Carbon regulation and competition in the European airline industry

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March 28, 2026

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, flight frequencies, 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. Consumer surplus declines by up to 25% overall, with medium-haul markets bearing the brunt at up to 90%, while short-haul markets experience positive net welfare gains (including carbon revenue and the social value of avoided emissions) as airlines reallocate capacity toward shorter routes. We find that airline profits decline by 8–45% across scenarios, while carbon tax revenue of \$0.9–3.1 billion and a social value of avoided CO_2 emissions of \$0.5–1.4 billion partially offset the welfare losses. We also show that a hypothetical Wizz Air–Ryanair merger primarily benefits firm profits through network expansion synergies.

Keywords: Carbon Regulation, Airline Competition, Welfare Analysis

JEL Codes: L93, L13, Q52

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 (over 55% of intra-European passengers in our sample versus approximately

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[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].

40% in the US; Bontemps et al. [2025a]).

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, incumbent hub 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 are due to be completely phased out, dramatically increasing the effective carbon price [European Commission, 2024]. This permanent carbon price increase will come on top of the large, potentially temporary, fuel cost shock caused by the 2026 Iran War and, in the longer run, 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 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 impacts of increasingly stringent carbon taxation, implemented through the EU ETS.[2] We simulate new network equilibria using an iterative algorithm in which airlines sequentially re-optimise route choices in response to higher distance-related costs.

Our key findings are as follows. First, our estimates reveal stark differences in the demand

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[2]While we don't simulate the impact of the 2026 Iran War, the effects of an exogenous fuel cost shock are equivalent to a carbon tax increase with all tax revenue eliminated.

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 most severe for regional carriers, whose flight frequencies decline by up to 54%, while FSCs and LCCs adjust primarily through route shortening rather than frequency reduction. Third, the policy induces a geographic redistribution of welfare: medium- and long-haul markets, which connect peripheral regions such as Iceland and Norway to the European core, are far more severely affected, while short-haul markets that dominate Central and Eastern European connectivity experience positive net welfare gains (including carbon revenue and the social value of avoided emissions) as airlines reallocate capacity toward shorter routes. Fourth, we find that the burden of carbon regulation is shared between consumers and airlines. Consumer surplus falls substantially across all scenarios, while airline profit losses become especially large as the carbon price rises. Carbon tax revenue and the social value of avoided CO_2 emissions partially offset these losses, resulting in total welfare losses of $0.4–0.7 billion across scenarios. Fifth, we simulate a hypothetical merger between Ryanair and Wizz Air under each carbon tax level and find that the merger increases firm profits by approximately $0.1 billion through network expansion synergies, while consumer surplus and other outcomes remain similar to no merger scenarios.

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., 2025a, 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., 2025b], 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 (vary-

ing 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 identification and estimation. 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.[3] 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 centralised

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[3]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).

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].

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 covering 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.[4] 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, although aviation initially received substantial free allocation upon entering the EU ETS, the 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 raises airlines' net compliance expenditure, converting the opportunity cost of emissions into a direct cash outlay. Third, because both airline networks and prices are endogenous, carbon pricing operates both through the extensive margin of route entry and exit and the intensive margin of pricing. Fundamentally, fuel costs are a per-flight cost determined by aircraft and passenger weight, engine efficiency, and distance. The carbon cost shock affects both fixed operating costs (through aircraft weight) and marginal costs (through passenger weight). Because each passenger contributes only a small fraction of total weight, the impact on fixed costs is larger than the impact on marginal costs. As a result, the network restructuring channel, absent in the manufacturing context where firms' production locations are relatively fixed in the short run, is the first-order margin of adjustment in aviation.

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[4]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.

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]. 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 \$50 to over \$250 per tonne, the additional operational cost per kilometre flown will increase from approximately \$0.5 to \$2.5, 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 kilometre 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. Because the carbon cost scales with distance flown per flight, all carriers face route-level cost shocks that increase with distance. However, the two dominant network architectures differ in their capacity to absorb these shocks. LCCs operate decentralised point-to-point networks serving direct origin-destination traffic, with high aircraft utilisation and route portfolios concentrated entirely within the EEA. Their point-to-point structure gives them broad flexibility to reallocate flights across city-pairs as relative route profitability shifts. FSCs, by contrast, are flag carriers whose hub-and-spoke networks are anchored at slot-controlled home-country airports. A uniform carbon tax can therefore induce heterogeneous responses in route entry and exit, network configuration, and, through changes in competitive structure, pricing 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. LCCs' share of flights (not passengers) has surged from just 1.6% in 1998 to approximately 32.5% by 2022 [EUROCONTROL, 2022]. In terms of passenger shares, a longer time series on passenger shares is not available, but Table 1 shows that LCCs accounted for more than half of all intra-European passengers during 2016–2019. The scale of this transformation is exemplified by Ryanair, which in 2023 carried 182 million passengers, more than any single FSC in Europe.[5]

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 LCCs 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 centralise operations, exploiting incumbent hub advantages, grandfathered slot holdings, 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 decentralised *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, lower fleet utilisation, and premium

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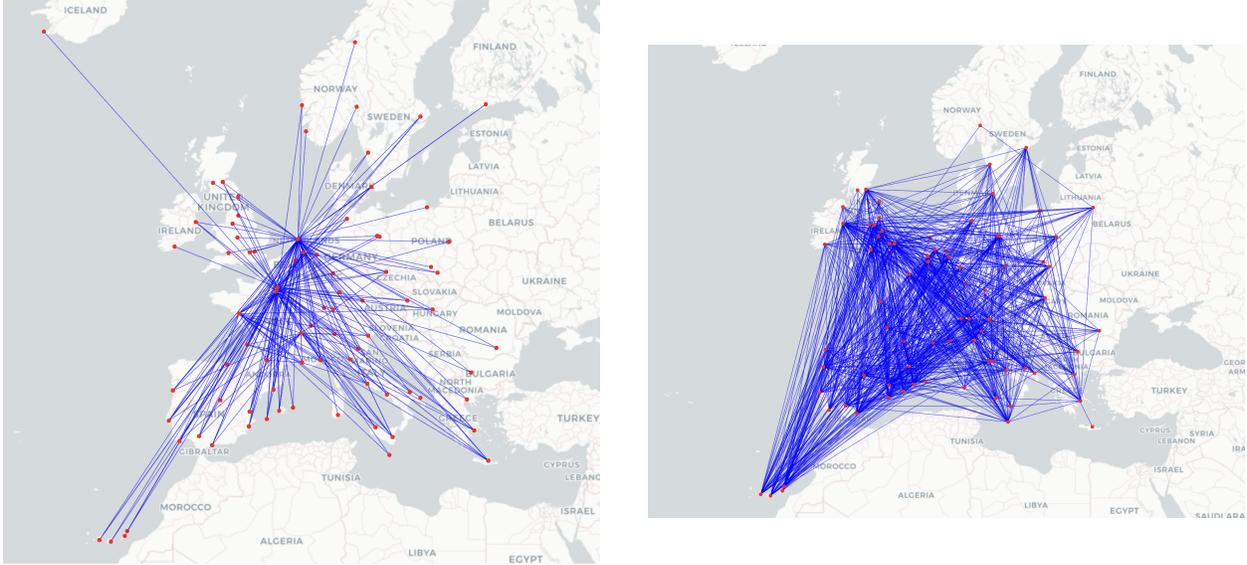[5]Ryanair Holdings plc, Annual Report FY2024.

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

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 handling and seat selection.[6] 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 London City and Southend airports cater to specialised segments.[7] 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

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[6]While FSCs increasingly adopt similar pricing practices, airline annual reports show that LCC revenue shares from ancillary charges range from 26-45% while FSC revenue shares range from 11-24%.

[7]London City mainly serves short-haul business routes while Southend is dominated by charter airlines.

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.[8]

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.[9]

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.

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[8]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.

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

Table 3: Full-service carrier groups and their subsidiaries

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	FRA, MUC, ZRH
	Swiss, Brussels Airline, Eurowings	VIE, BRU
SK	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.

Aircraft Utilisation. Aircraft utilisation rates directly limit an airline's ability 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 without expanding fleets.[10] 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

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

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. [2025a]. The top 100 airports serve 82 cities and 89.8% of passengers in 2016-2019. We define a product to be a non-directional route 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] 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 is about 1,400 kilometres. In total, the products in our 2019 sample served over 342 million passengers.

Table 4: Summary statistics

(a) Market dimensions		(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 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.[11]

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 summary statistics for each airline's hub cities. The Hub Index measures the total number of cities served by the hub, indicating its level of connectivity. Freq. is the average frequency of all flights to/from the hub. Concentration measures the proportion of flights to/from the hub city relative to all the airline's flights.

Table 6(a) 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. The standard deviation of fares in monopoly markets is also higher. Table 6(b) shows that FSCs operate, on average, about 1.6 times as many routes involving a hub as LCCs. Table 6(c) presents the average quarterly change in the number of routes

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[11]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.

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).

