Fare differentials

Analysis for the Airports Commission on the impact of capacity constraints on air fares

16 December 2013

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Scope

As part of PwC's support on analysis and strategy to the Airports Commission, we were asked to review historical evidence of the impact of capacity constraints on fares at major airports across Europe.

Scope of the analysis:

- Identify major European airports that have been capacity constrained over the period where fares data is available (i.e. 2004 – 2012)
- Identify an appropriate number of comparators in terms of broadly similar airports and routes both within the UK and across Europe with sufficient data to make statistical testing possible
- Review the trends in basic data and then consider what other factors should be taken into account and an appropriate methodology for doing this in order to isolate the impact of constraints on fares.

This paper sets out the approach and findings of this analysis.

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Executive Summary

As well as affecting an airport's resilience, capacity constraints may also affect the fares that passengers pay for travel. Where the supply of available seats is limited, be that through constraints on airline capacity or limitations on airport or airspace infrastructure, it is expected that the price paid, either by the passenger through air fares or the airline through airport charges, may be higher.

Given the many airport and airline specific factors which affect fares, we have conducted analysis which attempts to isolate the effect of capacity constraints on fares. This study utilised fare data from Sabre Airport Data Intelligence for a selection of European airports[1]; both constrained[2] and unconstrained, and used a variety of analytical techniques to examine the relationship.

Key findings:

- We found evidence of higher fares being associated with airports with capacity constraints. Across all airports and routes included in the study, fare revenue per passenger mile was found to be 18%[3] higher for constrained airports relative to unconstrained airports. We found these effects to be stronger when we considered premium classes.
- When considering the UK market in isolation, the effect was still present but at a lower level of around 10%[4].
- We found capacity constraints to have a more significant impact on fares for small airports compared to large airports.
- Using varying levels of capacity constraint we found that the effect of capacity constraints on fares is strongest at airports that are operating at over 99% of stated runway capacity and relatively weaker at airports that are operating at around 80% capacity.

[1] *All airports with scheduled passenger services in France, Spain, Italy, Germany, Netherlands and United Kingdom were included in the analysis.*
[2] *Constrained airports were defined as those operating at above 95% of their stated capacity in terms of air transport movements in any given year.*
[3] *8 – 29% depending on class of travel and route distance. Note that results are maintained whether passenger taxes are included or excluded.*
[4] *The lower effect when looking at the UK only is likely to be a result of the larger proportion of passengers flying from constrained airports in the UK compared with the full sample. Therefore, the relative impact of the constraint in the sample is lower.*

1. Introduction

1.1. Purpose of document

This document provides a summary of the analysis conducted by PwC on behalf of the Airports Commission to assess whether there is evidence that capacity constraints have affected fares at major constrained airports.

1.2. Scope

PwC were asked to review historical evidence of the impact of capacity constraints on fares at major airports across Europe.

Scope of the analysis:

- Identify major European airports that have been constrained over the period where fares data are available (i.e. 2004 – 2012)
- Identify an appropriate number of comparators in terms of broadly similar airports and routes both within the UK and across Europe with sufficient data to make statistical testing possible
- Review the trends in basic data and then consider what other factors should be taken into account and an appropriate methodology for doing this in order to isolate the impact of constraints on fares.

1.3. Data Sources

A variety of sources were used to compile data for the analysis in this report including segment and capacity data from Sabre Airport Data Intelligence (ADI), UK CAA traffic data, DfT airport runway capacity data, traffic data from flightglobalpro, economic data from the International Monetary Fund (IMF), crude oil data from Thomson Reuters and airport charges benchmarking data from Leigh Fisher. Further information on data sources and variables included can be found in section 2.3.

1.4. Structure of the Report

The report is structured as follows:

Chapter 2 – sets out the approach for the analysis;

Chapter 3 – presents the results;

Appendix A – contains the results of the fare trend analysis;

Appendix B – outlines a description of the variables utilised in the regression analysis;

Appendix C – presents the outputs of the regression analysis;

Appendix D – presents a description of the robustness tests used in the analysis; and

Appendix E – includes a glossary of the IATA codes used in the report.

2. Approach

2.1. Introduction

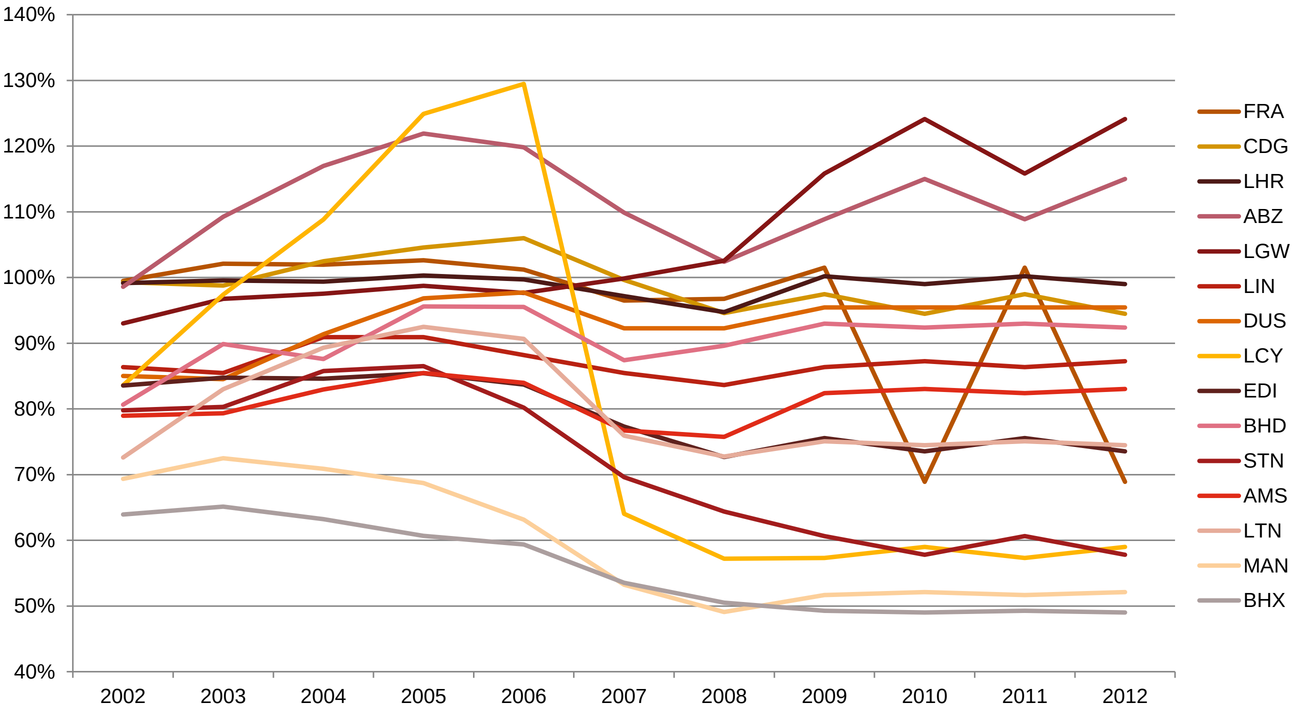
In order to test the impact of capacity constraints on air fares, we identified a range of European airports with known limitations on capacity (both infrastructure and regulatory) and assessed the level of constraint across a range of both constrained and unconstrained airports. We first conducted trend analysis to assess whether there were any apparent impacts of constraints. This did not provide any clear evidence so we explored the drivers of fares in more detail to attempt to isolate the impact of capacity constraints through statistical analysis. The approach to the analysis is outlined below.

2.2. Identify sample airports

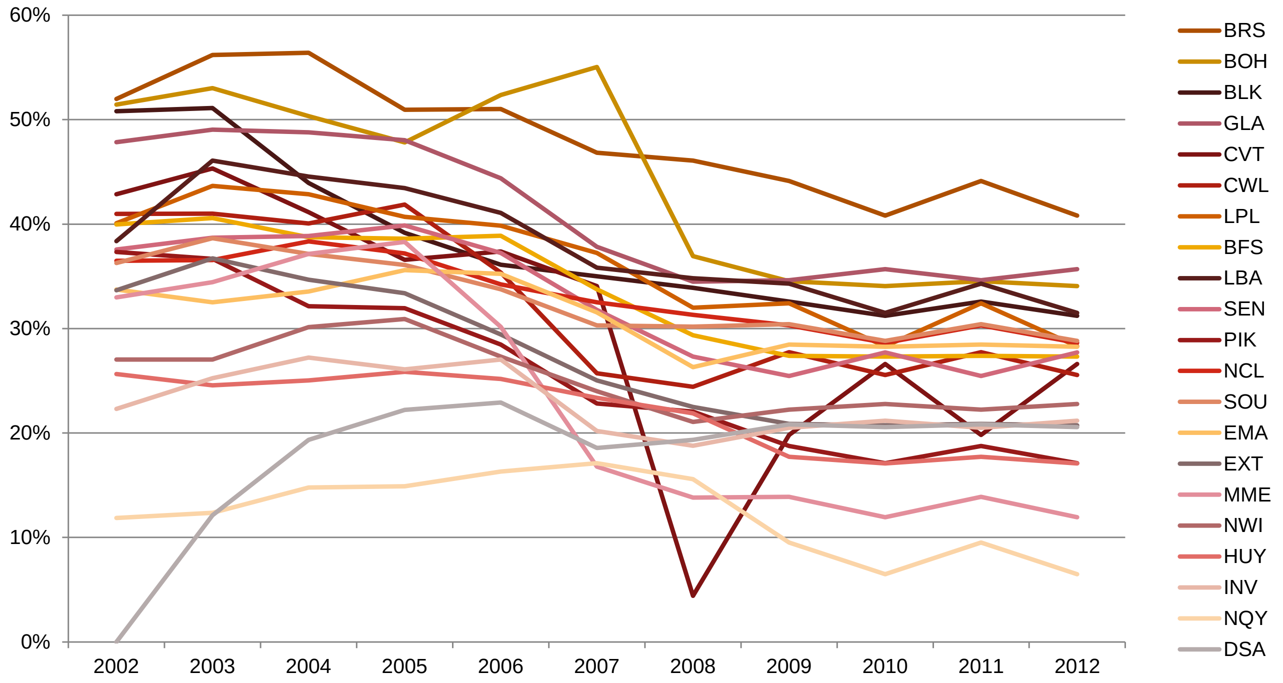
We identified major European airports with known limitations on capacity such as London Heathrow, London Gatwick, Frankfurt, Paris Orly, Milan Linate, Düsseldorf, Paris Roissy-Charles de Gaulle and Amsterdam Schiphol. We assessed the annual level of aircraft movements against the airport's stated runway capacity (both infrastructure and regulatory constraints). Given the availability of capacity data from the DfT, we also included all other UK airports.

Figure 2-1: Runway Utilisation
(Annual air transport movements as a % of stated runway capacity)

Airports operating at >60% capacity in 2002



Airports operating at <60% capacity in 2002



Note: A glossary of airport IATA codes has been included in Appendix E. -
Source: DfT, CAA, flightglobalpro, various airport websites

2.3. Data collection

We obtained data from Sabre Airport Data Intelligence (ADI) for local segment passengers (i.e. origin-destination passengers on a particular route segment, excluding passengers on the segment where the segment forms only part of the entire journey) and revenues for 2004 to 2012 for all route segments departing airports in UK, France, Spain, Italy, Germany, and Netherlands. We have excluded passengers and revenues where the route makes up only part of the total journey as total fares are allocated across segments and may not accurately reflect the true fare on the route.

The data was obtained one-way by route, airline, year and class of travel. The data provides origin airport, destination airport, operating airline, year, class of travel, passengers, load factor, total revenue, and revenue per passenger. We supplemented this information with capacity data from ADI including seat capacity, frequency and seat miles by route, airline and year.

Revenues obtained from ADI exclude air passenger taxes, so we have included these based on the year, class of travel and route distance for UK, France, Germany and Netherlands[5].

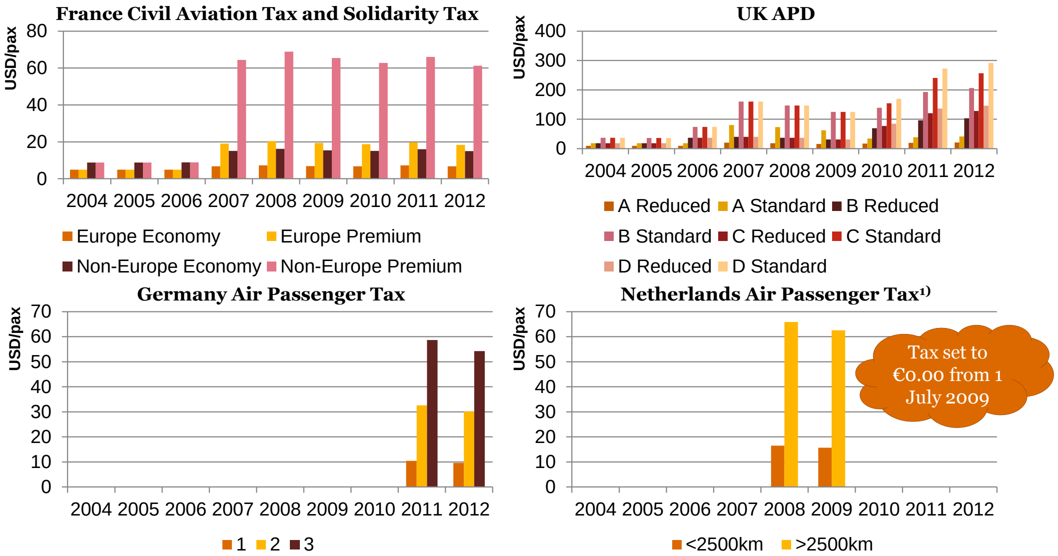
[5] Italy's passenger tax is at a much lower rate compared with the other taxes and has therefore been excluded from the analysis. Spain does not have a comparable air passenger tax.

Table 2-1: Air Passenger Taxes

Country	Tax	2012 Rate	Introduced
France	• Civil Aviation Tax • Solidarity Tax	• €4.24 for Europe, €7.62 for non-Europe • €1 for Europe economy, €4 for non-Europe economy (double for premium classes)	• Prior to 2004 • 2006
Germany	• Air Passenger Tax	€7.50 for group 1 (Europe), €23.43 for group 2 (medium haul) and €42.18 for group 3 (long haul)	2011
Netherlands	• Air Passenger Tax	EU destination/under 2500 km: €11.25, Other destinations: € 45	July 2008 – June 2009
United Kingdom	• Air Passenger Duty	Four band system (A:<2000miles, B :2001-4000 miles, C: 4001-6000 miles, D: >6000 miles) , £13 per passenger for Band A economy, £92 per passenger for Band D economy, double for premium classes.	1994

Source: IATA Airport Charges Monitor

Figure 2-2: Air Passenger Taxes for France, UK, Germany and the Netherlands



Note: Where rates changed during the year, the rate for the majority of the year was taken. 1) In the analysis for Netherlands, half the rates were assumed as the tax was only applied for 6 months of the year. The full rate is shown in the chart.
Source: IATA Airport Charges Monitor, converted from national currency to USD based on annual average exchange rates from Oanda

We then calculated key indicators such as revenue per passenger and revenue per passenger mile with and without taxes across all classes as well as split by economy class and premium classes.

