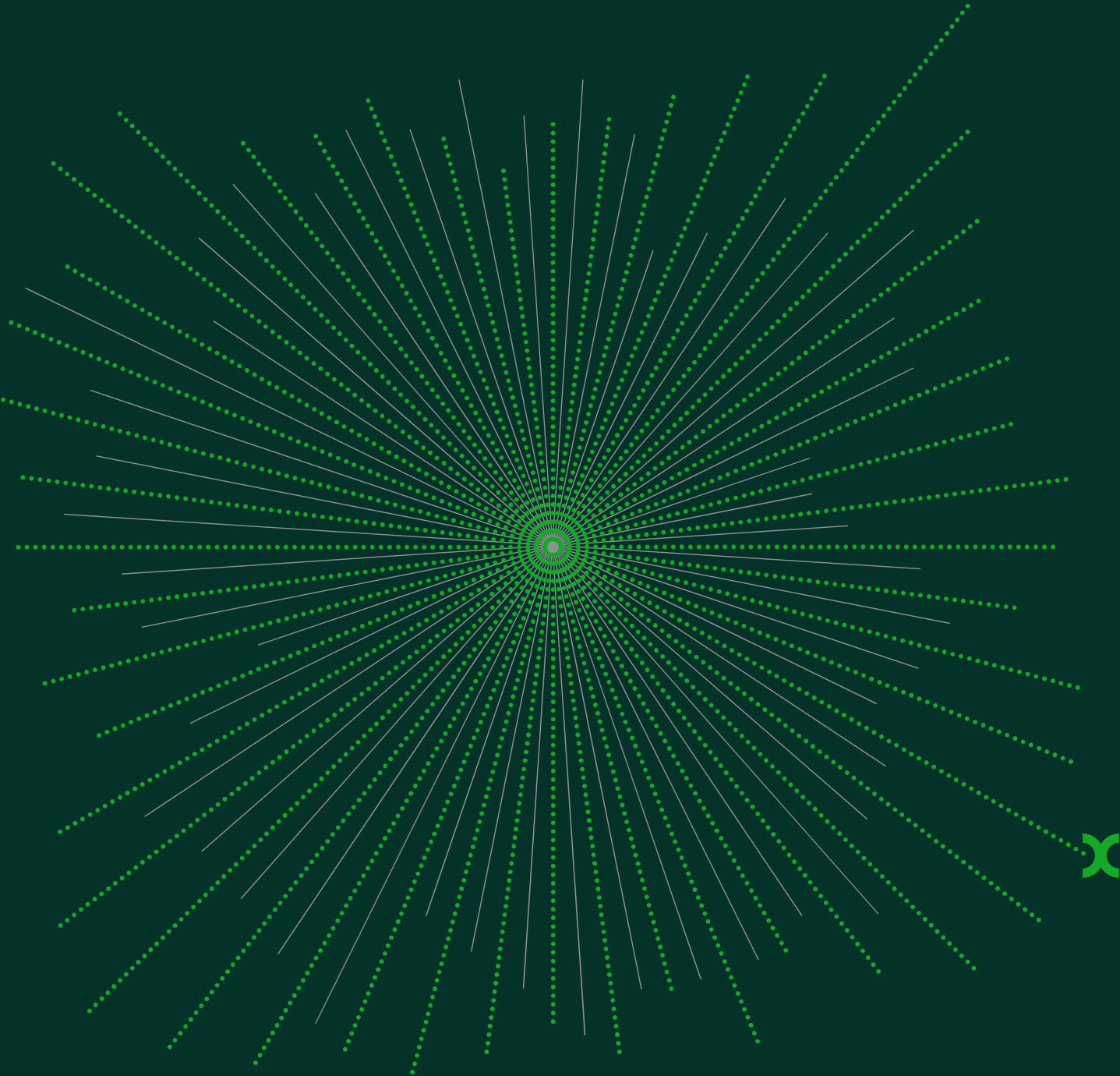


Drivers of airfares and impacts on consumer
outcomes



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Prepared for ACI Europe

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Executive summary

Scope of the study

The European Commission is currently undertaking a 'Fitness Check' of the EU aviation market legislative framework, and in particular three pieces of legislation that regulate EU airport capacity infrastructure: the Airport Charges Directive (ACD) 2009/12/EC,¹ the Slot Regulation (EEC) No 95/93,² and the Ground Handling Directive 96/97/EC.³

In this context, ACI EUROPE commissioned Oxera to examine **the key drivers of airfares** in Europe to understand **the extent to which consumer outcomes are being affected by the current Regulations, and the potential implications for the Commission's review**.

This study considers **four main drivers of airfares that are directly affected by the Slot Regulation and the ACD** to help determine how effectively the regulation functions and whether improvements can be made. The drivers are:

- (i) **flight timing**, capturing demand-side effects;
- (ii) **airport congestion**, representing capacity constraints and scarcity rents;
- (iii) **airline concentration**, capturing the effect of airline competition;
- (iv) **airport charges**, representing a direct input cost faced by airlines.

The novel dataset assembled for this study covers scheduled flights from 54 European airports handling more than 5m seats per annum across the EEA, the UK and Switzerland between 2023 and 2025.⁴

The analysis proceeds in two stages. First, the relationship between fares and each driver is examined graphically. Second, these relationships are quantified through regression analysis. On the basis of this analysis, we draw out

¹ European Parliament and of the Council (2009), '[Directive 2009/12/EC of the European Parliament and of the Council of 11 March 2009 on airport charges](#)', *Official Journal of the European Union*.

² Council of the European Union (1993), '[Council Regulation \(EEC\) No 95/93 of 18 January 1993 on common rules for the allocation of slots at Community airports](#)'.

³ Council of the European Union (1996), '[Council Directive 96/67/EC of 15 October 1996 on access to the groundhandling market at Community airports](#)'.

⁴ Specifically, IATA seasons Summer 2023 to Winter 2024/25. IATA seasons define the airline/airport scheduling calendar. The IATA Summer schedule begins on the last Sunday of March and ends on the last Saturday of October, while the IATA Winter schedule begins on the last Sunday of October and ends on the last Saturday of March.

implications for the revision of the Regulations and how certain changes could deliver better outcomes for passengers.

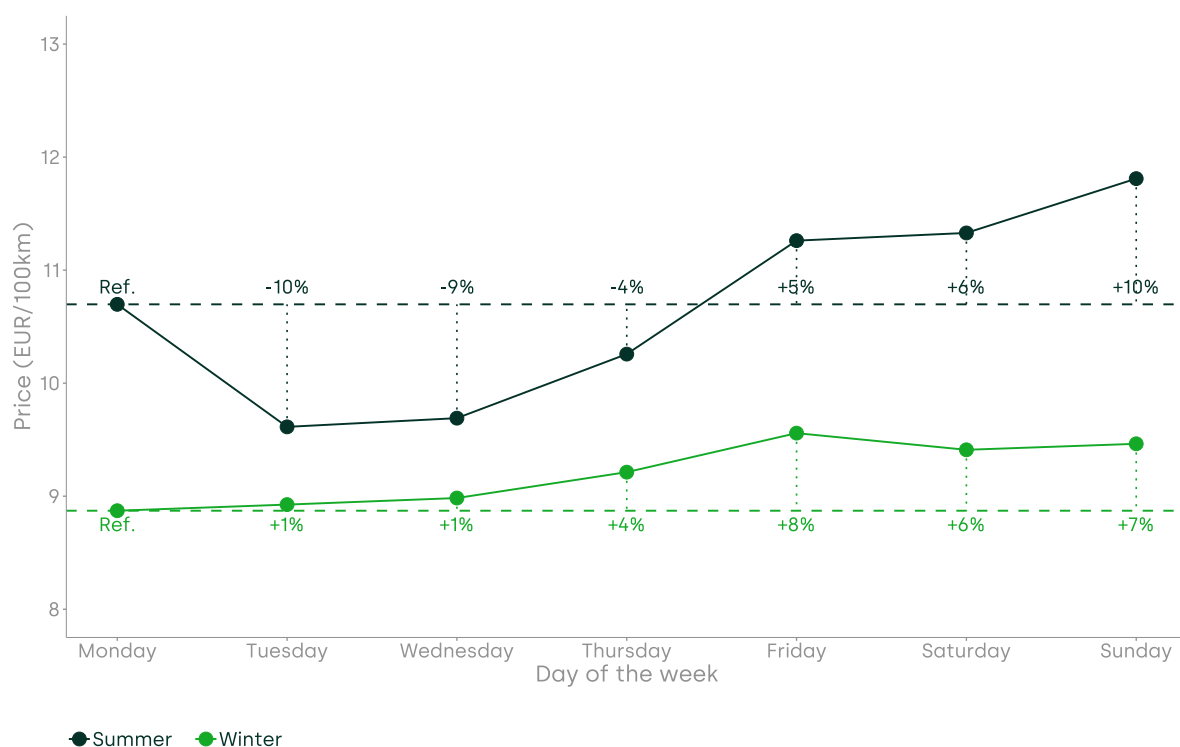
Key takeaways

Overall, the results of this assessment indicate that airfares are primarily driven by variations in demand and the intensity of airline competition. Airport congestion adds a scarcity premium to fares, particularly at highly congested airports, while airport charges have only a very limited impact on fares. These results are further explained below.

Demand is central

Most fare variations are explained by differences in demand, which are reflected in dynamic pricing from airlines. Time of day, day of the week, month, and route-specific variations, which all reflect differences in demand, explain a large part of the fare variations observed, as shown in the figures below.

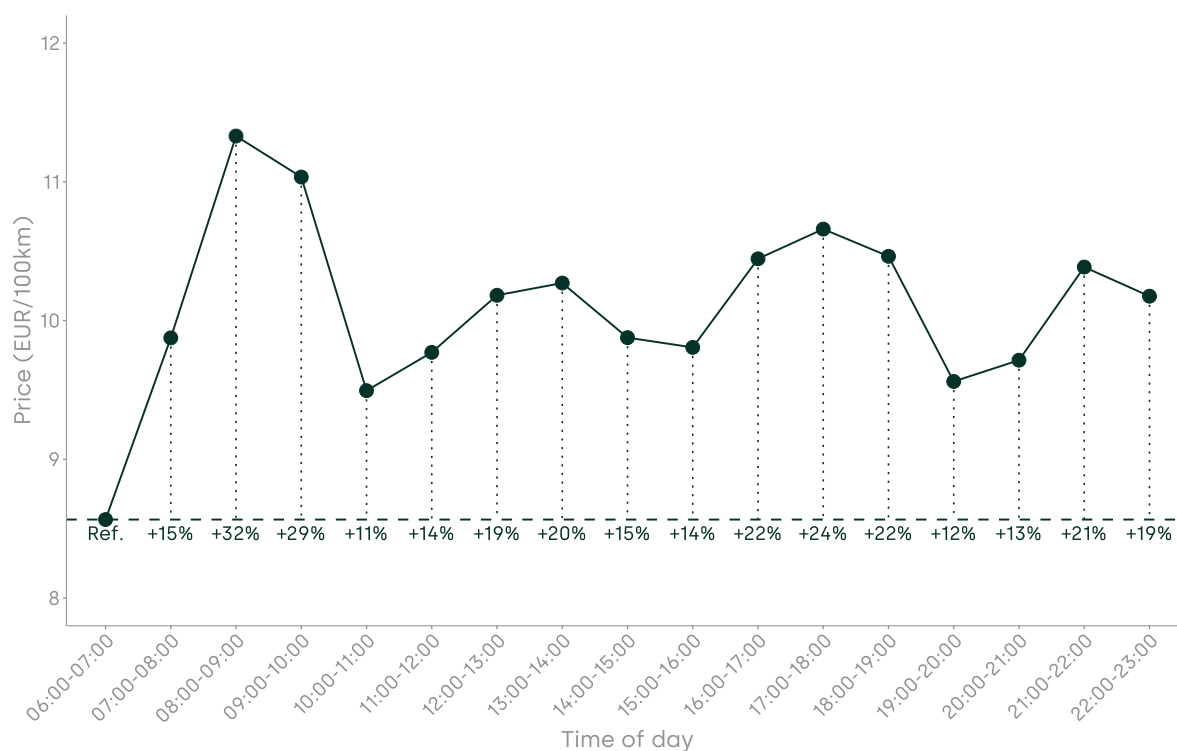
Figure E1 Price by day of the week (departure)



Note: The figure shows departing average fares across the full sample of routes by day of the week for summer and winter IATA seasons, indexed to Monday—i.e. values for other days should be read

as percentage increases (decreases) relative to average Monday fares. The dashed line indicates the Monday price level for each season.
Source: Oxera analysis.

Figure E2 Price by time of the day (departure)



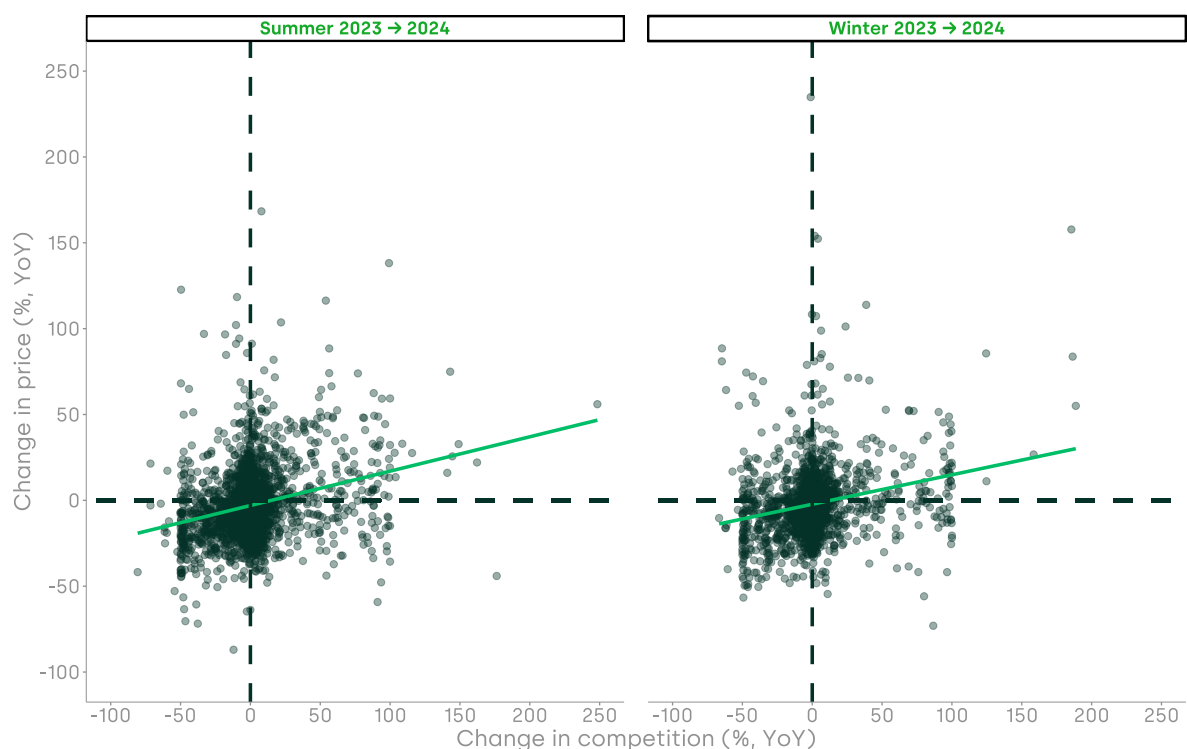
Note: The figure shows average fares by departure time of day across the full sample of routes, indexed to the hour slot 06.00–07.00—i.e. values for other hour slots should be read as percentage increases (decreases) relative to average 06.00–07.00 fares. The dashed horizontal line indicates the average 06.00–07.00 hour slot price.
Source: Oxera analysis.

Less competition between airlines leads to higher fares

The extent of airline competition has a strong relationship with fares, particularly on the short-haul segment. We find that routes that are characterised by higher market concentration (i.e. less competition) are associated with higher average fares (keeping other factors constant). This relationship between competition and fares holds across routes and over time.

Airline route dynamics such as entry or exit also have a material impact on prices (we estimate an impact of up to 10%). For example, routes that experience a reduction in competitive intensity between years tend to record higher price growth, while routes that experience an increase in airline competition show price reductions. The figure below shows, for instance, that between 2023 and 2024, routes for which intensity of competition decreased experienced higher prices.

Figure E3 Year-on-year changes in route-level competition and fares, by season



Note: YoY, year-on-year. The chart presents year-on-year changes in competition, measured using the Herfindahl–Hirschman Index (HHI),⁵ against year-on-year changes in average prices for individual origin–destination city pairs, separately for the Summer (S23→S24) and Winter (W23→W24) seasons. Routes where the competition was unchanged between the two seasons are excluded from the chart, as a zero change carries no information about the direction of any competitive shift.

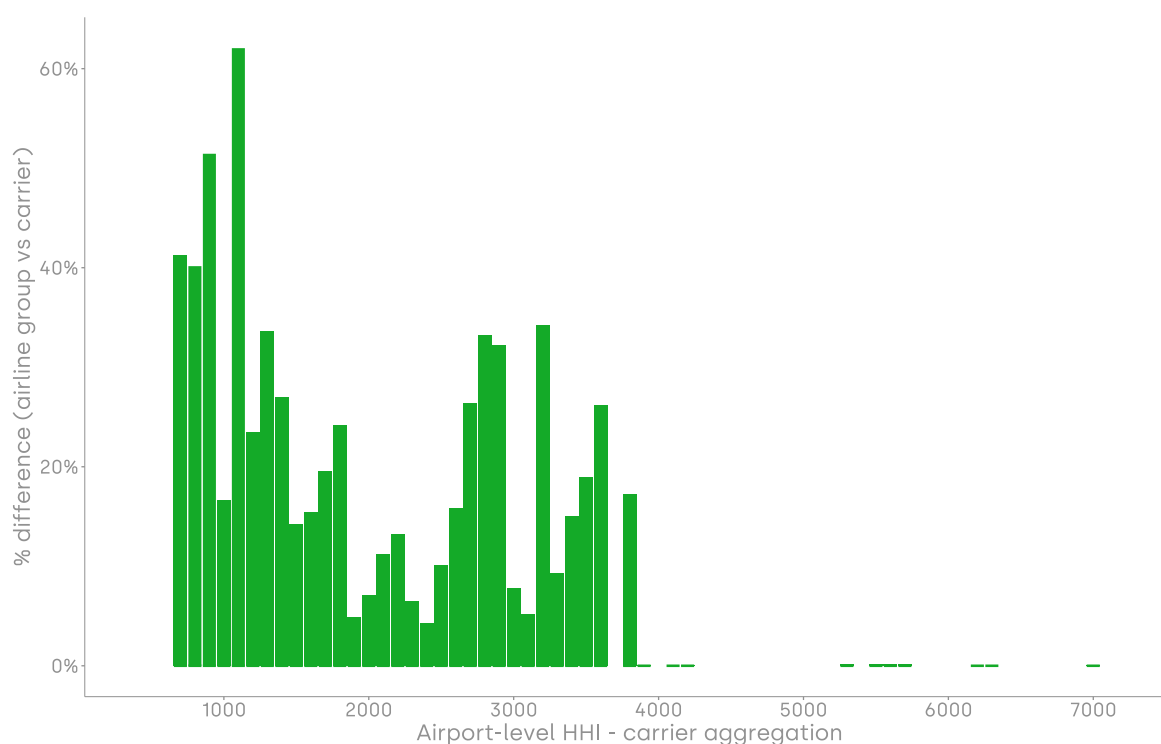
⁵ The HHI is a measure that is often used by the European Commission in merger analysis to assess the impact of a proposed transaction on competition by estimating the current and expected post-transaction market concentration.

Source: Oxera analysis.

In addition to the extent of competition, the type of competition matters

Accounting for competition at the level of the individual carrier (e.g. BA and Iberia), as is done in the Slot Regulation, is likely to lead to overestimating the level of competition at European airports, particularly as airlines within the same group are not effectively competing with each other. The figure below shows concentration with competitors defined as airline groups is 20% higher, on average, compared to the definition using individual carriers.

Figure E4 Difference in concentration between 'carrier level' and 'airline group' aggregation

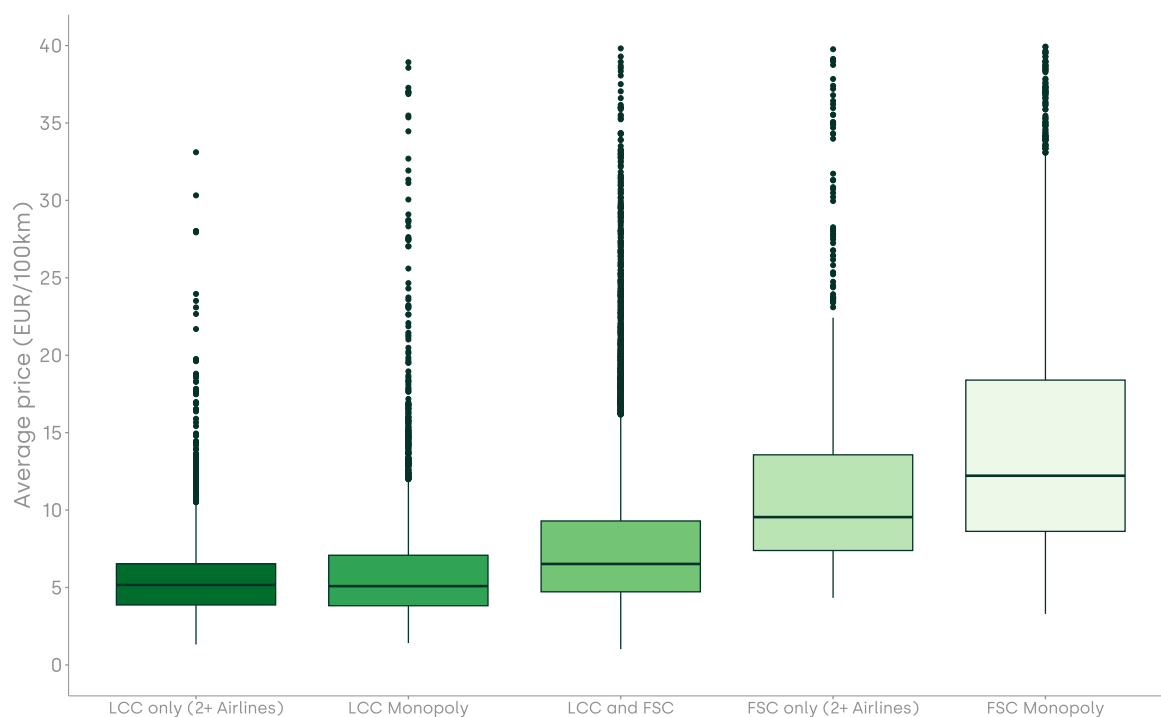


Note: The chart shows on the x-axis the airports in the sample according to their level of concentration (HHI) calculated on the basis of individual carriers as competitors (e.g. BA and Iberia). On the y-axis is presented the percentage difference with the concentration calculated on the basis of airline groups as competitors (e.g. IAG and Air France–KLM).
Source: Oxera analysis.

In addition, the profile of competition on routes—for instance, whether a low-cost carrier (LCC) is present—has a significant impact on fares. Full-service carriers (FSCs) are particularly sensitive to LCC competition and tend to offer lower fares, on average, on routes in which they compete with LCCs.

