries, currently covering approximately 40% of total EU greenhouse gas emissions. Tradeable permits—known as European Union Allowances (EUAs)—are issued for each tonne of CO_2 under the cap. Regulated entities must surrender one EUA for each tonne of CO_2 they emit in a given compliance year. They may purchase additional EUAs or sell surplus allowances on a European-wide market at a uniform price, and, within limits, bank or borrow allowances across years and trading phases. Because the total number of EUAs in the system is limited and declines linearly over time, scarcity commands a positive permit price, which provides the central economic incentive for emissions abatement (Ellerman et al. [2016]).

The EU ETS has evolved through several distinct trading phases, each marked by different regulatory stringency and permit price dynamics. Phase I (2005–2007) served primarily as a learning period; permit prices initially climbed above €30 per tonne but collapsed when evidence emerged that the cap was not binding, rendering phase I permits nearly worthless by end-2007. Phase II (2008–2012) coincided with the Great Recession, and prices fluctuated between €8 and €30 per tonne. Phase III (2013–2020) introduced centralized EU-wide allocation and a shift from predominantly free allocation toward auctioning, while Phase IV (2021–2030) further tightened the cap with a higher annual linear reduction factor. A substantial empirical literature has evaluated the effects of the EU ETS on manufacturing firms, finding that the scheme induced regulated firms to reduce CO_2 emissions by 14–16% with no detectable contractions in economic activity, primarily through targeted investments in cleaner production technologies rather than through carbon leakage to unregulated entities (Colmer et al. [2025]).

[2]Earlier environmental cap and trade systems included leaded gasoline production permits (USA 1982), tradable fishing quotas (Iceland 1984, New Zealand 1986), sulfur dioxide emissions permits (USA 1995).

Extension to Aviation. The inclusion of aviation in the EU ETS, beginning in 2012, represents one of the most significant extensions of the scheme beyond its original scope of stationary industrial installations. Under the current framework, all flights departing from and arriving at airports within the European Economic Area (EEA) are subject to the EU ETS.[3] Aircraft operators are required to monitor, report, and surrender allowances for the CO_2 emissions from each covered flight, calculated on the basis of fuel consumption multiplied by standard emission factors.

Aviation's inclusion in the EU ETS introduces a distinctive regulatory treatment compared to ground-based installations. First, the treatment variable in aviation is route-specific: an airline's carbon cost is a direct function of the distance flown and the fuel efficiency of the aircraft deployed, creating heterogeneous cost shocks across routes and carriers. Second, unlike manufacturing firms that received generous free allocations during early trading phases, the aviation sector has faced progressively tightening allocation rules. Critically, the system's application to aviation has been significantly strengthened in recent years, with 25% fewer free allowances allocated to aircraft operators in 2024, and complete removal of free allocation scheduled for 2026 (European Commission [2024]). This phase-out of free allocation means that airlines will increasingly bear the full marginal cost of carbon on every tonne emitted. Third, because airline networks are endogenous objects—carriers choose which routes to serve, at what frequency, and with which aircraft—carbon pricing affects not only the intensive margin of pricing and output but also the extensive margin of route entry and exit. This network restructuring channel is largely absent in the manufacturing context, where firms' production locations are relatively fixed in the short run.

The European Commission's "Fit for 55" impact assessment projects that EU ETS carbon prices will need to reach approximately €50–85 per tonne by 2030 under the central policy scenario (European Commission [2021]). Looking beyond 2030, international organisations and modelling agencies project dramatic price escalations consistent with net-zero pathways. For example, the IEA's World Energy Outlook estimates carbon prices in advanced economies could reach \$140 per tonne by 2030 and rise to \$205 per tonne by 2040 (International Energy Agency [2023]) and research by Enerdata indicates that EU ETS prices could increase to as much as €130/tCO_2 by 2040, before rapidly escalating to exceed €500/tCO_2 by 2044 (Enerdata [2025]). For typical narrow-body aircraft operating intra-European routes, these carbon price trajectories imply a substantial surge in carbon liabilities. If carbon prices rise from approximately \$100 to over \$500 per tonne, the additional operational cost per

[3] Directive 2008/101/EC extended the EU ETS to include aviation activities. Following the "stop the clock" decision, the scope was temporarily limited to intra-EEA flights from 2013 to 2023, but has since been expanded.

kilometre flown will increase from approximately \$1 to \$5, depending on fuel efficiency and load factor assumptions.

Interaction with Sustainable Aviation Fuel Mandates. Concurrent with carbon pricing pressures, the aviation industry faces mounting fuel cost challenges. 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; EASA's 2024 European Aviation Environmental Report documents conventional aviation fuel priced at €734 per tonne compared to aviation biofuels at €2,085 per tonne, with SAF prices projected to remain two to three times higher than conventional jet fuel until at least 2030 (European Union Aviation Safety Agency [2024]). While carbon prices will narrow the gap, the combined effect of EU ETS compliance costs and SAF mandates implies that airlines face a regulatory environment in which operating costs per kilometer will rise substantially over the next decade, reinforcing the policy relevance of understanding how carbon regulation reshapes airline competition and network structure.

Heterogeneous Impacts across Carrier Types. A key feature of the European airline market—and a central motivation for our structural model—is that carbon regulation does not affect all carriers symmetrically. Low-cost carriers (LCCs) and full-service carriers (FSCs) differ in several dimensions that determine their exposure and response to carbon pricing. LCCs typically operate shorter point-to-point routes with higher aircraft utilisation and load factors, implying lower per-passenger emissions but with a route portfolio concentrated entirely within the EEA and thus fully exposed to the EU ETS. FSCs, by contrast, operate hub-and-spoke networks that include long-haul intercontinental services. While their intra-European feeder flights fall under the EU ETS, a substantial share of their revenue-generating long-haul operations is currently outside its scope. Furthermore, FSCs and LCCs differ in their abilities to pass through carbon costs to consumers. FSCs serving price-inelastic business travellers may absorb less of the cost increase, whereas LCCs competing primarily on price in elastic leisure markets may find pass-through more difficult. These asymmetries imply that a uniform carbon tax can induce heterogeneous responses in pricing, route entry and exit, and network configuration across carrier types—precisely the margins our model is designed to capture.

2.2 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 share of flights have surged from just 1.6% in 1998 to approximately 32.5% by 2022 [EUROCONTROL, 2022]. Time series evidence on passenger shares is not available, but Table 1 shows that by 2016-2019, LCCs accounted for more than half of all intra-European passengers. The scale of this transformation is exemplified by Ryanair, which in 2023 carried 182 million passengers—more than any single FSC in Europe.[4] 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.

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. The cost per available seat kilometre for LCCs (excluding fuel) is typically 20%–30% lower than for FSCs (Doganis [2010]), 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

[4]Ryanair Holdings plc, Annual Report FY2024.

