AIRLINE COMPETITION: EMPIRICAL INSIGHTS FOR EUROPEAN AND INTERNATIONAL MARKETS

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Airline Competition: Empirical Insights for European and International Markets

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CERTIFICATE OF ORIGINALITY

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Abstract

This dissertation consists of three empirical studies on the assessment of airline competition among Low-Cost Carriers (LCCs hereinafter) and Full-Service Carriers (FSCs hereinafter). Airline competitions are analyzed in the European aviation market, and in the Australia-UK aviation market, separately. The increase in network overlaps and related airfare impact have been captured using fixed effects estimations in the first and second studies. Changes in consumer preferences and changes in cost structures arising from competitions have been captured using utility-based empirical models in the third study. This dissertation shows that airline competitions have a negative impact on airfares and airfare dispersion in the European aviation market, and that travelers in the Australia-UK aviation market had an increased preference for one-stop flights.

The first study uses a large dataset to consider the network change of the three largest European Low Cost Carriers (LCCs) easyJet, Ryanair and Wizz Air during the pre-Covid-19 period and the Covid-19 pandemic period. Network changes are characterized in terms of airport pairs, city pairs, numbers of flights and network overlaps. The results show that European LCCs increasingly expanded their networks into markets that had already been served by incumbent LCCs, which indicates that LCCs increasingly compete head-to-head among themselves. Difference-in-differences regressions estimate that network overlaps among these LCCs lead to airfare reductions of approximately six Euros, ten percent.

The second study uses airlines' posted prices to estimate the effect of competition on intertemporal price dispersion in the short and the long run in Europe. It argues that posted prices have the advantage of referring to a standardized trip. Intertemporal price dispersion is measured by the difference between prices for flights booked one week before departure and prices booked one month, three months or six months before departure. Event studies are used to establish causality. More efficient two-way fixed effects regressions are used to show that competition mainly benefits late bookers. Long differences are used to show that low-cost carrier competition has a lasting effect on pricing dynamics whereas full-service carrier competition does not.

The third study focuses on the three Gulf Carriers. Emirates, Etihad and Qatar Airways have gained substantial market shares over the last two decades. In the Australia-UK markets, their market shares increased sixfold between 2002 and 2012. This study shows that their success can be explained by the passengers' increasing preference for one-stop flights and a substantial drop in marginal cost after the financial crisis in 2008. The regressions indicate that frequency information substantially contributes to the quality of the empirical model. This raises a methodological problem because complete frequency information is difficult to obtain for international markets. This study offers a solution for this data problem by concentrating on the frequencies of outbound and inbound flight segments.

Publications Arising from the Thesis

Zhang, H., Czerny, A.I.*, Grimme, W., Niemeier, H-M, 2022a. The Big Three EU Low Cost Carriers Before and During the Covid-19 Pandemic: Network Overlaps and Airfare Effects. *Research in Transportation Economics* 101235.

Zhang, H., Czerny, A.I.*, Ommeren, J., Niemeier, H-M, 2022b. Dynamic Pricing and Competition: Evidence from the Airline Market. Unpublished manuscript.

Zhang, H., Bontemps, C., Chen, R., Czerny, A.I.*, Ommeren, J., Zheng L, 2022c. The Success of Gulf Carriers Explained: The Case of the Australia-UK Airway. Unpublished manuscript.

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Table of Contents

Chapter 1: Overview

The first two studies (Chapter 2 and 3) in this thesis analyze European aviation market. Europe accounted for more than one quarter of all flights worldwide and almost one quarter of all international flights in 2019 (IATA, 2019). A large share of those flights and the corresponding passengers are served by Low-Cost Carriers (LCCs) which typically operate point-to-point networks with a homogeneous fleet. This is in contrast to Full-Service Carriers (FSCs) which operate hub-and-spoke networks with a wide variety of different aircraft. LCCs provided 534 million seats reflecting more than 37 percent of the total capacity offered by airlines registered in Europe in the year of 2019 (OAG, 2020). The three biggest LCCs in terms of seats offered in Europe are easyJet, Ryanair and Wizz Air (Jimenez and Suau-Sanchez, 2020).

Chapter 2 arises from Zhang et al. (2022a) and considers the flight network changes of the three biggest European LCCs before and during the Covid-19 period. The objective is to describe changes in the competitive environment and to quantify how these changes affect airfares.

Chapter 2 complements previous studies which considered airline networks in Europe and elsewhere. Dobruszkes (2006) found that LCCs were drawing new networks complementing those of FSCs. In a subsequent study, Dobruszkes (2013) found that LCCs increasingly moved in frontal competition with FSCs on pre-existing airport pairs. de Wit and Zuidberg (2016) found that the route networks of LCCs in Europe were not stable and route churn occurred frequently. Dobruszkes et al. (2017) highlighted that LCCs were increasing their operations from major airports. The importance of major airports for LCC networks has been further highlighted in a recent study by Jimenez and Suau-Sanchez (2020). Major airports are often prone to delays. Bubalo and Gaggero (2015) highlighted that the LCCs' fast aircraft turn-around times improve the delay performances of airports.

Several studies have considered the airfare impact of overlapping flight networks. Morrison (2001) found that LCC competition exerted dramatic downward pressure on airfares. He used an original set of competition variables to quantify the impact that Southwest Airlines had on airfares through actual, adjacent, and potential competition. Brueckner, Lee and Singer (2013) discussed three types of markets and levels of competition: in-market airport pairs, adjacent city pairs for both legacy carriers and LCCs, and potential competition from LCCs. Their results indicated that the airline competition via the use of adjacent airports could effectively reduce airfares. Zou and Yu (2020) and Wang et al. (2020) considered network overlaps among LCCs in the US and New Zealand, respectively. They found that the LCCs' entry decisions on domestic airport pairs had become less sensitive or were not sensitive, respectively, to airline competition within the same market. Bilotkach (2011 and 2019) considered airline competition in non-price product characteristics such as flight frequencies.

Chapter 2 contributes to the above-mentioned studies by indicating that the three big European LCCs increasingly expanded their network and/or diverted flights into markets that had already been served by incumbent LCCs. These changes can be observed before and even during the Covid-19 pandemic period. This provides evidence for a trend that involves increasing overlaps among LCC networks in Europe. This study further contributes by quantifying the effect of network overlaps on airfares. Difference-in-differences estimations indicate that network overlaps reduce airfares by around six Euros or, approximately, ten percent of the airfares.