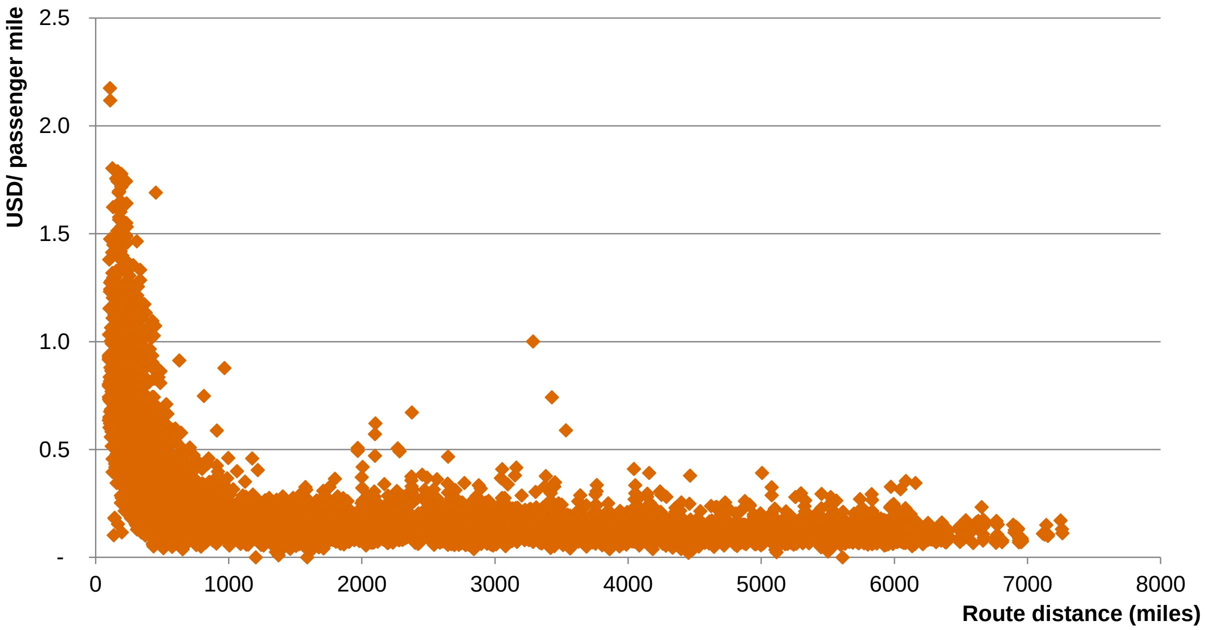
ADI's data is primarily based on airline bookings through the global distribution system (GDS). The database does not capture direct bookings with airlines such as low cost carriers (LCCs) and therefore LCC fares data is based on estimates. We have identified LCCs in our data set to enable these to be filtered out of the analysis.

2.4. Trends in fares

We have compared average fare revenue at a country and airport level. To account for distance, we have measured fares as segment revenue per passenger mile as well as segment fare per passenger (including taxes)[6]. As shown in Figure 2-3 below, revenue per passenger mile is generally higher for shorter routes due to the level of airline fixed costs to be covered; however, revenue per passenger is generally higher for longer routes.

[6] *Note that the analysis below includes taxes and the equivalent charts excluding taxes have been provided in Appendix A. -*

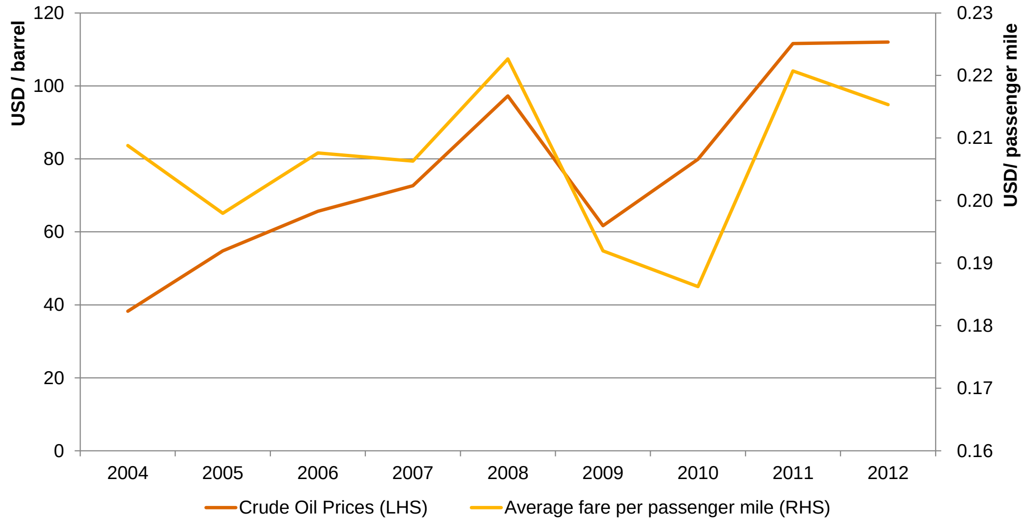
Figure 2-3: Segment revenue per passenger mile and distance (all routes, non-LCCs, economy class only, including taxes)



Source: Sabre Airport Data Intelligence

Since fuel costs make up a significant proportion of airline operating costs (up to around 30%), the oil price is a key driver of average fares at an aggregate level as shown in Figure 2-4 below.

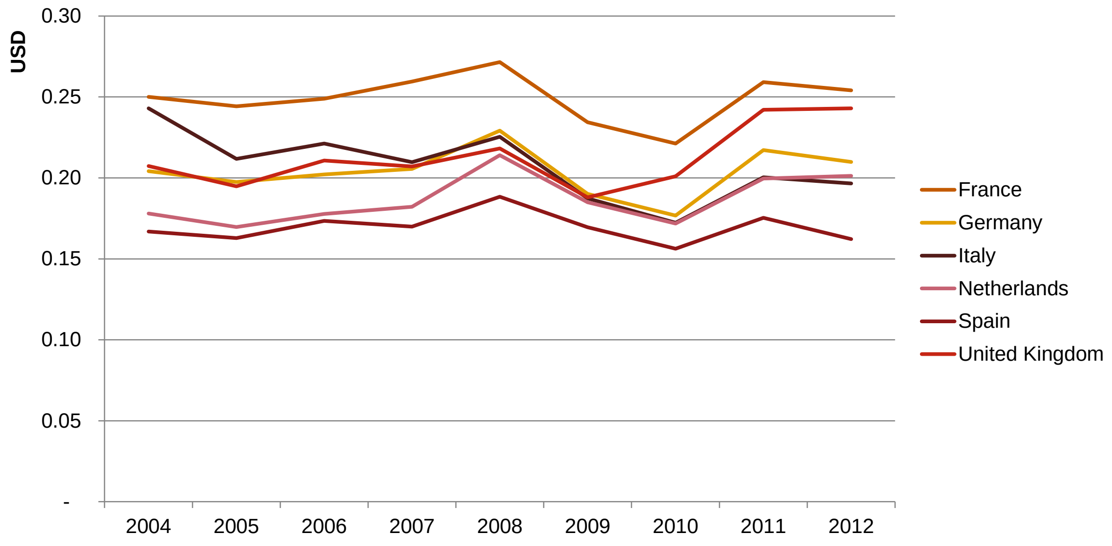
Figure 2-4: Oil prices vs. average fare revenue per passenger mile



Note: Average local segment fares per passenger mile at all airports across the 6 countries considered in this study
Source: Sabre Airport Data Intelligence, Thomson Reuters

Trends in fares have been similar across European airports. France has the highest revenue per passenger mile, probably driven by shorter average route distance. The UK has become the second most expensive country in terms of revenue per passenger mile, overtaking Italy and Germany over the last few years.

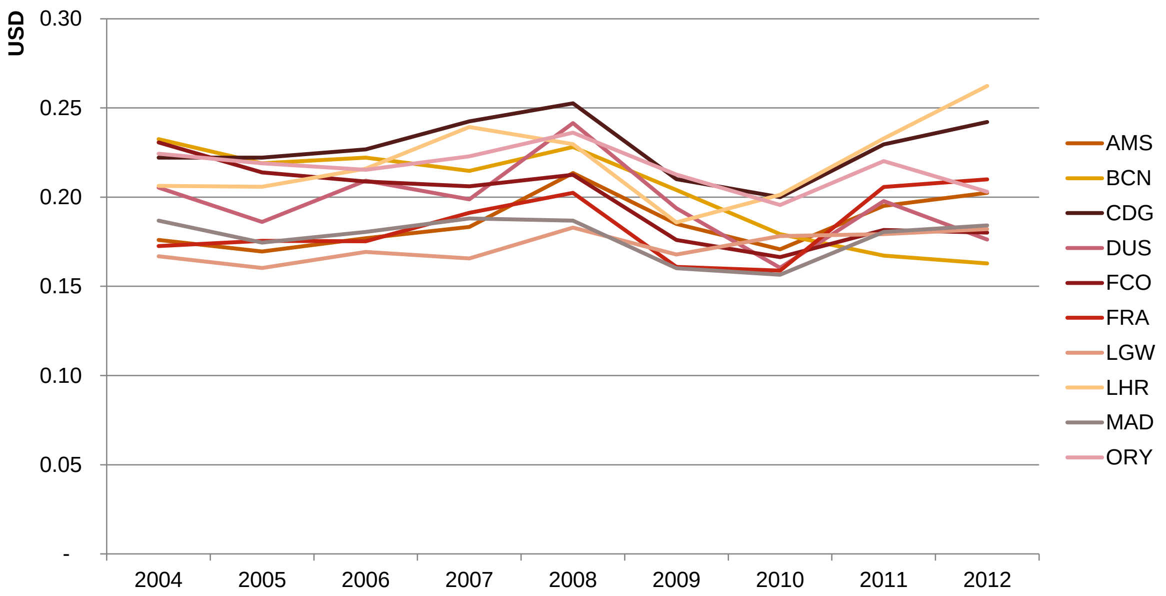
Figure 2-5: Segment revenue per passenger mile by country (incl taxes) (all routes, carriers and classes)



Note: Local segment revenue per passenger mile in USD (converted from local currency at the time of booking)
Source: Sabre Airport Data Intelligence

Fares at major hub airports (e.g. LHR, CDG and FRA) appear to have recovered more strongly. Over the last two years, Heathrow has surpassed Charles de Gaulle as the most expensive European hub for passengers, based on a revenue-per-passenger mile basis across all routes served.

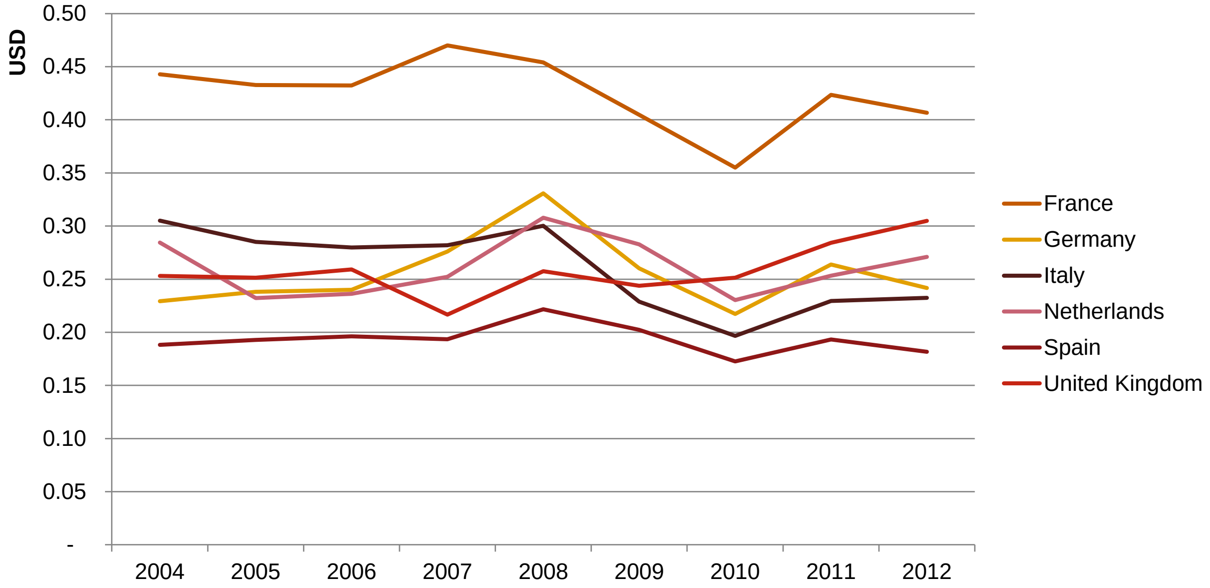
Figure 2-6: Segment revenue per passenger mile by airport (incl taxes) (all routes, carriers and classes)



Note: Local segment revenue per passenger mile in USD (converted from local currency at the time of booking)
Source: Sabre Airport Data Intelligence

As shown in Figure 2-7 below, European routes from France have higher revenue per passenger mile due to shorter sectors flown.

Figure 2-7: Segment revenue per passenger mile (incl taxes) (European Routes, Economy Class, excluding LCCs)

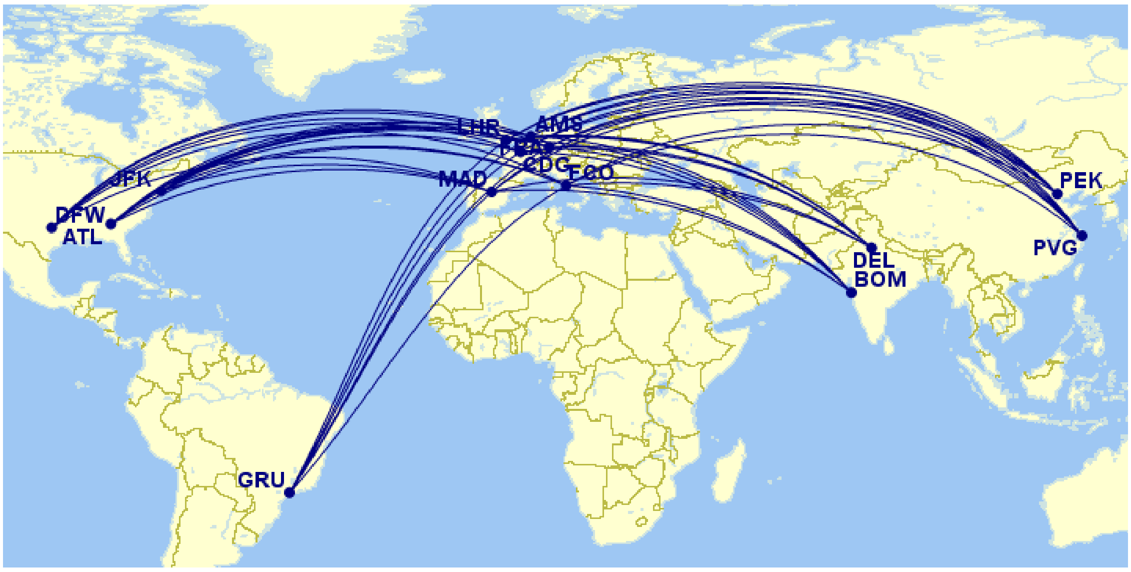


Note: Local segment revenue per passenger mile in USD (converted from local currency at the time of booking)
Source: Sabre Airport Data Intelligence

2.5. Route level analysis

We have compared average fares for individual routes across a range of long haul routes from EU hubs. Each of the routes analysed[7] is illustrated below in Figure 2-8[8].

Figure 2-8: Comparison of Long Haul Routes from European Hub Airports

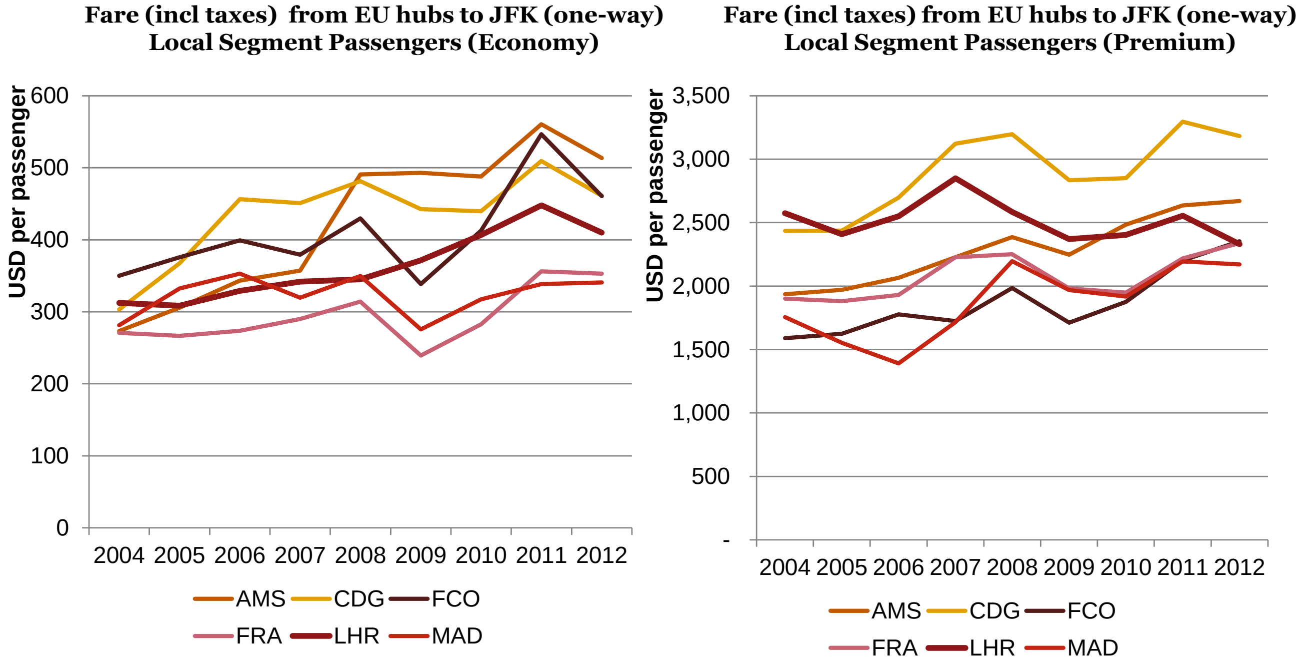


Source: Great Circle Mapper

[7] *A selection of long haul routes were chosen based on discussions with the Airports Commission Secretariat*
[8] *Note that version excluding taxes can be found in Appendix A. -*

A comparison of the fares to JFK from the principal European hubs has revealed that fares from Heathrow to JFK fall in the middle of the range of fares from these European hubs to JFK.