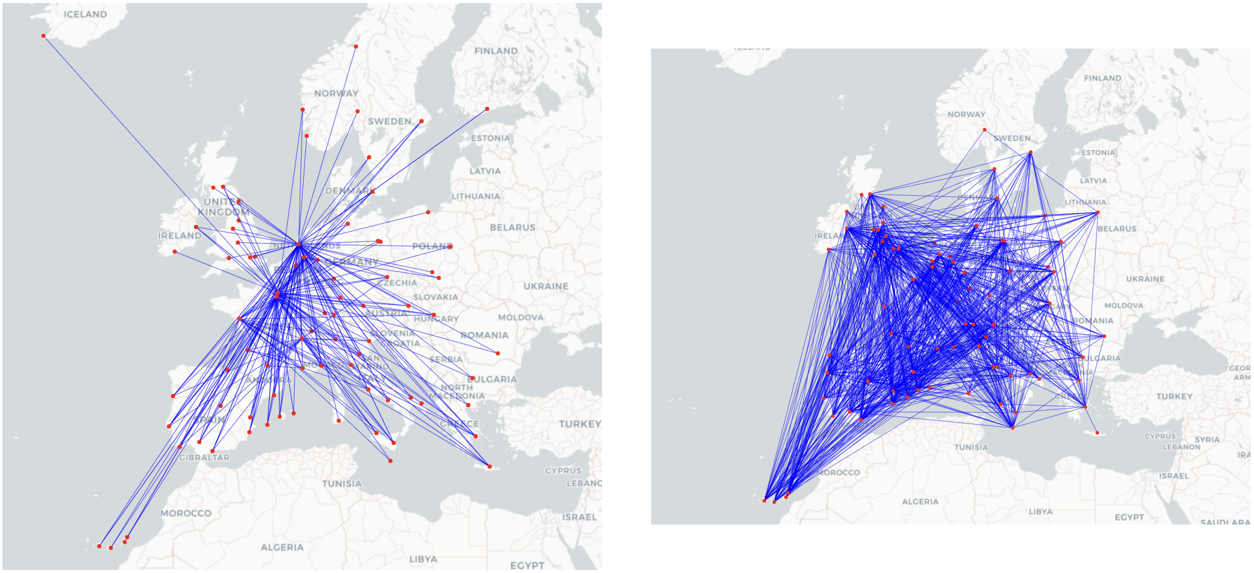

Figure 1: Route Maps of Air France-KLM (left) and Ryanair (right) in Q2 2019

handling and seat selection.[5] 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.[6] 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 world's IATA Level-3 airports, where demand for flights consistently exceeds capacity.[7]

[5]While FSCs increasingly adopt similar pricing practices, they are still generally perceived as offering higher service quality (see Pels [2008]).

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

[7]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.

European aviation policymakers have long debated the allocation of scarce airport slots. The current system, established in 1993, relies on "grandfathering," allowing airlines to retain their historical slots if they use them at least 80% of the time in a season (Council Regulation (EEC) No 95/93). 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.[8]

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 entry, exit and consolidation over the past 35 years. The current industry structure is detailed in Table 3 which lists the current parent airline groups, their associated operating carriers, and designated hub airports. Airlines are aggregated to the parent company level and we use industry-standard IATA codes to label the groups. 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 main 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 rates directly limit a airlines' abilities to adjust flight frequencies. In this regard, there are two important features of the 2019 market. First, European carriers operated with high levels of fleet efficiency, meaning most aircraft were already operating near full capacity, leaving little slack to increase total network frequency

[8]This phenomenon was widely reported during the COVID-19 pandemic.

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.

without expanding fleets.[9] 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.

2.3 Data

Our data comes from Sabre Market Intelligence (Sabre [2025]), 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 non-directional routes as in Yuan and Barwick [2024] and Bontemps et al. [2023]. The top 100 airports serve 82 cities and 89.8% passengers in 2016-2019. We define a product to be a non-directional route

[9]See the report from EUROCONTROL and FAA Air Traffic Organization [2024].

connecting two airports served by an airline and define a market to be all routes connecting pairs of cities. Finally, we supplement the Sabre data with metropolitan population data from Eurostat (Eurostat (European Commission) [2026]), which we use to construct our market size variable.

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 LCCs (Ryanair, EasyJet, and Wizz Air). In the following, we refer to these groups by the IATA codes of their principal carriers: BA for IAG, AF for Air France-KLM, and LH for Lufthansa Group. These six groups account for 87% of all intra-European passenger traffic. We observe 11,062 products across 1,954 city pairs. The average fare is $85, the average frequency is roughly one flight per day, and the average travel distance of about 1,410 kilometres. In total, the products in our 2019 sample served over 342 million passengers.

Table 4: Summary statistics

(a) Sizes:		**(c) Demand and cost**	**Mean**	**St.Dev**
# products	11062	fare (100 USD)	0.85	0.57
# city pairs	1954	frequency (daily)	0.95	1.74
# passengers (million)	342	distance (1,000 km)	1.40	0.72
		market size (1 million)	2.44	1.71
(b) Market shares				
British Airways	0.15			
Air France	0.09			
Lufthansa	0.12			
Ryanair (LCC)	0.25			
EasyJet (LCC)	0.21			
Wizz Air (LCC)	0.05			
Other	0.13			

Table 5 reports key summary statistics for each airline group'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.[10]

Table 5: Hub airport summary statistics

Airlines	Top Hub	Hub Index	Freq	Second Hub	Hub Index	Freq
(a) Full service:						
BA	Madrid	60	2.3	London	56	2.6
AF	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:						
BA	Madrid	14%		London	25%	
AF	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 products to/from a specific hub. Concentration refers to the proportion of products to/from this hub city relative to the total number of products.

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).

Figure 2 shows the passenger share, revenue share, and frequency share for each airline group. 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 4 shows a network analysis. The network size is the total number of airports

[10]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: Competition and Fare Statistics by Number of Competing Firms

Number of Competitors	**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 Competitors: 1.57; Median: 1.00

Table 7: Average Number of Routes with at Least One Hub per Competing 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 Competitor 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

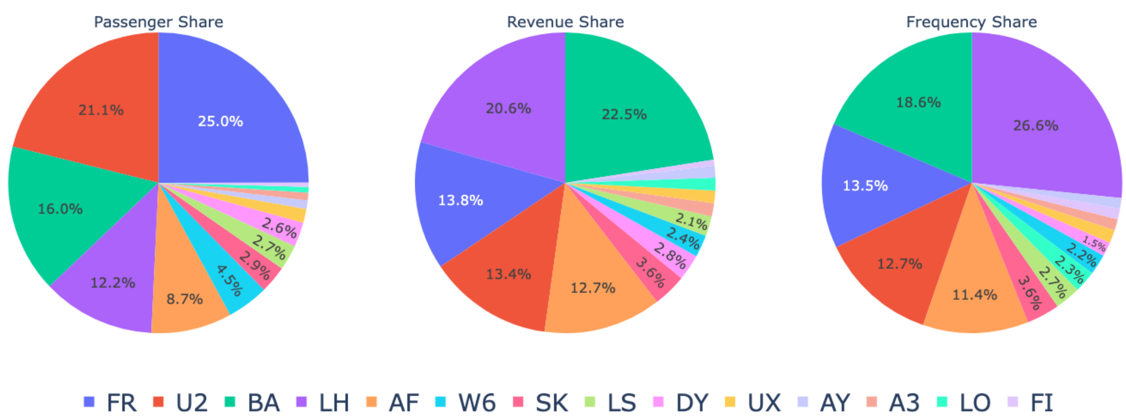

Figure 2: Market Share Analysis

served by each airline group. A larger network size implies a broader set of feasible route alternatives. The three largest full-service airline groups (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.

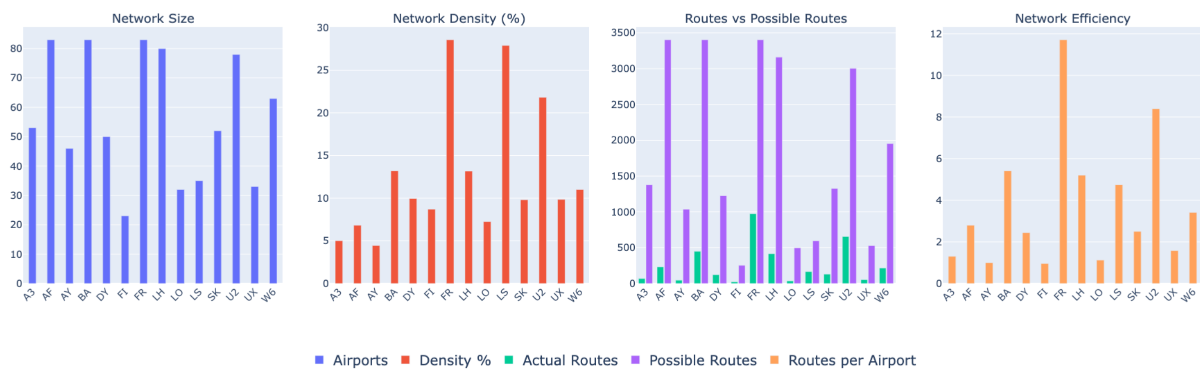

Figure 3: Network Analysis

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.