The chart below presents the distribution of average fares according to the level and type of competition on each route. It shows that prices are lower on routes where only LCCs operate than on routes where only FSCs operate. Furthermore, increased competition in settings where FSCs are present substantially reduces fares, while fares on routes where LCCs operate reduce more marginally with increased competition.

Figure E5 Distribution of fares by type of competition



Note: The figure presents route prices across five types of route: routes operated by a single LCC, by multiple LCCs, by a mix of LCCs and FSCs, by multiple FSCs, and by a single FSC. Each box plot displays the median (horizontal line), top and bottom quartile range (box), and whiskers extending to 1.5 times the quartile range. Outliers beyond this range are shown as individual points. The y-axis is capped at 40 EUR/100km. Observations above this threshold are cut off at 40 EUR/100km.

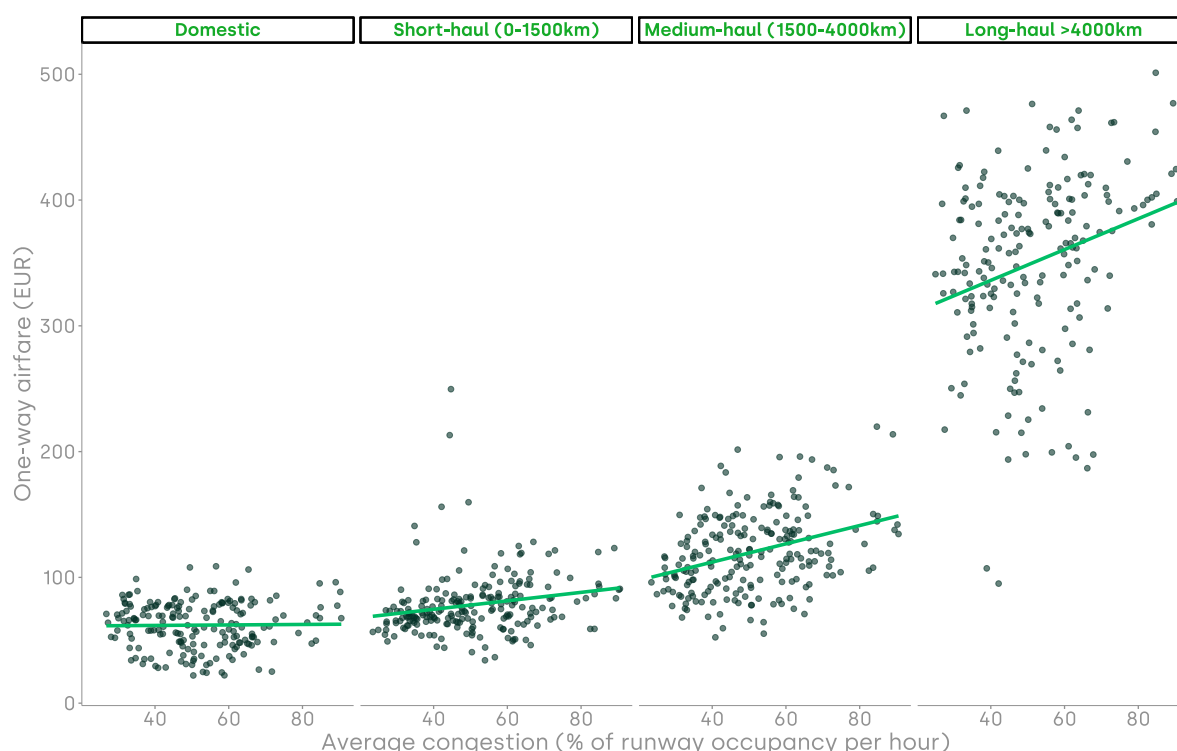
Source: Oxera analysis.

In our assessment, 44% of routes are operated by a single carrier, representing 8% of the seats supplied. For these routes in particular, the lack of airline competition means higher prices on average for passengers. While not all routes can sustain competition, for those that can passengers are paying a premium due to market concentration.

Lack of airport capacity leads to higher fares

More airport congestion leads to higher fares. The relationship between congestion and fares is stronger when airport congestion is higher—see figure below. Our analysis therefore confirms the existence of a congestion (or scarcity) premium on fares.

Figure E6 Relationship between congestion and fares (in levels), by flight segment



Note: The chart shows the relationship between congestion and fares, where each data point represents the average one-way fare and average congestion for a given departing airport, IATA season, and distance band. Average congestion is the mean percentage of maximum declared

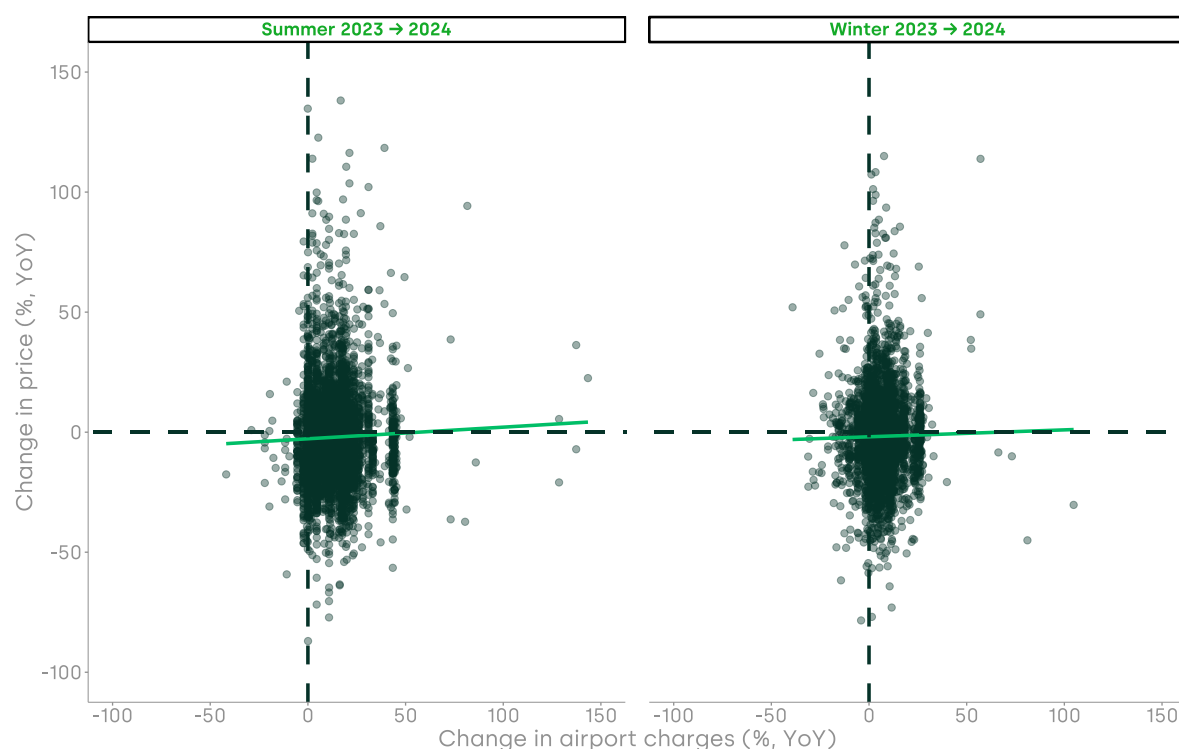
capacity utilised per time band at a given airport over the IATA season. Airports not serving a given distance band are excluded from that band's data points.

Source: Oxera analysis.

Airport charges are not a key cost driver

Airline costs play an important role in driving fares. For example, flight distance, which drives fuel costs and other variable costs, has a strong relationship with fare levels. Airport charges, as a cost factor for airlines, also affects fares. However, as the figure below demonstrates, changes in charges are not a significant driver of airfares.

Figure E7 Year-on-year changes in route-level charges and fares, by season



Note: The chart shows year-on-year changes in route-level charges (measured at the departing airport) against year-on-year changes in average fares, for the Summer (S23→S24). Routes where the airport charges or fares were unchanged between the two seasons are excluded from the chart, as a zero change carries no information about the direction of the relationship.

Source: Oxera analysis.

The regression analysis confirms the initial observations from the graphical analysis set out above.

First, **airline competition is the driver in the scope of our analysis with the greatest impact on fares**. Our analysis indicates that a 10% increase in market concentration is associated with a 1.06% increase in fares. A 10% increase in concentration would correspond to a shift in the dynamics of a route from two airlines having 50% market share each, to one carrier having a market share of 66% and the other 34%.

Our analysis of the effect of airline entry and exit on routes confirms these results. Airline entry is associated with a 6.7% reduction in fares, while exit is associated with a 9.7% increase in fares. The **extent of competition on routes therefore has a significant impact on fares**, and this effect differs depending on the current level of competition on a route. We show, for instance, that going from two to one airlines on a route is associated with increases in fares of 8.5%.

Second, congestion also has a significant impact on fares. Our analysis indicates that a 10% increase in congestion is associated with a 0.93% increase in fares (between 0.7% and 1.6% depending on the model specification). This is equivalent to an airport changing from, for example, 50% congestion to 55% congestion—changes which many European airports are likely to experience going forward given the forecasts for passenger growth.

Airport charges have a small and uncertain impact on fares. A 10% increase in airport charges is associated with a 0.35% increase in fares—approximately one third of the impact estimated for congestion and competition. Overall we estimate that a €1 increase in total turnaround charges is associated with approximately €0.26 higher fares per flight, **implying a pass-through rate of 26%**. This demonstrates that demand, competition and congestion (i.e. supply) are the key drivers of airfares.

The results of the assessment can be used to estimate the premium paid by passengers for congestion and concentration. **We have estimated that passengers currently pay a €6.4bn premium for congestion and a €1.7bn premium for concentration at the European airports within the scope of analysis**. This corresponds to an average airfare premium of €13.54 per one-way ticket at congested airports and an average airfare premium of €5.99 for concentrated airports.

Implications for the Fitness Check

As part of its consultation on the Fitness Check, the European Commission describes the Slot Regulation, Ground Handling Directive and ACD as three pieces of EU legislation that regulate EU airport capacity and infrastructure from a single market perspective. According to the Commission, they collectively aim to create competitive conditions in the market for airport infrastructure services, which are typically characterised by high entry barriers.⁶ They are described as key to ensuring that airport capacity and infrastructure can be accessed fairly by all market participants, and that airport infrastructure and services are priced efficiently and transparently.

However, this framework, which was established over three decades ago, may no longer be fit for purpose for an aviation market that has evolved significantly since.

The structure of the airline market has fundamentally changed since these pieces of legislation were introduced. The rise of LCCs has led to a change in the dynamics of the sector. The wave of airline mergers (Air France–KLM, IAG group, Lufthansa–SWISS–Austrian Airlines–Brussels Airlines–ITA) and the proliferation of metal neutral joint ventures (JVs) (Air France–KLM–Alitalia–Delta, Air Canada–Lufthansa–United, American Airlines–IAG) has reduced the number of competing airlines at European airports. It is therefore important that these regulations and directives **reflect the changing dynamics of airline competition at European airports and ensure that passengers have access to sufficient choice.**

EUROCONTROL's Aviation Outlook 2050⁷ predicts that demand for air traffic in Europe will grow by 44% by 2050 compared with 2019 levels, and that 3–12% of demand will not be accommodated by European airports in 2050. Investment into capacity expansion to accommodate this growth and maintain levels of operational performance and passenger satisfaction is critical. Expansion can result in short-term increases in airport charges. Airlines and regulators may oppose capacity expansion over concerns regarding the impact on price and affordability of travel, while national governments and local communities raise legitimate concerns over the impact on the environment. **Airport regulation needs**

⁶ The Commission cites as examples the limited availability of airport capacity and infrastructure, as well as high investment costs.

⁷ EUROCONTROL (2022), '[EUROCONTROL Aviation Outlook 2050](#)'.

to reconcile these differing constraints into a framework that can accommodate growth without compromising on affordability and environmental goals.

Considering the role that EU legislation aims to play in maintaining competitive conditions in the market, and the changes in the sector since the legislation was put in place, we set out below the implications of this study for future regulation.

Managing congestion should be a policy priority in the short term

With a growing number of congested airports in Europe, it is imperative to allocate the available capacity in a manner that optimises and maximises its utilisation. This would have benefits for passengers seeking to travel to and from these airports, as well as for the wider economy.

Congestion is costly to all stakeholders in the aviation sector. It generates:

- operational challenges and additional costs for airports;
- scheduling constraints for airlines;
- increased airport costs and, consequently, charges;
- environmental impacts;
- higher fares for passengers driven by higher airline costs, but also limits to airline competition.

Managing congestion through more effective slot allocation and ensuring that allocated slots are actually used would generate benefits for all stakeholders. Ultimately, optimising the use of existing capacity may reduce the need for airports to increase airport charges to fund infrastructure investment, especially in the short to medium term.

In the long term, there will be a need for investment in airports to increase capacity

While managing congestion through slot allocation can help in the short run, in the long run the only way to significantly increase capacity is through investment. Regulators may limit airport investment in pursuit of cost efficiency and limiting charge increases. However, our analysis suggests that increased investment will have only a small effect on airfares through increased airport charges, due to low charges pass-through, and that this effect is outweighed by a reduction in passenger fares through lower congestion and increased capacity-enabled competition. **In other words, airport investment improves consumer outcomes through more competition, choice and lower airfares that outweigh their costs.**

Passengers benefit significantly from airline competition

Our study identifies three key ways in which airline competition affects the level of passenger fares:

- 1 **market concentration**—i.e. the intensity of competition on a given route or at a given airport;
- 2 **type of competition**—i.e. whether LCCs, FSCs, or a mix are competing on a route;
- 3 **airline route dynamics**—i.e. the impact of entry or exit on fares.

Our analysis illustrates that **higher airline concentration drives up fares, FSCs are particularly sensitive to LCC competition, and airline entry / exit can impact fares by 7 to 9% on average**. With current slot rules affecting the use of slots at airports, changes to the Slot Regulation should ensure that passengers are not paying an unnecessary fare premium due to insufficient competition.

In particular, changes to the new entrant rule to encourage entry could reduce fares. The increasing airline concentration in the market indicates that the carrier definition used in the Slot Regulation for new entrants is no longer appropriate. An airline could qualify as a new entrant while effectively operating as one company with an incumbent airline that is part of the same group and already present at the airport. More broadly the new entrant rule under the Slot Regulation may be too limited in scope (five-slot limit for new entrant privileges) to ensure that airlines with a smaller presence at an airport can grow over time and act as effective competitors. In particular, **our analysis indicates that, beyond the number of competing operators, the intensity of competition between them (i.e. whether they share the market or whether one has a much stronger presence than the others) matters in determining the price that passengers pay to travel**. The Slot Regulation can play a role in levelling the playing field for airline access to congested airports. More generally, policymakers may consider ways to ensure that airlines make full and proper use of the slots allocated to them to guarantee that the extent of competition is maximised.

Furthermore, as noted above, there has been an increase in airline mergers and joint ventures in recent years. In many of these cases, the Commission has imposed slot remedies to try to ensure that competition in the market is not negatively affected. However, a number of issues have been identified with these remedies, meaning that they frequently fail to restore competition in the market. As such, structural slot reform is needed to ensure that the benefits of airline competition flow through to passengers.

Any changes to the ACD to try to constrain charge increases will not lead to significant passenger benefits

Any changes to the ACD to place further limits on the extent to which airports can raise charges could lead to increases rather than reductions in airfares. If airports are not able, for example, to invest and build capacity to enable more airline competition and reduce congestion, then airfares are likely to increase significantly. These increases would be much greater than any increase in charges required to fund such investments.

Policymakers have an opportunity to generate substantial benefits for passengers

The results from this study point to clear opportunities to generate significant savings and positive outcomes for passengers, as follows.

- Stimulating airline competition and slot use through an update to the Slot Regulation could lead to lower prices and more choice for passengers, and better use of existing infrastructure by airlines.
- Managing congestion in the short term and investing in capacity in the longer term will lower prices by reducing scarcity rents on fares at congested airports, and will allow for more airline competition, increased connectivity and better quality of service through improved on-time performance and resilience at European airports.
- In an environment with increasing airline concentration and pressure on infrastructure, the benefits to consumers of airport investment are likely to outweigh their costs as higher airport charges are only partially passed through to passengers.

Using the results of our analysis, we have estimated that **European passengers could save approximately €20 per one-way ticket, or a total of €8.2bn**, if all of the European airports within our sample operated at or below the current median levels of congestion and concentration.⁸

This does not account for the benefits of additional choice and better quality of service from airlines due to more competition, and from airports due to the additional available capacity. This also does not account for the fact that

⁸ This analysis is described in more detail in section 5.3 of the report.

congestion at airports is predicted to increase going forward, which will further add to this cost.

This analysis does not include the increase in charges that would be required, as it is challenging to estimate the corresponding increase in charges that would support the reduction in congestion and concentration. However, even assuming a significant 10% increase in charges for these airports, it would still result in net benefits for passengers.⁹ These results are shown in the figure below.

Figure E8 Estimated benefits to departing passengers of reducing congestion/airline concentration at European airports

	Per dep. passenger	Across the sample of airports
 Concentration -7%	€5.99 +	€1.7bn +
 Congestion -18%	€13.54	€6.4bn
Total	€19.53	€8.2bn

Note: The concentration and congestion premia are calculated using their respective elasticity results from the regression analysis and the average fare at each individual concentrated European airport in the sample. Impacts across the airport sample are calculated by multiplying the total number of departing passengers at airports in which congestion or concentration would decrease by the average fare impact.

Source: Oxera analysis.

⁹ A 10% increase in charges for each of the airports with reduced congestion or concentration identified in the analysis above would result in a €4.15 increase per one-way fare and a €2.4bn cost to passengers, or a net benefit of €5.8bn.

1 Introduction

1.1 Purpose of the study

The European Commission is currently reviewing the EU legislative framework applied to the internal aviation market. As part of this review, the Commission is undertaking a Fitness Check¹⁰ of three pieces of legislation that regulate EU airport capacity infrastructure in the single market: the Airport Charges Directive (ACD) 2009/12/EC,¹¹ the Slot Regulation (EEC) No 95/93,¹² and the Ground Handling Directive 96/97/EC.¹³ This Fitness Check aims to assess whether EU airport regulation remains fit for purpose in a market that has evolved significantly since this legislation was introduced, in particular as a result of the COVID-19 pandemic. According to the Commission's Call for Evidence, a key intended outcome of the review is to ensure positive outcomes for consumers.

In this context, ACI EUROPE commissioned Oxera to examine the key market factors that drive variations in airfares in Europe. By understanding how market factors such as congestion, airport capacity and airline concentration affect airfares, in addition to direct airline operating costs, this study can provide implications for the Fitness Check.¹⁴

Economic theory predicts that prices will be higher when demand is higher, when firms' input costs increase, when there is less competition, and when demand exceeds supply due to capacity constraints. In our analysis we consider three market factors—flight timing, airport congestion and airline concentration. We also assess airport charges given that the ACD is part of the Fitness Check. We quantify the impact of these factors on airfares in order to explain (changes in) the price passengers pay for air travel. Based on this analysis, we identify changes in the regulations being reviewed by the Commission that could have a positive impact on European consumers and the wider economy.

¹⁰ European Commission, '[Aviation – Fitness check of EU airport legislation](#)'.

¹¹ European Parliament and of the Council (2009), '[Directive 2009/12/EC of the European Parliament and of the Council of 11 March 2009 on airport charges](#)', *Official Journal of the European Union*.

¹² Council of the European Union (1993), '[Council Regulation \(EEC\) No 95/93 of 18 January 1993 on common rules for the allocation of slots at Community airports](#)'.

¹³ Council of the European Union (1996), '[Council Directive 96/67/EC of 15 October 1996 on access to the groundhandling market at Community airports](#)'.

¹⁴ This study builds on previous work undertaken in this area. For example, SEO Amsterdam Economics (2017), '[The impact of airport capacity constraints on air fares](#)'. ICF (2018), '[Identifying the Drivers of Air Fares](#)'. University of Leeds (2019), '[Independent Peer Review of Recent Research on the Existence of Scarcity Rents at Heathrow](#)', prepared for the UK CAA.

1.2 Scope of the assessment

The report is structured as follows:

- section 2 presents the key conclusions from our study and their implications for the ACD and Slot Regulation;
- section 3 provides an overview of the data used in the analysis and the final dataset;
- section 4 reports on the graphical analysis of the relationship between fares and the drivers considered;
- section 5 provides the results of the regression analysis.

The annexes set out further detail about the methodology and analysis.

2 Implications of our analysis for the European Commission's Fitness Check

2.1 The role of EU legislation and recent challenges with the framework

2.1.1 The role of the EU legislative framework

As part of its consultation on the Fitness Check,¹⁵ the European Commission describes the Slot Regulation, Ground Handling Directive and ACD as three pieces of EU legislation that regulate EU airport capacity and infrastructure from a single market perspective.

These three pieces of legislation have different roles in the overall framework.

- **The ACD** was adopted in 2009 and applies to all airports with more than 5m passengers per annum and the largest airport in each EU member state. The Directive provides a framework for charges determination at these airports, mandating consultation with airlines before new charges are introduced, requiring that sufficient financial and operational information is shared with users, that an independent regulator exists to oversee the process, and that charges are determined according to principles of transparency, non-discrimination, and objectivity.
- **The Slot Regulation**, which was adopted in 1993 (and subsequently amended), is informed by the Worldwide Airport Slot Guidelines¹⁶ and sets out the slot allocation system used in the EEA. The central elements of the Slot Regulation are the '80/20 Rule' (if an airline uses a slot at least 80% of the time in a season, they can retain it for the corresponding season in the following year),¹⁷ the allocation of slots by an independent coordinator, and the New Entrant Rule regulating slot access to new airlines at an airport.
- Finally, the **Ground Handling Directive** which was adopted in 1996 and started the liberalisation of the EU ground handling market, applies to EEA airports with more than 2m passengers per annum. These airports are only able to limit the number of third-party suppliers of ground handling services in specific cases—e.g. for some services (baggage,

¹⁵ European Commission, '[Aviation – Fitness check of EU airport legislation](#)'.

¹⁶ IATA (2025), '[Worldwide Airport Slot Guidelines \(WASG\)](#)'.

¹⁷ For instance if an airline uses 80% of its allocated slots in a given winter season, they retain them in next winter season.

ramp, fuel and oil, freight and mail) or due to capacity constraints. Airports need to provide access to airport infrastructure to suppliers, can reserve the management of centralised infrastructure for one body (e.g. de-icing), and may require operators to obtain a license.

According to the European Commission, these Directives and Regulations aim to create competitive conditions in the market for airport infrastructure services, which are typically characterised by high entry barriers.¹⁸ They are described as key to ensuring that airport capacity and infrastructure can be accessed fairly by all market participants, and that airport infrastructure and services are priced efficiently and transparently.

2.1.2 Recent challenges with this framework

Part of this framework was established three decades ago for an aviation market that has evolved significantly since.