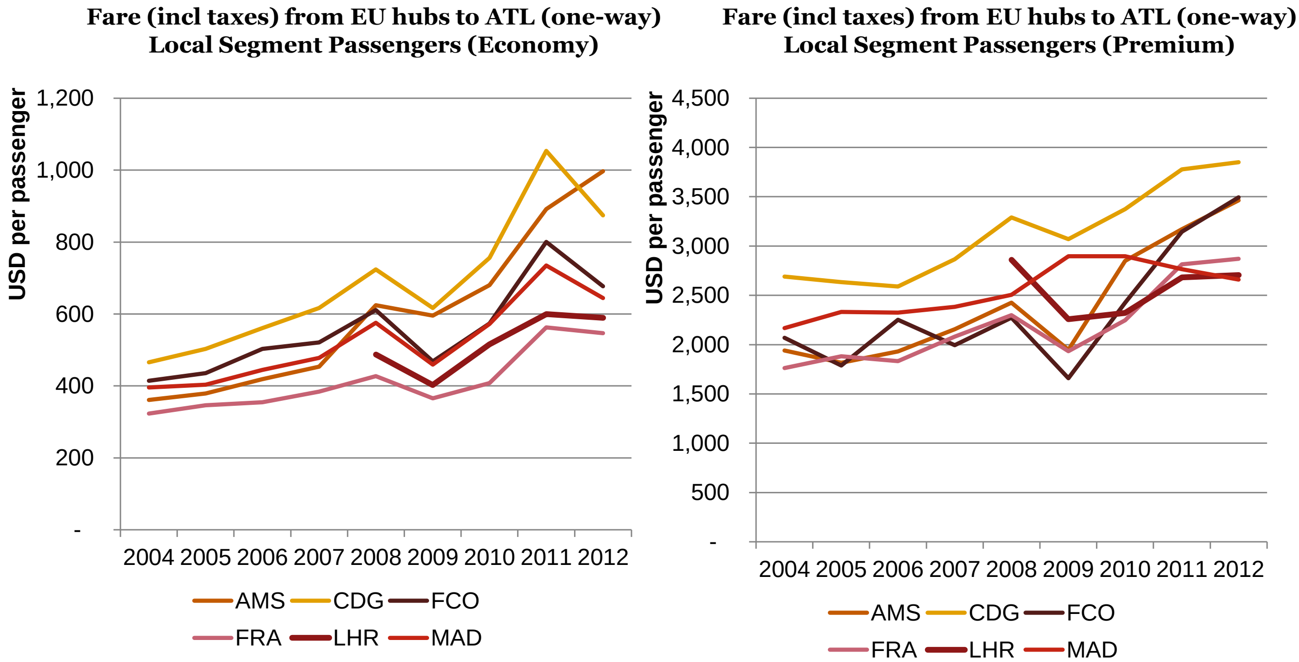
Figure 2-9: Fares from EU hubs to JFK



Source: Sabre Airport Data Intelligence

Fares to Atlanta have been increasing over the past 8 years. From the analysis it appears that fares from LHR and FRA are inexpensive relative to other EU hubs.

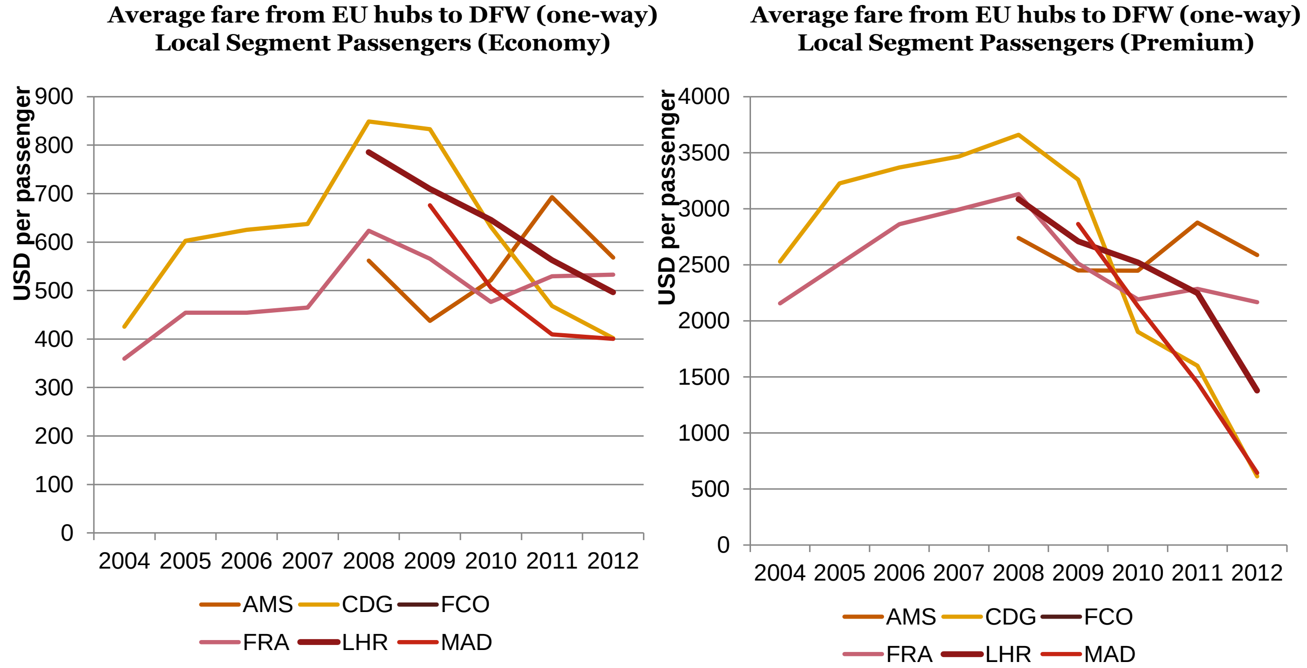
Figure 2-10: Fares from EU hubs to ATL



Source: Sabre Airport Data Intelligence

Fares from the selected European hubs to DFW have declined overtime following an increase in availability of direct capacity.

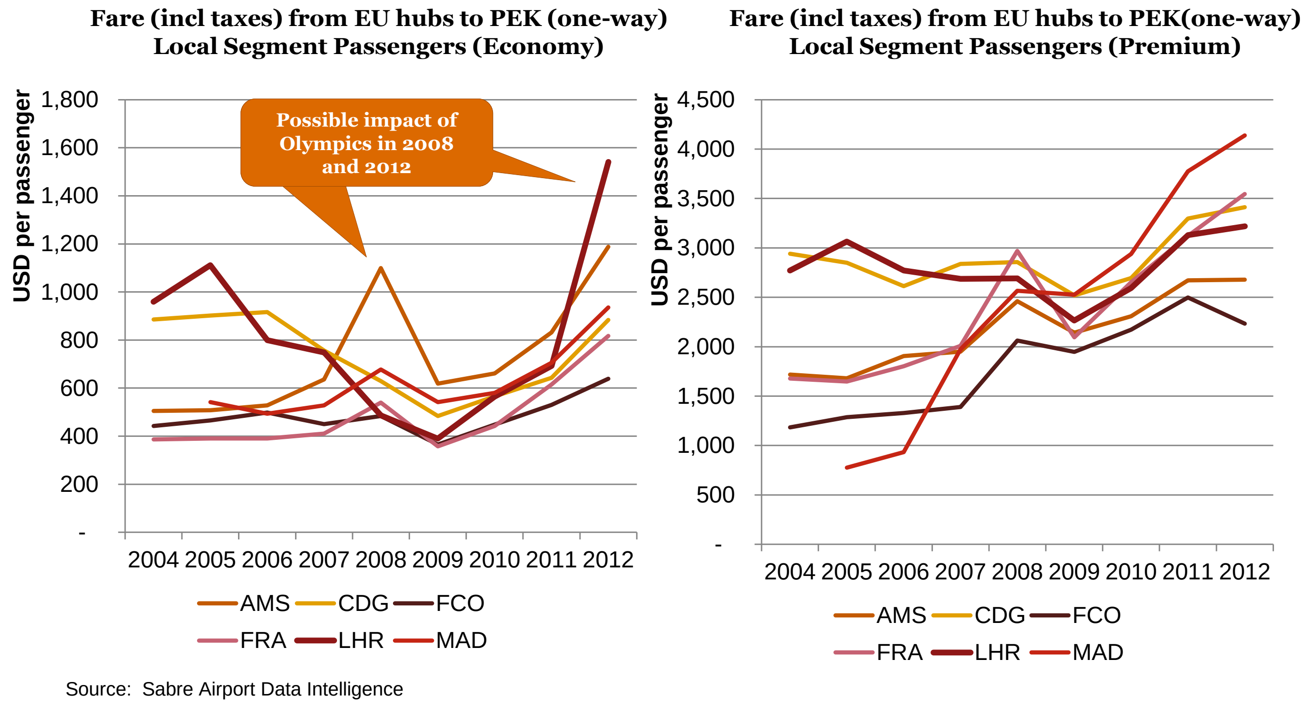
Figure 2-11: Fares from EU hubs to DFW



Source: Sabre Airport Data Intelligence

Fares to Beijing have increased across all EU hubs over the last few years with peaks in 2008 and 2012 which, however, might be a result of the Olympic Games held in those years.

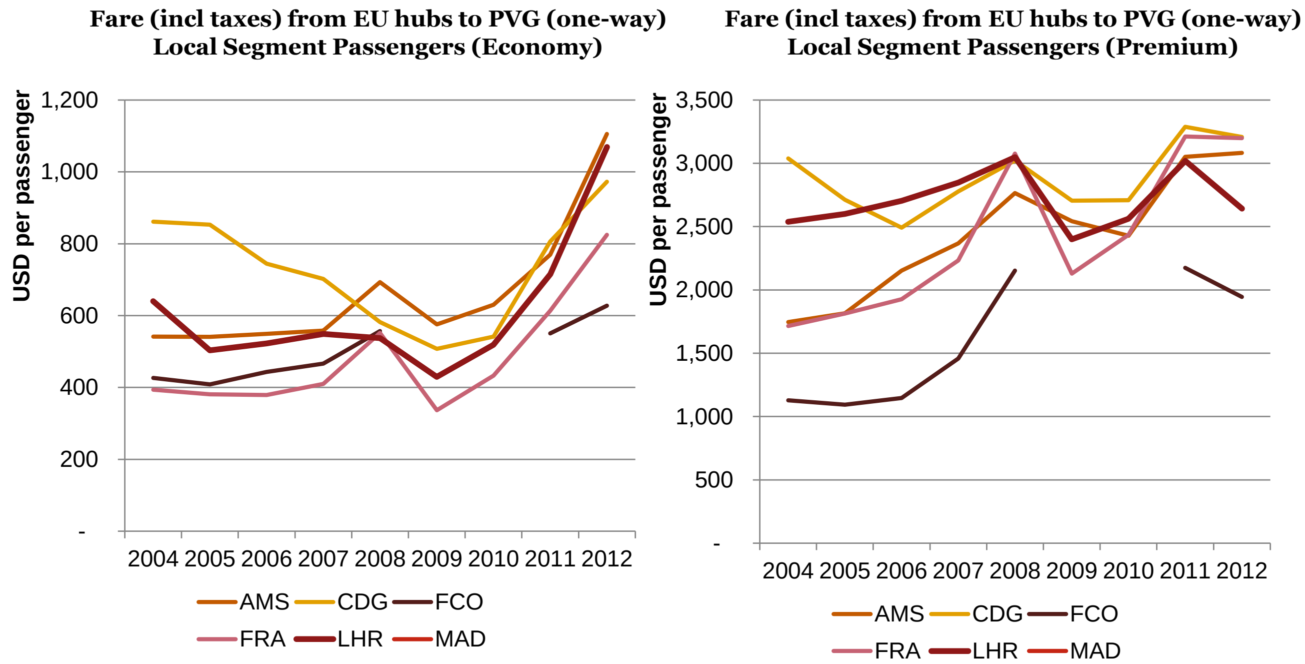
Figure 2-12: Fares from EU hubs to PEK



Source: Sabre Airport Data Intelligence

Similarly, fares to Shanghai have increased across all EU hubs over the last few years.

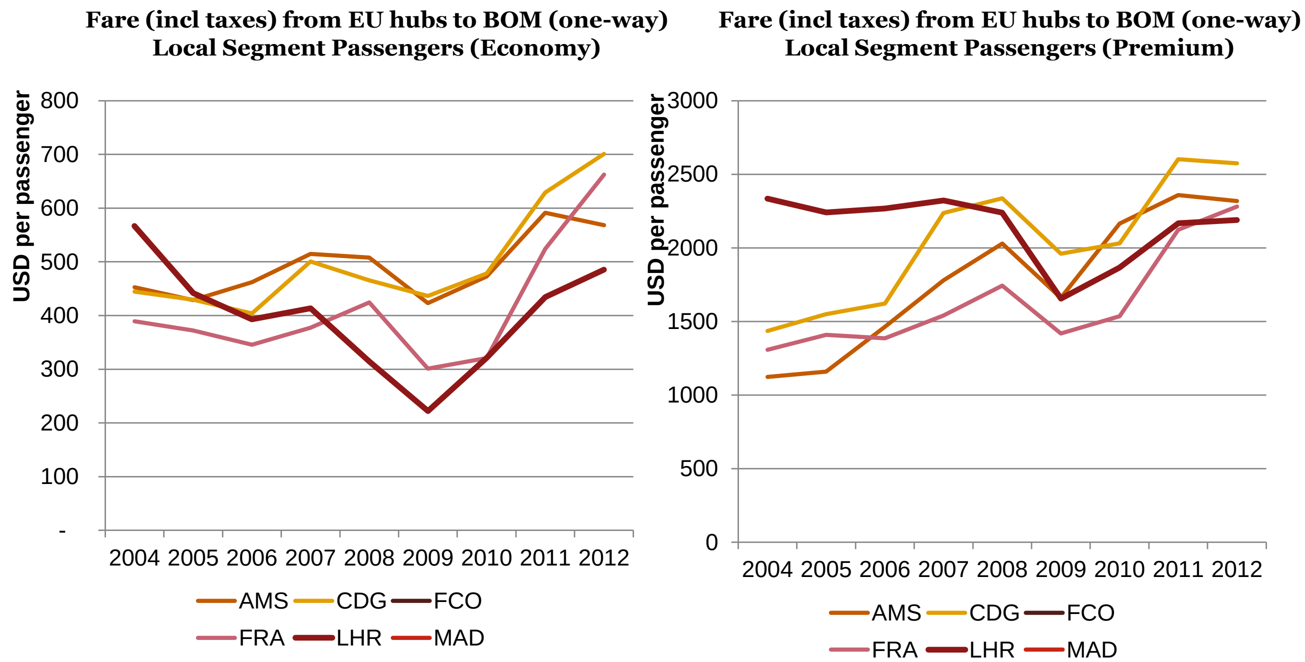
Figure 2-13: Fares from EU hubs to PVG



Source: Sabre Airport Data Intelligence

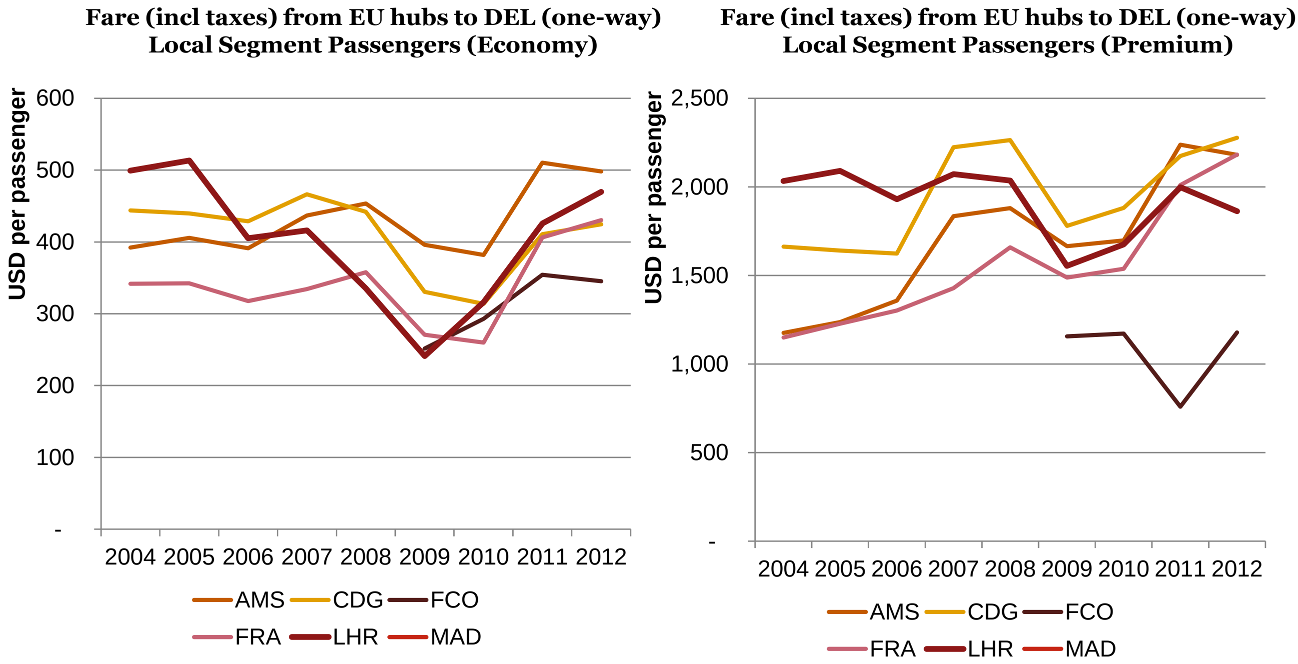
Economy fares to Mumbai and Delhi are comparatively low from LHR, however, premium class fares are comparable with other hubs.