Chapter 3 arises from Zhang et al. (2022b) and develops a more complete dataset involving a broader set of Full Service Carriers to study the effect of competition on dynamic pricing. Dynamic pricing refers to the differences in price levels that are related to differences in the timing of booking.

Chapter 3's main contribution is to the literature on the effect of competition on dynamic pricing, which captures an important part of the price dispersion[1]. Chapter 3 deals with a range of econometric issues to provide causal estimates as follows. First, Chapter 3 applies a two-way fixed effects approach after differencing over time of booking where carrier by route and time fixed effects are considered, that is, a triple difference. By triple differencing, it avoids the important endogeneity issue that carriers are more likely to enter (or exit) a route because price levels are high (or low) as well as the issue that airlines likely adjust prices because of the threat of entry[2].

Second, Chapter 3 addresses the issues in a recent set of papers that in staggered two-way fixed effects approaches, the estimate may not be informative on the average treatment effect because of negative weights, for example, de Chaisemartin (2020) and Callaway (2021). It deals with this by estimating a (non-staggered) long-difference fixed effects model, which avoids the issue of negative weights and provides long-run effects, so we reduce issues of (short-run) predatory pricing.

Third, Dai et al. (2014) have argued that endogeneity issues in the competition context cannot be ruled out. Endogeneity issues do exist however when airlines enter (or exit) a route where they expect that the difference in prices induced by differences in booking time before departure will change over time[3]. Chapter 3 deals with this issue by applying an event study to the two-way fixed effects approach. In this setup, it examines whether price differences induced by different booking times before departure change immediately after a change in competition (that is, entry or exit). In other words, it allows airlines to enter (or exit) a route when they expect that the difference in prices induced by differences in booking time before departure will

[1] Indirectly, this chapter also makes a contribution to the literature of competition and prices in the airline industry. In this literature, a number of studies focus on single events (for example, the entrance of one airline in a specific market, or the opening of high-speed rail). For example, Morrison (2001), Brueckner et al. (2013), Zou and Yu (2020), Wang et al. (2020), Bedford and Bilotkach (2022) and Zhang et al. (2022a). A typical finding of these studies is that increases in competition because of new entry reduce airline prices. A number of other studies focus on the average treatment effect using two-way fixed effects approaches and related difference-in-differences approaches. For example, Daraban and Fournier (2008), Mumbower et al. (2014), Zhang et al. (2017), Wang et al. (2018) and Bilotkach et al. (2019).

[2] To be more precise, there is no bias in estimates, given the assumption that any bias in the two-way fixed effects estimates in price levels is additive.

[3] Dai et al. (2014) address endogeneity issues of competition when focusing on price dispersion using instruments related to change in the size of the area where the airport is located for a dataset over a period of 18 years. These instruments are valid given the assumption that these instruments are uncorrelated to changes in the threat of entry perceived by the airlines. In our context, such instruments cannot be applied because we deal with a short observation period, so these instruments are weak.

change over time, but it assumes that it is unlikely that airlines know the exact month when the difference in prices will change. The event study approach fully supports our analysis.

Chapter 3 also contributes to, and improves on, the literature that examines the effect of competition on price dispersion by focusing on the dispersion entirely caused by the date of booking. Rather than using information on transacted prices this Chapter uses posted prices for standardized trips. Using posted prices, it becomes doable to estimate hedonic price models, i.e. models where one can convincingly argue that one has controlled for heterogeneous characteristics, which are prevalent in the airline market and are costly to producers (Rosen, 1974). The main issue with using transacted airline prices is that the empirical literature employing transacted prices has difficulties in distinguishing between pure (second-degree) price discrimination where the product on offer is homogeneous, which is key to the understanding of airline pricing (for example, Dai et al., 2014 and Chen, 2018), and price differences related to unobserved characteristic differences that are costly (for example, economy and business class, carry-on, and seat reservation).

The empirical issue of not being able to differentiate between important cost differences such as economy and business class is widespread (see, for example, Berry and Jia, 2010, and Dai et al., 2014), and has more subtly come to the fore in the last decade, because it has become standard that airlines charge different prices for luggage handling. Consequently, even if one knows class type, a higher price for a ticket may be the result of price discrimination or maybe due to that the ticket included carry-on or additional luggage (unless they have inner data directly from airlines).

In many empirical contexts, this issue may be argued to be of secondary importance, and can be assumed with random measurement errors. However in the context of competition on dynamic pricing this is highly problematic, as the composition of arriving customers changes over time to departure[4]. Different customers are likely to consume different products. For example, business travelers tend to book later and are less likely to travel economy class as well as have luggages (as they stay fewer nights)[5].

Chapter 4 studies a different aviation market: from Australia to the UK, which is a long-distance international market. This market is of particular interest because, in this market, Low-Cost Carriers are more or less absent while with the Gulf carriers such as Emirates, Etihad, and Qatar Airways, new players have entered the market and quickly gained market shares.

Chapter 4 makes several contributions to the extant literature. First, it is believed to be the first literature that focuses on the international airline market, rather than the domestic airline market, following the methodology developed by Berry, Levinsohn and Pakes (1995). The focus on an international market is important, because even if national policymakers maximize welfare, that is, the sum of the consumer surplus and producer surplus, this is definitely not the case in an international context. In international markets, policymakers are more likely

[4]See also the study by Hortaçsu et al. (2022) that focuses on economy class bookings, when studying the effect of dynamic competition on price setting by US airlines.

[5]Using posted prices has seemingly an important disadvantage, as in the end, one is interested in the effect of competition on transacted prices, that are key to welfare. Fortunately, given standard, but non-restrictive, assumptions on measurement error, our estimates of the effect of competition on posted prices can be interpreted as the effect of competition on transacted prices.

interested in maximizing the sum of domestic consumer surplus and producer surplus of their national carrier (if any). In such a context, policymakers presumably wish to know in which country the benefits of new entry fall. More specifically, this Chapter focuses on a market where a foreign entrant arguably increases consumer surplus of domestic residents, but strongly decreases producer surplus of domestic firms. In this case, focusing on the airline market is of particular interest, because all the evidence suggests that national governments particularly care (maybe irrationally) about their national carriers than about other national firms.