The structure of the airline market has fundamentally changed since these pieces of legislation were introduced. The rise of LCCs has led to a change in the dynamics of the sector. The wave of airline mergers (Air France–KLM, IAG group, Lufthansa–SWISS–Austrian Airlines–Brussels Airlines–ITA) and the proliferation of metal-neutral joint ventures (JVs) (Air France–KLM–Alitalia–Delta, Air Canada–Lufthansa–United, American Airlines–IAG) has reduced the number of competing airlines at European airports. It is therefore important that these regulations and directives **reflect the changing dynamics of airline competition at European airports and ensure that passengers have access to sufficient choice.**

EUROCONTROL's Aviation Outlook 2050¹⁹ predicts that demand for air traffic in Europe will grow by 44% by 2050 compared with 2019 levels, and that 3–12% of demand will not be accommodated by European airports in 2050. Investment into capacity expansion to accommodate this growth and maintain levels of operational performance and passenger satisfaction is critical. Expansion can result in short-term increases in airport charges. Airlines and regulators may oppose capacity expansion over concerns regarding the impact on price and affordability of travel, while national governments and local communities raise legitimate concerns over the impact on the environment. **Airport regulation needs**

¹⁸ The European Commission cites as examples the limited availability of airport capacity and infrastructure, as well as high investment costs.

¹⁹ EUROCONTROL (2022), '[EUROCONTROL Aviation Outlook 2050](#)'.

to reconcile these differing constraints into a framework that can accommodate growth without compromising on affordability and environmental goals.

Considering the role EU legislation aims to play in maintaining competitive conditions in the market and the changes in the sector since the legislation was put in place, we set out below the key takeaways and implications of this study for future regulation.

2.2 Implications of our analysis for the European Commission's Fitness Check

Considering the role EU legislation aims to play in maintaining competitive conditions in the market, and the changes in the sector since the legislation was put in place, we set out below the key takeaways from our assessment and their implications for future regulation.

2.2.1 Key takeaways from our analysis

Overall, the results of this assessment indicate that airfares are primarily driven by variations in demand and the intensity of airline competition. Airport congestion adds a scarcity premium to fares, particularly at highly congested airports, while airport charges have only a very limited impact on fares. These results are further explained below.

Demand is central

Most fare variations are explained by differences in demand, which is reflected in dynamic pricing from airlines. Time of day, day of the week, month, and route-specific variations, which all reflect differences in demand, explain a large part of the fare variations observed.

Less airline competition leads to higher fares...

Accounting for competition at the level of the individual carrier (e.g. BA and Iberia), as is done in the Slot Regulation, likely leads to overestimating the level of competition at European airports, particularly as airlines within the same group are not effectively competing with each other. More generally, the intensity of competition has a strong relationship with fares, particularly on the short-haul segment. We find that routes characterised by higher market concentration (i.e. less competition) are associated with higher average fares (keeping other factors constant). This relationship between competition and fares holds between routes but also over time, as routes that experience a reduction in competitive intensity between years tend to record higher price growth. Airline route dynamics such as entry or exit therefore have a material impact on prices

(we estimate an impact of close to 10%). While not all routes can sustain competition (e.g. lack of volume for more than one airline), on those which can, passengers benefit from it.

...and the type of competition also matters

Additionally, the profile of competition on routes—for instance, whether an LCC is present—has a significant impact on fares. Full-service carriers (FSCs) are particularly sensitive to LCC competition and tend to offer lower fares on average on routes in which they compete with LCCs.

Lack of airport capacity leads to higher fares

More congested airports lead to higher fares. The relationship between congestion and fares is stronger when airport congestion is higher. Our analysis therefore confirms the existence of a congestion (or scarcity) premium on fares. While changes in congestion affect airfares directly, they also indirectly affect airfares through charges as congestion is associated with higher airport charges.

Airport charges are not a key cost driver

Airline costs play an important role in driving fares. For example, flight distance, which drives fuel costs and other variable costs, has a strong relationship with fare levels. Airport charges, as a cost factor for airlines, also form part of airfares. However, charges are not a significant driver of airfares.

2.2.2 Implications for the Fitness Check

Managing congestion should be a policy priority in the short term

With a growing number of congested airports in Europe, it is imperative to allocate the available capacity in a manner that optimises and maximises its utilisation. This would have benefits for passengers seeking to travel to and from these airports, as well as for the wider economy.

Congestion is costly to all stakeholders in the aviation sector. It generates:

- operational challenges and additional costs for airports;
- scheduling constraints for airlines;
- increased airport costs and consequently charges;
- environmental impacts;

- higher fares for passengers driven by higher airline costs but also limits to airline competition.

Managing congestion through more effective slot allocation and ensuring allocated slots are actually used would generate benefits for all stakeholders. Ultimately, optimising the use of existing capacity may reduce the need for airports to increase airport charges to fund infrastructure investment, especially in the short to medium term.

In the long term, there will be a need for investment in airports to increase capacity

While managing congestion through slot allocation can help in the short run, in the long run the only way to significantly increase capacity is through investment. Regulators may limit airport investment in pursuit of cost efficiency and limiting charge increases. However, our analysis suggests that increased investment will only have a small effect on airfares through increased airport charges, due to low charges pass-through, and that this effect is outweighed by a reduction in passenger fares through lower congestion and increased capacity-enabled competition. **In other words, airport investment improves consumer outcomes through more competition, choice and lower airfares that outweigh their costs.**

Passengers benefit significantly from airline competition

Our study identifies three key ways in which airline competition affects the level of passenger fares:

- 1 **market concentration**—i.e. the intensity of competition on a given route or at a given airport;
- 2 **type of competition**—i.e. whether LCCs, FSCs, or a mix are competing on a route;
- 3 **airline route dynamics**—i.e. the impact of entry or exit on fares.

Our analysis illustrates that higher airline concentration drives up fares, and FSCs are particularly sensitive to LCC competition. With current slot rules affecting the use of slots at airports, changes to the Slot Regulation could ensure that passengers are not paying an unnecessary fare premium due to insufficient competition.

Changes to the new entrant rule to encourage entry could reduce fares. The increasing airline concentration in the market indicates that the carrier definition

used in the Slot Regulation for new entrants is no longer appropriate. An airline could qualify as a new entrant while effectively operating as one company with an incumbent airline that is part of the same group and already present at the airport. More broadly the new entrant rule under the Slot Regulation may be too limited in scope (five slot limit for new entrant privileges) to ensure that airlines with a smaller presence at an airport can grow over time and act as effective competitors. In particular, our analysis indicates that, beyond the number of competing operators, the intensity of competition between them (i.e. whether they share the market or one has a much stronger presence than the others) matters in determining the price passengers pay to travel. The Slot Regulation can play a role in levelling the playing field for airline access to congested airports. More generally, policymakers may consider ways to ensure that airlines make full and proper use of the slots allocated to them to guarantee that the extent of competition is maximised.

Any changes to the ACD to try to constrain charge increases will not lead to significant passenger benefits

Any changes to the ACD to place further limits on the extent to which airports can raise charges could lead to increases rather than reductions in airfares. If airports are not able, for example, to invest and build capacity to enable more airline competition and reduce congestion, then airfares are likely to increase significantly. These increases would be much greater than any increase in charges required to fund such investments.

Policymakers have an opportunity to generate substantial benefits for passengers

The results from this study point to clear opportunities to generate significant savings and positive outcomes for passengers.

- Stimulating airline competition and slot use through an update to the Slot Regulation could lead to lower prices and more choice for passengers, and better use of existing infrastructure by airlines.
- Managing congestion in the short term and investing in capacity in the longer term will lower prices by reducing scarcity rents on fares at congested airports, allow for more airline competition, increased connectivity, and better quality of service through improved on-time performance and resilience at European airports.
- In an environment with increasing airline concentration and pressure on infrastructure, the benefits to consumers of airport investment are likely

to outweigh their costs, as higher airport charges are only partially passed through to passengers.

Figure 2.1 below provides an estimation of the consumer benefits that could be generated by investing in airport capacity.

Using the results of our analysis, we have estimated that **European passengers could save approximately €20.00 per one-way ticket for a total of €8.2bn** provided that all European airports operated at or below the median levels of congestion and concentration.²⁰ **This does not account for the benefits of additional choice and better quality of service from airlines due to more competition, and from airports due to the additional available capacity.** This analysis does not include charges, as it is challenging to estimate the corresponding increase in charges that would support the reduction in congestion and concentration. However, even assuming a 10% increase in charges across airports, there would still be a net benefit for passengers.²¹

²⁰ This analysis is described in more detail in section 5.3 of the report.

²¹ A 10% increase in charges for each of the airports with reduced congestion or concentration identified in the analysis above would result in a €4.15 increase per one-way fare and a €2.4bn cost to passengers, or a net benefit of €5.8bn.

Figure 2.1 Estimated benefits to passengers of reducing congestion/airline concentration at European airports

	Concentration -7%	Per dep. passenger	€5.99	Across the sample of airports	€1.7bn
	Congestion -18%	+	€13.54	+	€6.4bn
Total		€19.53		€8.2bn	

Note: The concentration and congestion premia are calculated using their respective elasticity results from the regression analysis and the average fare at each concentrated European airport in the sample. Impacts across the airport sample are calculated by multiplying the total number of departing passenger at airports in which congestion or concentration would decrease by the average fare impact.

Source: Oxera analysis.

3 Preparing data for the analysis

3.1 Introduction

This section sets out the four main datasets used in the analysis.

- OAG schedules data provides a comprehensive overview of direct flights departing or arriving from each airport, enabling analysis of the number of flights and airlines per route, departure times, and route characteristics.
- Airfares for each flight are sourced from a dataset collected by Oxera from Google Flights.
- Airport charges are obtained directly from AirportCharges.com and linked to the departing airports in the sample.
- Finally, an internally constructed dataset provides the maximum declared Air Traffic Movements (ATM) capacity for each airport.

Each dataset is described in more detail below.

3.2 Datasets used in the analysis

3.2.1 OAG data

Type of data: OAG data provides a comprehensive overview of scheduled flight operations. For each direct flight, the dataset records the origin and destination airports served, scheduled departure and arrival times, flight distance, seat capacity, aircraft type and configuration, and the operating carrier.

Data coverage: the dataset records 24m unique scheduled flights across 1,000 airports and aerodromes located in European countries between January 2023 and December 2025, including close to 30,000 airport-to-airport routes operated by approximately 350 unique carriers.

How we use it: given its broad coverage, OAG data serves as the basis for constructing a number of key variables, including airport-level congestion, route-level market concentration, and indicators of airline entry and exit, as well as a range of additional airport, route, and airline characteristics. The steps taken to clean the dataset, the variables used, and the level at which they are aggregated are described in annexes A1.1 and A1.2, respectively.

3.2.2 Google Flights

Source of data: a proprietary Oxera dataset containing airfare data scraped from Google Flights for outbound flights 14 and 60 days before the date of departure, and return trips seven days after the departure date. For each search, ten random fare quotes are retrieved to ensure a representative sample of fares.

Type of data: the data is recorded at the flight level, and for each observation (flight), it captures the operating carrier, departure and arrival airports, offered fare on a round-trip basis, scheduled departure date and time, and itinerary characteristics including whether the flight is direct or indirect and, where applicable, the layover airport and duration.

Data coverage: the dataset records 100m fare observations for direct and indirect (or connecting)²² flights across close to 850 airports located in European countries between January 2023 and December 2025, including 20,000 airport-to-airport routes) operated by approximately 260 unique carriers.²³

How we use it: the Google Flights data is used exclusively as a source of information on airfares, providing the average observed fare for flights identified in the OAG data. Annex A1.1 details the steps taken to clean the dataset, while annex A1.4 outlines how the fare variables used in this report are computed. For most of the analysis, the fare is divided by the flight distance (obtained from the OAG data) to produce a fare per 100km measure. The distance-standardisation allows for the comparison of routes of differing flight lengths.

3.2.3 Airport charges

Type of data: the charges represent total turnaround charges (including all airport charges and ANSP terminal charges, excluding rebates/incentives, government aviation taxes, and ground handling costs) in euros at a range of European airports (discussed below). Data is provided separately for four aircraft: a Regional Jet (code CR9), a Turboprop (AT7), a Narrowbody (32N), and a Widebody (B789). These four aircraft types were selected to best capture the

²² Indirect flights correspond to connecting itineraries in which the passenger takes more than one flight to reach their final destination. For instance, a passenger could take a direct flight from Paris to Miami or take an indirect itinerary from Paris to London to Miami (one stop in London). In line with the decisional practice of the European Commission, only long-haul indirect flights with one layover shorter than three hours are retained in our dataset. See for reference European Commission (2024), [Case M.11071 – DEUTSCHE LUFTHANSA / MEF / ITA](#), para. 254.

²³ This is the number of unique carriers (before aggregating companies belonging to the same group) for direct flights.

range of aircraft operating across the different routes covered throughout each year of the sample, and therefore the range of charges applied to flights.

Data coverage: charges data is recorded annually for the years 2023, 2024, and 2025, for 76 major European airports²⁴ across the EEA, the UK, and Switzerland.

How we use it: the airport charges data is used to assign a charge level to each route and departing airport in the sample, as described in annex A1.5.

3.2.4 Airport capacity data

Source of data: collected by Oxera from national airport slot coordinators and airport management.

Type of data: we collected data on the maximum ATM capacity by hour. We assume that this peak capacity applies uniformly across all hours of the day; i.e. a single value is used for each airport across the period of analysis. Annex A1.6 reports the maximum ATMs for each airport within the scope of analysis.

Data coverage: all airports with more than 5m seats.²⁵

How we use it: we use the maximum hourly ATM capacity to construct a measure of congestion for each airport.

3.2.5 Overview of the final dataset

Since the OAG data represents a comprehensive view of scheduled flights, the OAG dataset constitutes the starting point to prepare the dataset for analysis. A key is constructed to merge OAG and Google Flights data comprising the following unique dimensions: **departing airport, arrival airport, departing city, arrival city, IATA season, and an indicator for low-cost carriers (LCCs).**²⁶

²⁴ The list of airports covered includes the top 50 European airports and a sample selection of representative smaller airports.

²⁵ Annex A1.6 reports the maximum ATMs for these airports. Seat counts are derived from the OAG data as the sum of seats across all arriving and departing flights at a given airport in a given IATA season. This threshold is defined to include airports of a sufficient size to be covered (or close to be covered) by the ACD within the EU. Given that the Directive's applicability threshold is based on the number of passengers, the resulting sample will include EU airports subject to the ACD and some airports that are close but below the threshold to be subject to the ACD.

²⁶ To classify carriers as LCCs and full-service carriers (FSCs), the [ICAO classification](#) is adopted.

Annex A1.7 describes the steps that were implemented to generate the final dataset used for the analysis, which is summarised in Table 3.1 below.

Table 3.1 Overview of final dataset

Data periods covered	S23 to W24/25
Number of...	
Individual observations, of which	62,407
Relate to LCCs	30,263
Relate to FSCs	32,144
Relate to direct flights	56,063
Relate to indirect flights	6,344
Number of unique...	
Airports, of which	697
in Europe ¹	54
Routes, of which ²	5,915
Domestic	587
Short-haul	2,395
Medium-haul	2,020
Long-haul	939
Served by direct flights	5,870
Served by indirect flights	858
Average number of competitors per route ³	2.64

Note: ¹ EU, Switzerland, UK, Norway and Iceland. ² The segments are defined as follows: domestic (flights within the same country), short-haul (international routes up to 1,500km), medium-haul (international routes between 1,500km and 4,000km), and long-haul (international routes above 4,000km). ³ Statistics are computed for direct routes only, based on prices recorded 60 days before departure.

Source: Oxera analysis.

4 Key drivers of airfares

4.1 Introduction

Airfares respond to a range of factors, including passenger demand (fares tend to be higher when demand is greater), airline operating costs (which vary across routes and times of day), congestion (fares may rise during peak travel periods), and/or the degree of competition on the route in question.

EU aviation regulation aims to create competitive conditions in a market with high entry barriers, and ensure that airport capacity and infrastructure can be accessed fairly and is priced efficiently and transparently. The four factors on which this assessment focuses together reflect the competition, capacity, and price dynamics within the sector, and were selected in order to determine how effectively the regulation functions in this regard, and whether there are improvements that can be made.

The analysis that follows focuses on four factors that are directly affected by the Slot Regulation and the ACD:

- **temporal variations in fares**—capturing differences in fares across different time dimensions (season, week, and hour of the day);
- **airline competition**—capturing the impact of market-structure as a constraint to airlines' pricing power;
- **airport congestion**—corresponding to the extent of capacity constraints at airports and the scarcity rents these may generate;
- **airport charges**—representing a direct input cost for airlines and the main mechanism through which airport-level pricing decisions could affect the prices paid by passengers.

For each of these factors, the rest of this section provides a short review of the relevant academic and industry literature before presenting the results of the graphical analysis.²⁷ Preliminary conclusions are summarised at the end of the section.

²⁷ For this analysis, only fares recorded 60 days ahead are used. Results remain robust when using 14-day-ahead fares.

4.2 Flight departure/arrival time

4.2.1 Introduction

Airlines use dynamic pricing to determine airfares based on the time at which a flight departs or arrives. These price variations reflect the preferences of passengers depending on their purpose of travel and the availability of outside options (other flights or other modes). However, the literature on the effects of time-related factors on airfares, which are comparable to those explored in this study, is limited.

Otreba and Sawik (2026)²⁸ examine how ticket purchase day of week, number of tickets bought, flight day of week, departure time of day and number of days to departure impact pricing on a small set of short-haul intra-European routes.²⁹ For departure day of week, findings suggest that fares tend to be higher on Mondays and Sundays, particularly among LCCs, while mid-week and Saturday departures are generally the cheapest. The day of purchase appears to have a less statistically significant impact, though there is some indication that buying tickets on the weekend may lead to marginally higher prices. Departure time is identified as a relevant factor affecting price, with FSCs pricing early morning flights more expensively, possibly reflecting the influence of business travel demand. It is however important to note that Otreba and Sawik's findings are limited in geographic scope and based on a limited set of routes, and so should be interpreted with that in mind.

Given that the dataset used for our analysis contains very disaggregated information on prices and schedules, we are able to expand on the limited academic evidence on temporal variations in fares. Variation in (distance-standardised) fares is considered along four dimensions: (i) day of the week; (ii) hour of departure; (iii) hour of arrival; (iv) month of departure.³⁰ The distance-standardisation allows for the comparison of routes of differing flight lengths.

²⁸ Otreba, P. and Sawik, B. (2026), 'Determinants of airfares in the short-haul European market: an empirical study', *Expert Systems with Applications*, **301**, pp. 1–23.

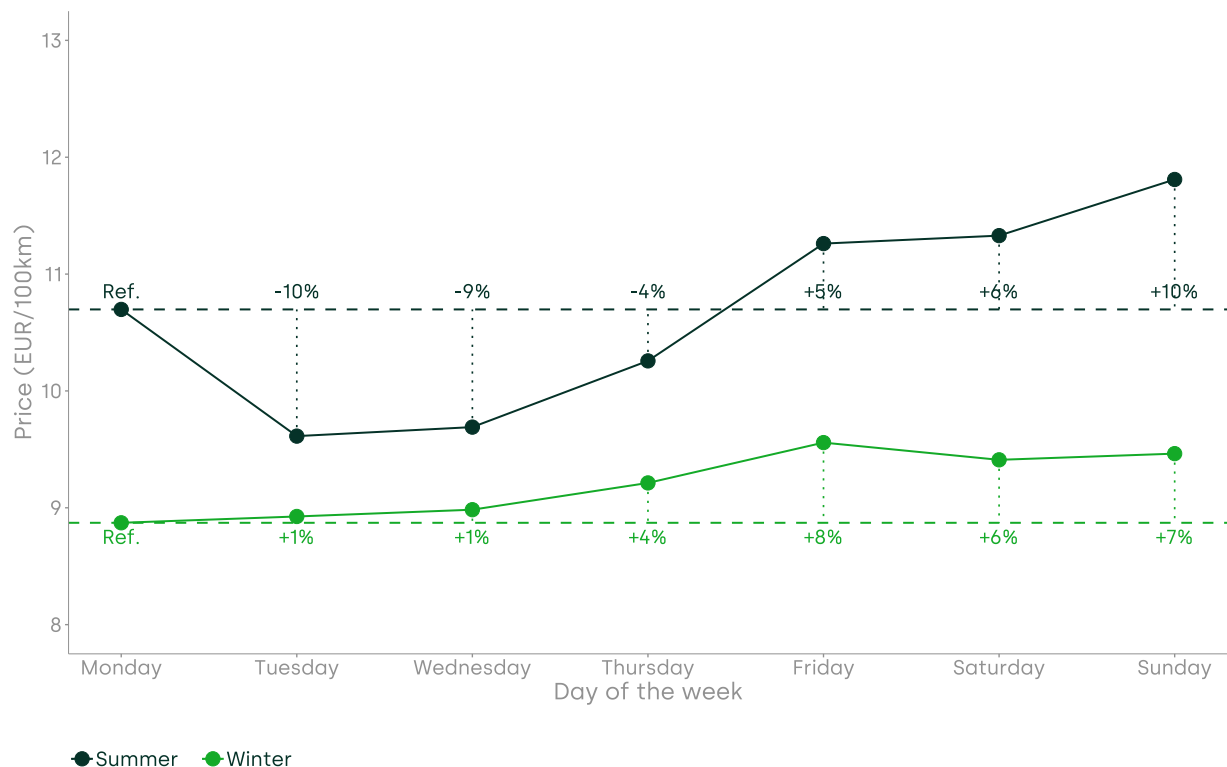
²⁹ Routes originating from Warsaw and Krakow to Paris and London over one week in May 2025, supplemented separately by Amsterdam, Frankfurt and Munich as alternative destinations over a 19-day period beginning at the end of April 2025.

³⁰ In the rest of this section, the fares used for the analysis are one-way prices divided by route distance, expressed in hundreds of kilometres for ease of comparison between different routes and segments, unless clearly stated otherwise. The analysis focuses on fares scraped 60 days prior to departure, and prices are averaged at the appropriate time aggregation (time of day, day of the week) for each month, year, and airport pair. For long-haul routes, no distinction is drawn between direct and connecting flights; instead, an average price is computed across both.

4.2.2 Departure day of the week

Figure 4.1 below shows that airfares are higher on weekends than on weekdays. In IATA summer seasons, the weekend price premium relative to the working week is particularly pronounced. Additionally, for a given day of the week, prices in summer are higher than in winter.