Figure 2-14: Fares from EU hubs to BOM



Source: Sabre Airport Data Intelligence

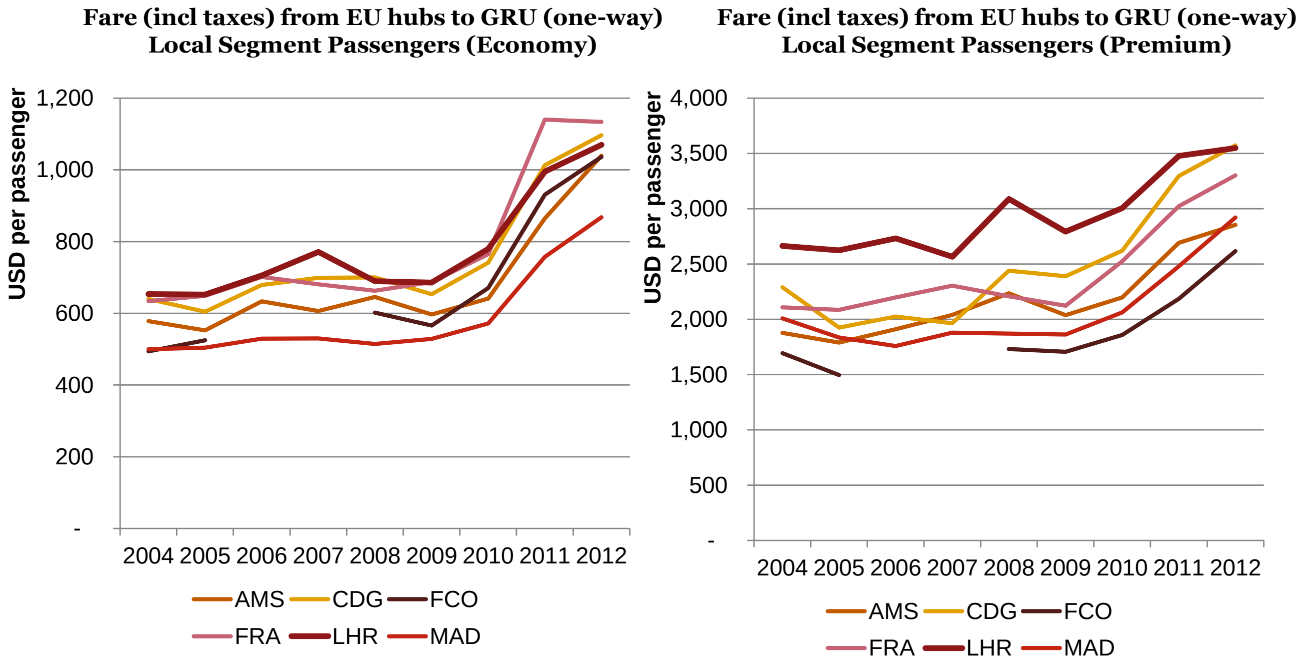
Figure 2-15: Fares from EU hubs to DEL



Source: Sabre Airport Data Intelligence

LHR has the highest premium class fares to Sao Paulo driven by limited capacity available on the route. Economy fares, on the other hand, are comparable with FRA and CDG.

Figure 2-16: Fares from EU hubs to GRU



Source: Sabre Airport Data Intelligence

Comparing fares across different airports is challenging given the range of factors that impact the prices passengers pay. Route distance is a key driver of fares due to fuel representing a significant share of an airline's operating cost. External factors such as competition and seasonality of demand also play a role in determining fares. For example, the analysis above suggests that fares from Heathrow are comparatively low relative to other EU hubs for flights to Mumbai, which is better-served from Heathrow than from its competitors, but comparatively high for flights to Sao Paolo, to which Heathrow has fewer services. So competition and frequency also play a role in determining fares.

2.6. Drivers of fares

We identified number of key factors that drive the level of fare on a particular route segment. These factors are summarised in the table below along with the expected impact on fares.

Table 2-2: Key Factors Driving Fares

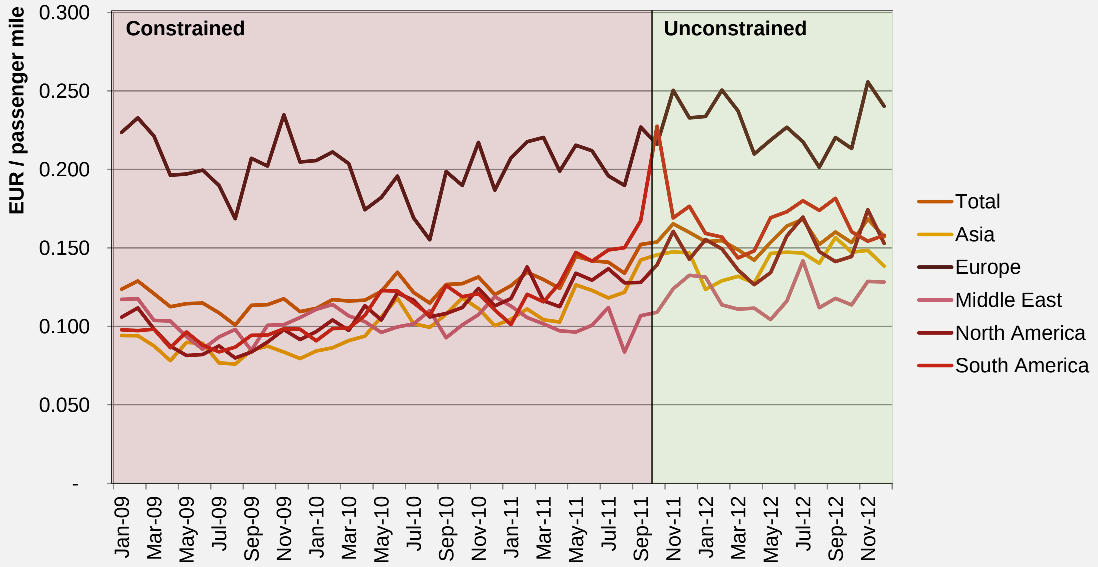
Demand/Supply	Factor	Expected Impact	Possible measure
Supply	Competition	-	Number of airlines, HHI
	Frequency	-	Flight frequency
	Seat capacity	-	Seat capacity, seats per movement
	Constraints	+	% utilisation, dummy variable
Demand	Size of Market	-	Segment passengers, Size of origin and destination airports
	Wealth of Market	+	GDP/capita
Airline Operating costs	Fuel costs	+	Oil Prices
	Route length	+	Route distance
	Airport charges	+	Airport aeronautical revenue/pax

Frankfurt Airport Case Study

Testing of the Impact of Capacity Constraints on Fares at Frankfurt Airport

We conducted a case study on fares at Frankfurt Airport to determine whether there was an apparent impact on fares when constraints were eased due to the opening of the new runway in October 2011. Routes to Asia, Europe, the Middle East, North America and South America were tested. However, as shown in the chart below, the analysis did not produce any clear evidence of a reduction in fares following the opening of a new runway.

Monthly segment revenue per passenger mile from Frankfurt (excluding taxes)



Note: Includes all airlines to all destinations from airports in Germany, segment fares converted from USD to EUR based on average annual exchange rate. Includes local segment only (i.e. Excludes partial fares for part of a journey), excludes LCCs

2.7. Econometric approach

As the trend analysis and case study presented in section 2.4 and 2.5 did not demonstrate clear evidence on the impact of capacity constraints on fares. We therefore considered more detailed econometric analysis to try and isolate the effect of capacity constraints on air fares. This analysis is discussed below.

2.7.1. Introduction

The nature and availability of data play an important role in determining the econometric approach we can use in our analysis. In order to study the effects of capacity constraints on fares, we can either use a time series approach or a panel data analysis. The former requires at least 30[9] or more observations for each variable in our econometric model. Furthermore, the capacity constraint variable needs to be a continuous variable. Whilst the time series approach is uni-dimensional, in that all the variables are observed over time, the panel data framework is multi-dimensional and involves the inclusion of entities or units of analysis observed over a relatively short period of time. For example, in our context, the entities or units of analysis are different routes.

2.7.2. Data

We have compiled a data set covering a range of variables to test for an impact of constraints. Section 2.3 discusses the fares data included. The segmentation, variables and filters are shown in the figure below. Appendix B. -shows all variables included in the data set and the source of data.

Figure 2-17: Description of data to be included in the econometric analysis

Segmentation • Route • Airline • Year **Dependent variables** • Average fare per passenger (total, economy, premium) (including or excluding passenger taxes) • Average fare per passenger mile (total, economy, premium) (including or excluding passenger taxes) **Filters** • LCC (dummy) • Origin Hub (dummy) • Capacity Filter (dummy)*	**Independent variables** • Capacity constraint (dummy) • Capacity measure (% utilisation)* • Scheduled seat capacity on route • Scheduled frequency on route • Distance (miles) • Average seats per movement • Origin country GDP / capita • Destination country GDP/ capita • Segment passengers on route • Size of origin airport (passengers) • Size of destination airport (passengers) • Origin Airport charge (airport aero rev/pax) • Destination Airport charge (airport aero rev/pax) • Crude oil price

*Note: * Capacity filter determines whether origin airport has been included in the capacity measure*

The variable measuring capacity constraint need not be continuous; instead we can use a dummy variable approach by coding routes that are constrained as 1 and 0 otherwise. Given that the continuous variable is not available for all airports, we have included a dummy variable to measure constraint. We have obtained capacity data for UK airports and European airports we know are operating at a high utilisation of their available

[9] For annual data for example, we will need at least 30 years of more. However, if we have evidence that the data is distributed symmetrically then we can use less that 30 observations.

capacity[10]. If an airport is operating at over 95% of its declared or regulated air transport movement capacity, we have assumed that capacity constraints exist and we have applied a capacity constraint dummy variable of 1. We have assumed that other European airports not included in the capacity analysis are not constrained and have applied a value of 0 to the dummy variable. All airports in the United Kingdom, France, Germany, the Netherlands, Italy and Spain have been considered.

Additional variables included in the data set were crude oil prices from Thomson Reuters, GDP per capita for the origin and destination countries from the International Monetary Fund (IMF) and aeronautical revenue per passenger from benchmarking provided to the Airports Commission by Leigh Fisher.

2.7.3. Model specification

For our analysis, the lack of long time series data coupled with the fact that the capacity constraint variable is not continuous mean that a panel data approach is more suitable. A panel data approach is attractive in the context of our analysis due to the fact that we have both many routes and many route level variables acting as explanatory variables for fares. Furthermore, the dummy variable approach in a panel framework provides us with a more natural way of assessing the effects of capacity constraint across different airports.

In order to estimate our model, we can either use a Random Effects (RE) or a Fixed Effects (FE) model. The former approach assumes that there is a certain correlation between the different units of analysis whilst the latter does not. Instead, the FE approach is concerned with analysing the variation within each unit of analysis. To determine which estimation approach between the RE and FE we ought to use, we employ the Hausman test. Our test reveals that in this case, a FE model is desirable. The benefit of this approach is that it allows us to account for all the unobserved route characteristics that are fixed over time. Our post estimation tests showed that the model estimated using a FE approach suffered from heteroskedasticity, serial correlation and cross-sectional dependence. It is important to note that in general, the problems identified by our post estimation tests do not affect the coefficient estimates but only the estimates of the standard errors. However, it is possible to obtain biased coefficients in the presence of more severe forms of cross sectional dependence. Our test does not tell us what form of cross-sectional dependence we have in our model so we cannot rule out bias in the estimated coefficients.

To deal with the issue with the estimates of the standard errors, we use the Driscoll-Kraay estimator. The standard errors of this estimator are well calibrated when cross-sectional dependence is present (Hoechle, 2007)[11]. Given that this estimator is based on an asymptotic theory, the results of this approach needs to be treated with caution when it is applied to panels that contain a large cross-section but only a short time dimension, as in our context. However, the standard errors of this estimator are also known to have considerably better small-sample properties than those of commonly applied alternative techniques for estimating standard errors when cross-sectional dependence is present (Hoechle, 2007). Compared to alternative estimators in the presence of cross-sectional dependence, the latter properties provide us with a strong rationale for re-estimating our model using the Driscoll-Kraay estimator.

[10] Refer to section 2.2.
[11] Daniel Hoechle, (2007) "Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence" *The Stata Journal*, 7, Number 3, pp.281-312.

3. Results

3.1. Introduction

We tested a wide range of variables[12] in determining the econometric models to use. We tested correlation between variables, levels of significance and segmentation to choose the most appropriate models. The results of this analysis are summarised below and model outputs can be found in Appendix C. - [13] We applied robustness checks to the chosen models, which can be found in Appendix D. -

3.2. Model specification

The dependent variable applied was revenue per passenger mile (including taxes) across all routes for full service carriers. We considered total, economy and premium classes and total, short haul and long haul routes. The observations were segmented by route, airline and year. The independent variables included were flight frequency, number of airlines operating on the route, seat capacity per movement, route distance, total segment passengers, GDP of the origin country and GDP of the destination country. A dummy variable was used for capacity constraint with a value of 1 was applied where the origin airport is operating at above 95% of its declared or regulated air transport movement capacity.

We used a log-log model[14] and our chosen model uses regression with Driscoll-Kraay standard errors as discussed in section 2.7.3. There were 18,585 observations for total and economy classes and 11,777 observations for premium classes. The coefficient of determination (R^2) for the models ranged between 0.11 and 0.72 depending on the class of travel and distance. All variables were found to be significant across the models with the exception of GDP of the destination country in some cases.

3.3. Model results

Below, we report the different coefficients on the capacity constraints variable in our chosen model. Overall, fare revenue per passenger mile (including taxes)[15] for airports with identified capacity constraints were 18% higher. The impact of capacity constraints was more pronounced for premium class fares with fare per passenger mile with identified capacity constraints being 29% higher than those without. The model outputs for the results in this table can be found in Appendix C.1.