Table 6: Competition and Network Statistics

(a) Price and competition

Number of Competitors	1	2	3	4	5
Number of markets	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

(b) Hub Exposure

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

Note: Number of routes with at least one hub per competing airline

(c) Quarterly dynamics

		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

Note: Average quarterly change in routes per competitor

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 3 shows a network analysis. The network size is the total number of airports 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
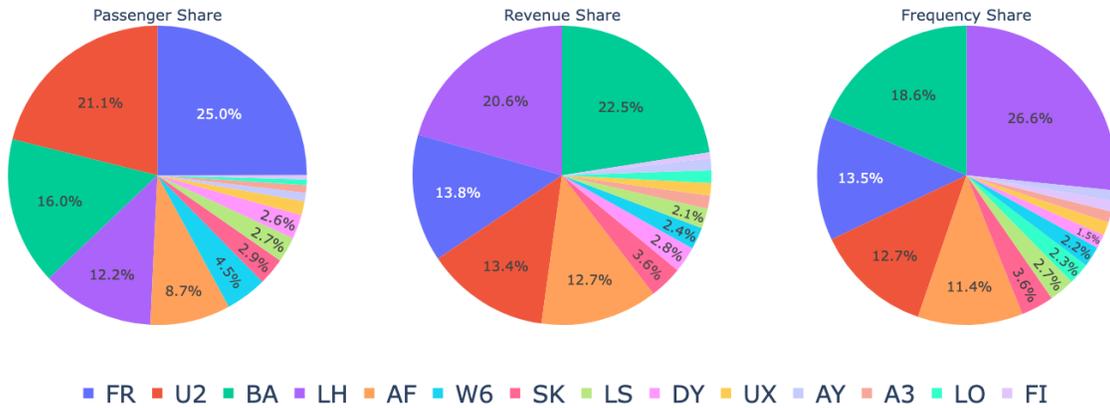
Figure 2: Passenger, revenue, and frequency shares by airline group, Q2 2019

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 size, density, and efficiency by airline group, Q2 2019

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[12] 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.[13] 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 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 $J_m = |\mathcal{J}_m|$. Note that 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 the total frequency across an airline's network is bounded above by the total observed frequency in the data.

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[12]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.

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

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:

$$U_{ijm} = \begin{cases} -\alpha p_{jm} + x_{jm}\beta + \xi_{jm} + \nu_{im}(\lambda) + \lambda\varepsilon_{ijm} & \text{if } j \in \mathcal{J}_m \\ \varepsilon_{i0m} & \text{if } j = 0 \end{cases}$$

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-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-hub fixed effect is important because major European hubs serve both intra-European passengers and a substantial volume of extra-European transfer passengers. Higher levels of demand due to these additional extra-European passengers are captured by these airline-hub fixed effects.[14]

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

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

$$\times \underbrace{\frac{\exp((-\alpha p_{jm} + x_{jm}\beta + \xi_{jm})/\lambda)}{\sum_{k\in\mathcal{J}_m} \exp((-\alpha p_{km} + x_{km}\beta + \xi_{km})/\lambda)}}_{\text{Conditional probability of choosing } j}$$

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

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[14]International transfer passengers travelling on single itineraries with short layovers are not included in our dataset. However, the intra-European legs of international passenger journeys with long layovers are included.

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

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

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

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:

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

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:

$$MC_{jm} = x_{jm}\theta_s + \omega_{jm} \tag{2}$$

where ω_{jm} is an unobserved cost shock and θ_s is a marginal cost parameter vector. Note that x_{jm} includes distance. When we compute our counterfactual simulations, increased fuel costs are modeled as in increase in the cost per kilometer. This is detailed in Section 6 below.

3.2 First Stage: Entry and Frequency

In the first stage, airlines simultaneously choose route networks and flight frequencies. Airlines incur fixed operating 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 operating cost is:

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

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 ETS 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.[15] 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:

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

In this expression, $\mathbf{p}_m$ is the equilibrium price vector that arises in 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:

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

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. [2025a] and Yuan and Barwick [2024]. We assume the existence of a first-stage equilibrium, but do not assume uniqueness and allow for multiple equilibria.

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

4 Identification and Estimation Strategies

Identification of demand and cost parameters is standard and straightforward. 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. As airlines choose to enter markets and set frequencies before the first-stage demand shocks are realised, these variables are exogenous.

Identification of the fixed cost parameters θ_{fc} requires more discussion. These parameters are set identified based on moment inequalities arising from the firms' entry/exit decisions.

Construction of Moment Inequalities. To ease notation, we suppress dependence on $(\mathbf{X}, \theta_s, \theta_d)$ 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 assume that market size and distance are independent of the fixed cost shocks and define indicator variables based on quantile cells of the variables to define K exogenous instruments. For each instrument Y_k:

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

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. [2025a], 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:

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

where the first inequality considers deviations to other markets, the second considers deviations that remove planes from service, and the last considers entering unserved markets. The variable $\bar{f}_g$ 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

As discussed in Section 4, demand and marginal costs parameters are estimated by applying GMM to equations (1) and (2). Table 7 reports the demand and marginal cost estimation results. The Kleibergen–Paap F-statistic [Kleibergen and Paap, 2006] is 11.81, indicating strong instruments. 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. This 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 derived from our parameter estimates is -3.01, which is close to the aggregate price elasticity of -3.13 reported in Marra [2024] for the French market. Compared to estimates from the US market, our estimate is slightly less elastic

Table 7: Demand and Marginal Cost Estimation Results

Variable	Demand		Marginal Cost	
	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)		

Note: 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.

than the estimate reported in Bontemps et al. [2025a] (-3.78) and more elastic than the estimate in Berry and Jia [2010] (-2.01). 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 elasticities against distance. We divide markets into 20 equal-sized bins and plot the average elasticity within each bin. The figure shows that price elasticity decreases with distance up to around 2,000 km before increasing again for the longest routes. 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 the elasticity. The pattern reverses for longer trips which are less likely to be quick getaways. For such trips, the elasticity increases again likely because the time cost of travel dominates making the outside option not to fly more attractive.

Table 8 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
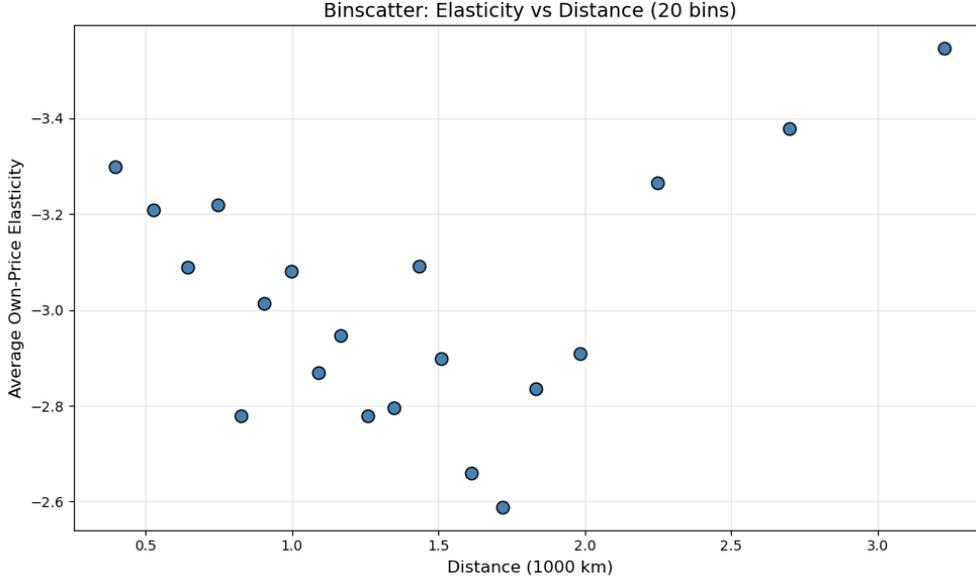
Figure 4: Price Elasticity by Distance

networks, and more efficient aircraft utilisation.[16] 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 margin estimates 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 8: 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

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

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[16]See IATA Annual Review and InterVISTAS (2007) *Estimating Air Travel Demand Elasticities*, which report CASK figures for major world regions.

5.2 Fixed Cost Estimation

We estimate bounds on the fixed cost parameters using the inequalities in (3). To compute expected profits, we randomly draw N 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. Since each node on our cluster has 36 processors, we use $N = 36$ to avoid excessive computational times. As discussed in Section 4, the instruments Y are indicator functions where $Y_k = 1$ if a market's exogenous characteristics 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]

Table 9 reports the results. The table reports, for each element of the vector θ_{FC}, the projection of the estimated 95% confidence region in that dimension.

Table 9: Fixed Cost Estimation

Freq. × 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: For each parameter, the table reports the projection of the 95% confidence region in that 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.

To compare our results to industry benchmarks, we draw parameter vectors uniformly from the confidence region, compute the fixed cost for each product in each market, average across products and markets, and plot in Figure 5 the resulting distribution of average fixed cost per flight hour (assuming average cruising speed of 860 km/h). Our estimated distribution has a median of \$4,604, a 2.5th percentile of \$4,059, and a 97.5th percentile of \$5,031. These estimates align with the industry reported operating costs per flight hour of \$4,829 for A320 family aircraft and \$4,337 for B737 NG aircraft [EUROCONTROL, 2024].

The fuel cost (frequency × distance) ranges from \$389 to \$1,555 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

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

[18]We use a grid search with a step size of 1 to construct the confidence region.
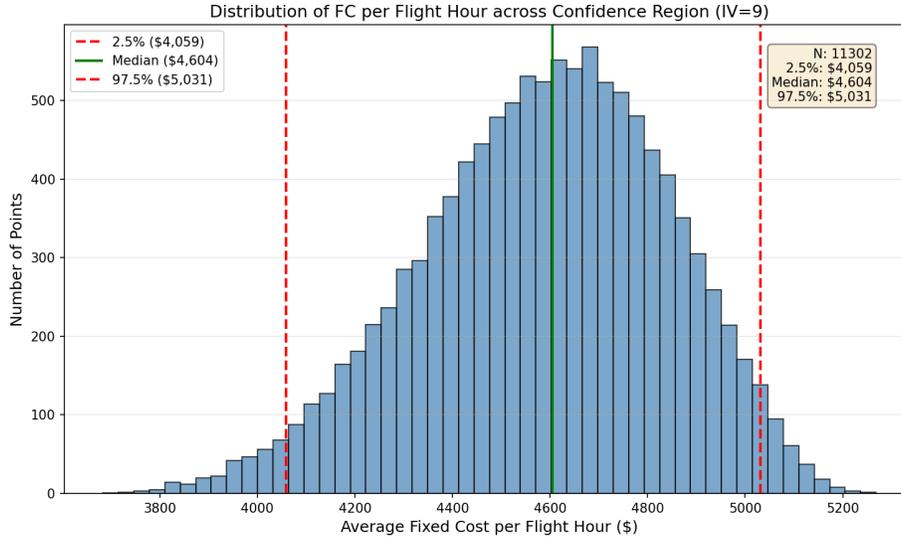
Figure 5: Distribution of Fixed Cost per Flight Hour

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 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 10 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.[19] 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.