We index time periods by t but omit the subscript for simplicity, unless otherwise specified. Let $g \in \mathcal{G}$ be an airline group in the intra-European[11] 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.[12] We restrict our analysis to direct flights only, which comprise around 94% of air travel in Europe. A route $r \in \mathcal{R}$ is defined by a non-directional airport-pair $a, b \in \mathcal{A}$ where $\mathcal{A}$ is the set of airports. A product j is defined to be an airline g offering flights on route (a, b). 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

[11] 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.

[12] The definition of a market as a city-pair follows Berry [1992], Aguirregabiria and Ho [2012], Yuan and Barwick [2024].

of products chosen by airline g in market m in stage one of the two stage game and let the vector $\mathbf{N}_g$ represent airline g's complete network where $\mathbf{N}_{g,ab} = 1$ if and only if $(g, a, b) \in \mathcal{J}_{gm}$ for some m. In equilibrium, the set of products available in market m in stage two of the game 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. Denote the number of products in market m by $J_m = |\mathcal{J}_m|$. Also note airlines may offer multiple products in some markets by offering services from multiple airports serving the same city.

Airlines' first stage choices and consideration sets: Each airline's first stage choices include choice of route network $\mathbf{N}_g$ and flight frequency $\mathbf{F}_g$ on each route. For the route network choice, we impose the following constraints on firms' consideration sets. We assume that, in the short run, an airline can only enter markets that serve cities it already serves as in Berry [1992]. Costs to expand to unserved cities are assumed to be too high to be profitable in the short run. 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 unless other airlines exit and free up slots. Finally, to capture legacy entry costs of flag carriers, we require that, when considering switching a flight from an observed route to an alternative route, the number of alternative route endpoints located in the airline's home country is weakly greater than the number on the observed route. These consideration set constraints capture the assumption 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. We use $\mathbf{R}_g$ to denote the consideration set for airline g, that is, the set of all feasible routes. Regarding the choice of flight frequency $\mathbf{F}_g$, we assume that an alternative route's frequency is bounded above by the observed frequency on the route that is being switched from.

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 a constant, the logarithm of flight frequency, distance, distance squared, airline-quarter fixed effects, major airport fixed effects, airline-airport-hub fixed effects, and fixed effects for the top 50 cities ranked by population. Within a market, distance has no meaningful variation, but distance affects substitution to the outside option. Higher frequency offers consumers more travel options and greater flexibility. The airline-airport-hub is important because major European hubs serve not only intra-European passengers but also a substantial volume of intercontinental transfer passengers. These additional incoming international passengers in effect increase demand for air travel relative to the outside option.[13] The hub fixed effect control for the influence of intercontinental layover traffic on observed demand.

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

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

where $\mathbf{p}_m = (p_{km} : k \in \mathcal{J}_m)$, $\mathbf{x}_m = (x_{km} : k \in \mathcal{J}_m)$, and $\boldsymbol{\xi}_m = (\xi_{km} : k \in \mathcal{J}_m)$. Taking the logarithm, the demand equation can be expressed as the following linear equation:

$$\ln(s_{jm}) - \ln(s_{0m}) = -\alpha p_{jm} + x_{jm}\beta + (1-\lambda)\ln(s^*_{jm}) + \xi_{jm} \tag{1}$$

where s_{0m} is the market share of the outside option, and s^*_{jm} is the within-nest market share of product j. The endogenous variables in this equation are the prices p_{jm} and the

[13]International transfer passengers travelling on a single itinerary with a short layover are not included in our dataset. However, for travellers with long layovers, the intra-European leg of the journey is included in our data.

within-nest market shares s^*_{jm}.

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.

We assume marginal cost is a function of observable product characteristics:

$$\mathrm{MC}_{jm} = x_{jm}\theta_s + \omega_{jm} \tag{2}$$

where ω_{jm} is an unobserved cost shock and θ_s is a marginal cost parameter vector. If data on additional marginal cost shifters were available, these variables could be included in (2).

3.2 First Stage: Entry and Frequency

In the first stage, airlines simultaneously choose route networks and 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:

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

where $z_j(f_j)$ is a vector of observable route characteristics including a constant, frequency times distance, the logarithm of market size, and the number of slot controlled airports on the route. The variable $\kappa_j(f_j)$ is an unobserved airline-route-frequency specific fixed cost shock, and θ_{fc} is a vector of fixed cost parameters. $\boldsymbol{\kappa}_g$ is the vector of all route-frequency-specific shocks for airline g. Note that fuel costs, which are impacted by carbon prices, are a fixed cost of operating a route and are proportional to frequency times distance. When we compute our counterfactual simulations, increases in EU TS prices will increase these fuel cost parameters. This is detailed in Section 6 below.

We assume that firms choose their route networks in stage one before the second-stage shocks, ξ_{jm} and ω_{jm} are realised.[14] Let $(\mathbf{N}, \mathbf{F}, \mathbf{X})$ be the networks, frequencies, and product characteristics of all airlines in all markets. Then, for each airline g, expected second-stage profits can be written as:

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

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 airlines know the distributions of these shocks when making entry and frequency decisions.

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

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

3.3 Equilibrium

Airlines choose networks and frequencies in stage 1 and prices in stage 2. In this two stage game, we consider pure strategy subgame perfect equilibria in 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. This section discusses identification and estimation of the linear fixed-cost parameters θ_{fc}.

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

Construction of Moment Inequalities: To ease notation, we suppress dependence on $(\mathbf{X}, \theta_c, \theta_d)$ and on the competitors' strategies and unobserved fixed cost shocks. Let $\Pi_{1g}(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc}) := \Pi_{2g}(\mathbf{N}_g, \mathbf{F}_g) - \mathrm{FC}_g(\mathbf{N}_g, \mathbf{F}_g, \boldsymbol{\kappa}_g; \theta_{fc})$ denote airline g's stage 1 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, alternative feasible actions $(\mathbf{N}_g^a, \mathbf{F}_g^a)$ must not increase profits. That is:

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

where $\Delta\Pi_{1g}(\mathbf{N}_g^*, \mathbf{F}_g^*, \mathbf{N}_g^a, \mathbf{F}_g^a; \theta_{fc})$ is the deterministic component of the difference in profit 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, the deterministic component can be written:

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

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.

Alternative Route Network and Frequency: Exploring all possible alternative route networks and frequencies 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. Nonetheless, we can construct an outer region covering the identified set by considering a subset of alternative route networks and frequencies. Thus, 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 actions: (1) exiting the entire market while keeping all other routes and frequencies unchanged; and (2) redeploying all aircraft providing services in that market to an alternative route in which the airline is not currently active, while keeping all other routes and frequencies unchanged. Finally, if no airline serves a market in a given quarter, we consider deviations that involve entry at an average frequency level. Such entry deviations, if feasible, must be unprofitable.