3.3.1. Summary of aggregate results

	Total	Economy	Premium
Total	0.176***	0.099***	0.289***
Short-haul	0.131***	0.081***	0.283***
Medium-Long haul	0.129***	0.032	0.236***

Significant at *** for 1%, ** for 5% and * for 10%

[12] A description of variables can be found in Appendix D. -
[13] We used STATA software to conduct the analysis.
[14] We also tested a linear model, however, results were more robust using the log-log model, and the log-log model linearizes the equation and provides coefficients that can be interpreted as elasticities.
[15] Note that slightly lower results were obtained where taxes were excluded given that UK airports have the highest passenger taxes and capacity constraints. Results excluding taxes can be found in Appendix C.6.

3.3.2. Testing the level of constraint

We tested whether varying the definition of a constrained airport had an impact on the coefficients. The model results shown in section 3.3.1 present the coefficient for capacity constraint where the variable is given a value of 1 where an airport is operating at >95% of capacity. The table below summarises results where the capacity constraint variable is set to 1 at various levels of capacity. The table shows that where airports are highly constrained (>99%), the impact of constraints is more pronounced and fare revenue per passenger mile (including taxes) is 23% higher than those without capacity constraints. It drops to 12% where the level of constraint is lowered to 80%. Once capacity utilisation falls below 80%, the estimated effect on fares begins to increase which indicates that the airports included at each level of constraint may have individual characteristics that drive fares (e.g. purpose of travel, catchment and surface access), so the relationship does not hold across all levels.

Constraint level	Coefficient	Observations	Airports included (in 2012[2)])
>0.99%	0.234***	7,473	ABZ, LHR, LGW
>95%	0.176***	12,411	Above plus DUS
>90%	0.147***	14,626	Above plus BHD
>80%	0.120***	19,596	Above plus AMS, LIN
>70%	0.179***	26,856	Above plus EDI, LTN, CDG
>60%	0.185***	29,479	Above plus FRA (until 2011 it was >95%)
>50%	0.191***	31,661	Above plus LCY, MAN, STN
<50%	n/a		All other UK airports

Significant at *** for 1%, ** for 5% and * for 10%

1) Includes all UK airports, AMS, CDG, ORY, FRA, DUS, LIN. Note that given that a large number of routes in this subset of data are operating from constrained airports, that the impact of constraints may be lower compared with the full dataset.
2) Varies depending on constraint level in each year

3.3.3. Summary of UK airport results

We also considered UK airports in isolation. The effect of capacity constraints was still present, but at a lower level of around 10%[16].

	Total	Economy	Premium
Total	0.104**	0.032	0.156**
Short-haul	0.026	-0.020	0.119**
Medium-Long haul	0.193***	0.090***	0.281***

Significant at *** for 1%, ** for 5% and * for 10%

[16] The lower effect is likely to be a result of the larger proportion of passengers flying from constrained airports in the UK compared with the full sample. Therefore, the relative impact of the constraint in the sample is lower.

3.4. Aeronautical charges

Aeronautical charges were also analysed. The Airports Commission provided data from Leigh Fisher for aeronautical charges per passenger for 35 airports globally from 2002 to 2010. We have included the origin and destination airport aeronautical charges for the airports and years available (GBP in 2011 prices). Since there are values missing for 2 airports for 2002-2005, STATA only includes values for 2006–2010. It was observed that:

- If both origin and destination airport aeronautical charges are included in the model, the number of observations decreases to 3099, the coefficient for the capacity constraint dummy variable decreases from 0.176 to 0.104 compared with the original log-log model with positive coefficients for airport charges, although only origin airport charges are significant;
- If only origin airport aeronautical charge is included, the number of observations is 20616, the capacity constraint dummy coefficient reduces to 0.013 and the origin airport aeronautical charge coefficient is positive and significant;
- If only destination airport aeronautical charge is included, there are 10014 observations, the capacity constraint coefficient increases to 0.256, but the destination airport aeronautical charge coefficient is not significant.

Given we only have a very small sample of airports where constraints exist and data for the aeronautical charges are available, these results have not been taken into account as we do not believe they are robust. The results can be found in Appendix C.5.

3.5. Additional tests

We also tested for the following:

- *time effects* - considering pre- and post- financial crisis, results were similar with a capacity constraint coefficient of around 0.17-0.18 in line with the aggregate model. See Appendix C.3.

- *size of the airport* – we found that smaller airports saw a larger fare impact with capacity constraints compared with medium and large airports. See Appendix C.4.

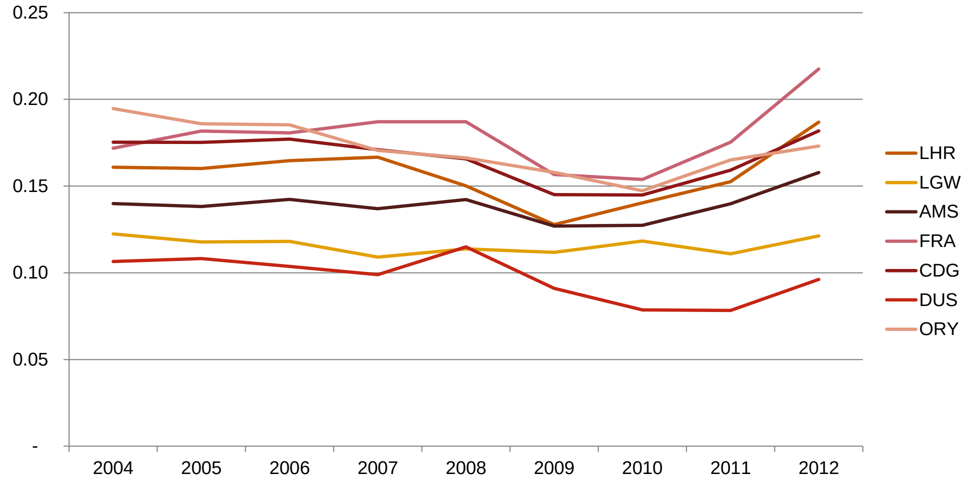
- *non-linearity of the constraint variable*. There was no clear evidence of non-linearity. See Appendix C.4.1.

Appendix A. - Fare trend analysis

A.1. Aggregate fares excluding taxes

As shown in the figure below, trends in fares have been similar across the major European airports analysed, with an increase in fares registered over the last year.

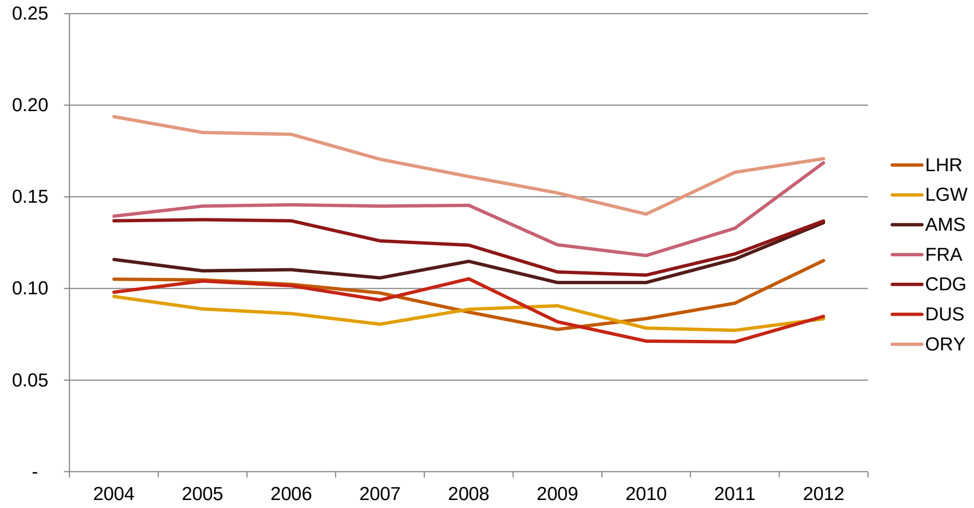
Figure A- 1: Segment revenue per passenger mile (all routes, carriers and classes)



Note: Local segment fares converted from USD to EUR based on average annual exchange rate
Source: Sabre Airport Data Intelligence

As illustrated below, fares at major hub airports (e.g. LHR, AMS and FRA) appear to have recovered more strongly.

Figure A- 2: Segment revenue per passenger mile (all routes, non-LCCs, economy class only)

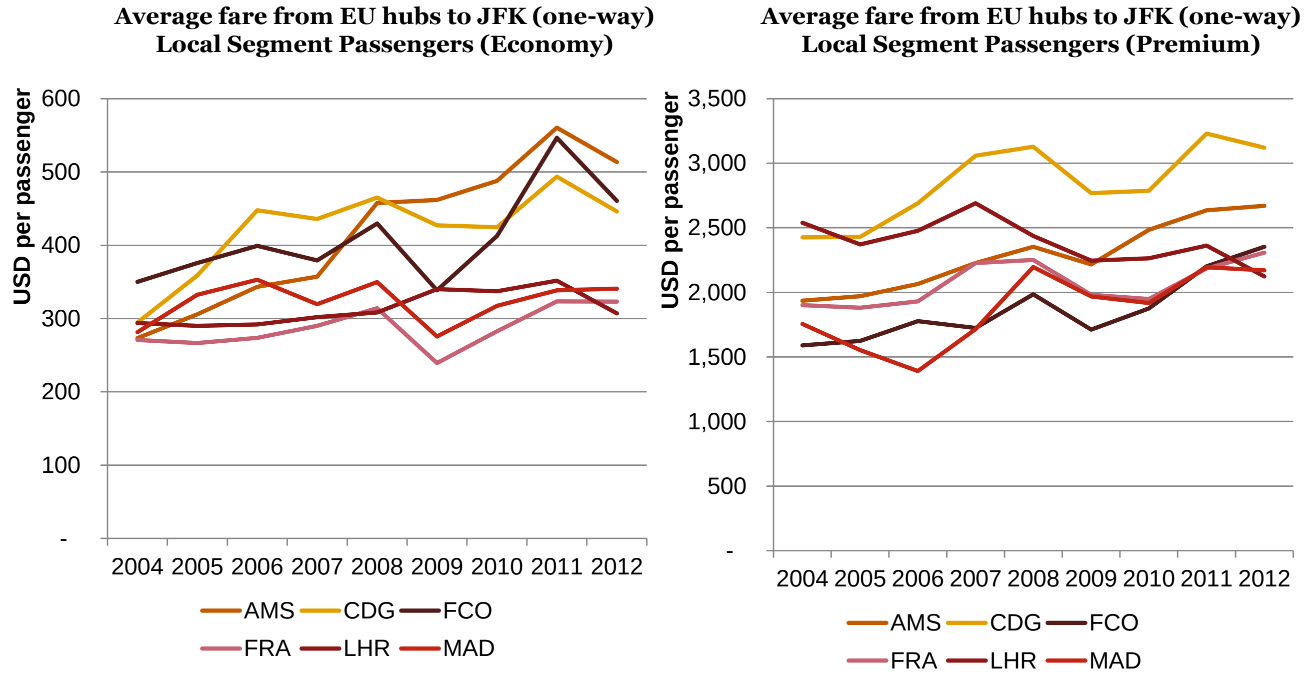


Note: Local segment fares converted from USD to EUR based on average annual exchange rate
Source: Sabre Airport Data Intelligence

A.2. Route level fares excluding taxes

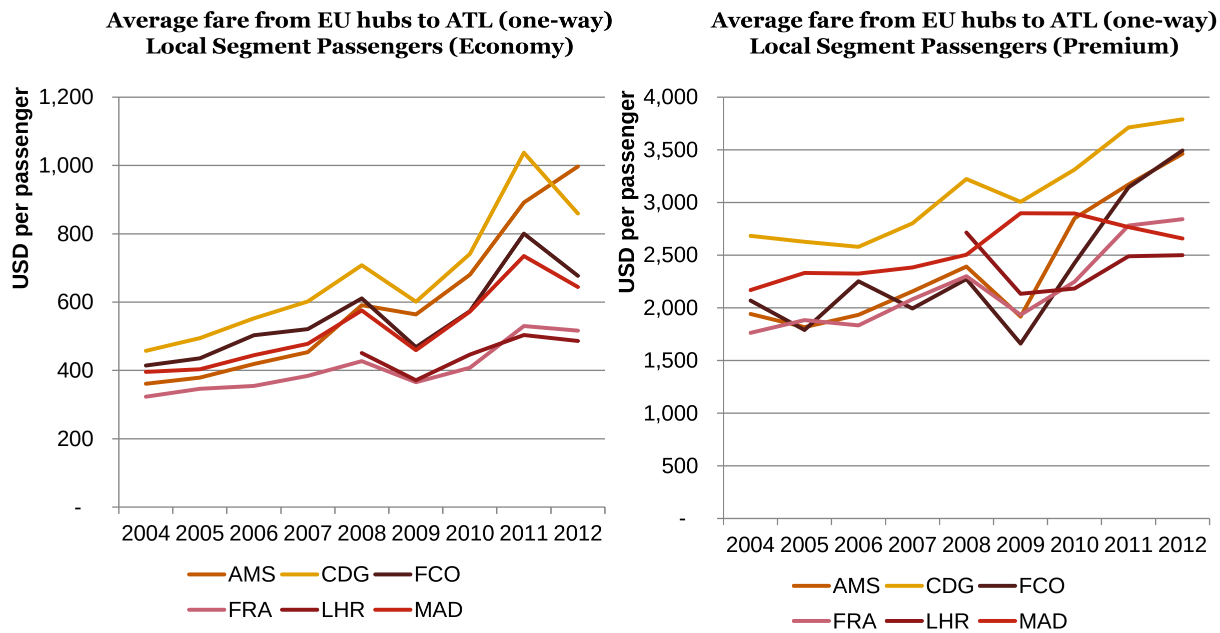
Even without the addition of taxes such as the APD, fares from LHR to JFK are still in the middle of the range compared to other EU hubs.

Figure A- 3: Fares from EU hubs to JFK



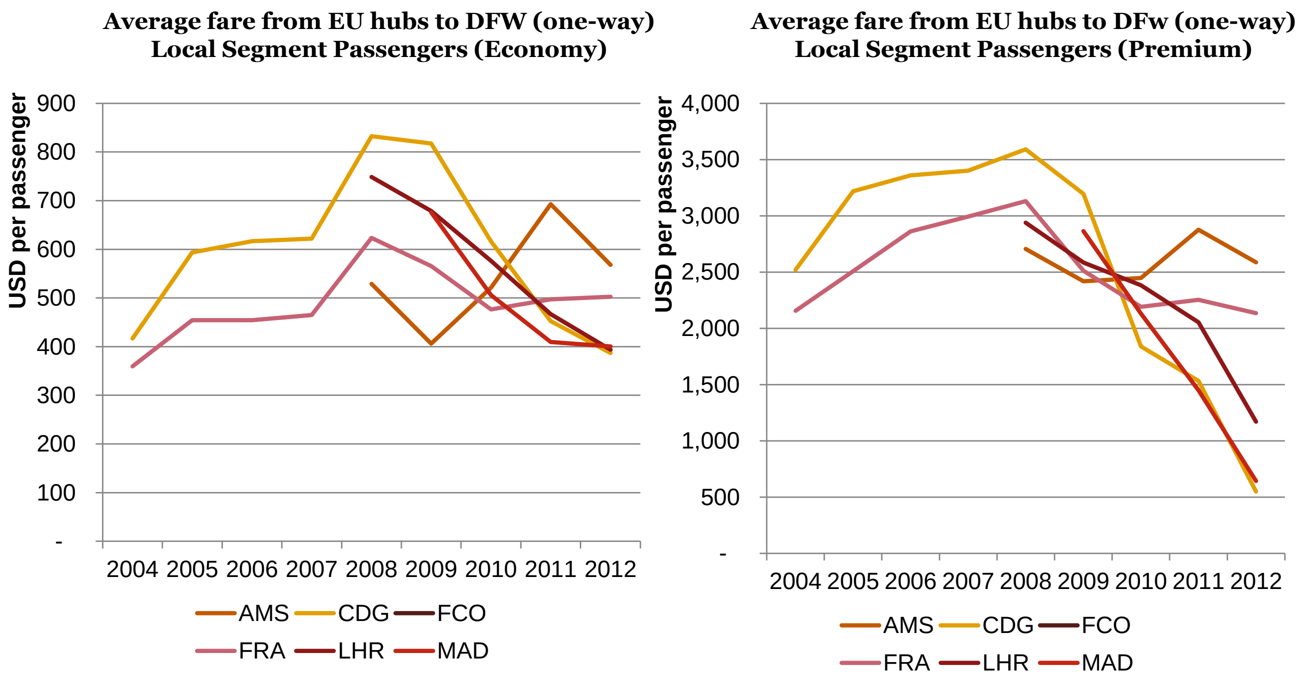
Fares to Atlanta have been increasing over the past 8 years. Similarly to what observed in the analysis of fares inclusive of taxes, fares from LHR and FRA are inexpensive relative to other EU hubs.