6 Counterfactual Simulations

As discussed in Section 2.1, the converging cost pressures from carbon pricing mechanisms and fuel supply constraints are expected to significantly reshape airlines' route network and

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[19]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.

Table 10: Marginal Cost and Total Cost per Passenger by Airline

Full-Service Carriers				Low-Cost Carriers			
Airline	MC/Pax	LB	UB	Airline	MC/Pax	LB	UB
British Airways	98.6	102.9	107.6	Ryanair	20.2	26.3	30.2
Lufthansa	118.4	123.6	129.8	EasyJet	27.2	31.6	34.1
Air France-KLM	98.5	101.3	105.8	Wizz Air	18.0	26.3	30.1
SAS	77.3	81.4	83.5	Jet2	39.8	51.2	56.1
Air Europa	59.1	61.0	64.3	Norwegian	61.3	66.2	68.6
Finnair	92.5	90.6	94.6				
Aegean	137.1	136.8	144.2				
LOT Polish	173.6	187.3	201.8				
Icelandair	96.1	106.0	116.3				

Notes: MC = Marginal Cost, Pax = Passenger, LB/UB = Lower/Upper Bound of Total Cost per Passenger. All values in USD. Bounds computed across confidence region.

pricing decisions. These cost pressures will increase both fixed operating costs and marginal costs. To quantify these effects, we implement five counterfactual scenarios that increase fuel costs by \$0.5-\$2.5 per kilometre flown. We label these scenarios Low, Medium, High, Very High, and Ultra High and use the abbreviations Low, Med, High, VH, and UH. The lower bound of \$0.5 reflects current EU ETS price levels with modest SAF adoption while the upper bound of \$2.5 corresponds to an ultra high carbon price scenario with extensive SAF mandates.

These scenarios increase fixed costs by increasing the coefficient on Frequency × Distance by 10, 20, 30, 40, and 50 respectively.[20] Additionally, each scenario adds a per-passenger carbon surcharge to the marginal cost, proportional to route distance. The surcharge equals $\tau \times 3.16 \times 2.5$ per 1,000 kilometre, where τ is the carbon tax rate, 3.16 is the CO_2 emission factor (kg CO_2 per kg fuel), and 2.5 is the marginal fuel burn rate (additional kg per additional passenger per 1,000 km).[21]

In addition to the carbon-only scenarios, we examine how carbon regulation interacts with airline consolidation by simulating a hypothetical merger between Wizz Air and Ryanair under each carbon tax level.

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[20]Since each frequency unit entails a round trip, the coefficient on Frequency × Distance reflects twice the one-way per-kilometre cost. The reported \$0.5–2.5 range corresponds to the one-way cost per kilometre.

[21]The carbon emission factor is obtained from the International Civil Aviation Organization [2024]. The fuel burn rate is from Steinegger [2017].

6.1 Counterfactual Simulation Algorithm

This section describes additional counterfactual assumptions and the counterfactual simulation algorithm. We assume the fixed cost parameters are uniformly distributed in the confidence regions and draw 20 fixed cost parameter vectors from this distribution. We assume the fixed cost shocks are drawn independently from a normal distribution with mean zero and with airline-specific variances set equal to 5% of the variances of the deterministic fixed costs.[22]

Feasible Deviations and Frequency Choices: We measure frequency as flights per day and discretize frequency choices as follows. First, we partition markets into cells based on market size (population, in increments of 2 million) and distance (short-haul $\leq$ 1,500 km vs. medium/long-haul). This results in 4 sizes of medium/long-haul markets and 7 sizes of short-haul markets. Then, for each market cell, we select the largest k frequency bins that account for 90% of observed flight frequencies. The k frequency bins are chosen from:

$$\left\{ \left(0, \frac{1}{7}\right], \left(\frac{1}{7}, \frac{2}{7}\right], \left(\frac{2}{7}, \frac{4}{7}\right], \left(\frac{4}{7}, 2\right], (2, 4], (4, 6], (6, 8], (8, 10], 10+ \right\}.$$

This discretisation ensures that airlines in the counterfactual can only choose among frequency levels that are empirically relevant for markets of similar size and distance. Table 11 reports the resulting frequency supports for each market cell. The frequency supports generally increase with market size reflecting that larger markets have higher frequencies.

Table 11: 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. 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

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[22]Here we follow Wollmann [2018] who also use normally distributed fixed cost shocks in their counterfactual simulations and set the variance to 5% of the variance of the disturbance-free portion.

operates route r with frequency f, let the set of feasible alternative routes be $\mathbf{R}_{gr}$.[23] We consider the following 5 types of deviations. Let $\bar{F}_g$ denote the pool of available flights for airline g, which accumulates frequencies released from exiting or reducing other routes within the same iteration. The deviations are: (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) stay or increase frequency on the current route (i.e., $f' \in \{f' \mid f' \in \mathcal{F}_r, f' \leq f + \bar{F}_g\}$); (iv) full exit and enter a new route $r' \in \mathbf{R}_{gr}$ with frequency $f' \in \{f' \mid f' \in \mathcal{F}_{r'}, f' \leq \bar{F}_g + f\}$; and (v) partial exit and enter a new route $r' \in \mathbf{R}_{gr}$ with frequency $f' \in \{f' \mid f' \in \mathcal{F}_{r'}, f' \leq \bar{F}_g + f - f''\}$, where f'' is the reduced frequency on the original route. Airline g deviates if the expected[24] net profit of the deviation is higher than the expected net profit of the current route.

Simulation Algorithm. We sequentially evaluate profitable single-market deviations for all airlines in all markets. Enumerating each of the equilibria is computational infeasible. Therefore, we follow Wollmann [2018], Yuan and Barwick [2024], and Bontemps et al. [2025a] and consider multiple orders of evaluation to explore the potential range of equilibrium outcomes. We consider 3 orders of network evaluation. The first order is based on variable profits. 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. The second order reverses the ranking of markets, starting with the market with the lowest total variable profits. The third order randomizes the ranking of markets and airlines. For each order, we repeat the process until no airline can find a profitable single-market deviation.[25]

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[23]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.

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

[25]The maximum number of iterations is set to 100. Note that the single-market deviation can be treated as the pairwise stability concept in the network formation game. Jackson and Watts [2002] shows that the improving paths emanating from any starting network lead to a pairwise stable network, or to a cycle. In this case, we report the average aggregate statistics across the cycle and interpret them as the expected outcomes of a mixed strategy equilibrium. If the maximum number of iterations is reached without convergence, we report the statistics at the final iteration. In most cases, the algorithm converges.

Drawing Fixed Cost Shocks. 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 f, 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 fixed cost parameter vector, we draw 1 fixed cost shock.

Aircraft Capacity Constraints. 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. Table 12 reports the aggregate welfare effects, and Table 13 decomposes outcomes by airline type.

Baseline Validation. Under the baseline (no policy change), the model generates aggregate annual profits of \$6.05 billion (s.d. 0.44), 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 expected number of passengers is 348 million (compared to 342 million observed in the data). The short-haul segment accounts for the majority of activity, with \$7.09 billion in consumer surplus, \$4.92 billion (s.d. 0.38) in profits, and 260 million passengers, while medium- and long-haul markets contribute \$2.38 billion in consumer surplus, \$1.13 billion (s.d. 0.07) in profits, and 88 million passengers.

Aggregate Welfare Effects. The low carbon tax reduces consumer surplus by 15.4% and reduces profits by 7.5%. The low carbon tax impact on consumers is more than twice as large as the impact on firms. However, the negative impact on firms increases more quickly

Table 12: Counterfactual Analysis Results

	Consumer Surplus	Profit	Carbon Revenue	Social Value of CO_2	Welfare Gain	Passengers
All Markets						
Base	9.47	6.05 (0.44)				348
Low	-15.43 (1.03)%	-7.54 (3.40)%	0.91 (0.02)	0.46 (0.05)	-0.56 (0.17)	-15.57 (1.08)%
Med	-17.29 (0.83)%	-19.33 (3.39)%	1.68 (0.04)	0.67 (0.05)	-0.47 (0.23)	-17.53 (0.92)%
High	-18.99 (1.12)%	-29.14 (3.39)%	2.31 (0.08)	0.87 (0.08)	-0.39 (0.25)	-19.39 (1.24)%
VH	-21.60 (2.01)%	-37.68 (2.88)%	2.77 (0.14)	1.11 (0.10)	-0.45 (0.19)	-22.15 (2.14)%
UH	-25.39 (2.44)%	-45.38 (2.49)%	3.05 (0.16)	1.37 (0.10)	-0.74 (0.18)	-26.10 (2.53)%
Short-haul Markets						
Base	7.09	4.92 (0.38)				260
Low	-2.71 (0.75)%	-3.23 (2.90)%	0.69 (0.01)	-0.08 (0.02)	0.25 (0.14)	-2.85 (0.80)%
Med	-0.69 (0.62)%	-13.03 (2.88)%	1.37 (0.02)	-0.07 (0.03)	0.60 (0.18)	-0.95 (0.68)%
High	0.51 (1.19)%	-22.03 (2.83)%	2.00 (0.07)	-0.01 (0.07)	0.93 (0.17)	0.07 (1.33)%
VH	-0.44 (2.60)%	-30.42 (2.31)%	2.48 (0.14)	0.13 (0.11)	1.08 (0.14)	-1.08 (2.76)%
UH	-3.80 (3.33)%	-38.38 (1.97)%	2.79 (0.18)	0.32 (0.11)	0.95 (0.17)	-4.65 (3.44)%
Medium-long haul Markets						
Base	2.38	1.13 (0.07)				88
Low	-53.29 (3.02)%	-26.28 (6.45)%	0.22 (0.01)	0.54 (0.04)	-0.81 (0.06)	-53.21 (3.00)%
Med	-66.69 (2.69)%	-46.68 (6.59)%	0.31 (0.02)	0.74 (0.03)	-1.07 (0.07)	-66.57 (2.69)%
High	-77.05 (1.94)%	-60.02 (6.87)%	0.32 (0.03)	0.88 (0.03)	-1.32 (0.09)	-76.92 (1.95)%
VH	-84.57 (1.38)%	-69.26 (6.48)%	0.29 (0.03)	0.99 (0.02)	-1.52 (0.11)	-84.46 (1.40)%
UH	-89.65 (1.14)%	-75.77 (5.74)%	0.25 (0.04)	1.05 (0.02)	-1.69 (0.12)	-89.56 (1.16)%