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

$$
\begin{aligned}
&\pi_{2g}(j^*) - \pi_{2g}(j^a) - (z^*_{j^*} - z^a_{j^a})\theta_{fc} - \kappa_{j^*}(f^*) + \kappa_{j^a}(f^*) \geq 0 \quad \forall\ j^* \in \mathbf{N}_g^*, j^a \in \mathbf{R}_g \\
&\pi_{1g}(j^*; \theta_{fc}) - \kappa_{j^*}(f^*) \geq 0 \quad \forall\ j^* \in \mathbf{N}_g^* \\
&\pi_{1g}(j^{un}; \theta_{fc}) - \kappa_{j^{un}}(\bar{f}_g) \leq 0 \quad \forall\ j^{un} \in \mathbf{N}_g^{un}
\end{aligned}
\tag{3}
$$

where the second inequality considers deviations that remove planes from service, the last inequality considers entering unserved markets, and $\bar{f}_g$ is the average frequency across all routes operated by airline g in the sample.

Inference: Following Cox and Shi [2023], we construct the following conditional likelihood ratio test statistic to conduct inference on the fixed cost parameters θ_{fc}:

$$
CLR(\theta_{fc}) = \min_{\mu \leq 0} (\hat{m}(\theta_{fc}) - \mu)' \Sigma(\theta_{fc})^{-1} (\hat{m}(\theta_{fc}) - \mu) \tag{4}
$$

where $\hat{m}(\theta_{fc})$ is the vector of sample moment inequalities evaluated at θ_{fc}, $\Sigma(\theta_{fc})$ is a consistent estimate of the covariance matrix of $\sqrt{N}\hat{m}(\theta_{fc})$, and μ is the vector that minimises the quadratic form above subject to the constraint $\mu \leq 0$. The critical value for the test is denoted by $\chi^2_{\hat{r},1-\alpha}$ where $\hat{r}$ is the number of active constraints in (4), α is the significance level, and $\chi^2_{\hat{r},1-\alpha}$ is the $(1-\alpha)$ quantile of a chi-squared distribution with $\hat{r}$ degrees of freedom. The confidence region for θ_{fc} is given by:

$$
CR_{1-\alpha} = \{\theta_{fc} \in \mathbb{R}^{d_{\theta_{fc}}} : CLR(\theta_{fc}) \leq \chi^2_{\hat{r},1-\alpha}\}
$$

5 Estimation Results

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

5.1 Demand and Marginal Cost Estimation

Table 9 reports the demand and marginal cost estimation results. There are two endogenous variables in (1), price and within-nest share. We use two types of instruments: (i) the number of competitors in each market, and (ii) the average frequency offered by other airlines in the same market. The Kleibergen-Paap F-statistic (Kleibergen and Paap [2006]) is 11.81, indicating strong instruments.

Table 9: Demand and Marginal Cost Estimation Results

	Demand		**Marginal Cost**	
Variable	**Coef.**	**SE**	**Coef.**	**SE**
Constant	−2.257	(0.703)	−0.014	(0.101)
Fare ($100)	−3.435	(0.755)		
Log Frequency	1.050	(0.037)	0.050	(0.004)
Distance	0.312	(0.087)	0.062	(0.017)
Distance^2	0.061	(0.028)	0.028	(0.004)
Nesting Parameter	0.910	(0.046)		

Notes: Airline-quarter fixed effects, major airport fixed effects, airline-hub fixed effects, and fixed effects for the top 50 cities ranked by population are included but not reported. Standard errors in parentheses.

The nesting parameter is 0.910, indicating a high degree of substitution among airline products within the same nest.

On average, consumers are willing to pay about $30.6 for a one-unit increase in the log of daily flight frequency, reflecting the high value passengers place on schedule convenience. It is lower than the estimate in Yuan and Barwick [2024] ($106.8). The marginal willingness to pay for distance evaluated at the sample average distance of 1,395 km is $14.04, which is lower than the estimate in Yuan and Barwick [2024] ($144.34) at the average U.S. domestic flight distance of 1,910 km. This difference likely reflects the shorter average trip lengths and greater availability of alternative transport modes (e.g., high-speed rail) in Europe, which reduce the premium passengers place on air travel for longer distances.

The average own-price elasticity is -3.01, which is close to the aggregate price elasticity of -3.13 reported in Marra [2024] for French market. Our estimate is slightly less elastic than the estimate reported in Bontemps et al. [2023] (-3.78) and more elastic than the estimate in Berry and Jia [2010] (-2.01) for the U.S. market. European air travelers are generally more price sensitive, as documented in both empirical studies and industry reports (InterVISTAS Consulting [2007]). 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. 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. This high responsiveness reflects the availability of close substitutes—both between airlines on the same city pair and across alternative modes of transport.

Figure 4 plots a binscatter of the estimated price elasticity against distance. We divide the distance into 20 equal-sized bins and plot the average elasticity within each bin. The figure shows that price elasticity decreases in distance up to around 2,000 km. This pattern aligns with economic intuition: for shorter routes, passengers have more alternatives (e.g., train, car), making them more price sensitive. As distance increases, air travel becomes the dominant mode of transport, reducing elasticity.

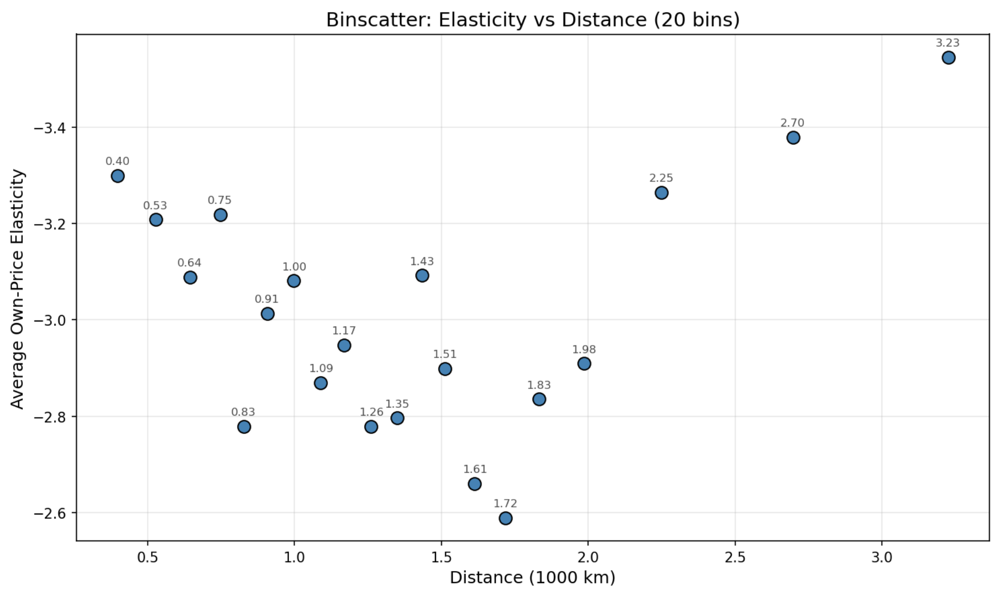

Figure 4: Price Elasticity by Distance

Table 10 presents average price, marginal cost, and variable profit by quarter. The average marginal cost per passenger is $56.9, 40% lower than comparable U.S. estimates in Yuan and Barwick [2024] ($95). 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.[15] Given the average route distance of 1,395 km in our sample, the per-mile cost is $0.07. 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. This figure is also comparable to Yuan and Barwick [2024]'s estimate of $0.08 and Berry and Jia [2010]'s $0.06 for U.S. domestic flights.

The average markup is 28.5% and the average variable profit per route is $0.90 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.

Table 10: Average Price, Marginal Cost, and Variable Profit by Quarter

Quarter	Avg Price	Avg MC	Avg Variable Profit
Q1	82.42	53.91	0.83
Q2	91.79	63.24	0.94
Q3	85.13	56.58	0.93
Q4	81.65	53.12	0.88
Overall	85.48	56.94	0.90

Notes: Price and marginal cost are in USD. Variable profit is in million USD.