Figure 4.1 Price by day of the week (departure)



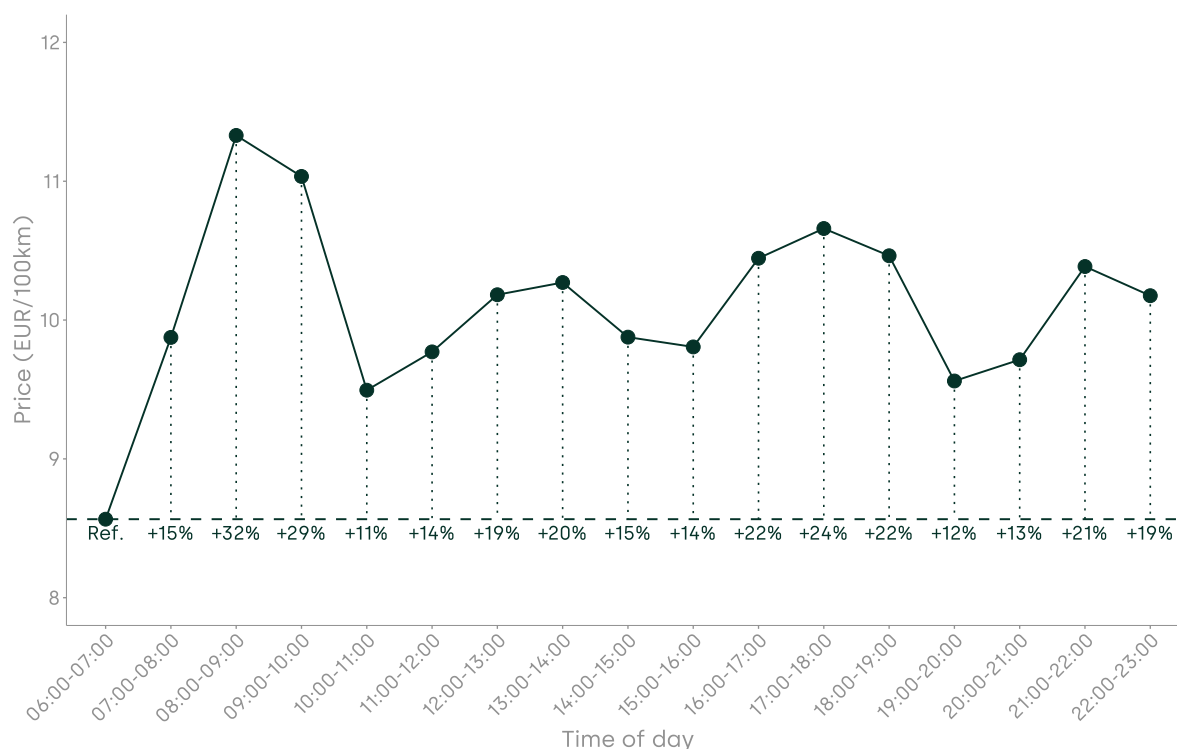
Note: The figure shows departing average fares across the full sample of routes by day of the week for summer and winter IATA seasons, indexed to Monday—i.e. values for other days should be read as percentage increases (decreases) relative to average Monday fares. The dashed line indicates the Monday price level for each season.

Source: Oxera analysis,

4.2.3 Departure time of the day

Figure 4.2 below shows that prices peak in the morning (08.00–10.00) and in the afternoon (16.00–19.00). These findings likely reflect passengers' preferences for departure times outside standard working hours—whether to accommodate business travel or to maximise time spent on holiday or visiting family and friends for leisure purposes.

Figure 4.2 Price by time of the day (departure)



Note: The figure shows average fares by departure time of day across the full sample of routes, indexed to the hour slot 06.00–07.00—i.e. values for other hour slots should be read as percentage increases (decreases) relative to average 06.00–07.00 fares. The dashed line indicates the average 06.00–07.00 hour slot price.

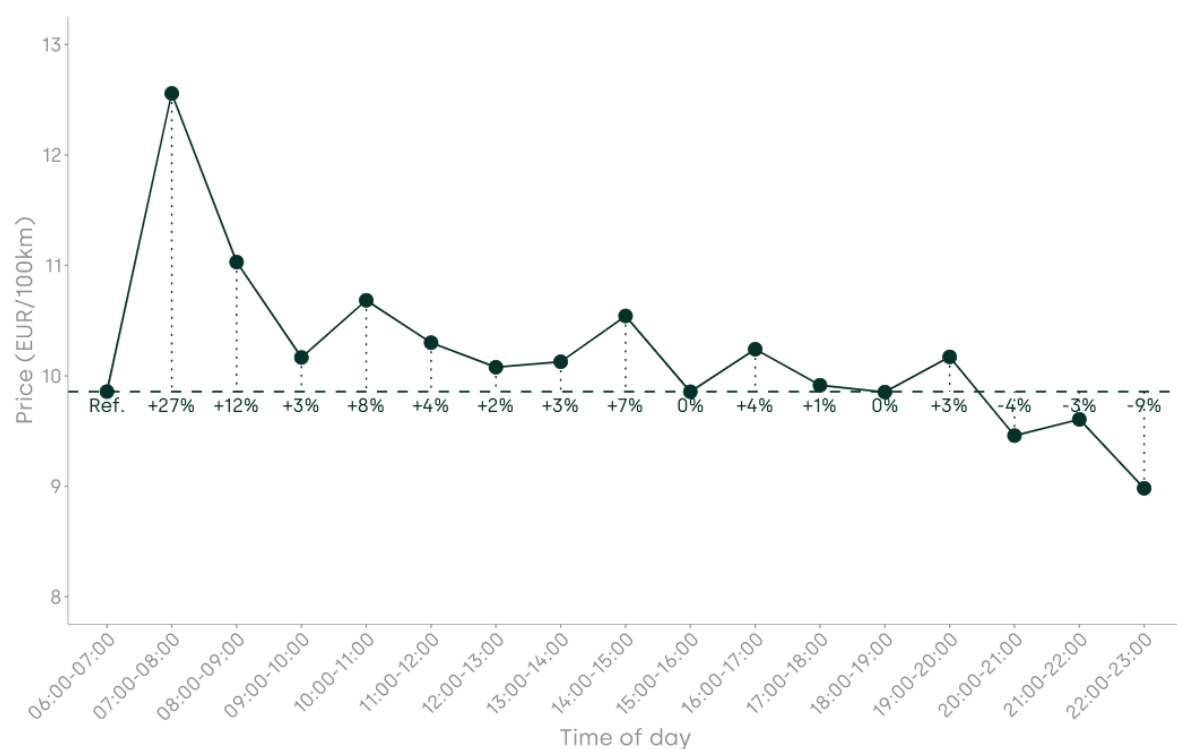
Source: Oxera analysis

4.2.4 Arrival time of the day

Figure 4.3 below shows that, in contrast to departure times, fares by arrival time exhibit a more concentrated pattern, dominated by a single sharp morning peak in the 07.00–08.00 slot, which has a premium of 27% relative to the least expensive time to travel. This likely reflects the high value business travellers place on early-morning arrivals (e.g. from long-haul night flights).

After this peak, fares decline steadily from mid-morning onward, with fares for late-evening arrivals (20.00–23.00) that are lower by up to 9%. Notably, the earliest slot (06.00–07.00) is priced at a similar level to afternoon and late-evening arrivals, suggesting that late-evening arrivals (20.00–23.00) are unattractive to most passengers and attract predominantly price-sensitive passengers.

Figure 4.3 Price by time of the day (arrival)



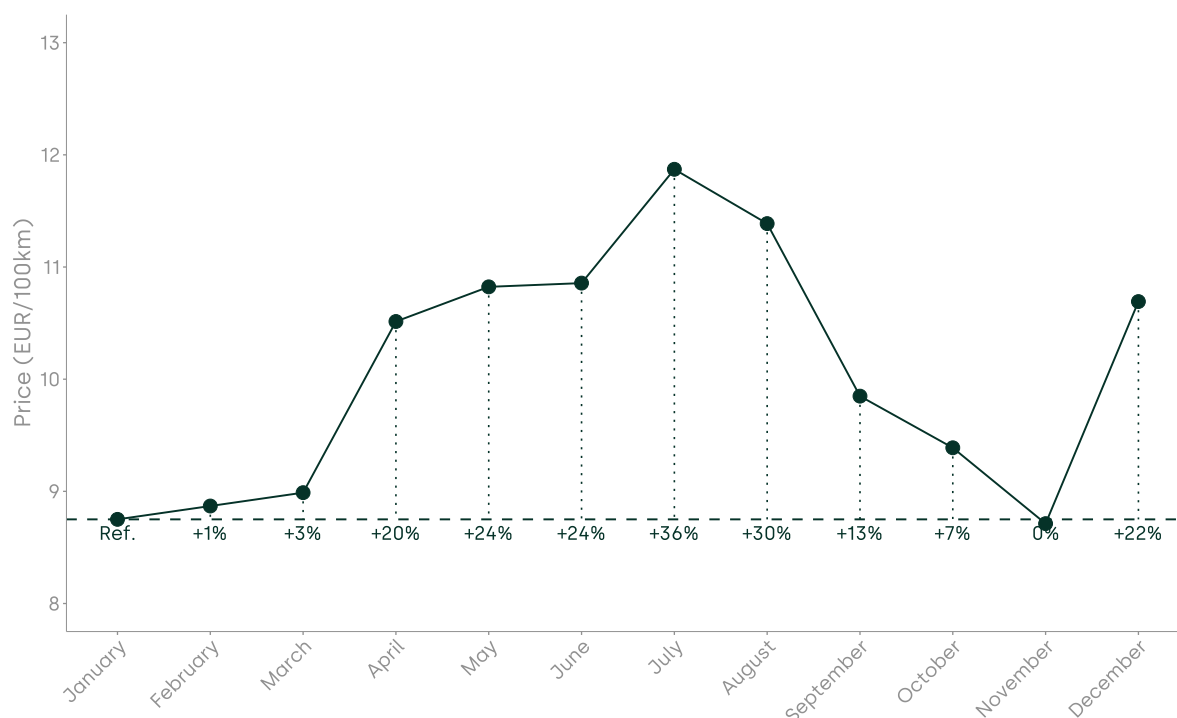
Note: The figure shows average fares by arrival time of day across the full sample of routes, indexed to the hour slot 06.00–07.00—i.e. values for other hour slots should be read as percentage increases (decreases) relative to average 06.00–07.00 fares. The dashed line indicates the average 06.00–07.00 hour slot price.

Source: Oxera analysis.

4.2.5 Departure month

As shown in Figure 4.4 below, prices are generally higher in spring and summer (April to August), with a peak in July/August, but also in December, consistent with the main holiday periods across Europe.

Figure 4.4 Price by month of the year (departure)



Note: The figure shows average monthly departure fares across the full sample of routes, indexed to the average fare in January—i.e. values for other months should be read as percentage increases (decreases) over average January fares. The dashed line indicates the average January price.

Source: Oxera analysis.

4.2.6 Conclusions on time variation

The four charts presented in this section show **intuitive variations of fares (e.g. higher fares during the weekend, peak early mornings, and the summer months)**. Fares appear to vary significantly along these dimensions, which can be explained by differences in demand that are reflected in dynamic pricing from airlines. However, fares also respond to a multitude of factors other than demand, such as airline scheduling (airlines may need to schedule flights late at night due to slot availability, and may strategically offer lower fares to attract demand for those flights) and congestion (fares may be higher during peak travel times). The sections that follow disentangle the relationship between fares and these other market factors.

4.3 Congestion

4.3.1 Introduction

Airport congestion arises when demand for take-off and landing slots approaches or exceeds the capacity of an airport. At many European airports, the demand passengers (and therefore airlines) have for air transport services can approach or exceed the capacity available to satisfy it. In these cases, the price for airport access (airport charges) does not increase such that demand meets supply as would happen in other markets as charges are subject to regulation or the countervailing buyer power of airlines. Where airlines hold slots at congested airports, they are able to increase prices such that flight demand matches available supply thereby generating a scarcity rent.³¹ The relationship between airport congestion and fares is accordingly expected to be positive, with the strength of the relationship increasing in the degree to which capacity is constrained.

The impact of airport capacity constraints on airfares is examined in a report by SEO Amsterdam Economics.³² Findings show that a 10% increase in congestion is associated with a 1.4% rise in short-haul fares and a 2.2% rise in long-haul fares, revealing a U-shaped relationship between capacity constraints and ticket prices. The report raises concerns that incumbent airlines may have incentives to oppose airport expansion, as they benefit from scarcity rents, which tend to be concentrated at congested airports (either at specific peak times or over the course of the day) and tend to be higher where market contestability is low. Notably, the study concludes that airports generally do not capture much of the scarcity rent through charges, partly because many European airports are regulated. Overall, the study estimates that consumers paid around €2.1bn extra in 2014 as a result of congestion in Europe, which is expected to triple in 2035.

Frontier Economics (2019)³³ estimated the congestion premium for Heathrow Airport by comparing ticket prices with those at other European hub airports. Findings suggest congestion premiums of 17% on short-haul routes and 25% on long-haul routes, which translate into an additional £47 per return fare on short-haul flights and £216 on long-haul flights. Overall, this amounts to £2.6bn across

³¹ This term refers to the value of scarcity, reflected in airfares that are higher than those that would prevail if there were no capacity constraints.

³² SEO Amsterdam Economics (2017), 'The impact of airport capacity constraints on air fares final report', commissioned by ACI Europe.

³³ Frontier Economics (2019), 'Estimating the congestion premium at Heathrow', a report prepared for Heathrow, May.

all passengers, which is in the same order of magnitude as the premium estimated by SEO Amsterdam Economics.

On the wider implications of congestion, a study by Adler et al. (2026)³⁴ assesses the societal consequences of tightening slot capacity at hub airports across North America and Europe. Modest slot reductions are found to reduce overall social welfare, as consumer surplus losses due to higher fares and reduced connectivity outweigh environmental and producer gains. On the airline side, limited slot reductions tend to boost profitability through enhanced market power, though more severe cuts eventually erode profits. However, the impact of slot reductions varies across airline types: hub incumbents initially benefit as constraints apply to all competitors, transcontinental carriers are the most adversely affected as they lose more profitable long-haul routes, and LCCs tend to gain by attracting passengers away from slot-constrained FSCs.

Building on the findings from the literature summarised above, the following subsection looks at the relationship between airport congestion and fares using the novel dataset assembled for this analysis. Airport congestion is defined as the percentage share of available runway capacity that is being utilised.³⁵

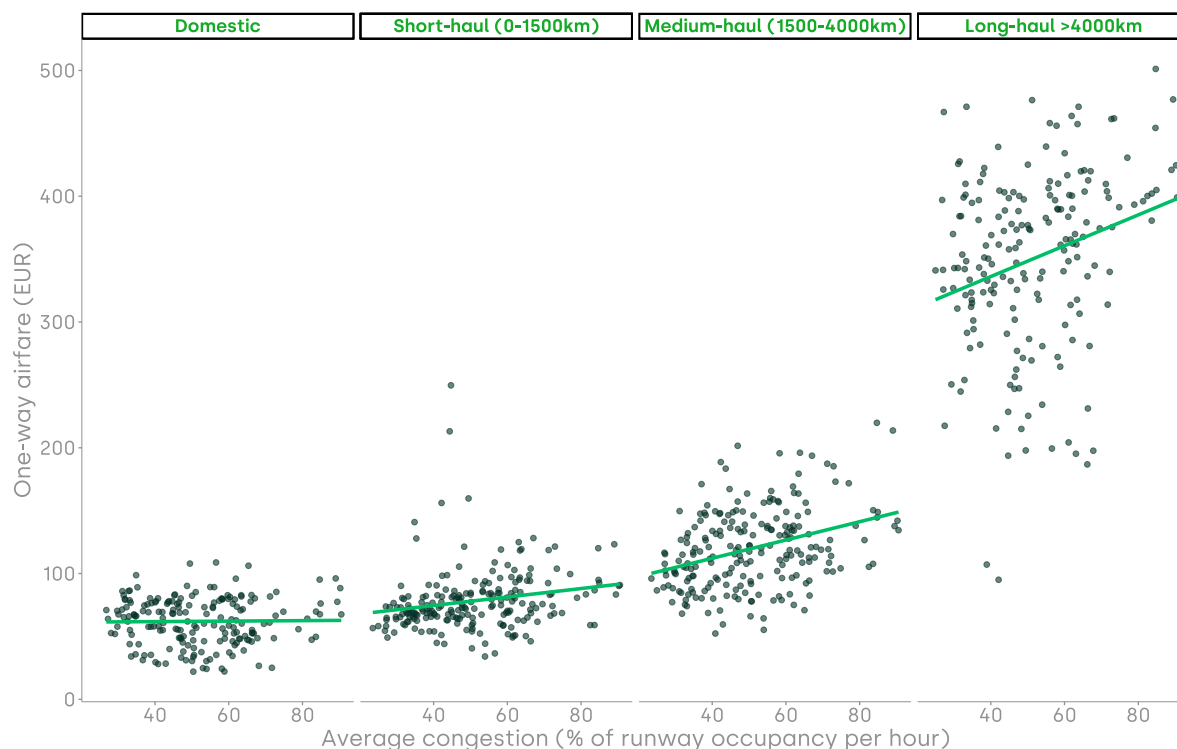
4.3.2 Congestion and fares, by flight segment

Figure 4.5 below presents the relationship between congestion and fares, with fares divided into four mutually exclusive categories: domestic (flights within the same country), short-haul (international routes up to 1,500km), medium-haul (international routes between 1,500 and 4,000km), and long-haul (international routes above 4,000km). The chart shows airfares in levels (without standardising by route distance) and airport congestion. It illustrates the relationship between fares, distance, and congestion discussed above as congestion is associated with higher fares on average, particularly on long-haul routes.

³⁴ Adler, N., Andreana, G. and De Jong, G. (2026), 'Estimating the societal value of airport slots', *Transportation Research Part B: Methodological*, **206**, pp. 1–28.

³⁵ From the OAG data, a congestion ratio is computed for each one-hour time band and calendar day at each airport. Specifically, the number of arriving and departing flights operating within a given one-hour window (from OAG data) is divided by the maximum ATM capacity of that airport (from separately collected data). The resulting ratio is then averaged across all daytime bands in the IATA season to obtain a single congestion measure per airport and IATA season.

Figure 4.5 Relationship between congestion and fares (in levels), by flight segment



Note: The chart shows the relationship between congestion and fares, where each data point represents the average one-way fare and average congestion for a given departing airport, IATA season, and distance band. Average congestion is the mean percentage of maximum declared capacity utilised per time band at a given airport over the IATA season. Airports not serving a given distance band are excluded from that band's data points.
Source: Oxera analysis.

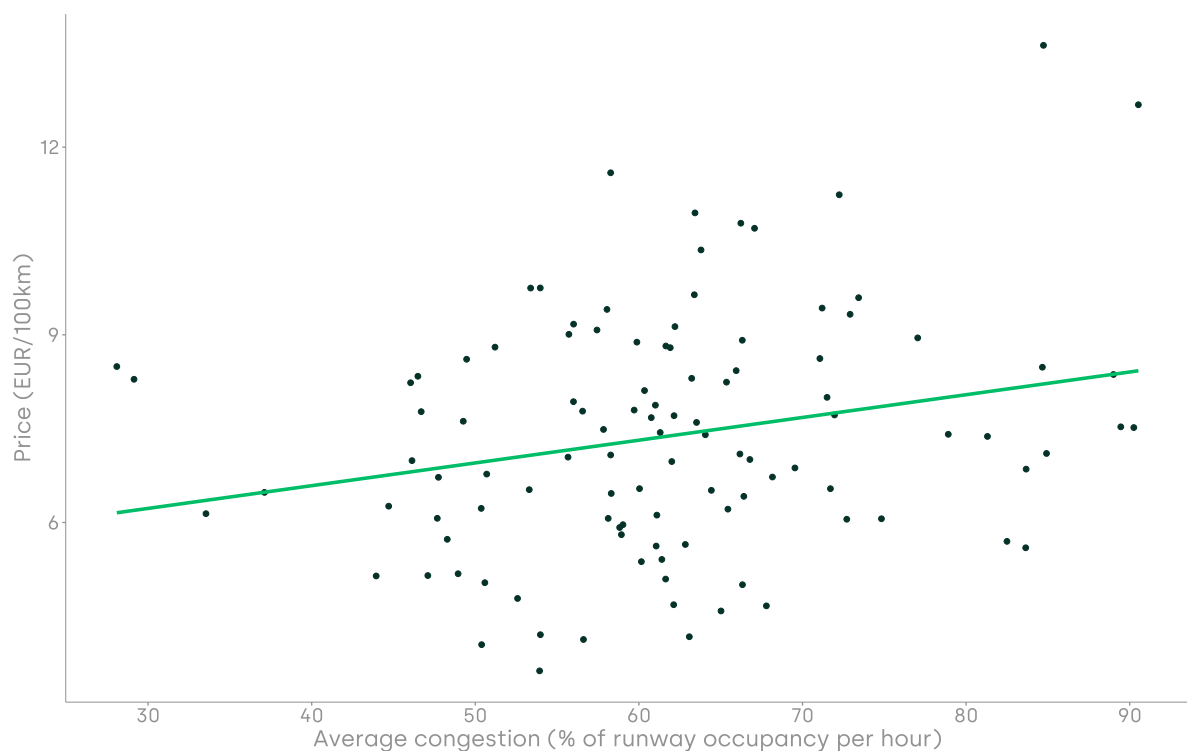
4.3.3 Congestion and fares, by airport category

We also consider whether more congested airports exhibit a stronger positive relationship between congestion and prices by dividing airports into two categories: congested airports above the median congestion value in the sample (i.e. above 52% congestion)³⁶ and less-congested airports below the median value.

³⁶ This value is based on the median congestion across IATA season S23, W23/24, S24, and W24/25.

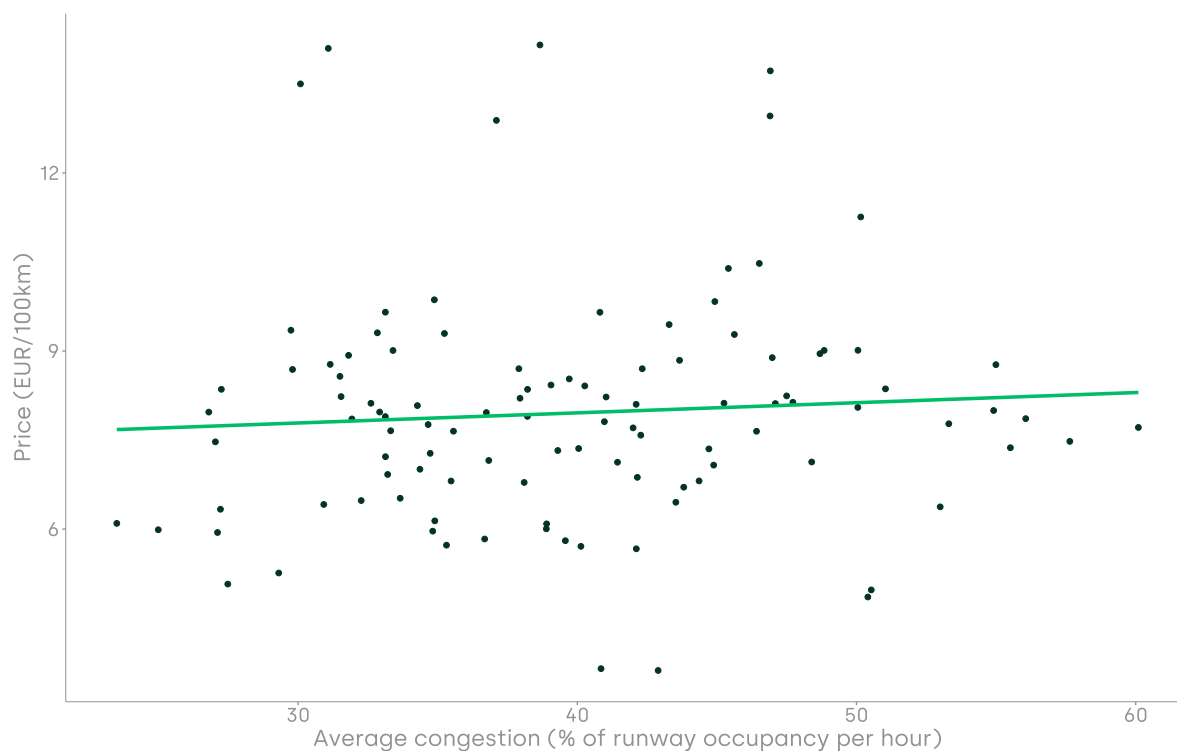
As Figure 4.6 and Figure 4.7 below show, the relationship between congestion and fares is positive for both categories of airports but stronger for the more congested airports, suggesting that for more congested airports fares increase more with congestion compared with less-congested airports.