Second, this could be the first literature to apply the above-mentioned methodology on ultra-long-distance travel (during the period examined, about 12,000 km-20,000 km, nowadays about 15,000 km-20,000 km). Ultra-long travel is defined by travel between destinations far apart where there are no direct flights (because of technical constraints of airplanes, not because of lack of demand), so travelers have to rely on travels with at least one stopover. Ultra-long distance has one important distinctive supply characteristic. For ultra-long travel, the range of alternative travel combinations (with at least one stop) with a similar travel distance, (but with very different destinations), is much larger than for short, but also non-ultra-long distance travel. In the extreme, because the Earth is a globe, for 20,000 km trips, there is potentially an infinite number of trips flying exactly the same distance. More specifically, this Chapter focuses on the Australia-UK market, and documents that for each travel between two cities, there are many flights with a similar distance, and therefore time traveled in the air. Hence, this implies that the market is potentially more competitive. Moreover, this implies that travelers will be rather indifferent between the range of flights on offer in terms of time in the air, except for the characteristics related to the number and quality of the stopover(s) and airline service. The latter is extremely convenient because it means that measurement of traveler preferences which will be based on the estimated effects of price and flight characteristics (such as number of stopovers) is much more straightforward, as these preferences strongly interact with travel time (for example, on an one hour flight, the willingness to be between business and economic classes will be different than on an eight hour flight).

Third, this is one of the first literature that focuses on the success of new entrant "full service carriers" as opposed to the success of "low cost carriers," which has been widely discussed in the literature (for example, Berry and Jia, 2010; Bontemps et al., 2022). Data availability may be the main reason for the lack of attention on full service carriers in intercontinental travel where the presence of low-cost carriers was minimal. For domestic markets and especially the US market, huge and detailed databases are readily downloadable for free triggering a large number of studies on the US domestic market, whereas comparable databases are not freely available for intercontinental markets.

Fourth, this is also the first literature that quantifies the success of Gulf carriers, and therefore implicitly the success of the EU deregulation efforts involving the UAE in 2007. Their success should undoubtedly be related to this 2007 aviation agreement because it removes nationality restrictions in the bilateral air services agreements, and therefore allows any EU airline to operate flights between any EU member state in which it is established and the UAE. It also acknowledges the existence of the European single market for air transport in the relations between the EU and the UAE.

Fifth, this Chapter addresses one of the main puzzles why the Gulf carriers has been able to grow so fast out competing other airlines such as Singapore Airlines with, at least from outside, a similar cost structure (O'Connell, 2011). For example, some commentators have discussed the alleged market distortions caused by the Gulf states such as UAE (de Wit, 2014). This study has two important findings. First, consistent with increases in income, it documents an increase in traveler preference for one stopover flights (rather than multiple stopovers flights) which helped the growth of Gulf carriers. Second, it shows that Gulf carriers behaved as if they had a strong cost advantage.

The remainder of this thesis is organized as follows. Chapter 2 considers LCC competitions within Europe in terms of network overlaps and their corresponding airfare impacts. Chapter 3 continues to study FSC and LCC competitions within Europe but focuses on dynamic pricing in terms of the differences in price levels that are related to differences in the timing of booking. Chapter 4 considers Australia-UK aviation markets and studies the influences of the entry of Gulf carriers on airfares and consumer surplus. Chapter 5 concludes the thesis.

Chapter 2: The Big Three EU Low Cost Carriers Before and During the Covid-19 Pandemic: Network Overlaps and Airfare Effects

2.1 Introduction

This Chapter considers the flight network changes of the three biggest European LCCs before and during the Covid-19 period. The objective is to describe changes in the competitive environment and to quantify how these changes affect airfares. Competition is considered as most intense on origin-destination routes which are operated in parallel by airlines. Therefore, the analysis especially concentrates on the change of network overlaps by distinguishing between origin-destination routes described by airport pairs or city pairs. The latter distinction allows identifying the role of adjacent airports in multi-airport regions.

Many flights were originally scheduled for operation during the Covid-19 pandemic but later canceled because of travel bans and demand reductions caused by compulsory quarantines among other regulations. To develop a valid dataset, this study uses flight information provided by Flightradar24. The virtue of this database is that it tracks actual flights in real time and, thus, does not include flights that are scheduled but not operated. This data source has been used by Bubalo and Gaggero (2015) and Sun, Wandelt and Zhang (2020) amongst others.

The Chapter is organized as follows. Subchapter 2.2 introduces the data sources. Subchapter 2.3 uses descriptive statistics to characterize the market position of the three big European LCCs before the Covid-19 period. Subchapter 2.4 analyzes monthly data and describes the change of LCC networks in terms of airport pairs/city pairs in the pre-Covid-19 and during the Covid-19 pandemic periods. Subchapter 2.5 develops and estimates various difference-in-differences regression models to quantify the effect of network overlaps on airfares. Finally, Subchapter 2.6 summarizes the findings and develops avenues for future research.

2.2 Data Sources

The panel data period starts 1st January 2018 and ends 30th November 2020. It involves around 3.3 million flights from three European LCC groups. The three groups involve the Wizz Air group, the easyJet group and the Ryanair group. The Wizz Air group includes Wizz Air (0.33 million observations) and Wizz Air UK (16 thousand observations). The easyJet group includes easyJet (1.1 million observations), easyJet Europe (5,800 observations), and easyJet Switzerland (300 observations). The Ryanair group includes Ryanair (1.72 million observations), Laudamotion (62 thousand observations) and Ryanair Sun (7,600 observations). The flight data is collected from Flightradar24, which records ADS-B messages transmitted by any aircraft operating IFR flights, as required by the European Union, from ground and satellite-based ADS-B receivers. Flighradar24 reports marketing carriers which is the relevant information for our study because it accurately captures the carriers' own passenger services.

Observations with a missing origin/destination airport, or observations with all five time stamps (duration, estimated time of departure, actual time of departure, estimated time of arrival, and actual time of arrival) missing were deleted. The corresponding share of missing data is around 0.15% of the total dataset. Airport pair observations are deleted for a specific LCC if this LCC serves the airport pair with fewer than 12 flights per year. This eliminates ferry flights which relocate aircraft from one airport to another. The corresponding share of these observations represents around 0.16% of the total dataset.