Note: Each cell reports the mean with standard deviation in parentheses, pooled across seeds and product-evaluation orderings. 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 25 draws. Social Value of CO_2 assumes fuel consumption of $2.5\,\mathrm{t}/1000\,\mathrm{km}$, CO_2 factor of $3.16\,\mathrm{kg/kg}$, and social cost of $\$0.215/\mathrm{kg}$ 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 13: Metrics Breakdown by Airline Type

Airline	Metric	Base	Low	Med	High	VH	UH
All	Profit	6.05 (0.44)	-7.54 (3.40)%	-19.33 (3.39)%	-29.14 (3.39)%	-37.68 (2.88)%	-45.38 (2.49)%
	Fare	93	6.63 (0.57)%	7.40 (0.54)%	8.09 (0.38)%	7.98 (0.74)%	6.74 (1.12)%
	Total Flights	18.3	-1.67 (0.14)%	-2.06 (0.33)%	-3.26 (1.37)%	-6.62 (2.57)%	-11.75 (3.08)%
	Distance Flown	19.0	-14.23 (1.51)%	-20.65 (1.68)%	-26.99 (2.47)%	-34.44 (3.21)%	-42.35 (3.10)%
	FC/Pax	12 (1)	-15.70 (4.76)%	1.89 (6.71)%	17.04 (9.29)%	28.83 (11.67)%	37.88 (13.33)%
	Cost/Pax	76 (1)	5.83 (0.65)%	9.44 (0.79)%	12.56 (1.45)%	14.19 (2.41)%	14.07 (3.04)%
Full Service	Profit	3.03 (0.28)	-3.83 (5.16)%	-16.45 (4.80)%	-27.01 (4.42)%	-36.39 (3.48)%	-45.26 (2.75)%
	Fare	135	-1.52 (0.20)%	-1.50 (0.19)%	-1.42 (0.25)%	-1.54 (0.41)%	-2.08 (0.55)%
	Total Flights	11.7	-0.61 (0.16)%	-1.12 (0.47)%	-2.92 (2.09)%	-8.03 (3.95)%	-15.87 (4.71)%
	Distance Flown	10.7	-7.15 (1.68)%	-13.66 (2.05)%	-20.44 (3.56)%	-29.56 (4.95)%	-40.00 (4.98)%
	FC/Pax	10 (2)	9.68 (9.68)%	35.05 (15.58)%	56.26 (22.07)%	71.08 (27.13)%	81.02 (30.54)%
	Cost/Pax	115 (2)	-1.13 (0.93)%	0.92 (1.04)%	2.69 (1.34)%	3.73 (1.76)%	3.91 (2.07)%
Low Cost	Profit	2.90 (0.16)	-10.65 (2.28)%	-21.62 (2.59)%	-30.68 (2.77)%	-38.41 (2.63)%	-44.97 (2.54)%
	Fare	58	4.21 (0.39)%	4.38 (0.51)%	4.66 (0.77)%	4.95 (0.88)%	5.26 (0.93)%
	Total Flights	6.11	-0.40 (0.15)%	-0.42 (0.14)%	-0.51 (0.14)%	-0.63 (0.18)%	-0.80 (0.23)%
	Distance Flown	7.67	-19.45 (1.75)%	-25.89 (1.71)%	-31.89 (1.74)%	-37.43 (1.77)%	-42.29 (1.58)%
	FC/Pax	13 (1)	-31.41 (5.02)%	-19.61 (5.57)%	-8.95 (5.80)%	1.04 (5.99)%	10.35 (6.05)%
	Cost/Pax	43 (1)	-3.24 (1.87)%	0.73 (2.12)%	4.43 (2.48)%	7.92 (2.66)%	11.21 (2.61)%
Regional	Profit	0.12 (0.01)	-24.48 (6.03)%	-35.35 (6.25)%	-44.93 (6.67)%	-52.30 (6.43)%	-58.12 (5.56)%
	Fare	98	-3.81 (1.79)%	-4.58 (1.54)%	-5.24 (1.65)%	-5.97 (1.77)%	-6.47 (1.62)%
	Total Flights	0.44	-47.54 (1.85)%	-50.01 (0.79)%	-50.83 (0.83)%	-51.99 (1.02)%	-53.69 (1.70)%
	Distance Flown	0.70	-64.27 (2.71)%	-69.19 (1.69)%	-72.55 (1.71)%	-75.67 (1.48)%	-78.41 (1.31)%
	FC/Pax	10 (1)	-65.47 (17.62)%	-39.70 (19.49)%	-15.50 (25.11)%	4.75 (28.13)%	21.20 (29.21)%
	Cost/Pax	80 (1)	-12.16 (4.43)%	-9.98 (4.39)%	-7.91 (5.07)%	-6.41 (5.32)%	-5.10 (4.81)%

Note: Each cell reports the mean with standard deviation in parentheses, pooled across seeds and product-evaluation orderings. Base profit is in billions of USD; Fare, FC/Pax, and Cost/Pax are in USD. Total flights are in 100,000. Distance is 100,000 km. 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.

as the carbon tax increases. For the ultra high tax, profits are reduced 45.4% while consumer surplus is reduced 25.4%. The impact on firms is 80% larger.

These large negative impacts on consumers and firms are partially offset by gains in the form of tax revenue and CO_2 emission reductions. As a result, the overall negative impacts of carbon regulation are more moderate. For low levels of carbon taxes, the gains increase faster than the losses and so, in the set of counterfactuals considered, the high carbon tax minimises the welfare losses (maximises net welfare).

The mechanisms are straightforward. Higher distance-related costs induce airlines to exit longer routes, shifting their networks toward shorter city-pairs. They also raise prices in response to increases in marginal costs. This reduces the number of available products and degrades schedule convenience on longer routes. All three channels reduce the utility of flying on affected routes, pushing passengers toward the outside option. Partly counter to this, on short-haul flights, airlines face more competition.

On the supply side, the contraction of route distance directly reduces variable profits, while the long-haul routes that remain in operation face higher per-passenger fixed costs due to lower traffic volumes. Partly counter to this, long haul flights face less competition.

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 53.3% (s.d. 3.0), while short-haul consumer surplus declines by only 2.7% (s.d. 0.8). At the UH level, medium-long haul consumer surplus declines by 89.7% (s.d. 1.1), effectively eliminating much of the longer-distance market. Short-haul consumer surplus changes are comparatively modest and even turn positive at intermediate tax levels: under the High scenario, short-haul consumer surplus *increases* by 0.5% (s.d. 1.2), before declining by 3.8% (s.d. 3.3) under UH. This non-monotone pattern reflects the partial reallocation of airline capacity from longer to shorter routes: as airlines exit medium- and long-haul markets, they redeploy aircraft to short-haul city-pairs, which dampens or even reverses the consumer surplus loss on those routes. Profit declines are also far larger for medium-long haul routes: 26.3% (s.d. 6.5) versus 3.2% (s.d. 2.9) under the Low scenario, widening to 75.8% (s.d. 5.7) versus 38.4% (s.d. 2.0) under UH.

This asymmetry has important geographic implications. Peripheral countries and regions such as Iceland, Norway, Greece, and the Canary Islands 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, prove resilient and experience positive net welfare gains

across all scenarios as airlines redirect capacity toward shorter, denser city-pairs. In short-haul markets, the net welfare gain (including carbon revenue and social value of CO_2) is positive across all scenarios, ranging from \$0.25 billion (Low) to \$1.08 billion (VH), whereas medium-long haul welfare losses deepen from \$0.81 billion (Low) to \$1.69 billion (UH).

Heterogeneous Responses by Airline Type. Table 13 reveals that the three carrier types, namely full-service carriers (FSCs), low-cost carriers (LCCs), and regional carriers,[26] 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 3.8% (s.d. 5.2), compared with 10.7% (s.d. 2.3) for LCCs and 24.5% (s.d. 6.0) 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. At higher carbon prices, the impacts on FSCs and LCCs are virtually identical . Under the UH scenario, LCC profits contract by 45.0% (s.d. 2.5), compared with 45.3% (s.d. 2.8) for FSCs. The near-parity between LCCs and FSCs under UH reflects LCCs' point-to-point network structure, which allows them to flexibly redeploy capacity toward shorter, more profitable routes as the carbon tax tightens, largely offsetting their larger initial losses relative to FSCs. Regional carriers are the hardest hit across all scenarios, with profit declines ranging from 24.5% (Low) to 58.1% (UH), consistent with their dependence on thin, distance-intensive routes.