Figure 4.6 Relationship between congestion and fares, congested airports (above median congestion)



Source: Oxera analysis.

Figure 4.7 Relationship between congestion and fares, less-congested airports (below median congestion)



Note: The charts show the relationship between congestion and fares (EUR/100 km) for airports with above-median (top) and below-median (bottom) average congestion. Each data point represents the average fare and average congestion for a given departing airport and IATA season. Average congestion is the mean percentage of maximum declared capacity utilised per time band over the IATA season.

Source: Oxera analysis.

4.3.4 Conclusions on congestion

The three charts presented above find **a positive relationship between congestion and fares**, though the strength of this relationship varies according to the flight segment and the level of congestion (stronger when airport congestion is high). The data therefore confirms the existence of a congestion premium on fares—i.e. scarcity rent.

4.4 Airline concentration

4.4.1 Introduction

The degree of concentration in a market is a fundamental determinant of the prices faced by consumers. Where few firms compete, prices tend to be higher; and where competitive pressure is stronger, prices tend to be lower. In the airline sector, this relationship has been extensively studied and is central to the assessment of mergers, alliances and JVs by competition authorities in Europe and elsewhere.

Gualini et al. (2024)³⁷ examine the effect of LCC competition on airfares across European non-stop routes. Their findings confirm that **the presence of at least one LCC on a route is associated with fares that are around 11% lower than on routes served exclusively by FSCs**. However, the relationship between LCC market share and fare levels is not straightforward: fares fall as LCC presence grows, but begin to rise with market shares, with the authors concluding that dominant LCCs can engage in monopoly-like pricing when there is limited (or no) competition on a route. The response of FSCs to LCC competition is also nuanced. When the LCC market share is low, FSCs tend to raise their prices, potentially to exploit perceived differences in service quality. However, once LCC presence becomes greater, FSCs lower fares to remain competitive.

Another study on airline competition, by Avogadro et al. (2021),³⁸ explores the circumstances under which LCCs charge higher fares than FSCs on the same routes. **While LCCs are generally understood to undercut FSCs on price, such price reversals do occur in practice—in nearly 10% of cases and on more than a third of routes at least once**. This is driven predominantly by LCCs raising their prices rather than FSCs lowering theirs, and becomes more likely as the departure date approaches. These findings challenge the conventional assumption that LCCs are always the lower-cost option, and highlight the role of dynamic pricing in blurring the traditional price hierarchy across carrier types.

This section describes the relationship between airline concentration, measured by the Herfindahl–Hirschman Index (HHI), and airfares. The HHI is a measure that is often used by the European Commission in merger analysis to assess the

³⁷ Gualini, A., Martini, G. and Porta, F. (2024), 'Are low cost carriers airfares still lower? A comparison with full service carriers in Europe', *Journal of the Air Transport Research Society*, **2**, pp. 1–13.

³⁸ Avogadro, N., Malighetti, P., Redondi, R. and Salanti, A. (2021). 'A tale of airline competition: When full-service carriers undercut low-cost carriers fares', *Journal of Air Transport Management*, **92**, pp. 1–10.

impact of a proposed transaction on competition by estimating the current and expected post-transaction market concentration.³⁹

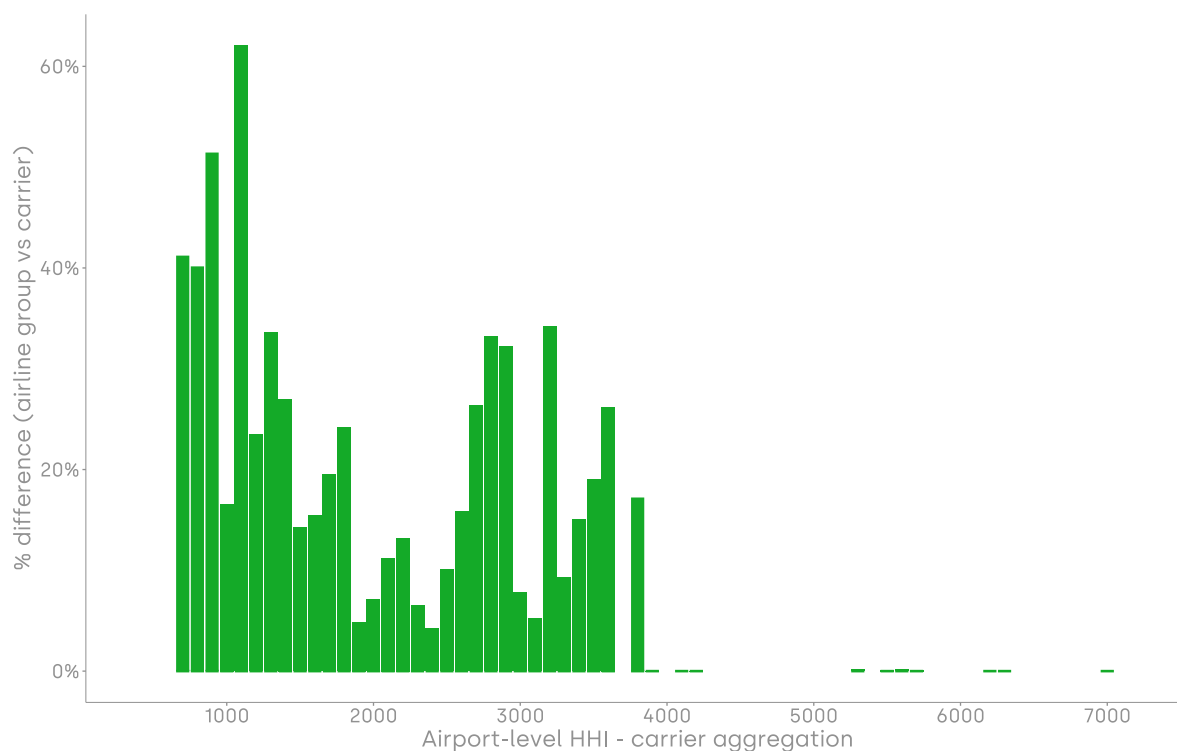
The figures presented below indicate a positive relationship between fares and concentration, the strength of which appears to vary by flight segment (it is stronger for short-haul and domestic flights) and by airline type (competition affects FSC fares more than LCC fares). This indicates that an increase in **airline competition reduces airfares**.

4.4.2 Concentration and airline groups

Figure 4.8 below shows the average difference in airport-level concentration—e.g. the level of concentration at a given airport calculating the market share of airline supply of seats taking the airport as a whole—considering individual airlines as competitors compared with considering airlines as part of groups. The chart shows that concentration with competitors defined as airline groups is 20% higher, on average, than the definition using individual carriers. **Considering airlines within a group as competitors, as is done in the Slot Regulation, would therefore result in overestimating the level of competition at European airports.**

³⁹ From the OAG data, we calculate the HHI as the sum of the squared seats market shares of all carriers operating on each route and in each IATA season, yielding a value ranging from near 0 (highly competitive) to 10,000 (monopoly). Airlines belonging to the same airline group (e.g. British Airways and Iberia in IAG) but also airlines belonging to the same metal-neutral JV (e.g. Blue Skies JV between Virgin Atlantic, Delta Airlines, Air France–KLM and Alitalia on routes to the USA) are treated as the same carrier in the HHI calculations. The relevant market is defined on the basis of city pairs rather than airport pairs (e.g. Paris–Milan instead of CDG–MXP).

Figure 4.8 Difference in concentration between 'carrier level' and 'airline group' aggregation

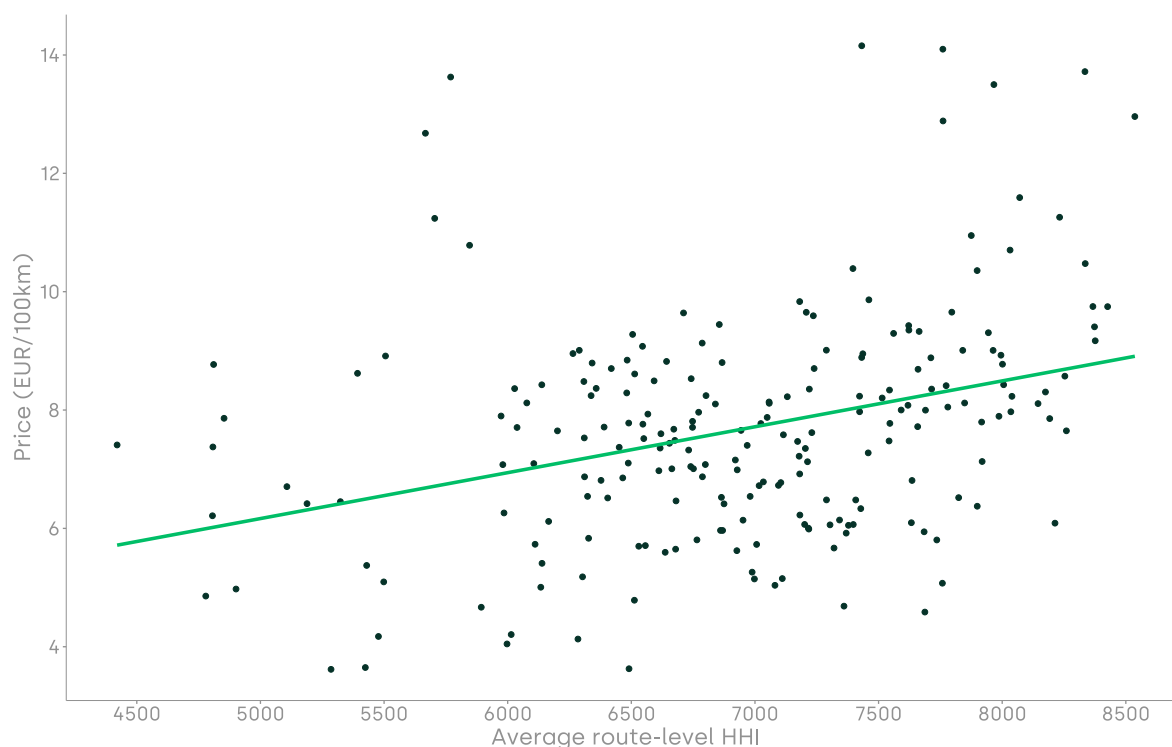


Note: The x-axis shows the airports in the sample according to their level of concentration (HHI) calculated on the basis of individual carriers as competitors (e.g. BA and Iberia). The y-axis presents the percentage difference with the concentration calculated on the basis of airline groups as competitors (e.g. IAG and Air France–KLM).
Source: Oxera analysis.

4.4.3 Concentration and fares, overall

Figure 4.9 below shows that the relationship between concentration and fares is positive, indicating that routes characterised by higher market concentration (i.e. less competition) are associated with higher average fares.

Figure 4.9 Relationship between concentration and fares



Note: The chart presents the relationship between airline concentration and fares. Prices and HHI are averaged at the airport and IATA season level (i.e. one fare per airport/IATA season combination). The chart also displays a fitted regression line, where fares are regressed on a constant and the HHI variable.

Source: Oxera analysis.

4.4.4 Concentration and fares, by flight segment

Figure 4.10 below indicates that the relationship between concentration and prices is positive for domestic and short-haul routes, while it is negative or weakly positive for medium- and long-haul routes. This suggests that airline concentration could play a more important role in driving fares for shorter-distance flights.

Figure 4.10 Relationship between concentration and fares, by flight segment



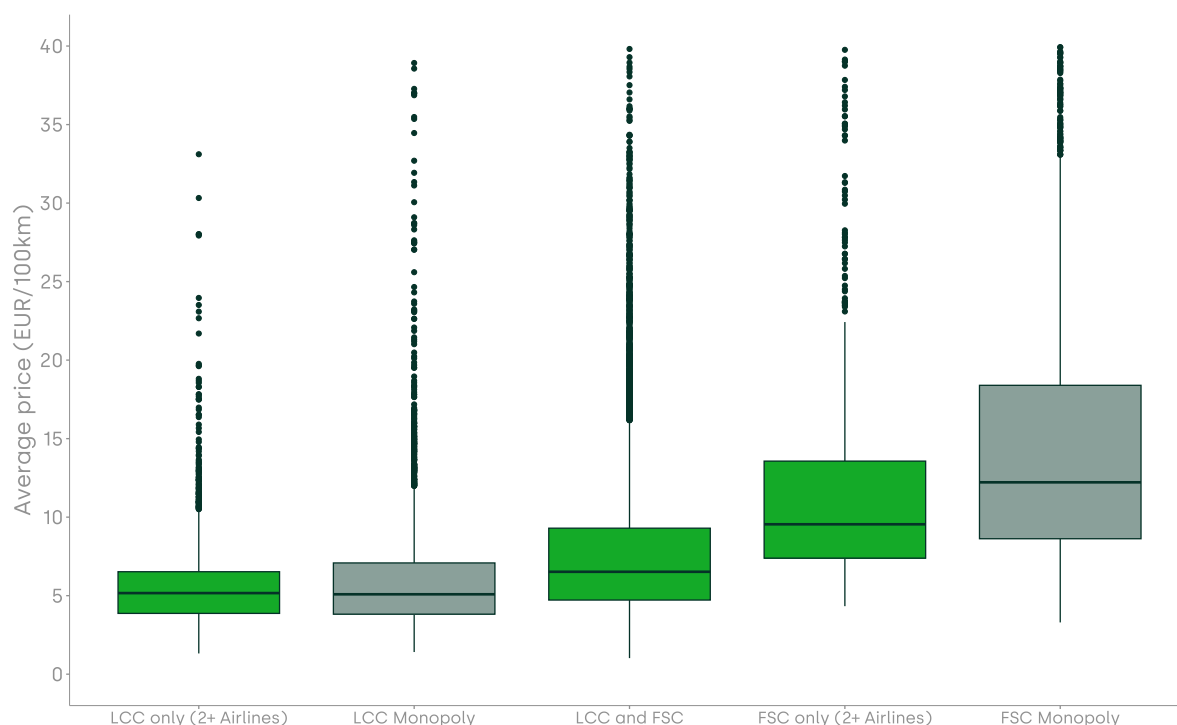
Note: The chart presents the relationship between airline concentration and fares by flight segment. Prices and HHI are averaged at the airport and IATA season level (i.e. one fare per airport and IATA season combination).

Source: Oxera analysis.

4.4.5 Distribution of fares by type of competition on route

Figure 4.11 below presents the distribution of average fares according to the level and type of competition on each route. The figure shows that prices are lower on routes where only LCCs operate than on routes where only FSCs operate. Furthermore, increased competition in settings where FSCs are present substantially reduces fares, while fares on routes where LCCs operate reduce more marginally with increased competition. Moreover, routes where LCCs are present exhibit lower price variation than those on routes where FSCs are present. This suggests that airline competition affects FSC fares more, in particular on routes where LCCs are present.

Figure 4.11 Distribution of fares by type of competition



Note: The figure presents route prices across five types of route: routes operated by a single LCC, by multiple LCCs, by a mix of LCCs and FSCs, by multiple FSCs, and by a single FSC. Each box plot displays the median (horizontal line), top and bottom quartile range (box), and whiskers extending to 1.5 times the quartile range. Outliers beyond this range are shown as individual points. The y-axis is capped at €40/100km. Observations above this threshold are cut off at 40 EUR/100km. The boxes corresponding to monopoly routes are in grey and those corresponding to competitive routes are in green on the chart.

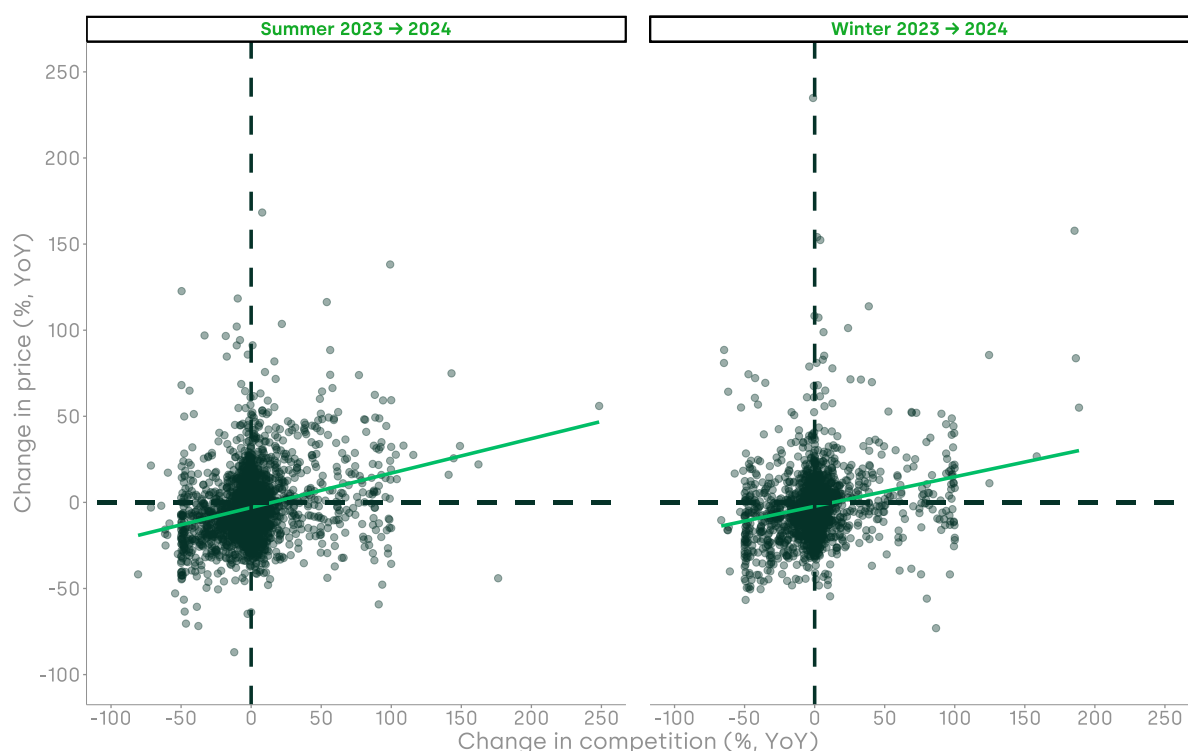
Source: Oxera analysis.

4.4.6 Relationship between route-level concentration and fares, by season

Figure 4.12 below compares changes in HHI and fares by route between Summer and Winter seasons in 2023 and 2024.

The figure indicates a positive association between changes in route-level concentration and changes in prices across the two seasons. Routes that experience an increase in HHI (indicating a reduction in competitive intensity) tend to also record higher price growth. However, routes where concentration fell (i.e. competition increased) were more likely to exhibit below-average or negative price changes relative to the previous IATA season.

Figure 4.12 Year-on-year changes in route-level HHI and fares, by season



Note: The chart presents year-on-year changes in HHI against year-on-year changes in average prices for individual origin–destination city pairs, separately for the Summer (S23→S24) and Winter (W23→W24) seasons. Routes where the HHI was unchanged between the two seasons are excluded from the chart, as a zero change carries no information about the direction of any competitive shift. Source: Oxera analysis.

The relationship between concentration and fares appears to be somewhat stronger in the Summer season, where the slope of the regression line (the green solid line) is visibly steeper, suggesting that price responses to changes in competition may be more pronounced during peak travel periods. This result could be driven by differences in the price sensitivity of passengers between the Summer and Winter seasons, with competition having a more pronounced impact when passengers are more price-sensitive. In both panels, however, the dispersion around the trend line is considerable, reflecting that route-level fare dynamics are also driven by a range of other factors that are not captured here.

4.4.7 Conclusions on airline concentration

Greater airline concentration drives up fares, and FSCs are particularly sensitive to LCC competition. When a LCC is present on a route that FSCs are operating,

FSC prices decrease. While not all routes can sustain competition (for example, due to lack of sufficient demand), on those that can, passengers benefit from it.

4.5 Airline costs in scope of the Fitness Check evaluation

4.5.1 Airport charges

Introduction

Airport charges are often discussed as a determinant of airfares. Airlines routinely cite airport charges as a driver of fares, particularly in the context of proposed charge increases, and regulators in turn scrutinise charge levels on the basis of their presumed pass-through to passengers. However, airports rely on charges as a principal source of revenue in a user-pays system where revenues generated by users cover the costs of providing the service. Airport charges are used to fund the significant costs associated with building, operating and expanding infrastructure. The question of whether, and to what extent, airport charges are reflected in fares is therefore of direct policy relevance.

Evidence on the specific impact of airport charges (excluding air navigation charges and ground handling costs) on airfares is limited, although a high-level analysis by ICF⁴⁰ undertaken in 2018 on the main drivers of airfares finds that airport charges represent a relatively small and stable component of an airline's overall cost base. Charges are estimated to account for between 3% and 17% of total airline costs (i.e. €3.00–€14.00 per passenger). Between 2006 and 2016 charges remained stable, with fluctuations rarely exceeding €1 per passenger. By contrast, other cost items such as fuel, staff and aircraft costs are much larger and more volatile. While a 10% increase in airport charges leads to a cost increase of €0.25–€1.40 per passenger, a 10% increase in the cost of fuel translates to an increase of more than €5.00 per passenger. These findings suggest that the influence of airport charges on airfares is likely to be limited relative to other cost drivers.

Related to airport charges, Koopmans and Lieshout (2016)⁴¹ find that the rate at which cost changes are passed through to passengers depends on whether the cost shock is firm-specific or sector-wide. Firm-specific cost increases are passed through at a rate below 50%, while sector-wide cost increases are passed through at a rate above 50%, ranging from 50% on monopoly routes to closer to

⁴⁰ ICF (2018), 'Identifying the drivers of air fares', prepared for ACI Europe.

⁴¹ Koopmans, C. and Lieshout, R. (2016), 'Airline cost changes: to what extent are they passed through to the passenger?', *Journal of Air Transport Management*, **53**, pp. 1–11.

100% under certain conditions. Notably, where airport capacity is constrained, the pass-through rate is effectively zero: in congested markets, prices are driven by scarcity rather than costs, meaning that cost increases are absorbed through lower rents to airlines rather than higher fares to passengers.

Building on the findings summarised above, the following section examines the observed relationship between airfares and airport charges. Airport charges are defined as the total turnaround airport charges at an airport.⁴²

Airport charges and fares, overall

Figure 4.13 below shows the average relationship between airport charges and fares. It shows that routes characterised by higher charges are associated with higher average fares, but, as the slope of the line is close to flat, the relationship is not strong. Therefore, this provides an indication that, while charges are reflected in airfares, they are not materially driving airfares.

⁴² From the OAG data, each aircraft type is mapped to one of the four representative categories used in the ACI charges dataset (outlined in annex A1.5). The most frequently operated aircraft type on each route (using OAG information) is identified and the corresponding charge for the departing airport is assigned to that route. Finally, a seasonal average charge is computed for each route. Hence, by construction, charges are fixed for a given airport, route, and IATA season period.