The dataset concentrates on airports located in the European Union before Brexit in January 2020 and on origin-destination routes connecting these airports. Therefore, the dataset keeps airports and origin-destination routes although they became and involved, respectively, non-European Union airports during the study period. The dataset includes 348 airports. The following considers non-directional airport pairs. This means that flights between airports A and B are considered to occur on the same airport pair independent of whether airport A or airport B is the origin or destination airport. Alternatively, directional airport pairs could be used. The results presented in this study are, however, robust with respect to the consideration of directional or non-directional airport pairs. Other studies such as Roucolle, Seregina, and Urdanoz (2020) also referred to non-directional airport pairs in their analysis of airline networks.

Regional GDPs are used to measure the hinterland demands for flight services[6]. The GDP data is obtained from the statistical office of the European Union Eurostat (2020), which is also used in Fageda et al. (2015). The whole European Union territory is classified into NUTS 1, NUTS 2 and NUTS 3 regions. There are over 2,000 regions classified as NUTS 3 regions which can be characterized as "city-level" information whereas NUTS 2 is "province/state-level" and NUTS 1 is "country-level." The hinterland identification is based on the IATA airport code and the corresponding airport locations as measured by their longitude and latitude obtained from OpenFlights Airport Database dated 2017. The airport location data was used to pinpoint the airport into its corresponding hinterland as classified by the NUTS 3 region to identify the relevant GDP information associated with each airport. The GDP information refers to the year 2017 (the 2017 information was unavailable for eight airports and the 2016 information was used instead in these cases).

City information from Flightradar24 can be used to identify 16 multi-airport regions (see Appendix A). This seems, however, only a small share of the airport regions because, for instance, Sun et al. (2017) identified 88 multi-airport regions in Europe using a more sophisticated geographical approach[7]. Anyway, despite this issue of accurately treating airport catchment areas in multi-airport regions, the approach produces results that are consistent with the results obtained by previous studies as will be highlighted later.

To shed light on how airfares were affected by the entry of other LCCs, Wizz Air's airfares have been collected from RDC aviation intelligence. RDC scrapes airfares from airline online booking platforms six-month, three-month, one-month, and one-week prior to the travel date. In total, 65,837 round-trip airfares have been included in our dataset.

[6] GDP is used although it may not properly capture the demand for short getaways and migration flows. The positive relationship between economic activity and flight demand is well-established (for example, Lim, 1997, and Morphet and Bottini, 2020). GDP also serves as a proxy for tourism demand as empirically demonstrated by Martins, Gan and Ferreira-Lopes (2017) and Massidda and Etzo (2012).

[7] Evangelinos, C., Staub, N., Marcucci, E. and Gatta, V. (2021) propose a theoretically justified, utility-based identification of catchment areas.

	easyJet	Ryanair	Wizz Air
		Total	
Total number of flights	981,092	1,477,755	266,828
Share of total (in percent)	36	54	10
Average GDPˆ per flight (in billion Euros)	33.3	33.3	21.2
		Airport pairs served	
Number of airport pairs	993	2,154	483
Share of total (in percent)	27	60	13
Average flight number	988	686	552
Coefficient of variation	1.4	1.3	1.2
Average GDPˆ per airport pair (in billion Euros)	26.7	25.3	19.9
		City pairs served	
Number of city pairs	878	2,054	478
Share of total (in percent)	26	60	14
Average flight number	1,117	720	558
Coefficient of variation	1.7	1.5	1.2

ˆGDP presents Average Geometric Mean in billion Euros and hereinafter for all Tables.

Table 1: Pre-Covid-19 pooled two-year data.

2.3 Two-year Pre-Covid-19 Period

The two-year period between 1st January 2018 and 31st December 2019 is called the pre-Covid-19 period. This Subchapter considers pooled data for the two-year pre-Covid-19 period to develop an overall understanding of the differences among the three biggest European LCCs. The statistics are summarized in Table 1. This table is divided in three parts. The first part considers total flight numbers, the second part airport pairs, and the third part city pairs.

2.3.1 Number of flights

The number of flights is a common measure for the size of airline networks. The table shows that Ryanair ranked number one among the three LCCs with almost 1.5 million flights for the whole two years during the pre-Covid-19 period. Ryanair was followed by easyJet with almost 1 million flights and Wizz Air with (only) slightly more than 0.26 million flights.

In Table 1 and elsewhere the term "share of total" is used. The share of total refers to the relative importance of one of the biggest three LCCs among themselves. In terms of share of total as measured by number of flights this translated into a share of 54 percent for Ryanair, 36 percent for easyJet and 10 percent for Wizz Air. Ryanair operated more than half of all the flights operated by the biggest three LCCs and, therefore, was the clear market leader, whereas Wizz Air was small relative to both Ryanair and easyJet.

Table 1, part 1 contains information about the "Average Geometric GDP Mean." The geometric GDP mean associated with a specific airport pair was calculated by using the GDP information of the two NUTS 3 regions associated with the origin and destination airports.

easyJet and Ryanair were both flying to high demand markets with Average Geometric GDP Mean of slightly more than 33 billion Euros relative to Wizz Air whose corresponding Average Geometric GDP Mean was only slightly higher than 21 billion Euros. This is consistent with the findings of Dobruszkes, Givoni, and Vowles (2017) and Jimenez and Suau-Sanchez (2020). One explanation is related to the geographical distribution of flights: Wizz Air flights largely covered the Eastern European area with low GDP relative to the Western European area which were largely covered by Ryanair and easyJet flights. Observe that easyJet and Ryanair had almost the same average geometric GDP mean although Ryanair operated many more flights. This indicates that these two LCCs were more likely to compete in and for markets with relatively high demand.