Pricing responses. The impact on prices is strikingly different across the three carrier types. LCCs average fares *increase* across all scenarios, with the increase growing monotonically from 4.2% (s.d. 0.4) under Low to 5.3% (s.d. 0.9) under UH. In contrast, FSC fares *decline* moderately with very little variation across scenarios and regional carrier fares *decrease* more strongly with the decrease growing across scenarios. A key driver of this asymmetry is that the per-passenger carbon surcharge, which is distance-based and uniform across carriers on a given route, represents a much larger fraction of LCC marginal costs than of FSC marginal costs: under the UH scenario, the surcharge amounts to 4.6% of LCC marginal costs compared with only 1.3% for FSCs, reflecting the substantially lower baseline cost structure of LCCs. In addition, LCCs' point-to-point networks give them greater flexibility to redeploy away from cost-intensive routes, so they face relatively less exit pressure and can exploit the reduction in competition from FSC and regional carrier exit to increase markups. 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.

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[26]The regional carrier category comprises Icelandair and Air Europa.

Network adjustments. A striking feature of the results is that FSCs and LCCs adjust primarily through *route shortening*, shifting their networks toward shorter city-pairs, rather than through large-scale frequency reductions (fewer flights). Under the Med scenario, FSC frequencies decline by only 1.1% (s.d. 0.5) while total distance flown falls by 13.7% (s.d. 2.1); LCC frequencies are virtually unchanged at -0.4% (s.d. 0.1) while distance contracts by 25.9% (s.d. 1.7). Even under the UH scenario, FSC frequency declines remain modest at 15.9% (s.d. 4.7) compared with a 40.0% (s.d. 5.0) reduction in distance, and LCC frequencies fall by only 0.8% (s.d. 0.2) while distance declines by 42.3% (s.d. 1.6). These patterns indicate that FSCs and LCCs redeploy aircraft from longer to shorter routes, preserving flight frequencies while substantially reducing total distance flown.

Regional carriers, by contrast, experience severe contraction on both margins. Under the Med scenario, regional frequencies decline by 50.0% (s.d. 0.8) and total distance by 69.2% (s.d. 1.7). Under UH, frequencies fall by 53.7% (s.d. 1.7) and distance by 78.4% (s.d. 1.3). 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 and lack alternative shorter routes to redeploy to; FSC networks are anchored by valuable hub slots that incentivise maintaining frequencies; while LCCs' point-to-point networks provide the flexibility to redeploy capacity across a broad set of alternative routes.

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 81.0% (s.d. 30.5) under UH, because the denominator (passengers) shrinks faster than the numerator (fixed operating costs). LCCs experience more moderate FC/Pax changes: FC/Pax initially *declines* by 31.4% (s.d. 5.0) under Low as the shift to shorter routes lowers per-flight operating costs, before rising to +10.4% (s.d. 6.1) under UH as the carbon tax erodes the cost advantage. Regional carriers exhibit a similar pattern, with FC/Pax declining by 65.5% (s.d. 17.6) under Low as the most cost-intensive routes are the first to exit, then rising to +21.2% (s.d. 29.2) under UH as the surviving network faces increasing cost pressure. Total cost per passenger (Cost/Pax) rises for LCCs, by 11.2% (s.d. 2.6) under UH, while FSC Cost/Pax increases by 3.9% (s.d. 2.1). Regional carriers see Cost/Pax *decline* by 5.1% (s.d. 4.8) 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 moderate welfare losses ranging from $0.39 - $0.74 billion (2.5% - 4.8% of baseline total surplus): somewhat large (in percentage terms) reductions in consumer surplus and airline profit are partially offset by carbon revenue and the social value of avoided emissions. 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 prove resilient and experience positive *net* welfare gains (including carbon revenue and the social value of CO_2) as airlines redirect capacity toward shorter routes. Among carriers, regional airlines are the most severely affected, while LCCs and FSCs converge to near-identical profit losses under UH despite FSCs being more resilient at lower carbon prices. Third, the primary adjustment margin for FSCs and LCCs is route shortening rather than frequency reduction: these carriers redeploy aircraft from longer to shorter city-pairs, preserving flight frequencies while substantially reducing total distance flown. This network restructuring shifts the competitive balance toward the low-cost segment, as LCCs raise fares and largely maintain frequencies while FSCs and regional carriers contract.

6.3 Carbon Regulation, Merger Screening and Merger Simulation

The carbon tax scenarios generate large changes in industry profitability and so potentially alter the incentives for firms to merge. To evaluate these incentive effects within the intra-European market, we evaluate the profitability of a merger between two LCC carriers, Ryanair and Wizz Air. In the face of large fuel cost increases, LCC consolidation is a realistic prospect. For example, Ryanair's CEO has publicly acknowledged approaching Wizz Air on multiple occasions regarding a buyout [Ušackas and Brueckner, 2024], Wizz Air submitted an unsolicited offer for easyJet in 2021 [Topham, 2021], and Wizz Air profit has been wiped out by fuel price increases due to the Iran War [Rees and Cambell, 2026].

What is the rationale for such a merger? Wizz Air is vulnerable to high fuel prices and the two LCC carriers operate exclusively short-haul, point-to-point networks from secondary airports, with no hub operations or intercontinental services. Their competitive interaction and network expansion are entirely within Europe and both carriers are fully exposed to intra-European carbon regulation. In contrast, most recent European airline mergers have been motivated by hub slot consolidation and intercontinental feed traffic: IAG sought Air Europa to build Madrid into a transatlantic gateway, and Air France-KLM acquired a stake in SAS to gain a third hub at Copenhagen. While such extra-European network incentives are important, analysis of their effects are beyond the scope of our intra-European model.

GUPPI analysis   To evaluate a potential Ryanair-Wizz Air merger, we first analyse the Gross Upward Pricing Pressure Index (GUPPI) [Farrell and Shapiro, 2010][27] and the com-

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[27]The GUPPI for product j owned by airline A merging with airline B is $\text{GUPPI}_j = D_{j \to B} \cdot (p_B - MC_B)/p_j$, where $D_{j \to B}$ is the diversion ratio from product j to the partner's products. Under the nested logit with nesting parameter λ, the diversion ratio is $D_{j \to k} = [(1-\lambda)s^*_{k|m} + \lambda s_{km}]/[1 - (1-\lambda)s^*_{j|m} - \lambda s_{jm}]$.

pensating efficiency level η^*.[28] The former provides a measure of the incentives to increase prices. The latter measures the minimum proportional reduction in marginal cost that would offset the merger's upward pricing pressure.

GUPPI measures the value of diverted sales as a percentage of the merging firm's own price. Competition authorities typically consider mergers with mean GUPPI below 5% as unlikely to raise significant competitive concerns. In terms of compensating efficiency, values of η^* exceeding 5–10% are generally considered implausible for firms already operating near the cost frontier.

Table 14: GUPPI Merger Screening

(a) Overall Merger Screening Results

Merger Scenario	N	Diversion Ratio		GUPPI				UPP ($)	Comp. Eff. (%)
		$A \to B$	$B \to A$	Mean	Median	P90	Max		
Wizz Air + Ryanair	200	0.051	0.064	0.035	0.033	0.050	0.111	0.02	10.6

Note: N is the number of overlapping market-quarters. UPP is in dollars per passenger. Compensating efficiency is the minimum marginal cost reduction needed to offset upward pricing pressure.

(b) Merger Screening by Market Concentration

N_{firms}	Products	Mean	Median	P90	Diversion
2	272	0.038	0.037	0.054	0.061
3	84	0.030	0.029	0.042	0.051
4	34	0.025	0.026	0.035	0.046
5	10	0.024	0.024	0.032	0.052

Note: N_{firms} is the pre-merger number of airlines in a market-quarter. The decline in GUPPI reflects reduced bilateral diversion as the competitive fringe expands.

For the Wizz Air–Ryanair merger, Table 14 reports both overall GUPPI andGUPPI conditional on market concentration. Panel (a) reports that the overall mean GUPPI is 3.5 percent. This falls below the 5 percent threshold at which competition authorities typically initiate in-depth investigation. However, the distribution of route-level GUPPI exhibits substantial right-skewness: the 90th percentile reaches 5.0 percent, and the maximum route-level GUPPI is 11.1 percent. This suggests 10% of routes might raise competition concerns. The compensating efficiency reported in the final column of panel (a) indicates that the Wizz Air–Ryanair merger requires a 10.6% reduction in marginal cost to offset upward pricing pressure, a magnitude that is difficult to justify given that both carriers already operate near the cost frontier with marginal costs per passenger of $18–20 (Table 10).

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[28]The compensating efficiency is $\eta^* = D_{j \to B} \cdot (p_B - MC_B)/MC_j$. It is derived by setting the Upward Pricing Pressure $\text{UPP}_j = D_{j \to B} \cdot (p_B - MC_B) - E_j$ to zero and solving for the required efficiency E_j as a fraction of marginal cost.

Panel (b) in Table 14 reveals a monotone relationship between market concentration and potential merger harm. In duopoly markets, mean GUPPI is approximately 50 percent larger than in markets with four or more competitors, reflecting the mechanical increase in bilateral diversion ratios as the competitive fringe shrinks. This gradient foreshadows our central finding that carbon-induced exit, by reducing the number of active competitors, can shift the GUPPI distribution rightward and push a previously benign merger above the regulatory threshold.