5.2 Fixed Cost Estimation

Table 11 reports the fixed cost estimation results.[16] The instrument Y_k includes dummy variables indicating whether a market's exogenous characteristic (e.g., market size or distance) falls within the k-th quantile cell.[17] Fewer instruments lead to a wider confidence region. However, overloading the number of instruments can result in an empty confidence region. We progressively increase the number of instruments until an empty set is reached.[18] Then, we report the projection of the 95% confidence region for each dimension.

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

[16] To compute expected profits, we randomly draw 36 pairs of (ξ, ω) from the empirical joint distribution with 2.5% and 97.5% percentiles as the lower and upper bounds of the respective marginals.

[17] For the first inequality, we use quantile cells for the alternative route's distance and market size. For the second and third inequalities, we use quantile cells for the market's own distance and market size.

[18] We use a grid search with a step size of 1 to construct the confidence region.

Table 11: Fixed Cost Estimation

Freq. $\times$ Dist.		log Market Size		Constant		Slot Controlled Airport	
Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
7	28	-5	49	8	42	-69	-42

Note: This table reports the projection of the 95% confidence region for the fixed cost parameters on each dimension. The instrument Y_k includes dummy variables indicating whether a market's exogenous characteristic (e.g., market size or distance) falls within the k-th quantile cell. We use 9 quantile cells for distance and market size. Cost is (in \$ 10,000). Distance is in 1000 km, population is in million.

Figure 5 plots the distribution of weighted average fixed cost per flight hour.[19] The median is \$4,212, 2.5% percentile is \$3,512, and 97.5% percentile is \$5,274. This aligns with the industry reported operating costs of \$4,829 for A320 family aircraft and \$4,337 for B737 NG aircraft (EUROCONTROL [2024]) per flight hour.

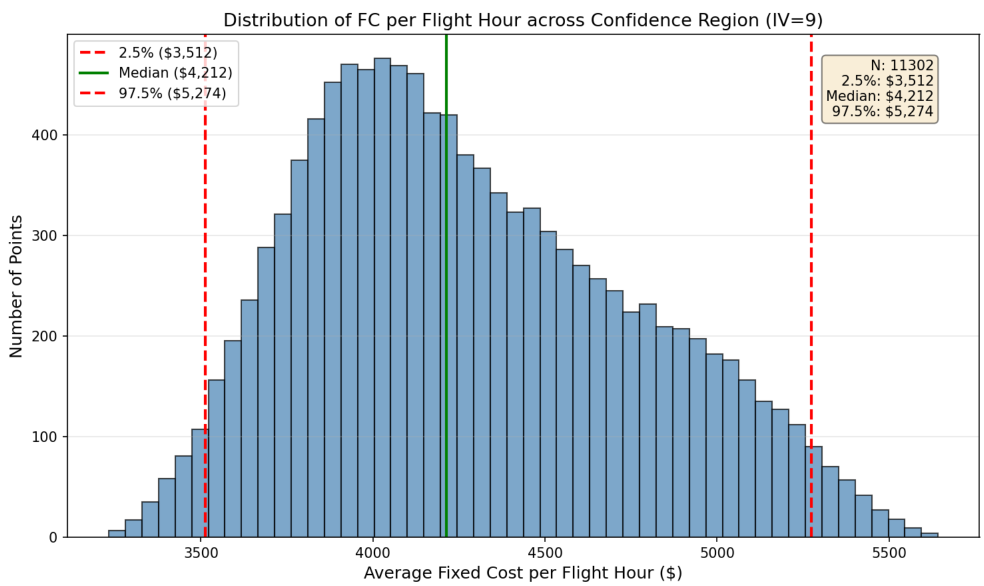

Figure 5: Distribution of Fixed Cost per Flight Hour

The fuel cost (frequency $\times$ distance) ranges from \$777 to \$3110 per 1,000 km flown. This is consistent with industry estimates of fuel cost. The Airbus A320 family burns approximately 2.5 tonnes of jet fuel per hour (International Civil Aviation Organization [2024]), translating to about 2.9 tonnes per 1,000 km. Given an average jet fuel price of around \$66.9 per barrel in 2019 (EUROCONTROL [2024]), this results in a fuel cost of approximately \$1,524 per 1,000 km. About 17–51% of the per-flight-hour operating cost is fuel cost, which is in line with industry data showing that fuel typically accounts for 48% of

[19]We use the average cruising speed of 860 km/h.

operating costs (EUROCONTROL [2024]).

The average value per weekly slot pair at slot-controlled airports ranges from \$140,450 to \$230,740, which is lower than the median slot value of €579,000 reported in Marra [2024]. However, our estimates have the same magnitude.

Table 12 reports the marginal cost from the demand estimation and the bounds on total cost per passenger computed by adding the marginal cost to the fixed cost estimates by airline. Low-cost carriers such as Ryanair and Wizz Air have total cost per passenger that is substantially lower than that of full-service carriers like British Airways and Lufthansa. Industry evidence confirms substantial variation in total costs: European low-cost carriers report per-passenger costs ranging from €50 for Ryanair to €71 for easyJet, while legacy carriers like IAG and Lufthansa operate at around €188 per passenger.[20] As our estimates are based on short-haul routes, and take into account the slot value, they are expected to be lower than the average cost per passenger across all routes.

Table 12: Marginal Cost and Total Cost per Passenger by Airline

Full-Service Carriers				Low-Cost Carriers			
	MC/Pax	Total Cost/Pax			MC/Pax	Total Cost/Pax	
Airline		LB	UB	Airline		LB	UB
British Airways	98.62	107.09	116.54	Ryanair	20.18	32.43	40.18
Lufthansa	118.41	128.89	141.15	EasyJet	27.19	35.93	41.05
Air France-KLM	98.53	104.08	113.04	Wizz Air	17.99	34.58	42.25
SAS	77.28	85.52	89.66	Jet2	39.79	62.68	72.40
Air Europa	59.12	62.79	69.56	Norwegian	61.33	71.01	75.86
Finnair	92.53	88.68	96.66				
Aegean	137.13	136.44	151.29				
LOT Polish	173.64	200.99	229.89				
Icelandair	96.15	115.95	136.40				

Notes: MC = Marginal Cost, Pax = Passenger. LB/UB denote lower/upper bounds computed across the confidence region. All values in USD.

6 Counterfactual Simulations

As discussed in Section 2.1, the converging cost pressures from both carbon pricing mechanisms and fuel supply constraints are expected to significantly reshape airlines' route network decisions. While the increased coefficients incentivise airlines to favour shorter routes, the

[20] Authors' calculations based on Ryanair Holdings plc FY2020 Annual Report, easyJet plc Annual Report 2019, IAG Annual Report 2019, and Deutsche Lufthansa AG Annual Report 2019.

change in route network affects all airlines' expected variable profits. To quantify these effects, we implement five counterfactual scenarios that increase the Frequency $\times$ Distance coefficient by 10, 20, 30, 40, and 50 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.

6.1 Counterfactual Simulation Algorithm

This section describes the counterfactual simulation algorithm. We choose the points on the fixed cost parameter corresponding to the 2.5% percentile, median, and 97.5% percentile of the weighted average of fixed cost per flight hour. We assume the fixed cost shocks follows an i.i.d normal distribution with mean zero. The variance is airline-specific and is set equal to 5% of the variance of deterministic fixed cost.