2.3.2 Airport pairs

A given number of flights can be used to integrate many airport pairs with low flight numbers per airport pair or few airport pairs with high flight numbers per airport pair. Table 1 considers non-directional airport pairs. In terms of the number of airport pairs, Ryanair operated the largest flight network involving more than 2,000 airport pairs, easyJet operated almost 1,000 and Wizz Air operated slightly less than 500 airport pairs. Ryanair's and Wizz Air's shares of total in terms of airport pair numbers were slightly higher than the shares of total based on the number of flights. Correspondingly, easyJet's share of total in terms of airport pair numbers was lower than its share of total in terms of the number of flights. This indicates that easyJet's average number of flights per airport pair was high relative to the other two LCCs. easyJet indeed operated the highest average number of flights per airport pair, Ryanair took the intermediate position and Wizz Air operated the lowest number of flights per airport pair. This is consistent with the findings of Dobruszkes (2006).

One may wonder whether easyJet operated high flight numbers across all airport pairs or whether easyJet boosted the average flight numbers by offering (very) high flight numbers at some airport pairs only. The coefficient of variation of flight numbers across airport pairs provides this information. If the coefficient of variation is high, then the distribution of flight numbers is uneven across the airport pairs whereas a low coefficient of variation value indicates that flight numbers are more evenly distributed across the LCC network. The coefficient of variation value was the highest for easyJet, Ryanair took the intermediate position, and that of Wizz Air was associated with the lowest coefficient of variation value. In this sense, easyJet operated the most heterogenous airport pair network relative to the other two LCCs.

The Average Geometric GDP Mean associated with easyJet's and Ryanair's networks in terms of airport pairs (Average GDP per airport pair) were lower than the corresponding values associated with flight numbers (Average GDP per flight). This indicates they operated relatively high flight numbers in markets with Geometric GDP Mean values higher than around 25 billion Euros. That was not true for Wizz Air because the Average Geometric GDP Mean associated with its flight and airport pair networks were almost equal.

2.3.3 City pairs

Some cities are served by multiple airports. The London, Paris and Rome regions may serve as European examples. The distinction between LCC networks in terms of airport pairs and city pairs in Table 1 is used to illustrate the implications of the existence of multi-airport regions. The difference, between the network sizes associated with airport pairs and city pairs, indicates to which extent LCCs served the same city pairs by using various adjacent airports.

The difference between network sizes as measured by the number of airport pairs and the number of city pairs was the highest for easyJet (993 minus 878) and the lowest for Wizz Air (483 minus 478). This indicates that easyJet made most use of adjacent airports in their network. As a consequence, the shares of total of Ryanair and Wizz Air in terms of city pairs were slightly increased compared to the first and second parts of the table, which considered flight and airport pair numbers, respectively. Another consequence is that easyJet's average flight number per city pair was high relative to the other two LCCs.

The consideration of city pairs for Ryanair and Wizz Air reveals no major qualitative change with respect to the coefficient of variation relative to the consideration of airport pair numbers. easyJet continues to have the most heterogenous city pair network. NUTS 3 and city areas collected by Flightradar24 can be equal or different, which makes it difficult to derive the city GDP from the NUTS 3 database. Therefore, the discussion of GDP values is omitted in this part of the table.

2.4 Network Changes

This Subchapter distinguishes between the two-year pre-Covid-19 period between 1st January 2018 and 31st December 2019 and the 11-month Covid-19 pandemic period between 1st January 2020 and 30th November 2020. It consists of three parts. The first part considers the LCCs' networks in isolation. The second part considers the change of network overlaps. The last part compares the top ten overlapping airport pairs from the end of the pre-Covid-19 period with top ten overlapping airport pairs from the peak Covid-19 month, August 2020 for each LCC pair. The top 10 overlapping airport pairs are used to illustrate the geographical coverage of network overlaps.

2.4.1 Monthly network adjustments

The left diagram in Figure 1 shows the change of the number of airport pairs operated by each LCC across time. This figure uses monthly data, which is different from Table 1 which presents pooled two-year summaries. The number of Wizz Air's routes increased substantially during the sample period. For instance, the peak number of routes in terms of airport pairs served by Wizz Air increased from 364 to 407 to 452 in 2018, 2019 and 2020, respectively (see Appendix B). The corresponding network expansions of Ryanair and easyJet were more modest considering the size of their networks.

The pre-Covid-19 period is characterized by substantial seasonal variations involving up to 30% of Ryanair's network and even 50% of easyJet's network whereas such variations were

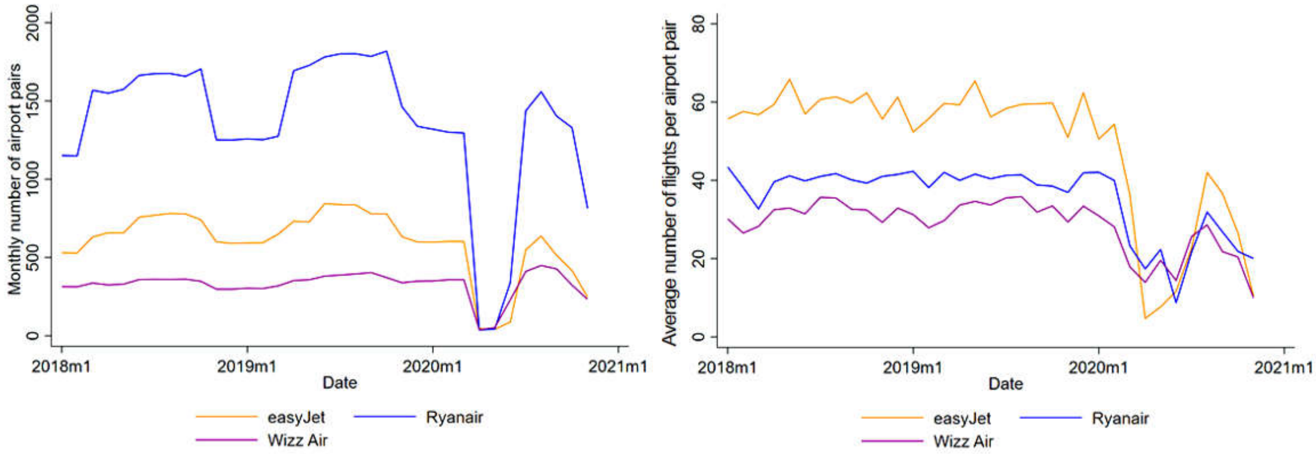

Figure 1: Monthly number of airport pairs served by easyJet, Ryanair and Wizz Air and the corresponding average number of flights per airport pair.

almost absent for Wizz Air. This reveals that some airlines are able to flexibly adjust substantial parts of their networks, which could affect airport competition as has been discussed by de Wit and Zuidberg (2016), Wiltshire (2018) and Thelle and la Cour Sonne (2018).