Network expansion as merger efficiency. The GUPPI analysis considers price changes and potential marginal cost efficiencies while holding network structure fixed. It is completely mute on how network restructuring might affect merger profitability. However, airline mergers generate a distinctive form of efficiency through network expansion. When two carriers merge, the combined entity can potentially enter any route connecting a city served by one partner to a city served by the other; expanding entry opportunities to routes that neither carrier could feasibly operate independently. This mechanism is the primary operational synergy in airline mergers, as it requires no marginal cost reduction but exploits complementary geographic presence [Ciliberto et al., 2021].

Table 15 provides indicative evidence for this network expansion channel for the Ryanair–Wizz Air merger. We assume that airlines can feasibly enter a market only if both endpoint cities are already in their served city sets. Post-merger, each partner's city set expands to the union of both networks, potentially unlocking a large number of new feasible routes.

The two carriers share 52 of a combined 80 cities, reflecting their overlapping point-to-point networks across Central and Eastern Europe. This high degree of network overlap (65% of the union) is precisely what makes this merger both competitively harmful (high diversion ratios on shared routes) and limited in its network synergies (most city-pairs are already accessible to both carriers). Nonetheless, while the network synergies are limited, they do exist. By merging, Ryanair would gain access to 8 new cities (primarily in Eastern Europe) and 250 new feasible routes, a 34.6% expansion, and Wizz Air, would gain 20 new cities and 710 new feasible routes, a 78.1% expansion of its feasible set. To gauge the magnitude of these countervailing forces, we simulate the merger.

Merger simulation. The GUPPI and network expansion table analysis are qualitative and at best indicative. To quantify the equilibrium merger impacts on pricing and network reconfiguration, we simulate the merger assuming the merged entity accrues profits from all partner flights and can feasibly enter any markets with at least one partner present. Formally, if airlines A and B merge, we modify the ownership matrix $\mathbf{O}_m$ by setting $O_{jk} = 1$ for all product pairs (j, k) where j belongs to A and k belongs to B (and vice versa), so that the merged entity internalises pricing externalities across the partners' overlapping routes. We

Table 15: Network Expansion from Merger: Wizz Air–Ryanair

	Ryanair	Wizz Air
Cities served (own)	72	60
Union cities	80	80
New cities gained	8	20
Overlapping cities	52	
Current routes	857	210
Feasible routes (pre-merger)	722	909
Feasible routes (post-merger)	972	1,619
New feasible routes	250	710
% increase	34.6%	78.1%

Note: Feasible routes are markets where the airline could potentially enter (i.e., both endpoint cities are in the airline's served city set) but does not currently operate. Post-merger, each airline's served city set expands to the union of both partners' cities. The number of overlapping cities indicates the degree to which the two networks already coincide. Total active markets: 1,954.

then re-solve the Bertrand–Nash pricing equilibrium under the modified ownership structure.

In addition to the pricing channel, the merged entity can enter routes between any pair of cities served by either partner. That is, the merged entity's feasible network becomes the union of both carriers' city sets: $\mathcal{C}_g^{\text{post}} = \mathcal{C}_A \cup \mathcal{C}_B$ for $g \in \{A, B\}$ where $\mathcal{C}_g$ denotes the set of cities served by airline g in the current network. A route (c, d) is feasible for the merged entity if and only if $c \in \mathcal{C}_g^{\text{post}}$ and $d \in \mathcal{C}_g^{\text{post}}$. Furthermore, the merged entity pools its available flights: when either partner exits or reduces frequency on a route, the freed flights become available to the other partner for reallocation.

Because carbon regulation induces route exit and shrinks airlines' city sets, one channel of network expansion, access to partner cities, is mechanically weakened at higher carbon prices, even as flight pooling may still increase the realised gains from consolidation in equilibrium. We quantify these offsetting forces by simulating the merger across all five carbon tax scenarios. The resulting comparison reveals whether a merger that appears benign under current market conditions becomes harmful in a carbon-constrained future, or conversely, whether the network restructuring benefits of consolidation become more valuable as standalone carriers contract their networks.

Results. Table 16 reports the incremental effect of the Wizz Air–Ryanair merger relative to the carbon-price-only counterfactual. Panel A presents the aggregate effects across all airlines. The merger raises aggregate profits by $0.10–0.12 billion across all tax scenarios, with the effect remarkably stable as carbon costs rise. Consumer surplus effects are negligible

across all tax levels. This pattern reflects the network expansion channel. As carbon regulation forces standalone carriers to contract, the merged entity's ability to pool flights and cities enables it to sustain service on routes that would otherwise be abandoned, partially offsetting the welfare loss from carbon taxation. Aggregate welfare gains from the merger range from $0.09 to $0.12 billion across tax scenarios.

Panel B reveals sharply asymmetric effects between the merging partners. Wizz Air is the primary beneficiary: its profits increase by $0.10–0.14 billion, passengers grow by 0.8–5.3 million, and its route count expands by 311–469 routes across tax scenarios. These gains grow monotonically with the carbon tax, as higher carbon costs create more opportunities for Wizz Air to exploit the merged entity's expanded city set and pooled flight capacity. In contrast, Ryanair's outcomes are mixed. While Ryanair gains 128–170 new routes from the merger, it loses 1.4–4.4 million passengers and its profits decline from $0.03 billion under Low to −$0.02 billion under UH. This suggests that the merger induces a reallocation of passengers from Ryanair to Wizz Air within the combined network, as Wizz Air, with its smaller pre-merger network, has more scope to expand into new markets using shared cities.

The merging firms' combined profits increase by $0.12–0.14 billion, with fare effects that are economically small (less than $0.20 per passenger). The combined route count grows substantially, from 439 additional routes under Low to 620 under UH, confirming that the network expansion synergy becomes more valuable as carbon regulation tightens. The small aggregate fare effects, coupled with positive profit and welfare gains, suggest that the merger's primary channel operates through network restructuring rather than through the exercise of market power on overlapping routes.

6.4 Geographic Distribution of Welfare Effects

Figures 9–14 depict the geographic distribution of net welfare, consumer surplus, and profit across European country-pairs. For each outcome, the figures show both baseline values (Figures 6, 9, and 12) and impacts of the Low and Ultra High carbon tax scenarios with and without the merger (remaining figures). Since the carbon tax effects are largely monotonic, we omit figures for the intermediate scenarios.

The figures display results for the top 15 countries ranked by baseline welfare, which account for 93.2% of total welfare and 86.7% of total passengers. Each tax scenario impact figure uses a split-matrix layout. The lower triangle reports the impact of the carbon-tax-only counterfactual (relative to the no-tax baseline) and the upper triangle reports the carbon-tax-plus-merger counterfactual. The figure subtitles display the aggregate impacts for each scenario.

Table 16: Merger Effect: Wizz Air–Ryanair Merger vs. Carbon-Only Counterfactual

Panel A: Aggregate Merger Effect (All Airlines)

	ΔProfit	ΔCS	ΔPassengers	ΔSocial CO$_2$	ΔWelfare
Low	0.12 (0.05)	-0.02 (0.04)	-0.63 (1.33)	0.0021 (0.0121)	0.11 (0.07)
Med	0.11 (0.05)	-0.02 (0.03)	-0.75 (1.10)	0.0017 (0.0112)	0.09 (0.06)
High	0.11 (0.04)	0.00 (0.03)	0.02 (1.26)	-0.0039 (0.0092)	0.11 (0.05)
VH	0.10 (0.04)	0.01 (0.03)	0.18 (1.18)	-0.0057 (0.0112)	0.11 (0.06)
UH	0.10 (0.05)	0.01 (0.03)	0.44 (1.14)	-0.0049 (0.0115)	0.12 (0.06)

Panel B: Merging Firms

	ΔProfit	ΔPassengers	ΔFare	ΔRoutes
Wizz Air (W6)				
Low	0.1018 (0.0304)	0.76 (0.43)	0.61 (0.69)	311.4 (48.0)
Med	0.1122 (0.0301)	1.61 (0.40)	0.50 (0.70)	359.5 (59.4)
High	0.1257 (0.0280)	2.96 (0.68)	0.60 (0.73)	414.1 (66.9)
VH	0.1367 (0.0239)	4.33 (0.85)	0.43 (0.69)	452.3 (74.0)
UH	0.1399 (0.0214)	5.32 (1.02)	0.40 (0.87)	469.1 (82.5)
Ryanair (FR)				
Low	0.0333 (0.0225)	-1.35 (0.47)	-0.26 (0.27)	127.5 (58.3)
Med	0.0186 (0.0196)	-1.84 (0.46)	-0.37 (0.27)	151.2 (61.3)
High	-0.0018 (0.0209)	-2.68 (0.60)	-0.64 (0.31)	170.2 (51.6)
VH	-0.0148 (0.0270)	-3.68 (0.71)	-0.65 (0.37)	161.3 (53.5)
UH	-0.0178 (0.0276)	-4.41 (0.77)	-0.72 (0.38)	150.8 (49.8)
Combined (W6+FR)				
Low	0.1351 (0.0508)	-0.59 (0.55)	0.17 (0.40)	438.9 (94.5)
Med	0.1308 (0.0462)	-0.24 (0.50)	0.07 (0.38)	510.7 (108.6)
High	0.1239 (0.0436)	0.27 (0.58)	-0.02 (0.42)	584.3 (105.4)
VH	0.1220 (0.0460)	0.65 (0.49)	-0.11 (0.39)	613.6 (110.8)
UH	0.1221 (0.0438)	0.91 (0.58)	-0.16 (0.45)	619.9 (108.2)

Note: This table reports the incremental effect of the Wizz Air–Ryanair merger relative to the carbon-only counterfactual, i.e. Δ = merger arm − carbon-only arm. Only seed-ordering pairs where both arms converged are included. Each cell reports the mean with standard deviation in parentheses, pooled across seeds and product-evaluation orderings. Panel A: all monetary values (Profit, CS, Social Value of CO$_2$, Welfare) are in billions of USD; Passengers are in millions. Panel B: Profit is in billions of USD; Passengers are in millions; Fare changes are in USD; Routes are counts. Social Value of CO$_2$ uses the same parameters as Table 12.