Feasible Deviations and Frequency Set: We partition markets into aggregate bins based on market size (population, in increments of 2 million) and distance (short-haul $\leq$ 1,500 km vs. medium/long-haul). We create nine daily frequency bins—0–$\frac{1}{7}$, $\frac{1}{7}$–$\frac{2}{7}$, $\frac{2}{7}$–$\frac{4}{7}$, $\frac{4}{7}$–2, 2–4, 4–6, 6–8, 8–10, and 10+. Then, we calculate the proportion of observed frequencies falling within each bin for every market cell. We then rank the bins by their proportion in descending order and select the top k bins until their cumulative mass exceeds 90%. The upper bounds of the selected bins form the feasible frequency support for that cell (for the last bin, we use 10) so that airlines in the counterfactual can only choose among frequency levels that are empirically relevant for markets of similar size and distance. Table 13 reports the resulting frequency supports for each market cell. The frequency supports generally increase with market size, reflecting the fact that larger markets tend to have higher frequencies.

Table 13: Feasible Daily Frequency Set

Market Size (Million)	Short Haul	Medium/Long Haul
0–2	$\{\frac{1}{7}, \frac{2}{7}, \frac{4}{7}, 2\}$	$\{\frac{1}{7}, \frac{2}{7}, \frac{4}{7}, 2\}$
2–4	$\{\frac{1}{7}, \frac{2}{7}, \frac{4}{7}, 2, 4\}$	$\{\frac{1}{7}, \frac{2}{7}, \frac{4}{7}, 2\}$
4–6	$\{\frac{2}{7}, \frac{4}{7}, 2, 4, 6\}$	$\{\frac{1}{7}, \frac{2}{7}, \frac{4}{7}, 2\}$
6–8	$\{\frac{2}{7}, \frac{4}{7}, 2, 4, 6\}$	$\{\frac{2}{7}, \frac{4}{7}, 2, 4\}$
8–10	$\{\frac{4}{7}, 2, 4, 6, 10\}$	—
10–12	$\{\frac{4}{7}, 2, 4, 6\}$	—
12+	$\{2, 4, 6\}$	—

Due to the computational complexity of the counterfactual simulation, we restrict airlines' action space to single-market deviations as in Yuan and Barwick [2024]. Let $\mathcal{F}_r$ be the set of feasible frequencies for route r based on the market cell it belongs to. For a product $j = (g, r)$ where airline g currently operates route r with frequency f, let the set of feasible alternative routes be $\mathbf{R}_{gr}$.[21] We consider the following 4 types of deviations: (i) full exit (i.e., frequency $f' = 0$); (ii) partial exit (i.e., $f' \in \{f' \mid f' \in \mathcal{F}_r, f' < f\}$); (iii) full exit and enter a new route $r' \in \mathbf{R}_{gr}$ with frequency $f' \in \{f' \mid f' \in \mathcal{F}_{r'}, f' < f\}$; and (iv) partial exit and enter a new route $r' \in \mathbf{R}_{gr}$ with frequency $f' \in \{f' \mid f' \in \mathcal{F}_{r'}, f' < f\}$. Airline g deviates if the expected[22] net profit of the deviation is higher than the expected net profit of the current route.

Simulation Algorithm: For each quarter, we rank markets and airlines in a market based on their variable profits. If an airline has multiple routes in the same market, we rank those routes based on their variable profits. Then, we begin with the market with the highest total variable profits. For each airline in that market, starting from the airline with the highest variable profits, we evaluate all feasible deviations. If an airline finds a profitable deviation, it deviates accordingly. After all airlines in the market have been evaluated and potential deviations executed, we proceed to the next market in the variable profit ranking and repeat the process. Unserved markets are explicitly excluded from this evaluation, as the added carbon costs ensure they remain unprofitable. At the end of each iteration, we update the rankings of markets, airlines, and routes based on the new variable profits.

Drawing Fixed Cost Shock: We draw fixed cost shocks to ensure the observed route network satisfies the single-market deviation constraints. For a product $j = (g, r)$ with frequency j, we first draw $\kappa_j(f)$ such that the net profit of the current route is nonnegative. For multi-product airlines, we draw $\kappa_j(f)$ such that exiting any single route is not profitable. Then, we draw alternative fixed cost shocks for all feasible deviations and frequencies such that the net profit of any deviation is not higher than the net profit of the current route. For routes that are not feasible but are in the consideration set (i.e., routes that are blocked by slot constraints or frequency constraints), we draw their fixed cost shocks from the normal distribution. We fix the fixed cost shocks during the counterfactual simulation. For each of 3 fixed-cost parameter estimates (2.5% percentile, median, and 97.5% percentile), we draw 10 fixed cost shocks.

[21] Section 3 provides the details of how we construct the set of feasible alternative routes. We fix the set of feasible routes for each airline throughout the counterfactual simulation.

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

Aircraft Capacity Constraint: We impose the capacity constraint that the implied passengers per flight cannot exceed 200. To do this, we add a smooth capacity penalty to the marginal cost of each product. The penalty takes the form: $\text{penalty}_j = 2.85 \cdot \ln(1 + \exp(0.1\,(L_j - 200)))$ where L_j is the implied passengers per flight for product j. The penalty is negligible when load is below the threshold. A 50% exceedance (i.e., 300 passengers per flight) imposes a penalty of \$28.50, which is half of the average marginal cost per passenger.

6.2 Carbon Regulation Simulation Results

We simulate counterfactuals separately for four quarters and five carbon price scenarios, averaging the results across quarters. Table 14 reports the aggregate welfare effects, and Table 15 decomposes outcomes by airline type.

Baseline Validation. Under the baseline (no policy change), the model generates aggregate annual profits of \$5.38–6.74 billion across the confidence region, which is broadly consistent with Eurocontrol's estimate of approximately €7 billion in net profits for European airlines in 2019 (EUROCONTROL [2019]) and with IATA's regional benchmarks (IATA [2019]). Total annual consumer surplus is \$9.47 billion, and the industry serves approximately 348 million passengers. The short-haul segment accounts for the majority of activity—\$7.09 billion in consumer surplus, \$4.33–5.45 billion in profits, and 260 million passengers—while medium- and long-haul markets contribute \$2.38 billion in consumer surplus, \$1.05–1.29 billion in profits, and 88 million passengers.

Aggregate Welfare Effects. Carbon regulation generates significant welfare redistribution. Even under the Low scenario, consumer surplus declines by 23–31% and airline profits fall by 12–15%. These effects intensify monotonically with the carbon price: at the UH scenario, consumer surplus contracts by 44–55% and profits decline by 53–56%. Passenger volumes track consumer surplus closely, falling by 23–31% (Low) to 44–55% (UH).

The mechanisms are straightforward. Higher distance-related costs induce airlines to exit longer routes and reduce frequencies, which reduces the number of available products and degrades schedule convenience. Both channels reduce the utility of flying, pushing passengers toward the outside option. On the supply side, the contraction of networks and frequencies directly reduces variable profits, while the routes that remain in operation face higher per-passenger fixed costs due to lower traffic volumes.