During the Covid-19 pandemic period, the number of flights operated by the LCCs were down to almost zero in April and May 2020. For Ryanair, the corresponding drop was most substantial in absolute terms because Ryanair operated the largest network in the pre-Covid 19 period. More specifically, the numbers of airport pairs operated by the three LCCs in April and May 2020 were approximately 57, 46 and 46 per month for easyJet, Ryanair and Wizz Air, respectively. The drop was caused by the spread of the Covid-19 virus and the corresponding severe restrictions on air transport markets including quarantine for arriving passengers, partial travel bans and border closures (Pearce, 2020). With relatively few Covid-19 cases in summer, the numbers of airport pairs largely recovered until August 2020 in Europe and fell again in the subsequent months given the second wave of the Covid-19 pandemic.

The lines in the right diagram in Figure 1 show the LCCs' monthly average flight numbers per airport pair. The ranking of the three LCCs in terms of these average flight numbers had also been stable during the pre-Covid-19 period in which easyJet ranked number one, Ryanair number two, and Wizz Air number three. The Covid-19 pandemic changed these rankings in the months of April, May and June, and the rankings returned to the pre-Covid-19 values after June 2020 until October 2020. Altogether, this demonstrates that easyJet consistently operated few airport pairs but with high average flight numbers relative to Ryanair.

2.4.2 Network overlaps

The previous part considered and compared each of the LCC networks in isolation. This part discusses the overlapping parts of the LCC networks pre-Covid-19 and during the Covid-19 pandemic period. Those overlapping parts are of interest because they can be considered as a measure for the level of competition between the LCCs. A difference-in-differences analysis will be applied in Subchapter 2.5 producing estimated airfare reductions by the incumbent airline of approximately six Euros or ten percent in response to the entry of a rival LCC.

This Subsubchapter develops around three figures. The first figure, Figure 2, shows the change of network overlaps in absolute numbers in terms of airport pairs and city pairs. The second figure, Figure 3, concentrates on the overlap between the networks of Ryanair and Wizz Air with and without considering the number of flights. The third figure, Figure 4, illustrates the magnitude of network overlaps relative to each LCCs' network.

Airport pairs versus city pairs

In London and other city regions, several airports exist. In such city regions, airlines may use one or several airports in parallel. Airport choices may depend on slot availability, airport charges and the presence of airline competitors. This part distinguishes between overlaps in terms of airport pairs and overlaps in terms of city pairs. This distinction is used to capture that the presence of multiple LCCs in the same airport pair should have a stronger competitive effect than the presence of multiple LCCs in the same city pair.

There were very few airport pairs and city pairs in which all three LCCs are present. Therefore, the following concentrates on the network overlaps of the three LCC pairs easyJet and Wizz Air (orange color), Ryanair and easyJet (blue color) as well as Wizz Air and Ryanair (purple color).

The two diagrams in Figure 2 depict the change of network overlaps as measured by the monthly number of overlapping airport pairs (left) and monthly number of overlapping city pairs (right). City pairs operated by different airlines count as overlapping even if airlines use different airports in the same city pair. For this reason, overlaps in terms of airport pairs are always lower than overlaps in terms of city pairs, which can be spotted by comparing the lines with the same color in the left and right diagrams. Ryanair and easyJet had much larger networks relative to Wizz Air, it is therefore unsurprising that the network overlaps based on the numbers of airport pairs and city pairs were higher for them than for the other two LCC pairs involving Wizz Air.

The changes in time can be described as follows. During the whole pre-Covid-19 period, the overlap between the networks of easyJet and Wizz Air stayed constantly low, whereas the overlap between the networks of Ryanair and easyJet slightly increased. The overlap between networks of Wizz Air and Ryanair increased substantially in October 2019 because Ryanair started serving 19 new airport pairs in which Wizz Air was the incumbent. The difference-in-differences analysis in Subchapter 2.5 will concentrate on these changes.

During the Covid-19 period, the difference in the order of magnitude in the overlaps for Ryanair-easyJet and Wizz Air-Ryanair narrowed down in the peak month August 2020. This is because the overlap for Ryanair-easyJet decreased whereas the overlap for Wizz Air-Ryanair increased. The overlap for easyJet-Wizz Air also increased. The involvement of Wizz Air in these changes indicates that Wizz Air tended to expand their networks before and during the Covid-19 pandemic period even though the expansion was associated with increased network overlaps with other major LCCs.

Ryanair versus Wizz Air

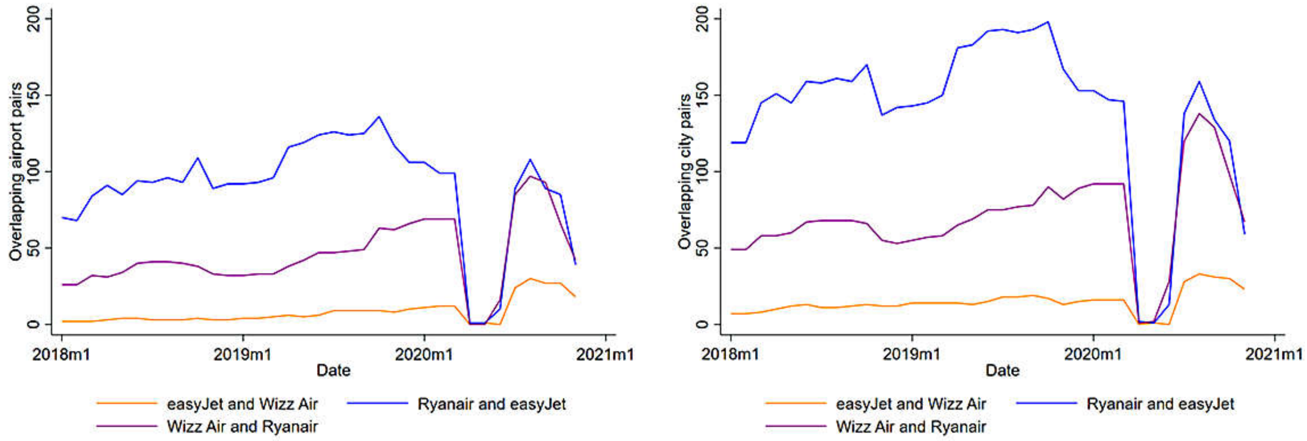

Figure 2: Monthly number of overlapping airport pairs (left), and city pairs (right) among the three LCCs.