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The baseline figures confirm that airline market welfare, consumer surplus and profits are concentrated among a small number of high-traffic corridors. The Spain–UK, UK–Germany, and Italy–France pairs account for the largest shares of both consumer surplus and profit. This concentration implies that even a modest percentage decline in welfare on these corridors translates into large absolute losses.

The tax scenario impact panels reveal two geographic patterns. First, impacts on medium- and long-haul pairs, particularly those involving the UK, Spain, and France, drive the aggregate welfare loss, consistent with the asymmetric market-segment effects documented above. Second, comparing the lower and upper triangles shows that the merger effect is geographically diffuse. The upper triangle is slightly less negative (or more positive) than the lower triangle on most pairs, but no single corridor dominates the merger's welfare contribution. This confirms that the merger operates primarily through broad network expansion rather than through competitive effects on specific high-traffic routes.

7   Conclusion

This paper 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: network contraction is most severe for regional carriers (frequency declines of up to 54%), while full-service and low-cost carriers adjust primarily through route shortening. Consumer surplus declines by up to 25% overall, with medium- and long-haul markets bearing the brunt, while short-haul markets experience positive net welfare gains as airlines reallocate capacity toward shorter routes. Airline profits decline by 8–45%, and carbon tax revenue of $0.9–3.1 billion together with a social value of avoided CO_2 emissions of $0.5–1.4 billion only partially offset these losses. A hypothetical Wizz Air–Ryanair merger increases firm profits by approximately $0.1 billion through network expansion synergies without materially affecting consumer surplus. These results demonstrate that carbon regulation can achieve meaningful environmental gains in European aviation, though at significant and unevenly distributed cost, falling most heavily on peripheral regions and the regional carriers that serve them.

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A   Geographic Heatmaps
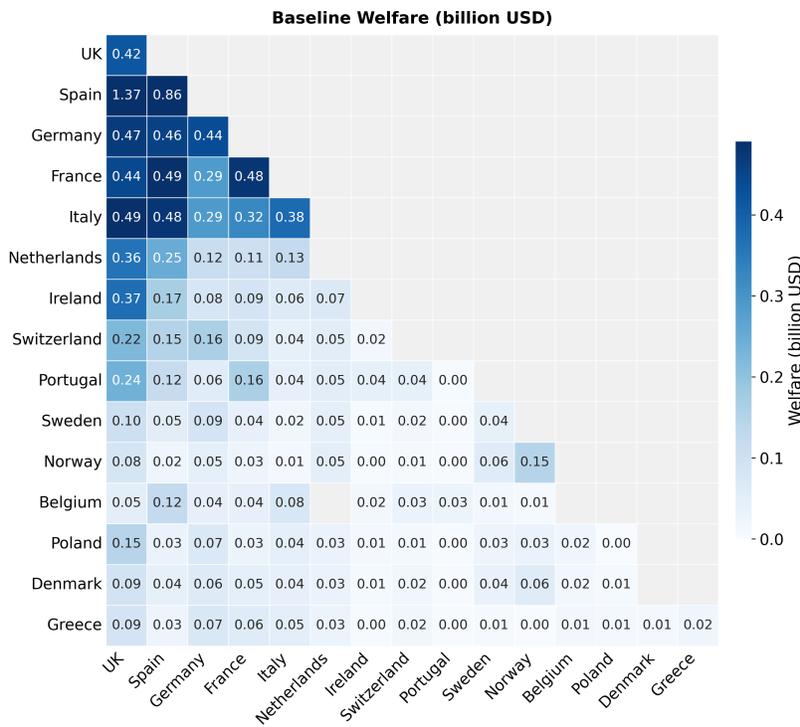
Figure 6: Welfare by country-pair: baseline.
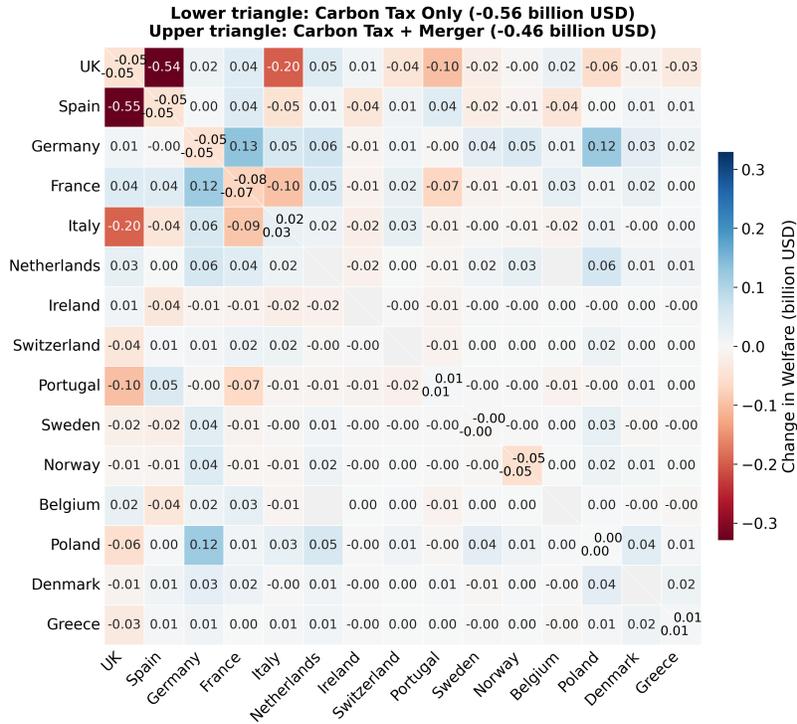
Figure 7: Welfare change by country-pair: Low scenario.
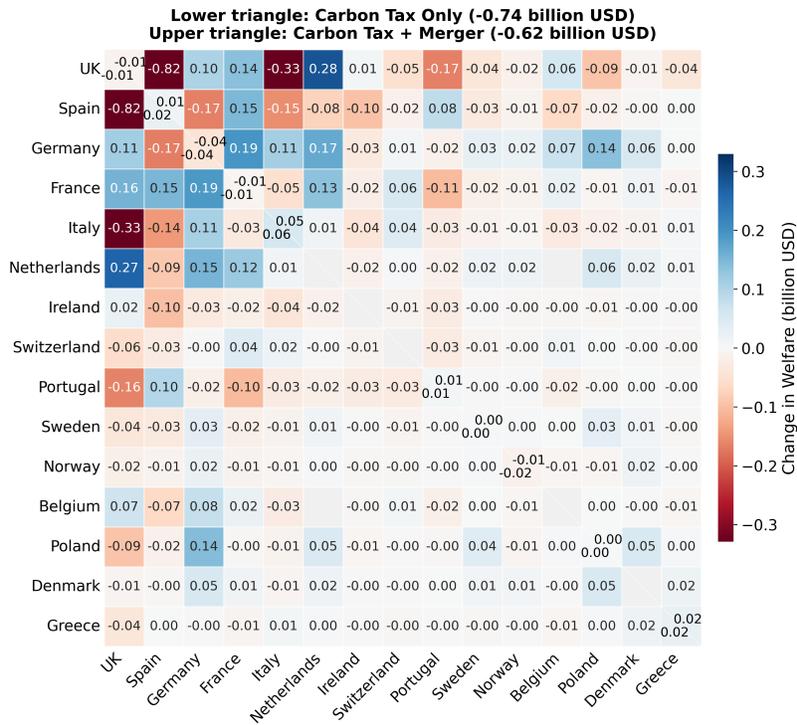
Figure 8: Welfare change by country-pair: Ultra High scenario.
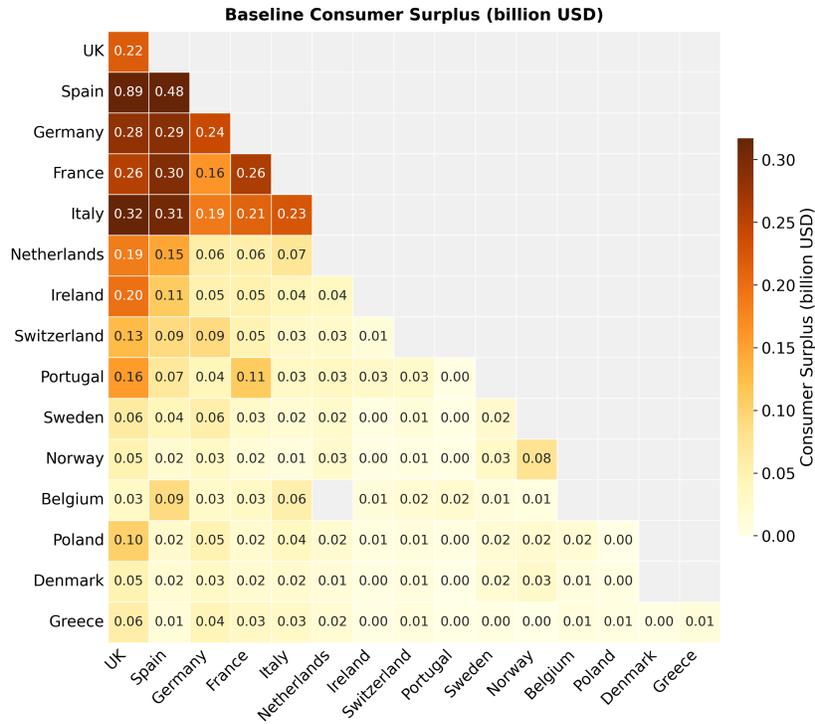
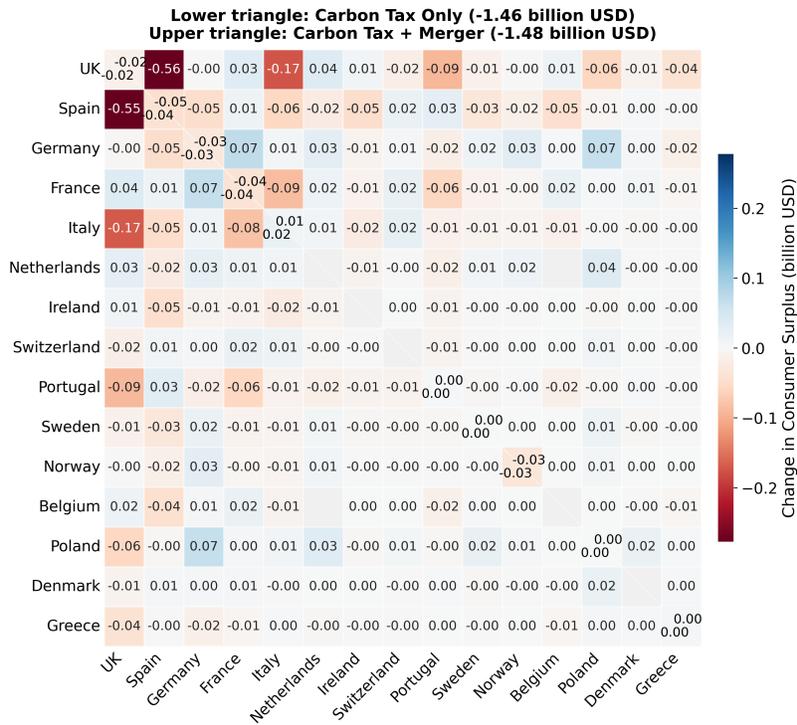Figure 9: Consumer surplus by country-pair: baseline.