Figure 4.13 Relationship between airport charges and fares, overall



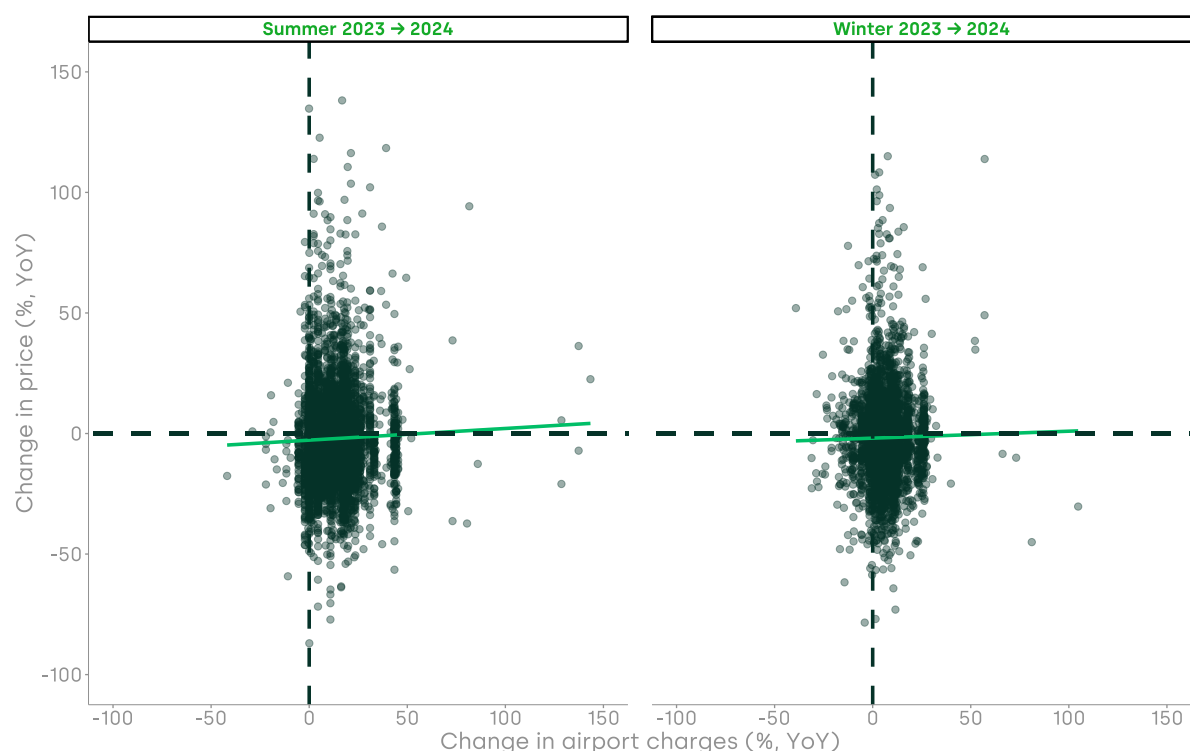
Note: The chart presents, for each airport and IATA season, the average airport charges and fares across all routes departing from that same airport.
Source: Oxera analysis.

Relationship between airport charges and fares, by season

Figure 4.14 below compares changes in airport charges and fares by route between Summer seasons in 2023 and 2024 to examine whether increases in route-level charges from one year to another are associated with fare increases.

The chart suggests that, despite increases in airport charges between S23 and S24 across the majority of airport routes, this has not translated into higher fares—the regression (solid green line) between charges and fares is flat. This indicates that increases in airport charges do not directly translate into increases in fares.

Figure 4.14 Year-on-year changes in route-level charges and fares, by season



Note: The chart shows year-on-year changes in route-level charges (measured at the departing airport) against year-on-year changes in average fares, for the Summer (S23→S24). Routes where the airport charges or fares were unchanged between the two seasons are excluded from the chart, as a zero change carries no information about the direction of the relationship.

Source: Oxera analysis.

Conclusions on airport charges

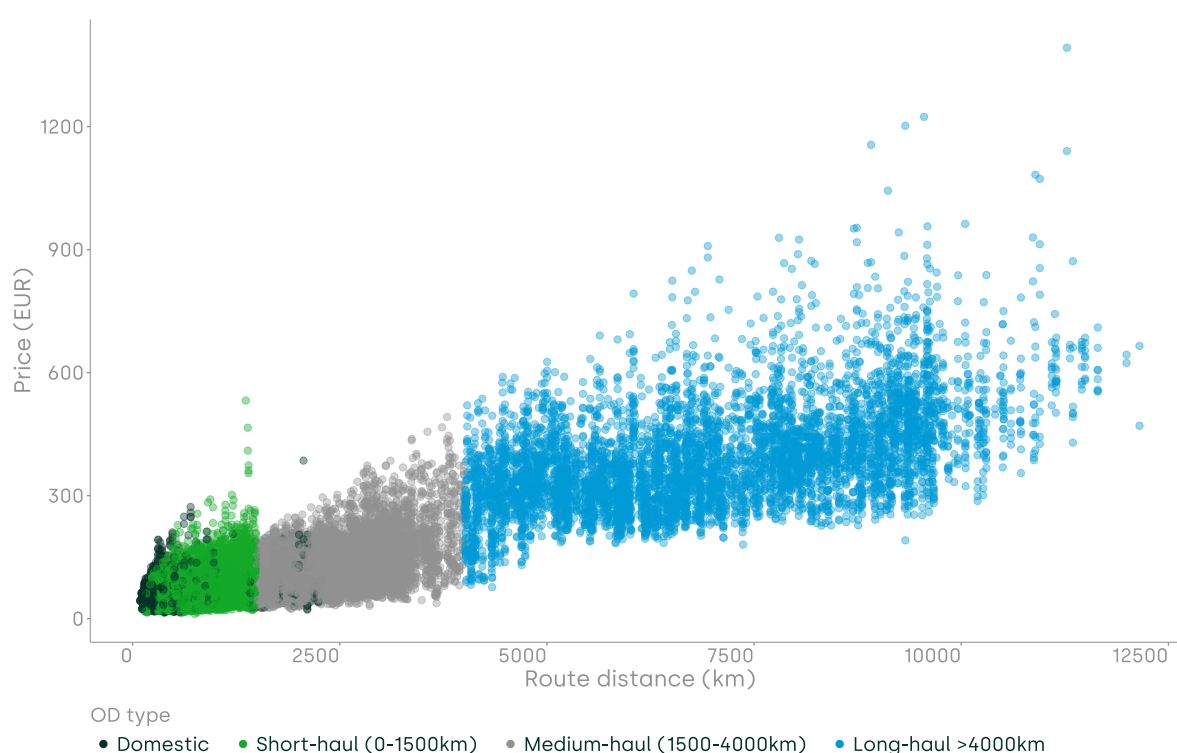
The charts presented above indicate **a weak relationship between fares and airport charges**. Other factors, such as congestion, have a positive impact on both fares and airport charges, as charges increase with congestion but so do fares.

4.5.2 Distance

Before summarising the overall results, an additional factor—flight distance—is presented below for completeness due to its relevance in the analysis. As is shown below, **flight distance is a significant driver of total airfares.**⁴³

Figure 4.15 below shows that absolute fares are positively correlated with distance: longer flights cost more in total. This reflects, among other factors, that the fact that total fuel consumption (a significant cost driver) increases with distance.

Figure 4.15 Relationship between route distance and price



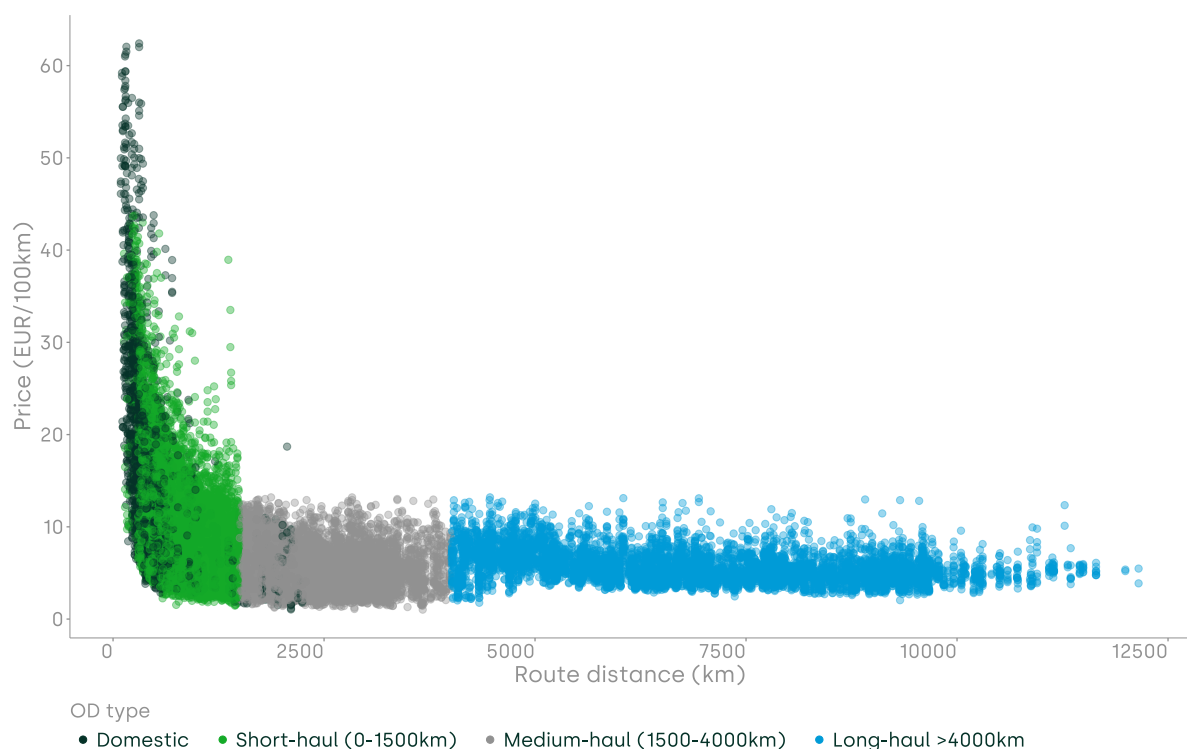
Note: OD, origin–destination. The figure shows the relationship between route distance and departing fare, where each data point represents the average price for a specific route. The observations are coloured by origin–destination type, which classifies routes into four categories based on distance: domestic (flights within the same country), short-haul (international routes up

⁴³ Neither the absolute fare nor the per-km fare is an ideal measure for empirical analysis, as both capture effects that are a direct function of distance itself (absolute fare increases with distance; per-km fare decreases with distance), making it difficult to isolate other determinants of price variation and to escape a composition effect when combining routes of very different lengths. This limitation is addressed in the regression analysis set out in section 6, which controls directly for the effect of distance on fares and employs route fixed effects such that the estimated coefficients on other variables are identified purely from variation within a given route over time.

to 1,500km), medium-haul (international routes between 1,500km and 4,000km), and long-haul (international routes above 4,000km). To improve visual clarity, 16 observations with distances exceeding 12,500km are excluded from this graph.
Source: Oxera analysis.

In contrast, Figure 4.16 below normalises fares by route distance and reveals an inverse relationship. Price per 100km falls sharply as distance increases, with domestic and short-haul routes exhibiting markedly higher per-km fares than medium- and long-haul routes.

Figure 4.16 Relationship between route distance and price per 100km



Note: OD, origin–destination. The figure shows the relationship between route distance and normalised fares by route distance (price per 100km), where each data point represents the average price for a specific route. The observations are coloured by origin–destination type, which classifies routes into four categories based on distance: domestic (flights within the same country), short-haul (international routes up to 1,500km), medium-haul (international routes between 1,500km and 4,000km), and long-haul (international routes above 4,000km). To improve visual clarity, 16 observations with distances exceeding 12,500km are excluded from this graph.
Source: Oxera analysis.

This relationship is explained by one key mechanism. Each flight incurs a set of fixed costs that are largely independent of distance, or do not vary directly with distance, such as crew costs, aircraft depreciation, and ground costs (e.g. ground handling and airport costs). Hence, for a short flight of a few hundred km, these fixed costs are spread over far fewer km. This, in turn, results in a higher cost per km on shorter flights that airlines must recover through higher fares per km travelled.

4.6 Preliminary observations

On the basis of the analysis presented above, we draw the following observations.

Demand is a key driver of airfare variations

Most fare variations appear to be explained by changes in demand and, as a result, dynamic pricing from airlines. **Time of day, day of the week, monthly, and route-specific variations, which all reflect demand, explain a large part of the fare variations observed.** While we have not considered airline costs as part of this study, which also play an important role in driving fares, we have shown that flight distance, which itself drives costs such as fuel, has a strong relationship to fare levels.

Airline competition drives lower prices

Higher airline concentration drives up fares. Accounting for competition at the level of the individual carrier (e.g. BA or Iberia), as is done in the Slot Regulation, leads to overestimating the level of competition at European airports, as airlines within the same group (e.g. BA and Iberia under IAG) are not effectively competing with each other. In addition, FSCs are particularly sensitive to LCC competition. When a LCC is present on a route that FSCs are operating, FSC prices decrease. **While not all routes can sustain competition (for example, due to lack of sufficient demand), on those that can, passengers benefit from it.**

Congestion has a significant impact on fares

Congestion drives up fares, beyond the level that can be strictly explained by time variations in demand—i.e. the more congested an airport is, the higher the fares; and this relationship between congestion and fares is stronger when airport congestion is greater. Our analysis therefore confirms the existence of airlines' scarcity rents—i.e. a congestion premium on fares. **Reducing congestion would therefore directly reduce fares.**

Charges have a weak relationship with airfares

Charges have a positive but marginal relationship with fares, which indicates that they may influence fares but are not a key driver and there is no one-to-one relationship. As the analysis presents the relationship between charges, excluding rebates and incentives, and fares, it is likely that this relationship would be even weaker if incentives and discounts were reflected in the charges.

As the graphical analysis presented above suggests, not only does each factor considered affect fares directly, but the factors also influence each other. For instance, the number of carriers that are present on a route (level of concentration) is likely to depend on the anticipated level of demand on that route. **There is therefore a need to disentangle the interlinked dynamics between these factors through additional analysis, and in the following section we present** the results of a regression analysis of fares against all of these factors.

5 Econometric analysis

5.1 Our approach and methodology

5.1.1 The value of regression analysis

The above section relies on visual inspection to identify patterns and potential relationships between airfares and a set of explanatory factors. While informative, visual analysis is inherently limited: it can examine only one relationship at a time and cannot control for the simultaneous influence of multiple factors. A chart may suggest, for example, that fares are higher at airports with higher airport charges. However, it cannot rule out the possibility that those airports are also more congested, handle more long-haul routes, or are predominantly served by FSCs rather than LCCs, all of which independently increase fare levels. To overcome these limitations, this section employs regression analysis to quantify the relationships between the factors considered in a more rigorous way.

Regression analysis is a standard statistical method that is widely used in both academic research and industry analysis. It estimates the independent relationship between each explanatory factor and the outcome of interest (in this case, airfares), while simultaneously controlling for the influence of all of the other factors included in the model.⁴⁴

5.1.2 Framework of analysis

Dataset used in the analysis

The data underpinning the regression analysis is the same as that described in section 3. Annex A1 provides more information on how the dataset was constructed.

The unit of observation is the individual route defined by its origin and destination airports observed across multiple IATA seasons. The dataset created allows for the analysis of changes in fares both across routes and over time. To account for differences in fares within a route, observations are disaggregated by carrier

⁴⁴ This allows us to isolate, for instance, the relationship between market concentration and fares after accounting for route distance, airport charges, congestion and other important factors.

type (LCC versus FSC), booking window (14 versus 60 days in advance), and whether the service is direct or indirect for long-haul routes.

Core model and key variables

The model is estimated using an ordinary least squares (OLS) regression with fixed effects.⁴⁵ This yields the following main specification:

$$\ln(\text{Airfare})_{rt} = \beta_1 * \ln(\text{HHI})_{ct} + \beta_2 * \ln(\text{Charges})_{at} + \beta_3 * \ln(\text{Congestion})_{at} + \beta_4 * \text{Lowcost}_{rt} + \beta_5 * \ln(\text{distance})_r + \beta_6 * \text{Direct}_{rt} + \beta_7 * \text{D14}_{rt} + \gamma_t + \delta_c + \epsilon_{rt}$$
⁴⁶

The key variable of interest (the dependent variable) is the natural logarithm (noted *ln* in the formula) of the average fare for a given origin–destination pair in a given IATA season.

The model incorporates the key following explanatory variables:

- **ln(charge)**—the natural log of turnaround airport charges at the departure airport in a given IATA season;
- **ln(congestion)**—the natural log of congestion at the departure airport in a given IATA season;
- **ln (HHI)**—the natural log of the HHI, measuring market concentration at the city-pair route level in a given IATA season;
- **Low-cost dummy**—a binary variable that is equal to 1 if the average fare is offered by a LCC;
- **ln(distance)**—the natural log of distance between the origin and destination airports in km;⁴⁷
- **D14 dummy**—a binary variable that is equal to 1 if the fare corresponds to a 14-day advance purchase window, as opposed to 60 days;
- **Direct dummy**—a binary variable that is equal to 1 if the fare corresponds to a direct long-haul fare, as opposed to an indirect long-haul fare;

⁴⁵ Fixed effects are a statistical tool for controlling for unobserved factors that cannot be directly measured or included as variables in the model. Rather than estimating the contribution of each such factor individually, fixed effects allow the model's intercept to shift freely across groups or time periods, absorbing their combined influence. This ensures that the estimated coefficients on the variables of interest reflect genuine variation in the data rather than spurious correlations driven by omitted factors.

⁴⁶ Where *r* denotes an airport-pair route within city pair *c*, *a* denotes the departure airport, and *t* denotes the IATA season. Airfares, LCC status, direct flight availability, and the booking window indicator vary at the route–season level; airport charges and congestion vary at the departure airport–season level; and market concentration (HHI) varies at the city-pair–season level.

⁴⁷ Distance is estimated only in Model (1), as discussed in further detail below. In the remaining specifications this variable is automatically dropped ('absorbed') when route fixed effects are included. This is because distance is constant over time within a given city-pair route and is therefore collinear with the city–city route fixed effects.

- **Route characteristics (δ_c)**—a set of binary variables controlling for all characteristics at the route level that are constant over time, the precise form of which (either segment or city pair) varies by specification;
- **Time fixed effects (γ_t)**—a set of IATA season fixed effects, reflecting common temporal shocks such as fuel price changes, macroeconomic conditions and seasonal demand patterns.

Both the dependent variable and the key explanatory variables are expressed in logarithmic form, which serves two purposes.

First, it reduces the influence of extreme values on the estimates. Second, which is important for the interpretation of the results, the coefficients on the log-transformed regressors can be read directly as elasticities: each coefficient represents the percentage change in fares associated with a one percent change in the relevant variable, holding all else constant. The coefficients on binary (or dummy) variables, by contrast, are semi-elasticities and measure the approximate percentage difference in fares between the indicated group and the reference group.⁴⁸

Finally, it is important to note that our econometric model has been set up to test the initial findings from our visual analysis and not to produce definitive causal inferences. The results of the regression analysis should therefore not be interpreted as establishing that changes in any one factor directly cause changes in airfares. Rather, they identify and quantify the associations between each factor and fare levels, after accounting for the influence of all other factors in the model.

5.2 Analysis of fare drivers

5.2.1 Model specification

We use three different specifications of the model in our analysis. Model 1 is the baseline specification, while Models 2 and 3 use the same explanatory variables as Model 1 but slightly different fixed effects structures, serving as robustness checks on the baseline findings.

- 1 Model 1 corresponds to the results of the baseline model as set out in section 5.1.2.

⁴⁸ For example, between LCCs and FSC carriers, or between 14-day and 60-day advance purchases. The exact percentage effect of a binary variable is given by: $(\exp(\beta) - 1) \times 100$. The percentage approximation $\beta \times 100$ is accurate for small coefficients but diverges for larger values.

- 2 Model 2 uses fixed effects by city-pair routes, instead of controlling for route distance and route type (domestic, etc.) as in Model 1.
- 3 Model 3 uses 'city pair x season' fixed effects (e.g. Paris–Milan Summer vs Paris–Milan Winter).

Using different fixed effects structures has an impact on the type of variation in fares that is exploited in the analysis. While Model 1 exploits both variations in fares within routes (across time) and between routes (e.g. between Paris–Milan and Brussels–Milan, and for Paris–Milan between 2023 and 2024), Models 2 and 3 exploit variations only within routes, as between-route variations are controlled for by the city-pair fixed effects.⁴⁹

All three models are presented, as certain models may be more appropriate for estimating the relationship between a given factor and airfares. For example, for a factor such as airport charges that varies infrequently within IATA seasons, Model 1 is preferable as it exploits fare variations both between and within routes. Model 3 is likely to provide more reliable estimates for factors that vary over time at the route level, such as airline concentration (HHI). Congestion varies only marginally over time but more significantly across routes, making Models 1 and 2 more appropriate than Model 3 in precisely estimating the impact of congestion. Taken together, the results of these models provide a range of reasonable estimates for the relationships between each of these factors and fares. Model 1 has been selected as the preferred model overall as it consistently produces estimates in the middle of the range and captures meaningful fare variations within and across routes.

5.2.2 Regression results

Table 5.1 below reports the estimates for the three models. Focusing on the preferred specification (Model 1), we note that all coefficients are statistically significant,⁵⁰ and that the direction of each estimated factor is consistent with economic intuition and theory.

⁴⁹ The difference between Model 2 and Model 3 is that Model 2 includes city-pair fixed effects (e.g. one fixed effect for Paris–Milan across all seasons), while Model 3 includes city pair x season-type fixed effects (e.g. separate fixed effects for Paris–Milan in summer and Paris–Milan in winter). This means that, while Model 2 compares fares on a given route across all winter and summer IATA seasons, Model 3 only compares fares on a given route within the same season type.

⁵⁰ Statistical significance indicates that a coefficient estimate is unlikely to be zero due to sampling variation alone. In other words, the data provides sufficient evidence to conclude that the observed relationship is unlikely to be due to chance, but rather reflects a genuine underlying pattern.

The three factors of interest to this study—airport charges, congestion, and market concentration—each exhibit a positive and statistically significant association with airfares:

- a 10% increase in congestion is associated with a 0.93% increase in fares;
- a 10% increase in market concentration is associated with a 1.06% increase in fares;
- a 10% increase in airport charges (as measured by total turnaround charges) is associated with a 0.35% increase in fares.

Table 5.1 Main specification regression results

Variable/Model	(1)	(2)	(3)
log charges	0.0354*** (0.0084)	0.0730** (0.0311)	0.0533* (0.0318)
log congestion	0.0930*** (0.0119)	0.0747*** (0.0214)	0.1632*** (0.0355)
log HHI	0.1058*** (0.0075)	0.0531*** (0.0105)	0.1870*** (0.0137)
lowcost	-0.5474*** (0.0064)	-0.4553*** (0.0068)	-0.4516*** (0.0068)
log km	0.3849*** (0.0109)	—	—
domestic	-0.1326*** (0.0205)	—	—
short haul	-0.1205*** (0.0112)	—	—
long haul	0.3639*** (0.0183)	—	—
direct	0.0683*** (0.0085)	0.0528*** (0.0078)	0.0531*** (0.0078)
fares 14 days ahead	0.1790*** (0.0020)	0.1794*** (0.0020)	0.1793*** (0.0020)
Fixed effects	IATA season + Flight segment	IATA season + city– city route	IATA season + city– city route x season

Variable/Model	(1)	(2)	(3)
Standard errors	Clustered at city–city route level	Clustered at city–city route level	Clustered at city– city route level
Adjusted R ²	0.83	0.92	0.93
Observations	62,407	62,337 ⁵¹	62,337

Note: The table presents the regression results for each explanatory variable for the three models. The first estimate presented is the variable coefficient (e.g. 3.5% for charges under model 1), which can be interpreted as an elasticity to fares (i.e. an increase in charges of 10% is associated with a 0.35% increase in fares). The second estimate in parentheses is the standard error of the coefficient, which is a statistical measure of precision. The stars next to the estimate correspond to different levels of statistical significance: (*) 10%, (**) 5%, (***) 1%. The table also reports the type of fixed effects and standard errors used in each model, the adjusted R² (measure of goodness of fit), and the number of observations used in the analysis. Adjusted R² measures the proportion of variation in airfares that is explained by all the explanatory variables included in the model, adjusted for the number of variables to penalise overfitting. Values range from 0 to 1, with higher values indicating better model fit.