Figure A- 4: Fares from EU hubs to ATL



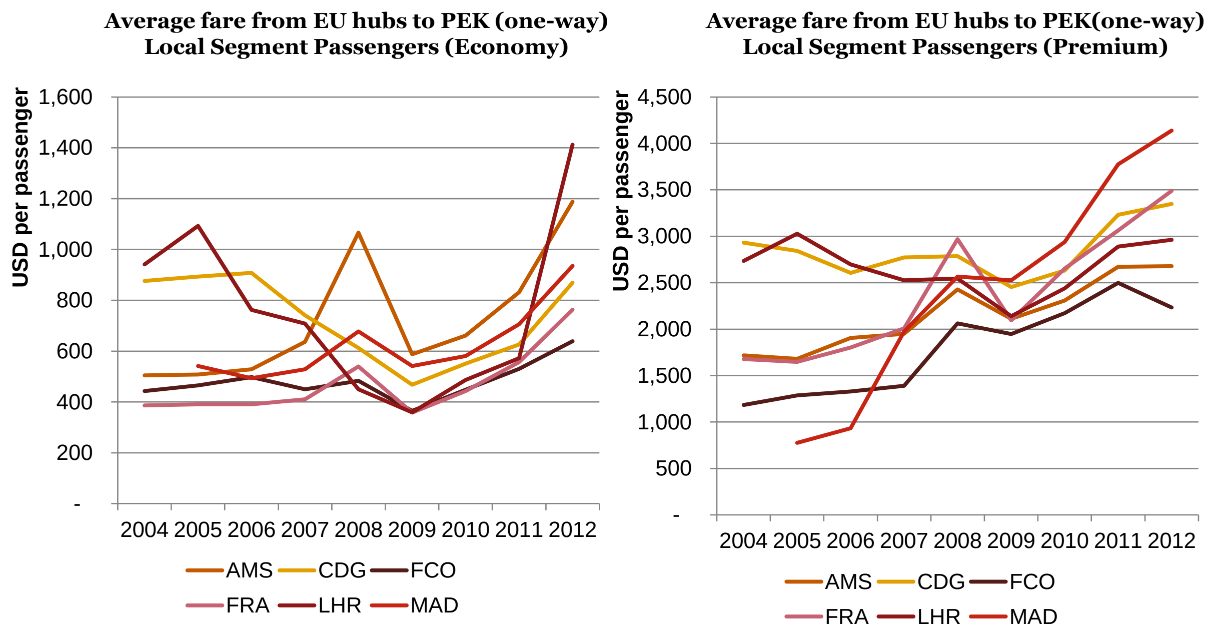
Fares from the selected European hubs to DFW have declined overtime following an increase in availability of direct capacity.

Figure A- 5: Fares from EU hubs to DFW



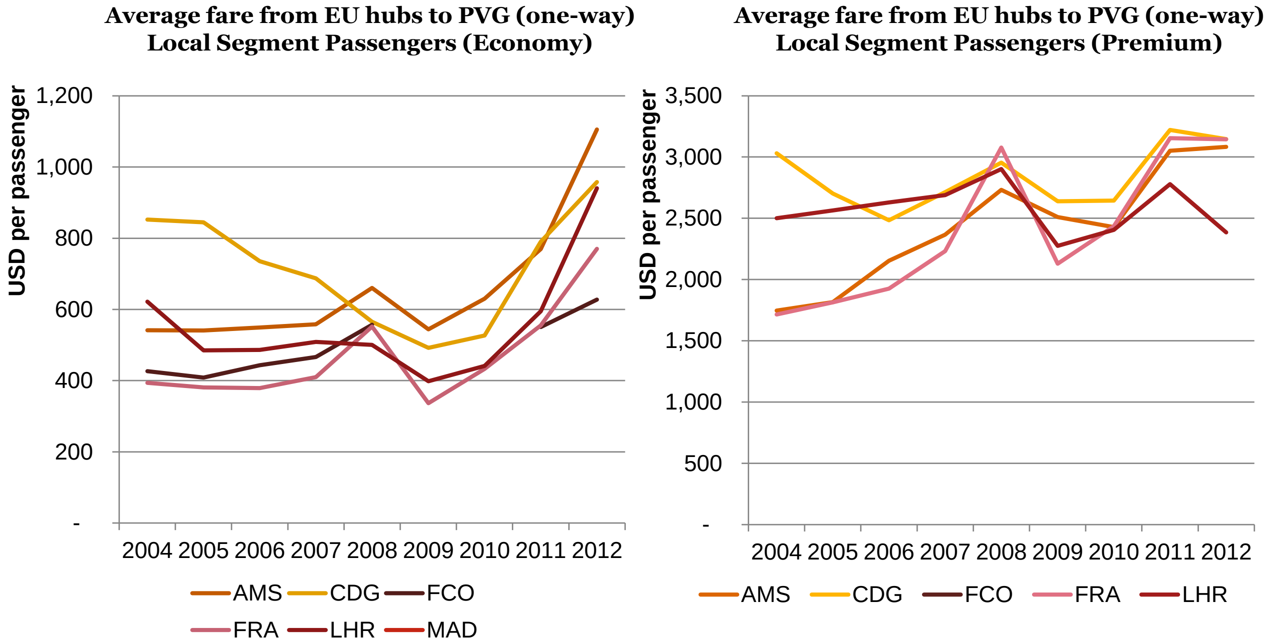
Similarly to what observed in the analysis carried out on fares inclusive of taxes, fares to Beijing have increased in later years with peaks in 2008 and 2012 associated with the Olympic Games.

Figure A- 6: Fares from EU hubs to PEK



Fares to PVG have also experienced an increase over the past few years across all EU hubs considered in the analysis.

Figure A- 7: Fares from EU hubs to PVG



As observed in the previous analysis inclusive of taxes, fares from LHR to BOM and DEL are particularly low when compared to other EU hubs. The drop in fares may be as a result of increased competition from Middle East hubs for flights to India.

Figure A- 8: Fares from EU hubs to BOM

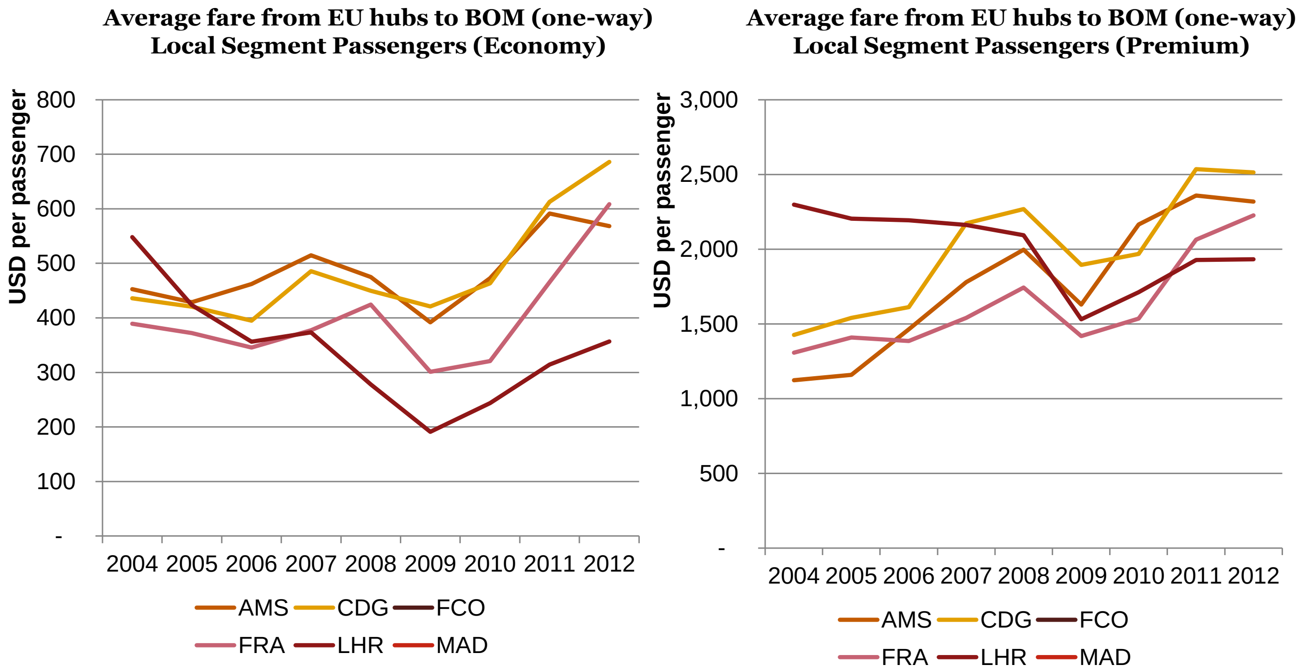
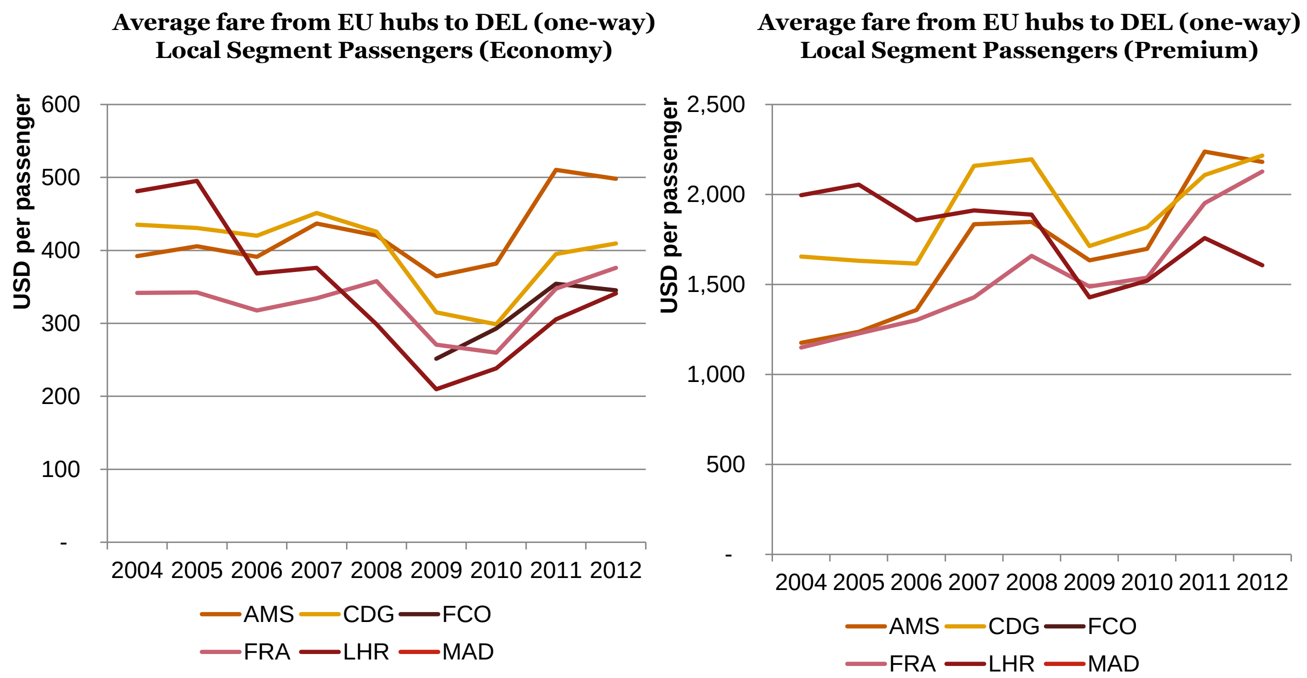
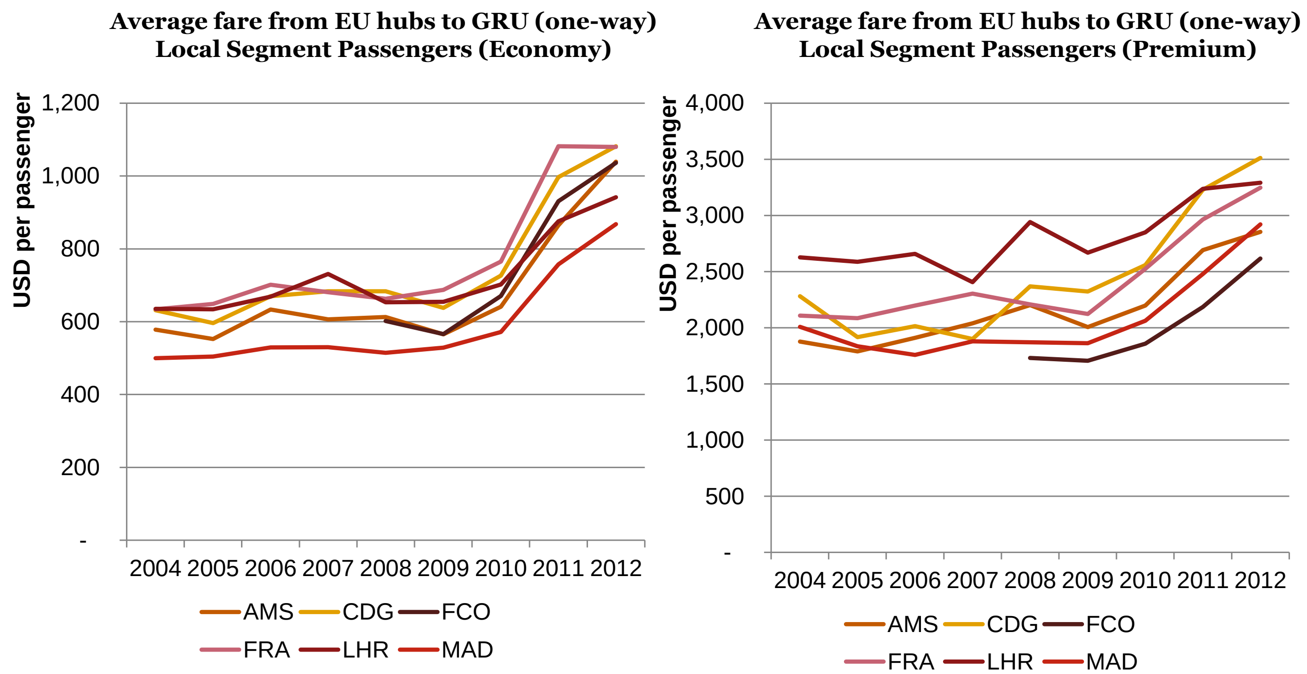


Figure A- 9: Fares from EU hubs to DEL



Fares to GRU appear to have started increasing since 2008. If inclusive of taxes, the premium fare from LHR to GRU is the highest, however, once taxes have been removed from the average fare in 2011 and 2012, CDG appears to be the hub with the highest premium fare.