Table 14: Counterfactual Analysis Results

	Consumer Surplus	Profit	Carbon Revenue	Social Value of CO_2	Welfare Gain	Passengers
All Markets						
Base	9.47	[5.38, 6.74]				348
Low	[-30.97, -23.30]%	[-15.32, -12.31]%	[0.70, 0.81]	[0.37, 0.55]	[-2.40, -1.99]	[-31.12, -23.29]%
Med	[-37.88, -28.12]%	[-28.06, -25.23]%	[1.15, 1.44]	[0.52, 0.74]	[-3.12, -2.50]	[-38.05, -28.15]%
High	[-44.20, -32.84]%	[-39.10, -36.36]%	[1.45, 1.90]	[0.65, 0.87]	[-3.88, -3.09]	[-44.39, -32.93]%
VH	[-49.99, -37.91]%	[-48.49, -45.40]%	[1.62, 2.18]	[0.78, 0.99]	[-4.63, -3.76]	[-50.21, -37.99]%
UH	[-55.26, -43.58]%	[-56.27, -52.90]%	[1.71, 2.32]	[0.90, 1.09]	[-5.34, -4.59]	[-55.49, -43.65]%
Short-haul Markets						
Base	7.09	[4.33, 5.45]				260
Low	[-23.07, -15.31]%	[-12.73, -12.24]%	[0.50, 0.58]	[0.12, 0.25]	[-1.46, -1.02]	[-23.21, -15.21]%
Med	[-28.08, -17.44]%	[-24.26, -23.14]%	[0.88, 1.10]	[0.18, 0.34]	[-1.83, -1.17]	[-28.24, -17.41]%
High	[-33.78, -20.48]%	[-34.56, -33.15]%	[1.15, 1.52]	[0.24, 0.43]	[-2.34, -1.43]	[-34.00, -20.53]%
VH	[-39.50, -24.76]%	[-43.77, -42.09]%	[1.31, 1.83]	[0.31, 0.52]	[-2.88, -1.84]	[-39.74, -24.81]%
UH	[-44.95, -30.31]%	[-51.68, -49.90]%	[1.41, 2.00]	[0.40, 0.58]	[-3.41, -2.43]	[-45.22, -30.37]%
Medium-long haul Markets						
Base	2.38	[1.05, 1.29]				88
Low	[-54.46, -47.09]%	[-26.23, -12.62]%	[0.20, 0.23]	[0.25, 0.31]	[-1.01, -0.93]	[-54.51, -47.16]%
Med	[-67.05, -59.93]%	[-47.16, -32.72]%	[0.27, 0.34]	[0.34, 0.40]	[-1.35, -1.27]	[-67.03, -59.90]%
High	[-75.19, -69.64]%	[-60.91, -46.81]%	[0.31, 0.37]	[0.41, 0.44]	[-1.66, -1.53]	[-75.12, -69.59]%
VH	[-81.23, -77.04]%	[-70.61, -57.20]%	[0.31, 0.35]	[0.47, 0.49]	[-1.93, -1.73]	[-81.17, -76.96]%
UH	[-86.06, -83.07]%	[-77.65, -65.32]%	[0.27, 0.32]	[0.50, 0.52]	[-2.16, -1.91]	[-85.96, -82.92]%

Note: Each cell reports the range [lower, upper] across the confidence region. All monetary values (Consumer Surplus, Profit, Carbon Revenue, Social Value of CO_2, Welfare Gain) are in billions of USD; Passengers are in millions. Consumer Surplus, Passengers, and Profits are ex-ante; Profits integrate the entry cost shock using 10 draws. Social Value of CO_2 assumes fuel consumption of 2.5 t/1000 km, CO_2 factor of 3.16 kg/kg, and social cost of \$0.215/kg CO_2. The social cost of carbon is based on the United States Environmental Protection Agency's Final Report on the Social Cost of Greenhouse Gases (see Table A.5). Welfare Gain = ΔProfit + ΔCS + Carbon Revenue + Social Value of CO_2. Consumer Surplus computation omits the Euler constant.

Table 15: Metrics Breakdown by Airline Type

Airline	Metric	Base	Low	Med	High	VH	UH
All	Profit	[5.38, 6.74]	[-15.32, -12.31]%	[-28.06, -25.23]%	[-39.10, -36.36]%	[-48.49, -45.40]%	[-56.27, -52.90]%
	Fare	93	[6.61, 7.97]%	[5.81, 8.10]%	[4.93, 7.46]%	[3.32, 6.29]%	[1.86, 5.02]%
	Freq	10166	[-25.14, -15.54]%	[-33.57, -20.44]%	[-40.62, -26.64]%	[-47.39, -33.29]%	[-53.32, -40.07]%
	Distance	10568	[-34.18, -23.22]%	[-45.49, -31.87]%	[-54.18, -40.22]%	[-61.66, -48.35]%	[-67.73, -56.15]%
	FC/Pax	[10, 14]	[-30.18, -20.01]%	[-22.52, -1.65]%	[-15.28, 16.06]%	[-9.71, 30.36]%	[-5.17, 41.87]%
	Cost/Pax	[74, 78]	[2.45, 7.27]%	[2.81, 9.99]%	[2.99, 11.49]%	[2.02, 11.90]%	[1.03, 11.79]%
Full Service	Profit	[2.61, 3.46]	[-13.99, -10.46]%	[-28.28, -25.65]%	[-41.00, -38.64]%	[-51.70, -48.84]%	[-60.12, -57.02]%
	Fare	135	[-0.88, -0.15]%	[-1.22, -0.35]%	[-1.41, -0.69]%	[-2.02, -1.20]%	[-2.83, -1.53]%
	Freq	6526	[-23.92, -12.03]%	[-33.99, -17.33]%	[-42.26, -25.32]%	[-50.56, -34.01]%	[-57.41, -42.48]%
	Distance	5917	[-31.24, -16.30]%	[-44.58, -25.17]%	[-54.57, -35.47]%	[-63.53, -46.11]%	[-70.29, -55.91]%
	FC/Pax	[7, 12]	[-15.84, 11.90]%	[-5.99, 47.56]%	[3.22, 76.50]%	[8.51, 97.87]%	[12.95, 114.30]%
	Cost/Pax	[113, 118]	[-2.86, 0.49]%	[-2.23, 2.44]%	[-1.52, 3.79]%	[-1.67, 4.48]%	[-2.15, 5.08]%
Low Cost	Profit	[2.66, 3.15]	[-16.36, -13.84]%	[-27.46, -24.55]%	[-36.78, -33.97]%	[-44.82, -41.92]%	[-51.97, -48.81]%
	Fare	58	[6.58, 7.75]%	[6.78, 7.63]%	[6.76, 7.60]%	[6.85, 7.92]%	[7.13, 8.16]%
	Freq	3395	[-25.06, -20.09]%	[-30.51, -23.98]%	[-35.46, -26.89]%	[-39.59, -29.91]%	[-44.03, -33.60]%
	Distance	4260	[-34.91, -29.61]%	[-43.85, -37.77]%	[-51.20, -43.79]%	[-57.10, -48.93]%	[-62.59, -54.26]%
	FC/Pax	[12, 15]	[-40.78, -32.95]%	[-34.68, -23.94]%	[-28.79, -14.64]%	[-22.53, -4.62]%	[-17.63, 4.98]%
	Cost/Pax	[41, 44]	[-4.92, 0.40]%	[-2.67, 3.29]%	[-0.79, 6.54]%	[1.36, 10.21]%	[3.27, 13.32]%
Regional	Profit	[0.11, 0.13]	[-26.31, -19.69]%	[-38.67, -31.70]%	[-48.91, -40.22]%	[-56.73, -47.80]%	[-63.75, -53.86]%
	Fare	98	[-6.11, -3.31]%	[-6.83, -4.71]%	[-7.65, -4.66]%	[-7.67, -3.81]%	[-8.30, -3.88]%
	Freq	244	[-58.84, -45.99]%	[-64.75, -54.52]%	[-68.40, -58.51]%	[-70.96, -61.14]%	[-73.32, -65.64]%
	Distance	392	[-70.45, -58.18]%	[-77.18, -69.03]%	[-80.70, -73.22]%	[-83.05, -76.03]%	[-85.08, -80.32]%
	FC/Pax	[7, 12]	[-86.79, -48.16]%	[-85.57, -32.71]%	[-76.43, -3.08]%	[-64.08, 27.50]%	[-51.62, 39.95]%
	Cost/Pax	[77, 81]	[-19.22, -8.30]%	[-19.88, -8.30]%	[-19.65, -5.42]%	[-17.95, -1.48]%	[-16.96, -0.43]%

Note: Each cell reports the range [lower, upper] across the confidence region. Base Profit is in billions of USD; Fare, FC/Pax, and Cost/Pax are in USD. FC/Pax is the fixed cost (entry cost + entry shock) per passenger; Cost/Pax is marginal cost + FC/Pax. Scenario columns show percentage changes from baseline.