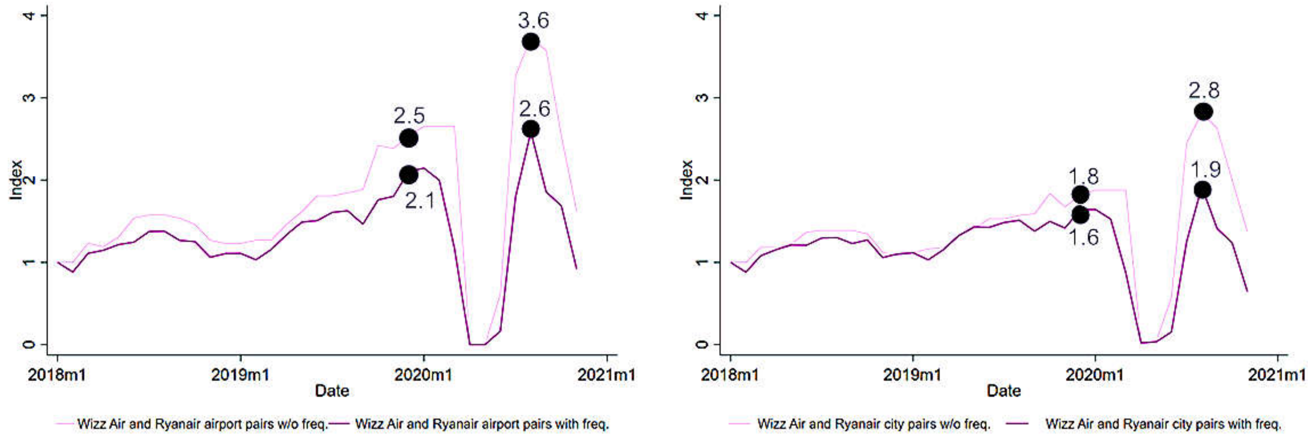

Figure 3: Indices of the monthly overlapping airport pairs (left) and city pairs (right) between Wizz Air and Ryanair.

The two diagrams in Figure 3 provide more details about the change of the Wizz Air-Ryanair network overlap. These can be used to illustrate the growing importance of adjacent airports for the new overlapping airport/city pairs and sacrifices in terms of flight frequencies measured by the average number of flights.

It uses indices to describe the change of network overlaps in terms of airport pairs (left) and city pairs (right) with base month January 2018. The diagrams distinguish between (i) the change of the monthly total number of overlaps (light purple) and (ii) the change of the monthly total number of flights operated on the overlapping airport/city pairs (dark purple).

The light purple line in the left figure shows a sharp increase in the number of airport pairs reaching an index value of 2.5 at the end of the pre-Covid-19 period. Compared to the base month, the number of overlaps in terms of airport pair more than doubled until the end of the pre-Covid-19 period. The overlap between networks of Wizz Air and Ryanair increased substantially in October 2019 because Ryanair started serving 19 new airport pairs in which Wizz Air was the incumbent. The light purple line in the right figure shows a sharp increase also in the number of city pairs reaching an index value of 1.8 at the end of the pre-Covid-19 period, which is lower than 2.5 indicating the use of adjacent airports. Therefore, compared to the base month, the number of overlaps in terms of city pairs almost doubled until the end of the pre-Covid-19 period. In the peak Covid-19 pandemic month, August 2020, these indices reached even higher values of 3.6 and 2.8, respectively, showing a further sharp increase in network overlaps compared to the end of the pre-Covid-19 period. Altogether, this indicates that Wizz Air/Ryanair expanded their network and/or diverted flights into markets that have already been served by the other LCC and that the use of adjacent airports had been a substantial part of this change in the pre-Covid-19 period and during the Covid-19 pandemic period.

The dark purple lines show network changes by calculating the monthly total number of flights operated on the overlapping airport/city pairs. For the changes in time, similar patterns can be observed for the dark and the light purple lines indicating that adjacent airports had been a substantial part of the change no matter whether flight numbers are considered or not considered. Observe that the dark purple lines are always below the light purple lines both during the pre-Covid-19 and the Covid-19 pandemic periods. Therefore, the increase in the overlap of Ryanair's and Wizz Air's networks was associated with relatively low average flight numbers compared to the base month. The Covid-19 pandemic period could have supported this change in the sense that removing flights from routes with low demands freed up capacity to extend operations to other routes and test the competitor's behavior.

Overlaps versus total network

Figure 4 shows the shares (ratios) of the number of the overlapping airport pairs between two LCCs to the total airport pairs of each of the two LCCs. This figure can be used to illustrate the increases in network overlaps relative to each LCCs' network indicating that LCC markets become more competitive.

The color code indicates the LCC in the denominator. Take the top-left diagram of Figure 4 as an example. The orange line considers easyJet's network as the reference network, (easyJet U Wizz Air)/easyJet, whereas the purple line considers Wizz Air's network as the reference