Figure A- 10: Fares from EU hubs to GRU



Appendix B. - Variable Description

Variable	Description	Source
lcc	Dummy variable: 1 if airline is classified as an lcc	SRSanalyser definition of LCC
airlinesonroute	Count of different airlines operating on the specific route in that year	Sabre airport data intelligence (capacity report)
capacityconstraint	Dummy variable: 1 where capacity constraints exist	Based on analysis of capacity constrained airports and % utilisation of annual ATM capacity. Assumed that where utilisation is >95% that constraints exist. DfT, Eurocontrol, various airport websites, PwC analysis.
capacitymeasure	% utilisation of ATM capacity each year for UK airports, FRA, CDG, AMS, LIN and DUS	DfT, Eurocontrol, various airport websites, PwC analysis.
capacityfilter	Dummy variable: 1 if the origin airport is included in the capacity measure	
originhub	Dummy variable: 1 if the origin airport is classified as a hub	Based on 1 hub airport in each country considered in the analysis (i.e. LHR, FRA, CDG, MAD, FCO)
gdppcorigin	GDP per capacity of the origin country (USD, current prices)	IMF world economic outlook
gdppcdestination	GDP per capacity of the destination country (USD, current prices)	IMF world economic outlook
originairportsize	Total passenger throughput at origin airport each year	Sabre airport data intelligence (segment report)
destinationairportsize	Total passenger throughput at destination airport each year	Sabre airport data intelligence (segment report)
crudeoilprice	Annual average Brent Crude Oil price per barrel (USD)	Thomson Reuters Datastream
totalseatcapacity	Total available seat capacity on the route by that airline in that year (one-way)	Sabre airport data intelligence (capacity report)
totalfrequency	Total flight frequencies on the route in that year (one-way)	Sabre airport data intelligence (capacity report)
asm	Total available seat miles on the route in that year (one-way)	Sabre airport data intelligence (capacity report)
seatspermovement	Average seats per movement	totalseatcapacity/totalfrequency
distancemiles	Route distance (miles)	asm/totalseatcapacity
localsegmentpassengerstotal	Passengers on route with OD on the route (i.e. excludes transfers), all classes	Sabre airport data intelligence (segment report)
localsegementpassengerseconomy	Passengers on route with OD on the route (i.e. excludes transfers), economy classes	Sabre airport data intelligence (segment report)
localsegmentpassengerspremium	Passengers on route with OD on the route (i.e. excludes transfers), premium classes	Sabre airport data intelligence (segment report)
localsegmentrevenueusdtotal	Fare revenue for local segment passengers in all classes (in USD)	Sabre airport data intelligence (segment report)
localsegmentrevenueusdeconomy	Fare revenue for local segment passengers in economy classes (in USD)	Sabre airport data intelligence (segment report)
localsegmentrevenueusdpremium	Fare revenue for local segment passengers in business and first classes (in USD)	Sabre airport data intelligence (segment report)
passengermilestotal	Passenger miles travelled, all classes	localsegmentpassengerstotal x distancemiles
passengermileseconomy	Passenger miles travelled, economy classes	localsegmentpassengerseconomy x distancemiles

passengermilespremium	Passenger miles travelled, business and first classes	localsegmentpassengerspremium x distancemiles
revenueppmt	Revenue per passenger mile, all classes (USD)	localsegmentrevenueusdtotal/passengermilestotal
revenueppme	Revenue per passenger mile, economy classes (USD)	localsegmentrevenueusdeconomy/passengermileseconomy
revenueppmp	Revenue per passenger mile, business and first classes (USD)	localsegmentrevenueusdpremium/passengermilespremium
totalrevperpax	Revenue per passenger USD (all classes) excluding taxes	localsegmentrevenueusdtotal/localsegmentpassengerstotal
economyrevperpax	Revenue per passenger USD (economy classes) excluding taxes	localsegmentrevenueusdeconomy/localsegmentpassengerseconomy
premiumrevperpax	Revenue per passenger USD (business and first classes) excluding taxes	localsegmentrevenueusdpremium/localsegmentpassengerspremium
totalfarerevincltax	Total fare revenue include relevant passenger taxes (USD)	localsegmentrevenueusdtotal + total passenger taxes calculated based on class of travel and route
economyfarerevincltax	Economy fare revenue include relevant passenger taxes (USD)	localsegmentrevenueusdeconomy + economy passenger taxes calculated based route
premiumfarerevincltax	First and business fare revenue include relevant passenger taxes (USD)	localsegmentrevenueusdpremium + business and first class passenger taxes calculated based route
totalfareppinctax	Revenue per passenger USD (all classes) including taxes	totalfarerevincltax/localsegmentpassengerstotal
economyfareppinctax	Revenue per passenger USD (economy classes) including taxes	economyfarerevincltax/localsegmentpassengerseconomy
premiumfareppinctax	Revenue per passenger USD (business and first classes) including taxes	premiumfarerevincltax/localsegmentpassengerspremium
totalfareppmincltax	Revenue per passenger mile, all classes (USD) including taxes	totalfarerevincltax/passengermilestotal
economyfareppmincltax	Revenue per passenger mile, economy classes (USD) including taxes	economyfarerevincltax/passengermileseconomy
premiumfareppmincltax	Revenue per passenger mile, business and first classes (USD) including taxes	premiumfarerevincltax/passengermilespremium
originairportcharge	Origin airport aeronautical revenue / pax (GBP)	Leighfisher
destinationairportcharge	Destination airport aeronautical revenue / pax (GBP)	Leighfisher

Appendix C. - Regression outputs

C.1. Model Outputs (aggregate model)

All classes, all routes
excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	66167
Method: Pooled OLS	Number of groups	=	18585
Group variable (i): routeid	F(8, 8)	=	21860.45
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.6276
	Root MSE	=	0.4593

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1644745	.0169816	9.69	0.000	.1253148	.2036342
lairlinesonroute	-.0722444	.0076904	-9.39	0.000	-.0899785	-.0545102
lseatspermovement	-.0822289	.0190299	-4.32	0.003	-.1261118	-.0383459
ldistancemiles	-.4692694	.0249137	-18.84	0.000	-.5267204	-.4118183
capacityconstraint	.175845	.0073896	23.80	0.000	.1588044	.1928855
llocalsegmentpassengerstotal	-.1049289	.0132925	-7.89	0.000	-.1355816	-.0742763
lgdppcorigincountry	.4031989	.0576636	6.99	0.000	.2702265	.5361713
lgdppcdestinationcountry	.0148442	.0120625	1.23	0.253	-.0129719	.0426604
_cons	-1.954177	.4532902	-4.31	0.003	-2.999466	-.9088884

Economy class, all routes
excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	66122
Method: Pooled OLS	Number of groups	=	18565
Group variable (i): routeid	F(8, 8)	=	87225.69
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.6814
	Root MSE	=	0.4293

leconomyfppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1109081	.016425	6.75	0.000	.073032	.1487843
lairlinesonroute	-.0863057	.0069371	-12.44	0.000	-.1023026	-.0703087
lseatspermovement	-.1135624	.0124095	-9.15	0.000	-.1421788	-.0849459
ldistancemiles	-.5317787	.0205791	-25.84	0.000	-.5792342	-.4843231
capacityconstraint	.0986155	.0067325	14.65	0.000	.0830904	.1141406
llocalsegmentpassengerstotal	-.0710635	.0117051	-6.07	0.000	-.0980554	-.0440715
lgdppcorigincountry	.3893159	.0616598	6.31	0.000	.2471281	.5315037
lgdppcdestinationcountry	-.0013793	.0118068	-0.12	0.910	-.0286058	.0258473
_cons	-1.171662	.4612352	-2.54	0.035	-2.235272	-.1080519

Premium classes, all routes
excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	45596
Method: Pooled OLS	Number of groups	=	11777
Group variable (i): routeid	F(8, 8)	=	32062.84
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.3651
	Root MSE	=	0.7204

lpremiumfppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.3635038	.0210696	17.25	0.000	.3149173	.4120904
lairlinesonroute	.0534428	.0130924	4.08	0.004	.0232517	.0836339
lseatspermovement	-.0927483	.0510238	-1.82	0.107	-.2104094	.0249127
ldistancemiles	-.211172	.0118564	-17.81	0.000	-.2385129	-.183831
capacityconstraint	.2894685	.0585665	4.94	0.001	.1544139	.4245232
llocalsegmentpassengerstotal	-.2776403	.0230311	-12.06	0.000	-.33075	-.2245305
lgdppcorigincountry	.6204634	.1831741	3.39	0.010	.1980632	1.042864
lgdppcdestinationcountry	.0573246	.0215202	2.66	0.029	.0076989	.1069503
_cons	-5.142379	2.116863	-2.43	0.041	-10.02387	-.2608844

All classes, short-haul routes (<2000miles)

excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	53617
Method: Pooled OLS	Number of groups	=	15584
Group variable (i): routeid	F(8, 8)	=	932253.96
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.6906
	Root MSE	=	0.4155

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.0839141	.0139798	6.00	0.000	.0516767	.1161515
lairlinesonroute	-.0569549	.0115514	-4.93	0.001	-.0835926	-.0303173
lseatspermovement	-.1877757	.0230265	-8.15	0.000	-.2408749	-.1346765
ldistancemiles	-.6876504	.0078587	-87.50	0.000	-.7057727	-.6695281
capacityconstraint	.1308871	.0072863	17.96	0.000	.114085	.1476893
llocalsegmentpassengerstotal	-.0478849	.0085733	-5.59	0.001	-.067655	-.0281148
lgdppcorigincountry	.3229036	.0597426	5.40	0.001	.1851368	.4606703
lgdppcdestinationcountry	.0142481	.0192711	0.74	0.481	-.0301911	.0586873
_cons	.5852007	.6396501	0.91	0.387	-.8898352	2.060237

Economy classes, short-haul routes (<2000miles)

excludes LCCs

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     53584
Method: Pooled OLS                               Number of groups  =     15567
Group variable (i): routeid                      F(  8,      8)    =  27895.20
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.6906
                                                 Root MSE          =    0.4091

------------------------------------------------------------------------------------------
                          |             Drisc/Kraay
       leconomyfppmincltax |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
          ltotalfrequency |   .0611807   .0125543     4.87   0.001     .0322305    .0901309
         lairlinesonroute |  -.0778205   .0101662    -7.65   0.000    -.1012638   -.0543773
       lseatspermovement  |  -.1856248   .0212233    -8.75   0.000    -.2345658   -.1366839
           ldistancemiles |  -.6968996   .0088259   -78.96   0.000    -.7172523    -.676547
       capacityconstraint |   .0808721   .0093445     8.65   0.000     .0593235    .1024206
llocalsegmentpassengerstotal |  -.0337395   .0078283    -4.31   0.003    -.0517915   -.0156874
       lgdppcorigincountry |   .3549012   .0812405     4.37   0.002     .1675602    .5422422
  lgdppcdestinationcountry |   .0148015    .019474     0.76   0.469    -.0301057    .0597088
                     _cons |   .2693051   .8024914     0.34   0.746    -1.581243    2.119854
------------------------------------------------------------------------------------------
```

Premium classes, short-haul routes (<2000miles)

excludes LCCs

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     35379
Method: Pooled OLS                               Number of groups  =      9567
Group variable (i): routeid                      F(  8,      8)    =   4682.71
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3945
                                                 Root MSE          =    0.7163

------------------------------------------------------------------------------------------
                          |             Drisc/Kraay
       lpremiumfppmincltax |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------------+---------------------------------------------------------------
          ltotalfrequency |   .2840528   .0313371     9.06   0.000     .2117893    .3563164
         lairlinesonroute |    .093116   .0196706     4.73   0.001     .0477555    .1384765
        lseatspermovement |  -.2278596   .0583033    -3.91   0.004    -.3623072   -.0934121
           ldistancemiles |  -.4182575   .0123658   -33.82   0.000    -.4467731   -.3897419
       capacityconstraint |   .2830837   .0541796     5.22   0.001     .1581454     .408022
llocalsegmentpassengerstotal |  -.2207371   .0304594    -7.25   0.000    -.2909766   -.1504976
       lgdppcorigincountry |   .5601601   .2506207     2.24   0.056    -.0177723    1.138092
  lgdppcdestinationcountry |   .0667734    .032375     2.06   0.073    -.0078834    .1414302
                     _cons |  -2.862405    2.91341    -0.98   0.355    -9.58074    3.855931
```

All classes, medium-long haul routes (>2000miles)

excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	12545
Method: Pooled OLS	Number of groups	=	3008
Group variable (i): routeid	F(8, 8)	=	11777.14
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.2183
	Root MSE	=	0.4059

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1941832	.0180951	10.73	0.000	.1524559	.2359105
lairlinesonroute	-.0806823	.0103777	-7.77	0.000	-.1046133	-.0567514
lseatspermovement	-.0208184	.0446407	-0.47	0.653	-.12376	.0821232
ldistancemiles	-.1108866	.0230554	-4.81	0.001	-.1640525	-.0577207
capacityconstraint	.1289535	.0178454	7.23	0.000	.087802	.170105
llocalsegmentpassengerstotal	-.109458	.0083482	-13.11	0.000	-.128709	-.090207
lgdppcorigincountry	.3245437	.0656107	4.95	0.001	.173245	.4758424
lgdppcdestinationcountry	.0106421	.0047737	2.23	0.056	-.0003661	.0216504
_cons	-4.243251	.9423017	-4.50	0.002	-6.416202	-2.070299

Economy classes, medium-long haul routes (>2000miles)

excludes LCCs

Regression with Driscoll-Kraay standard errors	Number of obs	=	12533
Method: Pooled OLS	Number of groups	=	3005
Group variable (i): routeid	F(8, 8)	=	4979.69
maximum lag: 2	Prob > F	=	0.0000
	R-squared	=	0.1090
	Root MSE	=	0.3537

leconomyfppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.0733597	.019728	3.72	0.006	.0278669	.1188525
lairlinesonroute	-.082022	.0118351	-6.93	0.000	-.1093138	-.0547302
lseatspermovement	-.0677275	.0678955	-1.00	0.348	-.2242949	.0888399
ldistancemiles	-.2079273	.0223393	-9.31	0.000	-.2594418	-.1564127
capacityconstraint	.0319855	.0201798	1.59	0.152	-.0145493	.0785202
llocalsegmentpassengerstotal	-.0539539	.0094303	-5.72	0.000	-.0757003	-.0322075
lgdppcorigincountry	.2572895	.0577691	4.45	0.002	.1240736	.3905053
lgdppcdestinationcountry	-.0167133	.0058958	-2.83	0.022	-.0303091	-.0031176
_cons	-2.374639	.8988729	-2.64	0.030	-4.447443	-.3018341

Economy classes, medium-long haul routes (>2000miles)

excludes LCCs

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     12533
Method: Pooled OLS                               Number of groups  =      3005
Group variable (i): routeid                      F(  8,       8)   =   4979.69
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.1090
                                                 Root MSE          =    0.3537
```

leconomyfppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.0733597	.019728	3.72	0.006	.0278669	.1188525
lairlinesonroute	-.082022	.0118351	-6.93	0.000	-.1093138	-.0547302
lseatspermovement	-.0677275	.0678955	-1.00	0.348	-.2242949	.0888399
ldistancemiles	-.2079273	.0223393	-9.31	0.000	-.2594418	-.1564127
capacityconstraint	.0319855	.0201798	1.59	0.152	-.0145493	.0785202
llocalsegmentpassengerstotal	-.0539539	.0094303	-5.72	0.000	-.0757003	-.0322075
lgdppcorigincountry	.2572895	.0577691	4.45	0.002	.1240736	.3905053
lgdppcdestinationcountry	-.0167133	.0058958	-2.83	0.022	-.0303091	-.0031176
_cons	-2.374639	.8988729	-2.64	0.030	-4.447443	-.3018341

Premium classes, medium-long haul routes (>2000miles)
excludes LCCs

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     10217
Method: Pooled OLS                               Number of groups  =      2216
Group variable (i): routeid                      F(  8,       8)   =    687.83
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.2608
                                                 Root MSE          =    0.6056
```

lpremiumfppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.3508252	.0267954	13.09	0.000	.2890348	.4126156
lairlinesonroute	-.143688	.0315553	-4.55	0.002	-.2164547	-.0709212
lseatspermovement	.0348757	.050686	0.69	0.511	-.0820065	.1517578
ldistancemiles	.1217516	.0844784	1.44	0.187	-.073056	.3165591
capacityconstraint	.2362527	.0638193	3.70	0.006	.0890851	.3834204
llocalsegmentpassengerstotal	-.1771984	.0112063	-15.81	0.000	-.2030401	-.1513567
lgdppcorigincountry	.4995843	.090742	5.51	0.001	.2903329	.7088357
lgdppcdestinationcountry	.013586	.0116026	1.17	0.275	-.0131697	.0403417
_cons	-7.552798	1.353266	-5.58	0.001	-10.67343	-4.432162

C.2. Model outputs (UK airports only)

Including only UK airports in the analysis indicates a positive and significant impact of capacity constraints of 10% on fares. The lower effect when looking at the UK only is likely to be a result of the larger proportion of passengers flying from constrained airports in the UK compared with the full sample. Therefore, the relative impact of the constraint in the sample is lower.