Carbon regulation does generate two offsetting welfare gains. First, carbon tax revenue—ranging from \$0.70–0.81 billion (Low) to \$1.71–2.32 billion (UH)—represents a transfer from airlines to the government. Second, the social value of avoided CO_2 emissions increases from \$0.37–0.55 billion (Low) to \$0.90–1.09 billion (UH), reflecting the environmental benefits of shorter average routes and reduced total flying. However, these gains are insufficient to offset the combined losses in consumer surplus and profits: total welfare (defined as ΔProfit $+\Delta$CS + Carbon Revenue + Social Value of CO_2) declines by \$1.99–2.40 billion under the Low scenario and by \$4.59–5.34 billion under the UH scenario.

Asymmetric Effects by Market Segment. The aggregate figures mask sharp heterogeneity between short-haul and medium- to long-haul markets. Medium- and long-haul routes are far more exposed to the carbon tax because the treatment variable—the cost per kilometre flown—scales with distance. Under the Low scenario, consumer surplus in medium-long haul markets falls by 47–54%, compared with 15–23% for short-haul markets. At the UH level, medium-long haul consumer surplus declines by 83–86%, effectively eliminating much of the longer-distance market. Profit declines are also larger for medium-long haul routes, though the differential is less extreme: 13–26% (Low) versus 12–13% (Low) for short-haul.

This asymmetry has important geographic implications. Markets connecting peripheral countries such as Iceland, Norway, and Greece to the European core rely disproportionately on medium- and long-haul routes. The carbon tax therefore imposes a geographically concentrated welfare loss on these regions. By contrast, short-haul markets—which dominate Central and Eastern European connectivity—are relatively more resilient, implying that the policy redistributes connectivity towards shorter, denser city-pairs.

Heterogeneous Responses by Airline Type. Table 15 reveals that the three carrier types—full-service carriers (FSCs), low-cost carriers (LCCs), and regional carriers—respond to carbon pricing along fundamentally different margins.

Profit impacts. At low to moderate carbon prices, FSCs are the most resilient: under the Low scenario, FSC profits decline by 10–14%, compared with 14–16% for LCCs and 20–26% for regional carriers. This ordering reflects the combination of FSCs' higher initial fare levels, which provide a larger buffer to absorb cost increases, and the relative insulation of hub-based networks from marginal route exits. However, this ranking partially reverses at higher carbon prices. Under the UH scenario, LCC profits contract by 49–52%, compared with 57–60% for FSCs and 54–64% for regional carriers. This reversal reflects the fact that LCCs operate shorter-haul networks that are less exposed to the distance-based carbon tax, giving them a structural advantage as the policy becomes more aggressive. Regional carriers are the hardest hit across all scenarios, with profit declines ranging from 20–26% (Low) to 54–64% (UH), consistent with their dependence on thin, distance-intensive routes.

Pricing responses. The three carrier types exhibit strikingly different pricing behaviour. LCCs *raise* fares across all scenarios, by 6.6–7.8% (Low) to 7.1–8.2% (UH). This pattern is consistent with LCCs' competitive position under the carbon tax: because LCC networks are concentrated on shorter routes that are less affected by the distance-based cost shock, LCCs face relatively less exit pressure and can exploit the reduction in competition from FSC and regional carrier exit to increase markups. In contrast, FSCs exhibit slightly declining fares: changes range from −0.9 to −0.2% (Low) to −2.8 to −1.5% (UH). Regional carriers *reduce* fares more sharply, by 3–6% (Low) to 4–8% (UH). For FSCs and regional carriers, the fare reductions reflect the competitive dynamics of a shrinking market: as these carriers contract their networks and lose passengers on longer routes, the remaining services shift toward shorter, more competitive markets where price-elastic demand constrains pricing power.

Network adjustments. Network contraction is most severe for regional carriers. Under the Med scenario, regional carrier frequencies decline by 55–65% and total distance flown falls by 69–77%, reflecting their dependence on thin, longer-distance routes. FSCs exhibit intermediate contraction—frequencies fall by 17–34% and distance by 25–45% under the Med scenario—while LCCs are the least affected, with frequencies declining by 24–31% and distance by 38–44%. Under the UH scenario, regional carrier frequencies fall by 66–73% and distance by 80–85%, compared with 42–57% and 56–70% for FSCs, and 34–44% and 54–63% for LCCs. This ordering reflects the structural differences in network composition: regional carriers operate the thinnest, most distance-intensive routes that are fully exposed to the carbon tax; FSC networks are anchored by valuable hub slots and intercontinental connectivity; while LCC point-to-point networks are concentrated on shorter, denser city-pairs that are relatively insulated from the distance-based cost shock.

Cost structure. The carbon tax induces a recomposition of per-passenger costs. Fixed cost per passenger (FC/Pax) rises substantially for FSCs at higher tax levels—by up to 114% under UH—because the denominator (passengers) shrinks faster than the numerator (fixed operating costs). LCCs experience more moderate FC/Pax changes, ranging from −18% to +5% under UH, reflecting their relatively smaller network contraction. Regional carriers exhibit wide variation, with FC/Pax changes spanning from −52% to +40% under UH, driven by the interaction between severe route exits and the highly heterogeneous nature of regional operations. Total cost per passenger (Cost/Pax) rises modestly for LCCs, by 3–13% under UH, while FSC Cost/Pax changes are bounded between −2% and +5%. Regional carriers see Cost/Pax *decline* by 0–17% under UH, indicating that the exit of the most cost-intensive routes rationalises the surviving network.

Summary. The counterfactual analysis reveals three key findings. First, carbon regulation generates substantial welfare redistribution rather than a pure efficiency loss: consumer surplus and airline profits decline, but carbon revenue and environmental benefits partially compensate. Second, the impacts are highly asymmetric across both market segments and carrier types. Medium- and long-haul markets bear disproportionate adjustment costs, while short-haul markets are more resilient. Among carriers, regional airlines are the most severely affected, while LCCs—concentrated on shorter routes—prove the most resilient at high carbon prices despite being intermediately affected at low levels. Third, the competitive reordering is notable: LCCs exploit their structural advantage on shorter routes to raise fares and maintain networks, while FSCs and regional carriers contract and reduce prices, suggesting that carbon pricing shifts the competitive balance toward the low-cost segment.

7 Conclusion

This paper develops and estimates a two-stage model of airline competition with endogenous route entry and pricing to quantify the impact of carbon regulation on the European airline industry. Our counterfactual simulations reveal that the effects of carbon pricing under the EU ETS are highly asymmetric across carrier types, market segments, and geographies. Network contraction falls disproportionately on regional carriers, whose flight frequencies decline by up to 73%, while low-cost carriers' networks prove comparatively resilient. The policy redistributes welfare geographically: consumer surplus in medium- and long-haul markets—connecting peripheral regions to the European core—declines by up to 86%, whereas short-haul markets that underpin Central and Eastern European connectivity are relatively less exposed, with consumer surplus declining by up to 45%. Across all scenarios, the tax burden falls predominantly on airlines, whose profits decline by 12–56%, while consumer surplus declines by 23–55% and passenger volumes fall by 23–55%. Carbon tax revenue of \$0.7–2.3 billion and a social value of avoided CO_2 emissions of \$0.37–1.09 billion partially offset these losses, but aggregate welfare remains negative in every scenario. These results demonstrate that carbon regulation can achieve meaningful environmental gains in European airline markets, though at significant cost to industry profits and consumer welfare, and that its incidence is far from uniform—falling most heavily on peripheral regions and the regional carriers that serve them.

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