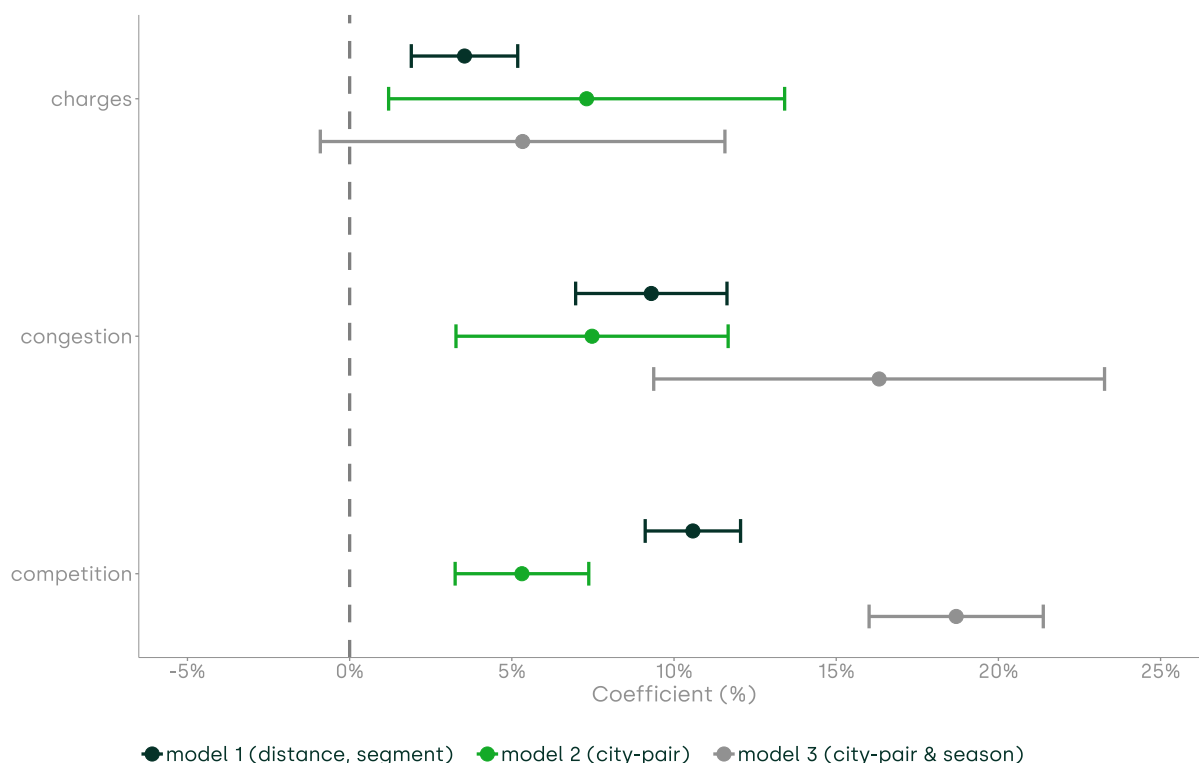
Source: Oxera analysis.

To illustrate the range of results, Figure 5.1 below presents the elasticity estimates (point) and 95% confidence intervals (range around the estimate) for the three key explanatory variables across all three specifications. The effect of market concentration on airfares is the greatest of the three factors considered. It also exhibits the most variation across specifications, although it is always positively correlated with airfares—i.e. a higher concentration is associated with higher airfares.⁵² Congestion has the second greatest impact on airfares, with a range of values that largely overlap with concentration impacts. Finally, the effect of charges is the smallest in relative magnitude, and is the only variable that is statistically insignificant at the 5% level when using city pair x season fixed effects—i.e. the confidence interval includes the value 0 as shown in the chart below. This confirms that the relationship between airport charges and fares is imprecisely estimated when identification relies solely on within-route variation over time.

⁵¹ When estimating the model with city-pair-level fixed effects, observations appearing in only one IATA season period are dropped because they contain no within-group variation after the fixed effects are applied. This occurs in 70 cases. Indeed, while the dataset includes all routes observed in at least two IATA season periods, in 70 cases average prices are available only for one IATA season period, creating singleton observations.

⁵² The increase in the HHI elasticity between Models (2) and (3) is consistent with market concentration having a stronger estimated effect when comparing changes within the same route–season type. That is, when a route becomes more or less concentrated from one summer (or winter) to the next, than when comparing across routes more generally, given that dynamics between IATA Summer and Winter seasons can be completely different.

Figure 5.1 Estimated coefficients of key variables across all specifications



Note: The figure presents estimated coefficients (in percentage terms) for $\ln(\text{charges})$, $\ln(\text{congestion})$, and $\ln(\text{HHI})$ across our three model specifications, accompanied by 95% confidence intervals. A coefficient is statistically significant at the 5% level if the confidence interval does not overlap with the dashed reference line at zero.

Source: Oxera analysis.

The coefficients on the remaining explanatory variables are as follows:

- fares increase with distance, with a 10% increase in route distance associated with 3.8% higher prices;
- short-haul and domestic routes are, on average, 11% and 12% cheaper than medium-haul, while long-haul routes are 44% more expensive than medium-haul;
- LCC fares are approximately 42% lower than those of FCCs;
- direct long-haul flights command a 7% premium over indirect services, consistent with passengers valuing the convenience of non-stop travel;
- fares observed 14 days before departure are approximately 20% higher than those observed 60 days in advance.

5.2.3 Interpreting regression results

To illustrate the magnitude of these effects, Table 5.2 below translates the elasticity of three key explanatory variables into monetary terms by applying a 10% increase in each factor. For example, it considers the effect on airfares if congestion increases by 10% from 50% to 55%.

The table shows that increasing market concentration by 10% would increase fares by €1.82, whereas a 10% increase in congestion would increase fares by €1.60, and an increase in airport charges of 10% would raise charges by only €0.61.

Table 5.2 Illustrative interpretation of a change in key explanatory variables

Variable	Elasticity estimates	What a 10% increase represents	Estimated fare effect
Congestion	0.0930	A rise in the average airport-level congestion from 50% to 55% in a given IATA season	+€1.60
HHI	0.1058	A shift in the dominance of a given airline on a city–city route in a given IATA season from 50/50 to 66/34	+€1.82
Airport charges	0.0354	A rise in total turnaround charges from €5,000 to €5,500	+€0.61

Note: In the middle column, the table presents for each factor an example of a 10% increase in the variable—e.g. airport charges increasing from €5,000 to €5,500. These impacts are translated into fare impacts in euros. The fare effects of a 10% change in each variable are computed by multiplying the estimated elasticities by 10% and by the average fare in the full sample.

Source: Oxera analysis.

Calculating airport charges pass-through

The above analysis also enables us to calculate a pass-through rate from an increase in airport charges to airfares. As referenced in section 4.5, the anticipated rate of airport charges pass-through can vary by route, as cost increases that only some airlines face are less likely to be passed through than more widespread sector-wide cost changes.

Our results indicate that a €1 increase in total turnaround charges is associated with approximately €0.26 higher fares per flight, implying **a pass-through rate of 26%**.⁵³ This result confirms economic intuition that airport charges are only partially passed through to fares. In practice, this implies that airlines have other strategic responses to increases in airport charges, such as a reduction in supply or absorbing increases in charges by reducing the premiums the airline earns on the route.

Estimating the scarcity rents paid by passengers

Our empirical analysis shows that airport congestion generates a scarcity premium that leads to increased fares. The total amount of additional rents currently paid by passengers at European airports adds up to €6.4bn. This corresponds to an average airfare premium of €13.54 per one-way ticket at congested airports. This is shown in Table 5.3 below.

Table 5.3 Illustrative calculation of the total scarcity premium for passengers

	Value
Average scarcity premium at congested airports	€13.54
Passengers departing from airports with congestion levels higher than the benchmark (2024)	476m
Total additional fare premium paid	€6.4bn

Note: The scarcity premium is calculated using the congestion elasticity results from the regression analysis and the average fare at each individual congested European airport in the sample.
Source: Oxera analysis.

The total fare premium is calculated as the increase in fare level at congested airports with respect to a certain benchmark level. The congestion benchmark level is set at 57.1%,⁵⁴ the median congestion level at the European airports within the sample. This level is comparable with the congestion level of airports such as Geneva or Stansted.

⁵³ To compute the implied marginal effect (€0.26) of airport charges on fares, the coefficient on log charges is first converted into a level effect by scaling it with the ratio of average departure prices to average charges for each origin–destination pair in a given IATA season. This effect is then weighted by the number of seats on each route in each IATA season and averaged across all observations to obtain the average marginal effect in the sample.

⁵⁴ This value is based on the median airport congestion for the IATA season S24.

Estimating the concentration premium paid by passengers

Similarly to the analysis presented above on congestion, we can also use our empirical analysis on airfares to estimate the premium paid by passengers due to the current levels of airline concentration. The total amount of additional fares currently paid by passengers at European airports adds up to €1.7bn. This corresponds to an average airfare premium of €5.99 per one-way ticket. This is shown in Table 5.4 below.

Table 5.4 Illustrative calculation of the total concentration premium for passengers

	Value
Average concentration premium at higher concentration airports	€5.99
Passengers departing from airports with concentration levels higher than the benchmark (2024)	289m
Total additional concentration premium paid	€1.7bn

Note: The concentration premium is calculated using the HHI elasticity results from the regression analysis and the average fare at each individual concentrated European airport in the sample.
Source: Oxera analysis.

The concentration benchmark level is set at the median HHI level at the European airports within the sample.⁵⁵ This level is comparable to the HHI level of airports such as Dublin or Hamburg.

5.3 Analysis of airline entry and exit events

5.3.1 Entry/exit analysis

The regression analysis above indicates a clear positive relationship between airline concentration and airfares. As concentration increases (indicating less competition on a given route), average fares also increase. In this section we consider in more detail how changes in concentration—defined here as an airline entering or exiting a route—affects airfares.

⁵⁵ This value is based on the median HHI level for the IATA season S24.

Entry/exit events in our dataset

We first calculate the number of airlines operating on each city-pair route for each IATA season (between S23 and S24, and between W23 and W24) and compare this with the number of carriers operating in prior IATA seasons. We then define:

- **entry**, which takes the value of 1 if at least one additional airline began operating on the route relative to the prior season;
- **exit**, which takes the value of 1 if at least one airline ceased operating on the route relative to the prior season.⁵⁶

The results of this analysis are presented in Table 5.5 below. As illustrated, the large majority of routes (85%) exhibit no change in the number of carriers between consecutive IATA seasons. Entry events account on approximately 9% of routes (912), while exit events account for 6% of routes (586).

Table 5.5 Entry/exit events

Change	Number of routes	Percentage of all routes
Entry	912	9%
Exit	586	6%
No change	8,692	85%
Total	10,190	100%

Note: The table presents the number of routes defined at the city pair × season level (for example, London–Rome–Summer) according to whether the net number of carriers increased, decreased, or remained the same between consecutive seasons.

Source: Oxera analysis.

⁵⁶ Both variables take the value zero if no carrier entry or exit occurs, or if the number of entering and exiting carriers is equal between two consecutive seasons.

Regression results

In the entry/exit regression analysis, we keep all variables and fixed effects from model 3, with the difference that the HHI variable (airline concentration) is replaced by the entry and exit indicators defined above.⁵⁷

Table 5.6 below shows the results of this regression, demonstrating that the entry of an additional carrier on a route is associated with a reduction in fares of 6.7%, while the exit of a carrier is associated with a fare increase of 9.7%, both significant at the 1% level.⁵⁸ The coefficients on all other variables are consistent with results presented in section 5.2, indicating that these results are stable.

Table 5.6 Entry and exit analysis

Variable/Model	(1)
log charges	0.0514** (0.0318)
log congestion	0.1634*** (0.0355)
entry	-0.0670*** (0.0080)
exit	0.0968*** (0.0094)
lowcost	-0.4516*** (0.0068)
direct x long haul	0.0531*** (0.0078)
fares 14 days ahead	0.1793*** (0.0020)

⁵⁷ Using city-pair and season fixed effects allows the model to isolate the precise effect of carrier entry or exit on fares within a given route–season combination. For example, if a new airline begins operating on the London–Rome route in Summer 2024 that was not present in Summer 2023, the model estimates the associated fare change by comparing fares on that same route across the two summer seasons, holding all other route–season characteristics constant. The models identify entry/exit effects occurring within the W23/24 and S24 IATA seasons. Since entry and exit are mechanically correlated with changes in the HHI, the two cannot be included simultaneously in the same regression specification.

⁵⁸ For ease of exposition, the raw regression coefficients are reported as approximate percentage effects. The exact percentage effects, calculated as $(\exp(\beta) - 1) \times 100$, are -6.48% for entry and 10.16% for exit.

Variable/Model	(1)
Fixed effects	IATA seasonal periods + seasonal city–city route
Standard errors	Clustered at city–city route level
Adj. R ²	0.94
Observations	62,321

Note: The table reports OLS regression results from a specification that includes entry and exit indicators among the explanatory variables. The first estimate presented is the variable coefficient (e.g. 5.14% for charges), which can be interpreted as an elasticity to fares (i.e. an increase in charges of 10% is associated with a 0.514% increase in fares). The second estimate in parentheses is the standard error of the coefficient, which is a statistical measure of precision. The stars next to the estimate correspond to different levels of statistical significance: (*) 10%, (**) 5%, (***) 1%. The table also reports the type of fixed effects and standard errors used in the model, the adjusted R² (measure of goodness of fit), and the number of observations used in the analysis. The number of observations is slightly lower than in Model 3 as shown in Table 5.1 because, for some routes, although they are observed in two IATA seasonal periods, they are not observed in the same season and are therefore dropped in this analysis.

Source: Oxera analysis.

5.3.2 Impact of number of competitors

Building on the entry and exit analysis above, we extend the assessment to examine the effect of changes in the number of airlines on a route. The entry and exit indicators in the previous model are replaced with a more granular set of variables capturing changes in the number of carriers, such as routes moving from one to two carriers (entry), from two to one (exit), from two to three (entry), and so forth.

Type of entry/exit events in our dataset

The dataset contains 10,190 route–season combinations across 39 different scenarios for a change in the number of carriers (e.g. one to two carriers and three to four carriers are two distinct scenarios).⁵⁹ In most cases (85%), the number of carriers on a route is unchanged between consecutive seasons, with the most common being routes served by a single carrier throughout (56%), followed by routes with two carriers (28%) and three carriers (11%).

⁵⁹ A unique observation is defined at the city pair × season type level (for example, London–Rome–Summer).

The most common entry event was a route moving from one to two carriers (4.1%), followed by two to three (2.6%). The most common exit event was a route moving from two carriers to one (2.7%), followed by three to two (1.5%).

Regression results

The model specification used for this analysis is the same as the one used for the entry and exit analysis above. The only difference is that the general entry and exit indicators are replaced by individual indicator variables for each of the changes in the number of carriers described above.

Table 5.7 below presents the results of the analysis, reporting only the coefficients on the changes in the number of competitors for readability. The full set of regression results, including all control variables, is provided in Table A2.1 in annex A2.⁶⁰

Consistent with the findings in Table 5.6 above, airline exits have a greater effect on airfares than entry. Considering specific changes in the number of competitors, our analysis produces the following results:

- entry is associated with fare reductions from 3.4% (four to five carriers) to 9.9% (three to four);
- exit is associated with fare increases from 6.4% (four to three) to 12.2% (five to four).

Notably, the effects do not follow a strictly linear pattern, i.e. the exit of an airline from a two-carrier to a one-carrier route (8.5%) is smaller in magnitude than the exit from three to two (11.2%). This is because the specific fare effects depend on the competition dynamics and underlying demand on each route. For instance, if airline exit from a route is a result of a lack of demand and therefore its inability to profitably operate, a change from two to one airlines on a route may have a smaller (but still substantial at 8.5%) impact on prices than moving from three to two carriers.

⁶⁰ The coefficients on charges, congestion and all other variables remain in line with those reported in the main entry and exit specification above.

Table 5.7 Analysis of changes in the number of competitors

	(1)
Entry (1 to 2)	-0.0783*** (0.0137)
Entry (2 to 3)	-0.0552*** (0.0127)
Entry (3 to 4)	-0.0986*** (0.0165)
Entry (4 to 5)	-0.0340 (0.0235)
Exit (2 to 1)	0.0853*** (0.0134)
Exit (3 to 2)	0.1117*** (0.0190)
Exit (4 to 3)	0.0639*** (0.0237)
Exit (5 to 4)	0.122*** (0.0243)
Fixed effects	IATA season + city–city route and season
Standard errors	Clustered at city–city route level
Adjusted R ²	0.94
Observations	62,321

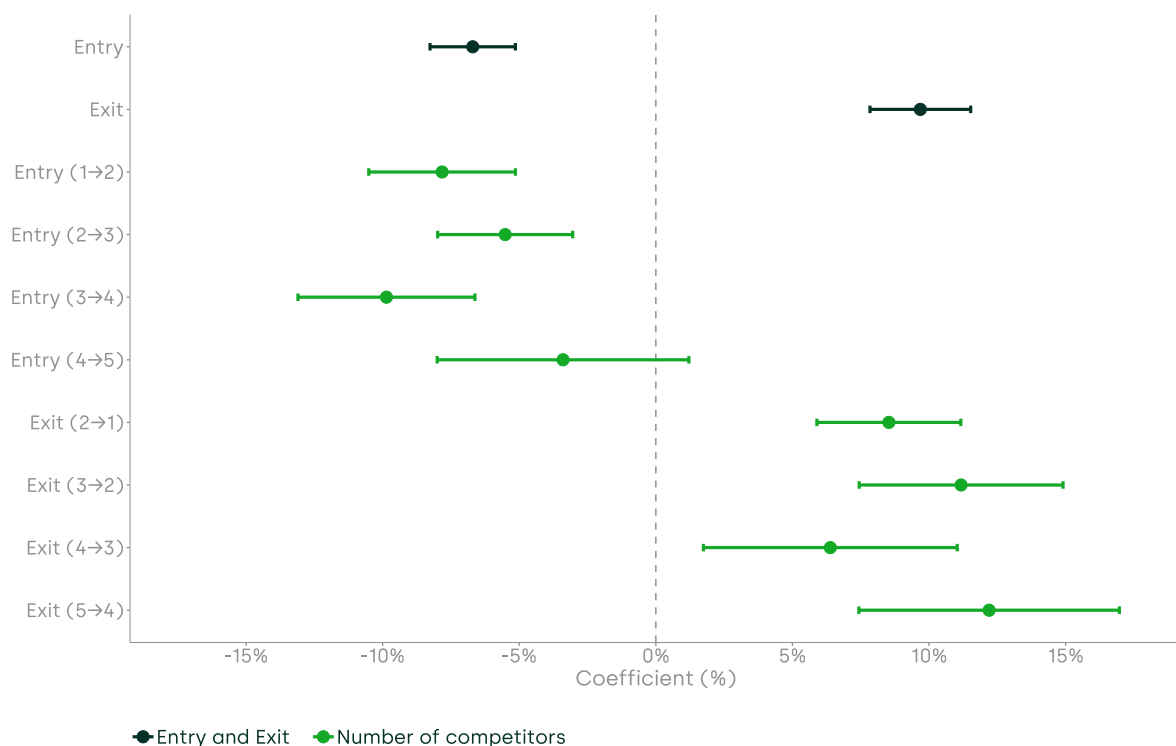
Note: The table presents the regression results for each entry and exit indicator variable. The control variables are the same as in the baseline entry/exit model above, but have been omitted for readability since their coefficients are stable. The full data with all coefficients is available in Table A2.1 in annex A2. The first estimate presented is the entry–exit variable coefficient (e.g. approximately 8% decrease in fares when the number of carriers increases from one to two), which can be interpreted as an approximate percentage effect on fares by multiplying the coefficient by 100. The second estimate in parentheses is the standard error of the coefficient, which is a statistical measure of precision. The stars next to the estimate correspond to different levels of statistical significance: (*) 10%, (**) 5%, (***) 1%. The table also reports the type of fixed effects and standard errors used in the model, the adjusted R² (measure of goodness of fit), and the number of observations used in the analysis.

Source: Oxera analysis.

To illustrate the magnitude and range of the entry and exit effects, Figure 5.2 below presents the estimated coefficients and 95% confidence intervals for the analysis set out above. The dark lines correspond to the baseline specification, which uses a single entry and single exit indicator, while the green lines correspond to the detailed specification, which includes separate indicators for each individual scenario of changes in carrier count.

As expected, the confidence intervals for the baseline entry and exit coefficients are narrower than those of the detailed specification, reflecting the greater statistical power that results from pooling all entry or exit events into a single variable. The disaggregated estimates nonetheless reveal a broadly consistent pattern: entry events are associated with fare reductions regardless of the existing number of airlines on a route, while exit events are associated with fare increases. Importantly, the single entry and exit coefficients from the baseline specification fall approximately in the middle of the range of disaggregated estimates, which is consistent with the interpretation that the baseline coefficients can be read as an average effect across the main entry and exit instances.

Figure 5.2 Estimated coefficients for entry and exit analysis



Note: The figure presents the estimated coefficients and 95% confidence intervals for the entry and exit variables. The dark lines correspond to the baseline specification using a single entry and exit indicator, while the green lines correspond to the disaggregated specification with separate indicators for each scenario of the changes in carrier count.

Source: Oxera analysis.

5.4 Key takeaways from the regression analysis

The regression analysis presented in this section largely confirms the initial observations from the visual analysis discussed in section 4.6.

First, **airline competition is the factor in the scope of our analysis with the greatest impact on fares**. Our analysis indicates that a 10% increase in market concentration (measured by the HHI) is associated with a 1.06% increase in fares. A 10% increase in HHI would correspond to a shift in the dynamics of a route in a given IATA season from two airlines having 50% market share each, to one carrier having a market share of 66% and the other 34%.

Our analysis of airline entry and exit on routes confirms these results. Airline entry is associated with a 6.7% reduction in fares, while exit is associated with a 9.7% increase in fares. **The extent of competition on routes therefore has a significant impact on fares**. We show, for instance, that moving from two to one airlines on a route is associated with increases in fares of 8.5%.

Second, congestion also has a significant impact on fares. Our analysis indicates that a 10% increase in congestion is associated with a 0.93% increase in fares (between 0.7% and 1.6% depending on the model specification).

Airport charges have a small impact on fares. A 10% increase in airport charges is associated with a 0.35% increase in fares. For some specifications, the impact of charges is not statistically significant at the 5% level. We estimate the pass-through of airport charges to ticket prices in our preferred approach (Model 1 in Table 5.1): a €1 increase in total turnaround charges is associated with approximately €0.26 in higher fares per flight, **implying a pass-through rate of 26%**.