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     11114
Method: Pooled OLS                               Number of groups  =      3512
Group variable (i): routeid                      F(  8,      8)    =   8076.78
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.6829
                                                 Root MSE          =    0.4183
```

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1471955	.0265849	5.54	0.001	.0858907	.2085003
lairlinesonroute	-.0169517	.0214837	-0.79	0.453	-.0664931	.0325897
lseatspermovement	-.1310283	.0237759	-5.51	0.001	-.1858557	-.0762009
ldistancemiles	-.4055981	.0436558	-9.29	0.000	-.5062684	-.3049277
capacityconstraint	.1043413	.0350214	2.98	0.018	.0235818	.1851009
llocalsegmentpassengerstotal	-.0794394	.013911	-5.71	0.000	-.1115181	-.0473606
lgdppcorigincountry	.5565339	.2195002	2.54	0.035	.0503656	1.062702
lgdppcdestinationcountry	.0407529	.0110454	3.69	0.006	.0152822	.0662235
_cons	-3.958181	2.229636	-1.78	0.114	-9.099731	1.183369

C.3. Testing the effect of time

Testing for time fixed-effect using a regression with Driscoll-Kraay standard errors indicates that time trend is needed, however, the effect on the capacity constraint coefficient is not material.

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     66165
Method: Pooled OLS                               Number of groups  =     18584
Group variable (i): routeid                      F( 16,      8)    = 105390.16
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.6391
                                                 Root MSE          =    0.4515
```

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1673527	.0167997	9.96	0.000	.1286126	.2060928
lairlinesonroute	-.0733434	.0070201	-10.45	0.000	-.0895316	-.0571551
lseatspermovement	-.0770975	.020229	-3.81	0.005	-.1237457	-.0304492
ldistancemiles	-.4715805	.0251683	-18.74	0.000	-.5296187	-.4135423
capacityconstraint	.1679793	.0137822	12.19	0.000	.1361975	.1997612
llocalsegmentpassengerstotal	-.1071763	.0136715	-7.84	0.000	-.1387028	-.0756497
lgdppcorigincountry	.4562956	.0416367	10.96	0.000	.3602813	.5523099
lgdppcdestinationcountry	.0146072	.0107496	1.36	0.211	-.0101816	.0393959
_Iyear_2005	-.0336554	.0029606	-11.37	0.000	-.0404825	-.0268284
_Iyear_2006	-.0509306	.002937	-17.34	0.000	-.0577034	-.0441577
_Iyear_2007	-.0476273	.0046734	-10.19	0.000	-.0584041	-.0368505
_Iyear_2008	.1069828	.0050211	21.31	0.000	.0954042	.1185614
_Iyear_2009	-.0221416	.0033736	-6.56	0.000	-.0299212	-.014362
_Iyear_2010	-.1885228	.0053846	-35.01	0.000	-.2009398	-.1761059
_Iyear_2011	-.1158775	.005805	-19.96	0.000	-.1292638	-.1024912
_Iyear_2012	-.0417345	.0037336	-11.18	0.000	-.0503442	-.0331248
_cons	-2.453893	.3655255	-6.71	0.000	-3.296797	-1.61099

The following test shows that the time dummies are different from 0, therefore a time dummy is required.

H0: The time dummies are equal to zero

P < 0.05, therefore H0 is rejected.

```
( 1)  _Iyear_2005 = 0
( 2)  _Iyear_2006 = 0
( 3)  _Iyear_2007 = 0
( 4)  _Iyear_2008 = 0
( 5)  _Iyear_2009 = 0
( 6)  _Iyear_2010 = 0
( 7)  _Iyear_2011 = 0
( 8)  _Iyear_2012 = 0

      F(  8,     8) = 9.6e+07
           Prob > F =    0.0000
```

We also tested pre-financial crises (2004-2008) and post financial crises (2008-2012) to test whether the coefficient for capacity constraint changes. The coefficients remain fairly consistent across both time periods.

2004 - 2008

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|
ltotalfrequency	.1648541	.0080233	20.55	0.000
lairlinesonroute	-.0643455	.0044693	-14.40	0.000
lseatspermovement	-.0927113	.0257112	-3.61	0.023
ldistancemiles	-.502807	.009445	-53.24	0.000
capacityconstraint	.176181	.0169783	10.38	0.000
llocalsegmentpassengerstotal	-.0994398	.0100767	-9.87	0.001
lgdppcorigincountry	.5301889	.0271737	19.51	0.000
lgdppcdestinationcountry	.0062829	.013414	0.47	0.664
_cons	-2.902903	.3137429	-9.25	0.001

2009 - 2012

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|
ltotalfrequency	.1575607	.0454947	3.46	0.041
lairlinesonroute	-.0857962	.0116539	-7.36	0.005
lseatspermovement	-.0508119	.0125566	-4.05	0.027
ldistancemiles	-.4281388	.028783	-14.87	0.001
capacityconstraint	.1688395	.0040046	42.16	0.000
llocalsegmentpassengerstotal	-.1069827	.0330049	-3.24	0.048
lgdppcorigincountry	.3989781	.063499	6.28	0.008
lgdppcdestinationcountry	.0349213	.0018323	19.06	0.000
_cons	-2.528443	.8146236	-3.10	0.053

C.4. Testing the effect of airport size

Constraints have a more significant impact on smaller airports

Category	Size	Airports	Airports with capacity data	Airports with capacity constraint
Small (<10mppa)	< 10 mppa	88	27	3
Medium (10-40 mppa)	10 - 40 mppa	14	4	2
Large (>40mppa)	> 40 mppa	5	4	2

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|
ltotalfrequency	.1574499	.0167118	9.42	0.000
lairlinesonroute	-.0710495	.0070476	-10.08	0.000
lseatspermovement	-.083457	.0184579	-4.52	0.002
ldistancemiles	-.4699404	.0240999	-19.50	0.000
interactionconstraintsmall	.4316618	.0480165	8.99	0.000
interactionconstraintmedium	.0120433	.0235902	0.51	0.623
interactionconstraintlarge	.2296871	.0167717	13.69	0.000
llocalsegmentpassengerstotal	-.0994987	.0128664	-7.73	0.000
lgdppcorigincountry	.4159985	.0570783	7.29	0.000
lgdppcdestinationcountry	.0154962	.0116882	1.33	0.222
_cons	-2.095573	.4800983	-4.36	0.002

C.4.1. Testing for non-linearity of the capacity constraint measure

There isn't clear evidence of non-linearity of the capacity constraint measure

We test for non-linearity by including the square of the capacity constraint variable as an additional variable. We find no evidence of non-linearity. Although the sign on the square of capacity constraint is negative, the coefficient is insignificant.

totalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|
totalfrequency	.0002383	8.35e-06	28.53	0.000
airlinesonroute	.0034093	.0030002	1.14	0.289
seatspermovement	-.0008823	.0000715	-12.34	0.000
distancemiles	-.0000141	2.90e-06	-4.85	0.001
capacitymeasure	-.0422618	.043029	-0.98	0.355
localsegmentpassengerstotal	-2.69e-06	8.77e-08	-30.64	0.000
gdppcorigincountry	-2.05e-06	1.43e-06	-1.43	0.190
gdppcdestinationcountry	3.23e-06	2.78e-07	11.62	0.000
_cons	.4486353	.0653888	6.86	0.000

totalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|
totalfrequency	.0002376	8.16e-06	29.13	0.000
airlinesonroute	.0040685	.0028146	1.45	0.186
seatspermovement	-.0008852	.0000749	-11.82	0.000
distancemiles	-.0000134	2.87e-06	-4.67	0.002
capacitymeasure	-.566348	.1252091	-4.52	0.002
sqcapacitymeasure	.3561738	.0612324	5.82	0.000
localsegmentpassengerstotal	-2.64e-06	7.83e-08	-33.70	0.000
gdppcorigincountry	-3.03e-07	1.38e-06	-0.22	0.831
gdppcdestinationcountry	3.14e-06	2.83e-07	11.07	0.000
_cons	.5759067	.0868526	6.63	0.000

C.5. Inclusion of airport charges

Destination airport charge is not significant when origin airport charge is included

```
Regression with Driscoll-Kraay standard errors   Number of obs     =      3099
Method: Pooled OLS                               Number of groups  =       858
Group variable (i): routeid                      F( 10,       6)   =    276.52
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.6602
                                                 Root MSE          =    0.3917
```

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.0716289	.0115136	6.22	0.001	.0434561	.0998017
lairlinesonroute	-.0363328	.0315792	-1.15	0.294	-.1136044	.0409387
lseatspermovement	-.184446	.0200922	-9.18	0.000	-.2336097	-.1352822
ldistancemiles	-.5352798	.0121872	-43.92	0.000	-.5651009	-.5054587
capacityconstraint	.1039126	.0087597	11.86	0.000	.0824783	.1253468
llocalsegmentpassengerstotal	-.03689	.0114084	-3.23	0.018	-.0648053	-.0089747
lgdppcorigincountry	.1263487	.0551022	2.29	0.062	-.0084815	.261179
lgdppcdestinationcountry	-.0480668	.0325987	-1.47	0.191	-.1278331	.0316994
loriginairportcharge	.184765	.0441409	4.19	0.006	.076756	.292774
ldestinationairportcharge	.004092	.0218618	0.19	0.858	-.0494019	.0575859
_cons	1.984636	.5696139	3.48	0.013	.5908407	3.378431

The impact of including the origin airport charge reduces the impact of the capacity constraint – indicating possible autocorrelation or issues with the data

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     20616
Method: Pooled OLS                               Number of groups  =      6044
Group variable (i): routeid                      F(  9,       6)   =   1074.81
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.6665
                                                 Root MSE          =    0.4273
```

ltotalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
ltotalfrequency	.1574666	.0201713	7.81	0.000	.1081091	.206824
lairlinesonroute	-.0476714	.0140577	-3.39	0.015	-.0820693	-.0132734
lseatspermovement	-.0573348	.0167796	-3.42	0.014	-.0983929	-.0162767
ldistancemiles	-.443115	.0149145	-29.71	0.000	-.4796094	-.4066205
capacityconstraint	.0134189	.0112437	1.19	0.278	-.0140934	.0409313
llocalsegmentpassengerstotal	-.1040594	.0094157	-11.05	0.000	-.1270986	-.0810201
lgdppcorigincountry	-.0737208	.0713424	-1.03	0.341	-.2482894	.1008478
lgdppcdestinationcountry	.0376849	.0135569	2.78	0.032	.0045123	.0708576
loriginairportcharge	.2588741	.0703063	3.68	0.010	.0868408	.4309074
_cons	1.866488	.7508412	2.49	0.047	.029246	3.70373

Including both origin and destination airport charges in the linear model does not yield significant results

```
Regression with Driscoll-Kraay standard errors   Number of obs     =      3378
Method: Pooled OLS                               Number of groups  =       887
Group variable (i): routeid                      F( 10,       6)   =   1012.80
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.2500
                                                 Root MSE          =    0.2756
```

totalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
totalfrequency	.0001404	5.21e-06	26.94	0.000	.0001276	.0001531
airlinesonroute	.0179823	.0040828	4.40	0.005	.0079921	.0279724
seatspermovement	-.0009693	.0000384	-25.22	0.000	-.0010633	-.0008752
distancemiles	-.0000396	5.08e-06	-7.78	0.000	-.000052	-.0000271
capacityconstraint	.0433623	.0090357	4.80	0.003	.0212527	.0654719
localsegmentpassengerstotal	-1.76e-06	2.26e-07	-7.77	0.000	-2.31e-06	-1.21e-06
gdppcorigincountry	-1.82e-06	8.28e-07	-2.20	0.070	-3.85e-06	2.04e-07
gdppcdestinationcountry	8.06e-07	1.22e-07	6.62	0.001	5.08e-07	1.10e-06
originairportchargeusd	.0018761	.0017286	1.09	0.319	-.0023537	.0061058
destinationairportchargeusd	-.0012951	.0017203	-0.75	0.480	-.0055046	.0029143
_cons	.5259337	.0184946	28.44	0.000	.480679	.5711884

Including the origin airport charge in the linear model leads to the capacity constraint variable becoming insignificant

```
Regression with Driscoll-Kraay standard errors   Number of obs     =     21421
Method: Pooled OLS                               Number of groups  =      6151
Group variable (i): routeid                      F(  9,      6)    =  10012.54
maximum lag: 2                                   Prob > F          =    0.0000
                                                 R-squared         =    0.3583
                                                 Root MSE          =    0.2391
```

totalrppmincltax	Coef.	Drisc/Kraay Std. Err.	t	P>|t|	[95% Conf.	Interval]
totalfrequency	.0001786	.0000141	12.65	0.000	.000144	.0002131
airlinesonroute	.0101742	.0030207	3.37	0.015	.0027828	.0175655
seatspermovement	-.0009046	.0000808	-11.19	0.000	-.0011024	-.0007069
distancemiles	-.0000211	2.16e-06	-9.79	0.000	-.0000264	-.0000158
capacityconstraint	.0105171	.0037591	2.80	0.031	.0013188	.0197154
localsegmentpassengerstotal	-2.24e-06	2.26e-07	-9.93	0.000	-2.79e-06	-1.69e-06
gdppcorigincountry	9.12e-07	1.37e-06	0.66	0.531	-2.44e-06	4.27e-06
gdppcdestinationcountry	3.12e-06	9.16e-08	34.07	0.000	2.90e-06	3.34e-06
originairportchargeusd	.003623	.0015021	2.41	0.052	-.0000525	.0072986
_cons	.2983799	.0318463	9.37	0.000	.2204548	.3763051

C.6. Regression outputs (aggregate model with fares exclusive of taxes)

The table below presents the coefficients which resulted from the analysis of fares exclusive of taxes. Given that UK airports are highly constrained and have the highest taxes, the impact of capacity constraint with taxes is expected to be lower, however, there is still a clear effect of capacity constraints on fares.

Table C- 1: Coefficient for capacity constraint

	Total	Economy	Premium
Total	0.15***	0.06***	0.26***
Short-haul	0.11***	0.05***	0.27***
Medium-Long haul	0.10***	-0.01	0.21**

Significant at *** for 1%, ** for 5% and * for 10%
Note: log-log model, capacity constraint dummy not logged. All routes, excluding LCCs.

Appendix D. - Robustness tests

We have used robustness tests that have been adapted to panel data analysis, the results have been provided below. The upshot of these tests have resulted in us applying a regression approach with Driscoll-Kraay standard errors. Under this approach, the error structure is assumed to be heteroskedastic, autocorrelated up to some lag, and possibly correlated between the groups (panels).

D.1. Hausman test Random Effect (RE) vs. Fixed Effect (FE)

The Hausman test suggests that FE should be used. However, the sign on GDP of country of origin is negative. We therefore run some additional test on the FE model to ensure that other econometrics problems are not driving our results.

```
    Test:  Ho:  difference in coefficients not systematic

                  chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      342.82
                Prob>chi2 =      0.0000
```

D.2. Modified Wald test for groupwise heteroskedasticity in fixed effect regression model

The Modified Wald test for groupwise heteroskedasticity in fixed effect regression model suggest that the null hypothesis of no groupwise heteroskedasticity should be rejected.

```
Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (15584)  = 1.4e+37
Prob>chi2 =      0.0000
```

D.3. Wooldridge test for autocorrelation

The Wooldridge test for autocorrelation suggests shows that the null hypothesis of no first order autocorrelation should rejected.

```
Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation
    F(  1,    6944) =    734.703
           Prob > F =      0.0000
```

D.4. Pesaran cross-sectional dependence test (CD)

We were unable to run the Pesaran cross-sectional dependence test (CD) because of how large our data set was. Though, the heteroskedasticity and autocorrelation test could be used as indirect evidence of cross-sectional dependence.

Appendix E. - IATA Code Glossary

IATA Code	Airport	Country
ABZ	Aberdeen	UK
AMS	Amsterdam	Netherlands
ATL	Atlanta	United States
BCN	Barcelona	Spain
BFS	Belfast International	UK
BHD	Belfast City	UK
BHX	Birmingham	UK
BLK	Blackpool	UK
BOH	Bournemouth	UK
BOM	Mumbai	India
BRS	Bristol	UK
CDG	Paris Charles de Gaulle	France
CVT	Coventry	UK
CWL	Cardiff	UK
DEL	Delhi	India
DFW	Dallas Fort Worth	United States
DSA	Doncaster Sheffield	UK
DUS	Dusseldorf	Germany
EDI	Edinburgh	UK
EMA	East Midlands	UK
EXT	Exeter	UK
FCO	Rome Fiumicino	Italy
FRA	Frankfurt	Germany
GLA	Glasgow	UK
GRU	Sao Paulo Guarulhos	Brazil
HUY	Humberside	UK
INV	Inverness	UK
JFK	New York Kennedy	United States
LBA	Leeds Bradford	UK
LCY	London City	UK
LGW	Gatwick	UK
LHR	London Heathrow	UK
LIN	Milan Linate	Italy
LPL	Liverpool	UK
LTN	Luton	UK
MAD	Madrid	Spain
MAN	Manchester	UK
MME	Manston	UK
NCL	Newcastle	UK
NQY	Newquay	UK
NWI	Norwich	UK
ORY	Paris Orly	France
PEK	Beijing	China
PIK	Glasgow Prestwick	UK
PVG	Shanghai	China
SEN	Southend	UK
SOU	Southampton	UK
STN	Stansted	UK