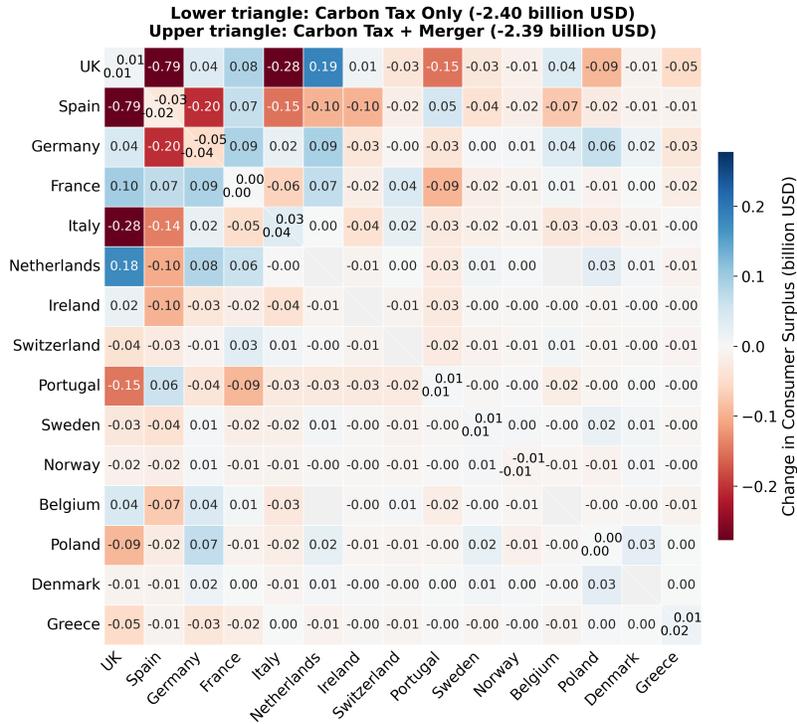Figure 10: Consumer surplus change by country-pair: Low scenario.

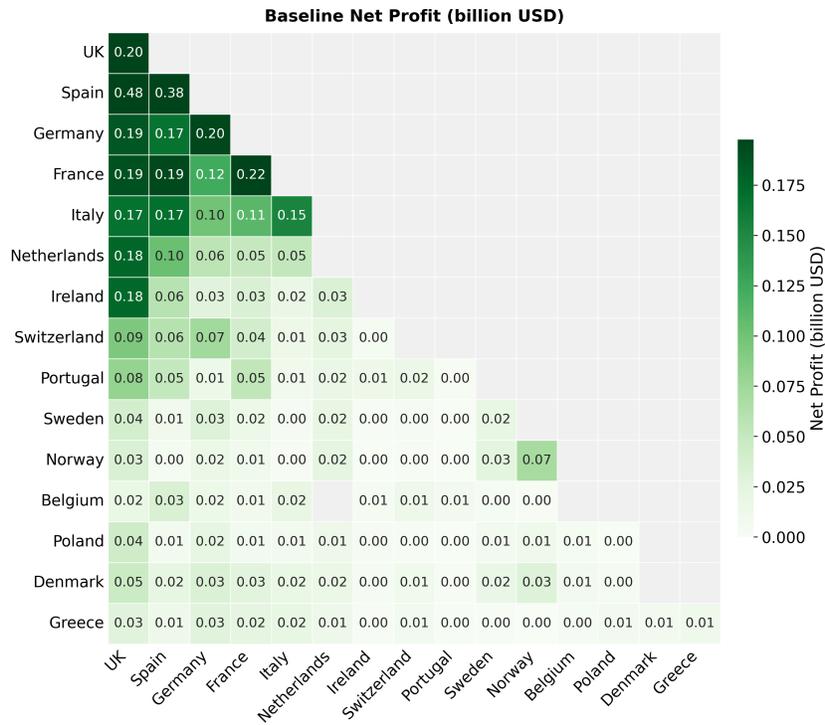Figure 11: Consumer surplus change by country-pair: Ultra High scenario.

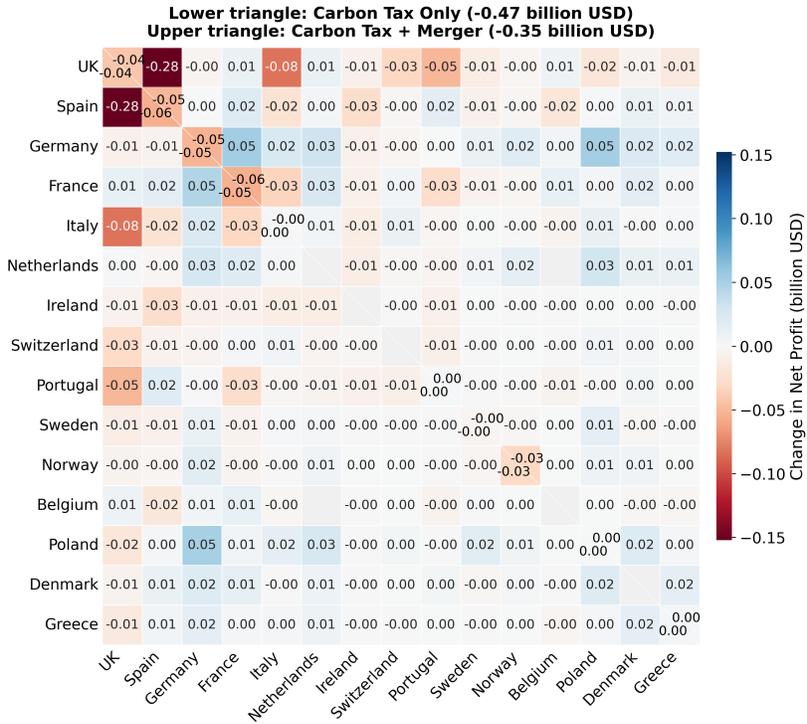

Figure 12: Net profit by country-pair: baseline.

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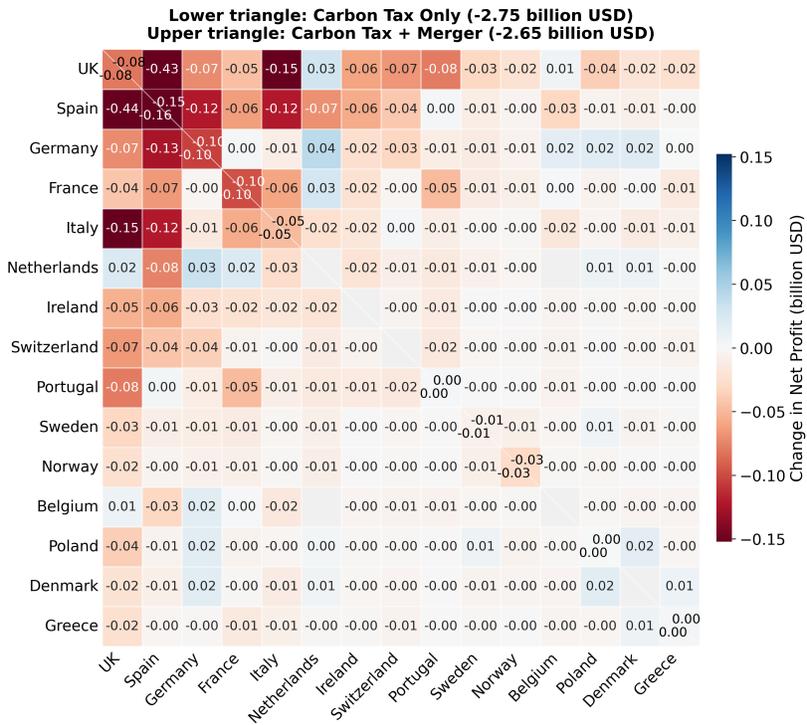Figure 13: Net profit change by country-pair: Low scenario.

Figure 14: Net profit change by country-pair: Ultra High scenario.