Finally, the results of the assessment can be used to estimate the premium paid by passengers for congestion and concentration. **We have estimated that passengers currently pay a €6.4bn premium for congestion and a €1.7bn premium for concentration at the European airports within the scope of analysis**. This corresponds to an average airfare premium of €13.54 per one-way ticket at congested airports and an average airfare premium of €5.99 for concentrated airports.

A1 Annex 1: data description and cleaning

In this annex, we provide further detail on the steps that we have taken to clean the data presented in this report and combine it into the final dataset used in the analysis.

A1.1 Cleaning OAG and Google Flights datasets

Given the volume of observations across the four datasets used (OAG, Google Flights, airport charges, and airport capacity data) as well as their different geographic and time period coverage, we have implemented several cleaning steps prior to combining the datasets for analysis, as follows.

A1.1.1 Carrier names

Carrier names are fully harmonised across the OAG and Google Flights datasets to ensure consistency.⁶¹ Each unique carrier is then assigned a low-cost or full-service carrier indicator across both datasets. The decision to assign a carrier to a low-cost or a full-service carrier is based on the ICAO classification.

A1.1.2 Sample definition

The core sample of airports for the analysis is defined according to two conditions. First, the departing airport must be located in the EEA, the UK, or Switzerland and record a minimum of 5m seats in total across the S24 and W24 IATA seasons.⁶² Second, airport charges data must be available for the airport in the ACI dataset. Together, these restrictions yield a final sample of 54 airports.⁶³ Finally, we focus on data from 1 April 2023 to 31 March 2025, covering four IATA seasons from Summer 2023 to Winter 2024/25,⁶⁴ to focus on the post-COVID-19 period in the analysis.

⁶¹ The harmonisation process involves, for example, removing suffixes such as S.p.A. and S.L., or the word 'airlines', from the listed airline name in the raw data, so that the same company appears with the same name across both the Google Flights and OAG datasets.

⁶² Seat counts are derived from the OAG data as the sum of seats across all arriving and departing flights at a given airport in a given IATA season. This threshold is defined to include airports of a sufficient size to be covered (or close to be covered) by the ACD within the EU. Given that the directive's applicability threshold is based on the number of passengers, the resulting sample will include EU airports subject to the ACD and some airports that are close but below the threshold to be subject to the ACD.

⁶³ The full list of 54 airports (referred to by their IATA codes) is as follows: AGP, ALC, AMS, ARN, ATH, BCN, BER, BGY, BHX, BIO, BRU, BUD, CDG, CPH, CTA, DUB, DUS, EDI, FCO, FRA, GLA, GVA, HAM, HEL, KEF, LCA, LGW, LHR, LIS, LPA, LTN, MAD, MAN, MRS, MUC, MXP, NAP, NCE, OPO, ORY, OSL, OTP, PMI, PMO, PRG, RIX, STN, TFS, TLS, VCE, VIE, WAW, ZAG, ZRH.

⁶⁴ For the purposes of this analysis, the winter IATA seasons (W23/24 and W24/25) are assumed to run from 1 October to 31 March, and the summer seasons (S23 and S24) from 1 April to 30 September.

A1.1.3 OAG data cleaning

After restricting the sample to the selected airports and the time period of interest, the OAG dataset contains approximately 9.4m flights. Further cleaning steps are then applied sequentially:

- removing night flights departing between 23.00 and 06.00 (~225,000 flights removed);
- excluding cargo carriers (~40,000 flights);
- eliminating routes where all carriers present operate infrequently in a given IATA season (routes where all carriers have fewer than 25 flights per season—i.e. fewer than one flight per week on average, ~50,000 observations).

Finally, routes observed in only one summer season (i.e. S23 but not S24, or vice versa) are excluded, as are routes observed in only one winter season. We implement this cleaning step as the analysis requires routes observed in both winter or both summer seasons, reducing the sample by ~100,000 observations. The resulting final sample has approximately 9m observations.

A1.1.4 Google Flights data cleaning

The same sample restrictions are applied to the Google Flights dataset as the OAG data, as described above:

- observations are limited to the 54 departing airports of interest from 1 April 2023 to 31 March 2025 (this results in a dataset with ~80m observations);
- night flights are excluded (~1.8m observations removed);
- fare observations from cargo carriers and other non-relevant operations (e.g. charter services) are excluded (~5,000 observations removed).

In the Google Flights dataset, we also have indirect itineraries with a layover of less than three hours. Among these, only those with a route distance exceeding 4,000km and for which a direct flight is also available in the OAG data are retained for the analysis, on the basis that indirect flights constitute a credible competitive alternative only on long-distance routes (~50m observations removed). The resulting Google Flights data sample contains approximately 23m observations in total.

To assess the representativeness of the Google Flights cleaned fare data, we compare its coverage with the OAG cleaned data across several dimensions. As shown in Table A1.1 below, the match rate is high across airport–airport routes,

and airlines, lending confidence to the reliability of the fare data used in the analysis.

Table A1.1 Data coverage between OAG and Google Flights

	OAG	Google Flights
Airlines	250	230
Direct routes (airport pair)	7,600	7,500

Note: This count includes only carriers operating direct flights.

Source: Oxera analysis.

A1.2 Variables prepared from the OAG dataset

Below we set out how the variables that are used for the analysis were constructed on the basis of the of the datasets highlighted above.

A1.2.1 Flight segment type

From the OAG data, based on the country of departure and country of arrival of the flight, we construct a variable denoting whether a flight is domestic. For all non-domestic flights, we further classify each flight by distance into three categories: short-haul (below 1,500km), medium-haul (between 1,500km and 4,000km), and long-haul (above 4,000km).⁶⁵ Together, these classifications yield a categorical variable *segment type* with four mutually exclusive values: domestic, short-haul, medium-haul and long-haul.

A1.2.2 Average airport-level congestion

From the OAG data, a congestion ratio is computed for each one-hour departure time band and calendar day at each airport. Specifically, the number of arriving and departing flights operating within a given one-hour window (from OAG data) is divided by the maximum ATM capacity of that airport (from separately collected airport capacity data). The resulting ratio is then averaged across all day-departure time bands in the IATA season to obtain a single average congestion measure per airport and IATA season.

⁶⁵ EUROCONTROL definition of haul. See, for instance, EUROCONTROL (2011), '[Study into the impact of the global economic crisis on airframe utilisation](#)', p. 21.

A1.2.3 Airline concentration index (HHI or Herfindahl–Hirschman Index)

Consistent with European Commission decisional practice, we define the relevant market for the calculation of this metric on the basis of city pairs rather than airport pairs (e.g. Paris–Milan instead of CDG–MXP). From the OAG data, we calculate the HHI as the sum of the squared seats market shares of all carriers operating on each route and in each IATA season, yielding a value ranging from near 0 (highly competitive) to 10,000 (monopoly).⁶⁶ In this calculation, all carriers belonging to the same airline group (e.g. British Airways and Iberia in IAG) but also airlines belonging to the same metal-neutral joint-venture (e.g. Blue Skies JV between Virgin Atlantic, Delta Airlines, Air France–KLM and Alitalia on routes to the USA) are treated as the same carrier for the purposes of the HHI calculations. This airline group cleaning is described in more detail in annex A1.3.

In computing the HHI, carriers with fewer than 25 flights per season or a market share below 1% are excluded.⁶⁷ To exclude these airlines, market share is measured in two alternative ways:

- as the number of seats offered by a given carrier on a specific route during a given IATA season, divided by the total number of seats offered on that route by all carriers;
- as the share of flights operated by a given carrier relative to the total number of flights operated by all carriers over the same route and period.

A carrier is excluded if, in a given IATA season, either its seat-based market share or its flight share falls below 1%.

Since the HHI is computed using OAG data, which contains information only on direct flights, it may be overstated for city pairs that are also served by indirect routes, as carriers operating connecting services would not be accounted for. This limitation is mitigated by the inclusion of distance and route fixed effects, which absorb any time-invariant confounding effect arising from carriers operating indirect services between the same city pairs.

⁶⁶ As we do not have data on passenger traffic for this analysis, we are not able to include in the HHI calculations in the impact of indirect routes for which seats share cannot proxy the market share of carriers. For the purposes of the analysis presented in this report, we use the same HHI value for direct and indirect long-haul routes. The results of the regression analysis are not sensitive to this assumption.

⁶⁷ If two or more carriers belong to the same group, the thresholds are applied at the group level. Similarly, if there are JVs involved, the thresholds apply at the JV level.

A1.2.4 Entry and exit indicators

Entry and exit indicators are constructed from the OAG data at the city-pair route level, capturing changes in the number of carriers operating a given route across comparable IATA seasons. The carrier count reflects the cleaning for airline groups and joint ventures mentioned above. For each city pair and season (summer or winter), this indicator measures the change in the number of active carriers between seasons. As there are four IATA seasons in our dataset (S23, W23/24, S24, W24/25), the comparison is undertaken based on summer to summer and winter to winter. A route is classified as having experienced entry if the number of active carriers increases between the two comparable seasons, and exit if it decreases. As with the HHI, the entry or exit of carriers with fewer than 25 flights per season or a market share below 1% is not considered based on the same rules described above.

A1.3 Airline groups and joint venture cleaning

Each of the approximately 250 carriers in the cleaned OAG dataset is assigned to its parent group where applicable. For example, British Airways, Vueling, Iberia and Aer Lingus all belong to IAG; Air France–KLM encompasses Air France, KLM and Transavia; and The Lufthansa Group encompasses Air Dolomiti, Austrian Airlines, Brussels Airlines, Discover Airlines, Edelweiss Air, Eurowings, Eurowings Discover, Lufthansa City Airlines, SunExpress⁶⁸ and Swiss.

In addition, for certain companies operating on specific routes, carriers are assigned to the same JV and are therefore treated as a single entity on those routes. The JVs included in our data are described below.

- Blue Skies JV—applies on transatlantic routes (between the USA and Europe) for the following carriers: Virgin Atlantic, Delta Air Lines, KLM and ITA Airways.
- Oneworld Atlantic Joint Business—applies on transatlantic routes (between the USA and Europe) for American Airlines, IAG and Finnair.
- A+ JV—applies on transatlantic routes (between the USA and Europe) for Air Canada, United Airlines and Lufthansa.
- Siberian Joint Business—applies on routes between Japan and Europe for IAG, Japan Airlines and Finnair.
- J+ JV—applies on routes between Japan and Europe for Lufthansa and All Nippon Airways.

⁶⁸ SunExpress is treated as part of the Lufthansa Group, although it operates as a JV with Turkish Airlines.

- C+ JV—applies on routes between China and Europe for Lufthansa, Air China and Shenzhen Airlines.
- Singapore Airlines JV—applies on routes between Singapore and Europe for Lufthansa and Singapore Airlines.
- BA Qatar Airways Codeshare—applies on routes between London and Doha for IAG and Qatar Airways.

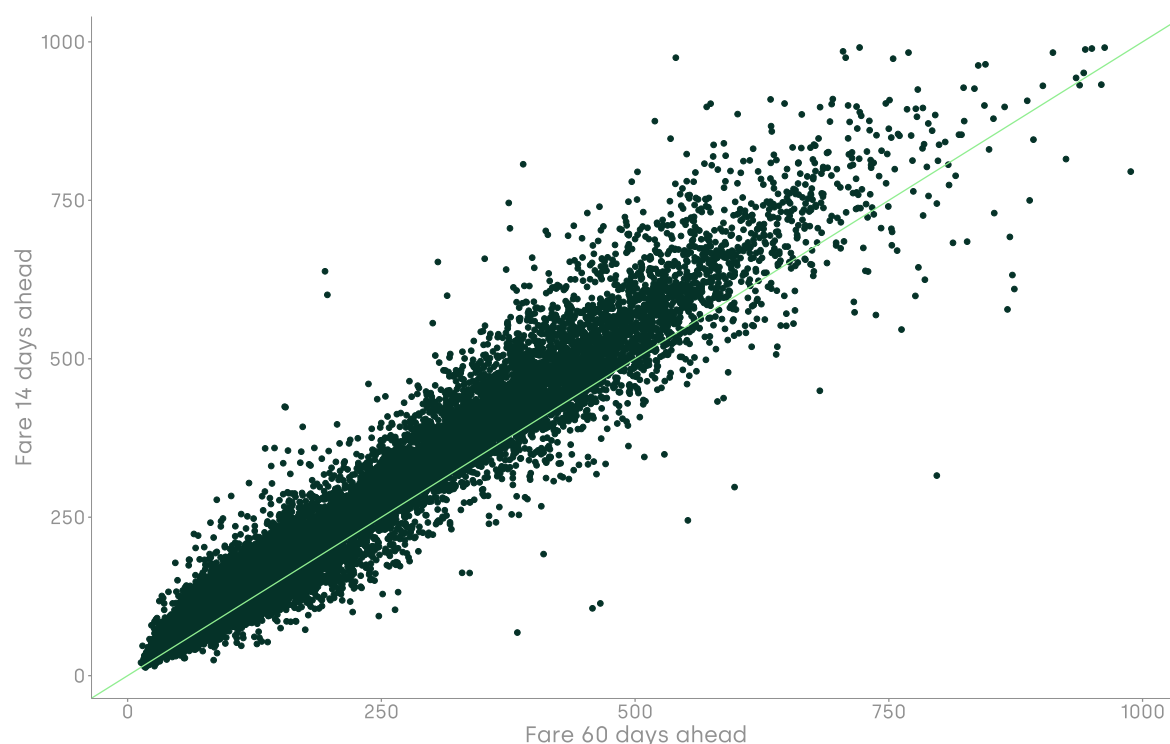
A1.4 Variables prepared from the Google Flights dataset

A1.4.1 Departing fares

The departing fare variable is calculated as the average fare for a given airport-to-airport route and IATA season, computed separately by carrier type (low-cost or full-service), itinerary type (direct or indirect for long-haul flights), and the number of days prior to which the price was scraped (14 or 60 days ahead), across all flight observations in the dataset. Since the data collected from Google Flights corresponds to fares on a round trip, with the return leg operating on the same route (and by the same carrier), the quoted fare is divided by two to obtain an approximation of the one-way departing fare.

Figure A1.1 below shows the relationship between departing fares 14 and 60 days ahead for the same route, in the same IATA season. The graph shows that fares 14 days before departure are higher than those 60 days before—namely, the mass of points lies above the 45° line. The average ratio of fares 14 days before compared with 60 days before is 1.22.

Figure A1.1 Fares 14 days ahead vs 60 days ahead



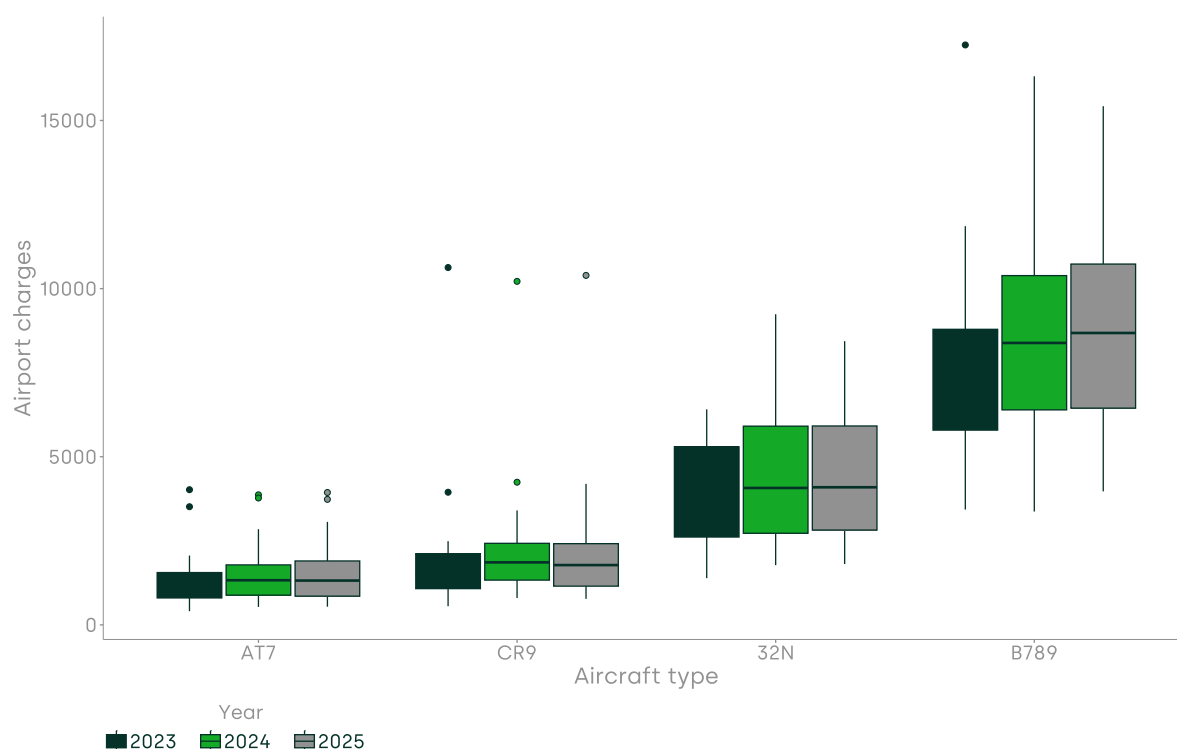
Note: The scatter plot shows the relationship between fares recorded 14 and 60 days ahead for the same route and IATA season. The green line represents the 45° line.

Source: Oxera analysis.

A1.5 Variables prepared from the airport charges data

Figure A1.2 below shows the airport charges for 2023, 2024 and 2025 for 54 European airports in the scope of the analysis across the four representative aircraft categories referenced in the ACI charges dataset: a Regional Jet (CR9), a Turboprop (AT7), a Narrowbody (32N) and a Widebody (B789). The graph shows that smaller aircraft, such as the AT7 and CR9, have lower turnaround charges. As aircraft size increases, the average level of charges rises.

Figure A1.2 Distribution of airport charges



Note: The figure presents charges across the four types of aircraft for 2023, 2024 and 2025. Each box plot displays the median (horizontal line), top and bottom quartile range (box), and whiskers extending to 1.5 times the quartile range. Outliers beyond this range are shown as individual points. Source: Oxera analysis.

A1.5.1 Airport charges

Each aircraft type listed in the OAG data is mapped to one of the four representative categories referenced in the ACI charges dataset: a Regional Jet (CR9), a Turboprop (AT7), a Narrowbody (32N) or a Widebody (B789). For instance, A318/319/320/321 were matched with the Narrowbody category, and Boeing 777 or A380 were matched with the Widebody category. Then, the most frequently operated aircraft type on each route in a given IATA season is identified and the corresponding charge for the departing airport is assigned to that route. For a route operating in S23 or S24, the corresponding charges used are those for 2023 and 2024 respectively. For routes operating in W23/24 or W24/25, the corresponding charge depends on whether the flight was operated before or after 31 December.

For each route, charges are then averaged at the IATA season level. Specifically, for winter seasons, the final charge is a weighted average of the charges—based

on the most common aircraft type for that route—for 2023 and 2024 (for W23/24) and 2024 and 2025 (for W24/25), where the weights are defined as the number of flights in the dataset operating before and after 31 December in the respective IATA season for that route.

A1.6 Airport capacity data

This dataset on the maximum ATM capacity by hour was collected by Oxera from national airport slot coordinators and airport management. In our analysis, we assume that this peak capacity applies uniformly across all hours of the day; i.e. a single value is used for each airport across the period of analysis. Table A1.2 below reports the maximum ATMs for each airport in the scope of the study.

Table A1.2 Maximum ATM capacity by hour

AGP	46	CTA	22	LIS	40	PMI	66
ALC	36	DUB	56	LPA	40	PMO	21
AMS	108	DUS	45	LTN	37	PRG	44
ARN	84	EDI	42	MAD	100	RIX	39
ATH	44	FCO	90	MAN	56	STN	50
BCN	78	FRA	104	MRS	48	TFS	33
BER	78	GLA	34	MUC	90	TLS	34
BGY	26	GVA	40	MXP	70	VCE	32
BHX	40	HAM	48	NAP	28	VIE	68
BIO	22	HEL	80	NCE	50	WAW	48
BRU	74	KEF	32	OPO	24	ZAG	18
BUD	60	LCA	18	ORY	70	ZRH	66
CDG	120	LGW	57	OSL	80		
CPH	83	LHR	92	OTP	39		

Note: The table reports the maximum ATM capacity per hour assumption for 2024.

Source: Oxera analysis.

A1.7 Dataset aggregation and merging

A1.7.1 Aggregation key

Since OAG and Google Flights data contain tens of millions of observations, and are at the flight level, both datasets are aggregated to a common level of granularity: *route (origin–destination airport pair) × IATA season × carrier type (LCC vs FSC) × direct × days ahead*.

To illustrate the aggregation, consider the route AMS–JFK during the 2023 Summer IATA season. The average 60-day-ahead fare for direct flights is calculated across all LCC observations for that route–IATA season combination; the same procedure is also applied to FSC observations. This is repeated for seasons W23, S24 and W24, yielding up to eight average prices per route (two carrier types × four IATA seasons). With 14-day-ahead fares, the same procedure is applied, adding up to eight additional prices. Where indirect fares are added to the scope of analysis, they are averaged separately, yielding up to four additional averages for 60-day-ahead fares and up to four for 14-day-ahead fares.

Turning to the OAG data, since the variables of interest—namely congestion, HHI and charges—are already defined at the IATA season, aggregation amounts to retaining a single observation per origin–destination airport pair and per IATA season.

A1.7.2 Dataset merging

Finally, the two datasets are merged, dropping any OAG observations for which no average fare is available. This results in the exclusion of 2,800 observations. The resulting dataset with 62,400 observations is used for the analysis in this report.

A2 Annex 2: analysis of changes in the number of competitors

Table A2.1 below presents the full data with all coefficients for the analysis presented in section 5.3.2.

Table A2.1 Analysis of changes in the number of competitors with all regressors

	(1)
log charges	0.0516 (0.0318)
log congestion	0.1631*** (0.0355)
Entry (1 to 2)	-0.0783*** (0.0137)
Entry (2 to 3)	-0.0552*** (0.0127)
Entry (3 to 4)	-0.0986*** (0.0165)
Entry (4 to 5)	-0.0340 (0.0235)
Exit (2 to 1)	0.0853*** (0.0134)
Exit (3 to 2)	0.1117*** (0.0190)
Exit (4 to 3)	0.0639*** (0.0237)
Exit (5 to 4)	0.122*** (0.0243)
lowcost	-0.4517*** (0.0068)
direct x long haul	0.0531*** (0.0078)

	(1)
fares 14 days ahead	0.1793*** (0.0020)
Fixed effects	IATA season + city-city route and season
Standard errors	Clustered at seasonal city-city level
Adjusted R ²	0.94
Observations	62,321

Note: The table presents the regression results for each entry and exit indicator variable. The control variables are the same as in the baseline entry/exit model above, but have been omitted for readability since their coefficients are stable. The first estimate presented is the entry-exit variable coefficient (e.g. approximately an 8% decrease in fares when the number of carriers increases from one to two), which can be interpreted as an approximate percentage effect on fares by multiplying the coefficient by 100. The second estimate in parentheses is the standard error of the coefficient, which is a statistical measure of precision. The stars next to the estimate correspond to different levels of statistical significance: (*) 10%, (**) 5%, (***) 1%. The table also reports the type of fixed effects and standard errors used in the model, the adjusted R² (measure of goodness of fit), and the number of observations used in the analysis.

Source: Oxera analysis.



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