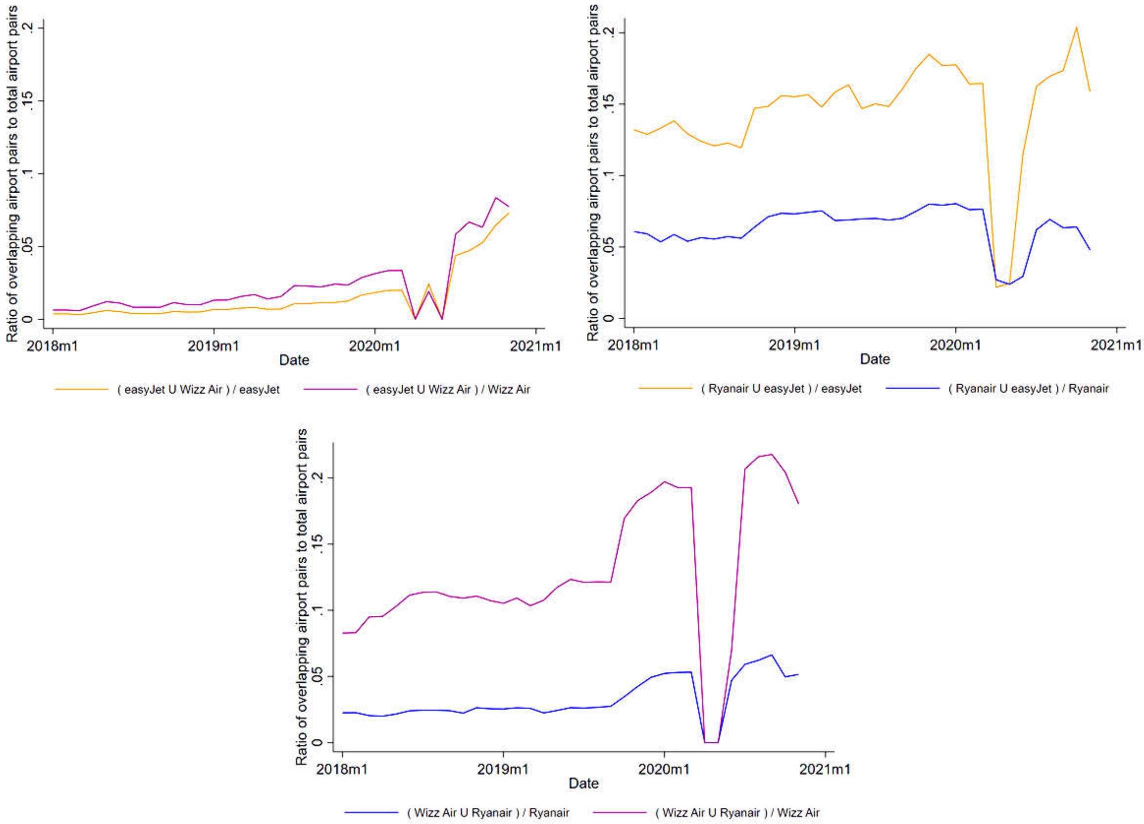

Figure 4: Shares of overlapping as measured by the number of overlapping airport pairs to total airport pairs per month.

network, (easyJet U Wizz Air)/Wizz Air.

All lines in Figure 4 have in common that they show a positive trend in the relative importance of network overlaps. The share of overlapping airport pairs between easyJet and Wizz Air (top-left) nearly tripled for Wizz Air and more than tripled for easyJet relative to the corresponding shares at the end of the pre-Covid-19 period. The relative importance of the overlaps between the networks of Ryanair and easyJet (top-right) is substantially higher for easyJet than for Ryanair; it reaches around 20 percent for easyJet whereas the share does not exceed 9 percent for Ryanair.

A similar situation can be seen for Wizz Air and Ryanair (bottom). For Wizz Air, the share of the overlapping part had approximately doubled from around 10 percent at the beginning of the pre-Covid-19 period to almost 20 percent until the end of the pre-Covid-19 period. As mentioned before, a big increase in the overlap between networks of Wizz Air and Ryanair happened in October 2019 because Ryanair started serving 19 new airport pairs in which Wizz Air was the incumbent. During the Covid-19 pandemic period, the magnitude of network overlap between Wizz Air and Ryanair even slightly exceeded 20 percent and exceeded the corresponding value for the network overlap between easyJet and Ryanair. This could not be observed in the pre-Covid-19 period.

The number of airport pairs operated by all three LCCs at the same time is almost zero (in average fewer than one pair per month). The increase in network overlaps is particularly high for Wizz Air. The shares of network overlaps displayed in Figure 4 can be used to illustrate this point. Summing Wizz Air's shares of overlapping airport pairs with easyJet and Ryanair for the beginning of the sample period (2 plus 8 percent) and for August 2020 (10 plus 20 percent) yields an increase in the total share of network overlaps from 10 to 30 percent. This illustrates that the share of Wizz Air's network overlaps tripled within the sample period. It further illustrates that at times as much as one third of Wizz Air's whole flight network overlapped with the networks of the other two major European LCCs. In this sense, Wizz Air operated in an increasingly competitive market environment.

2.4.3 Top ten overlapping airport pairs

The next illustrates the network overlaps during the pre-Covid-19 and Covid-19 pandemic periods geographically by considering the top ten overlapping airport pairs for each LCC pair.

Table 2 lists the top ten overlapping airport pairs as measured by their average daily flight numbers in December 2019[8]. Average daily flight numbers are calculated by summing the number of flights of the two LCCs associated with the overlapping airport pair and dividing it by the corresponding number of days. The table also lists the average daily flight numbers across all overlapping airport pairs for the three LCC pairs for comparison (third row), and the share of the top ten overlapping airport pairs in terms of their number of flights relative to the total number of flights associated with the whole overlapping networks (last row and indicated by "^"[9]). The third and the last rows can be used to illustrate the differences between the top ten overlapping airport pairs and the rest of the overlapping airport pairs.

The top ten overlapping airport pairs show that network overlaps involve the London airport region where easyJet's base is located, and Budapest where Wizz Air's base is located. They do not, however, involve Dublin airport where Ryanair's base is located.

The top ten overlapping airport pairs are in average served with high daily average flight numbers relative to the average daily flight numbers of the LCCs during the two-year pre-Covid-19 period. To see this, divide the average flight number in the second-last row of Table 2 by two because the average flight numbers in Table 2 refer to the sum of daily flights of the two involved LCCs. This yields numbers 1.6, 4.3 and 2.5 for easyJet-Wizz Air, Ryanair-easyJet, and Wizz Air-Ryanair, respectively. To obtain the benchmark value for the two-year pre-Covid-19 period, use the average flight numbers associated with airport pairs in Table 1 and divide this number by 730 representing the total number of days during the two years. This yields average daily flight numbers of 1.4, 0.9 and 0.8 for easyJet, Ryanair and Wizz Air, respectively. Comparing these average flight numbers reveals that the overlapping airport pairs are relatively important with respect to the LCCs' own flight networks.

Table 3 lists the average daily number of flights across all overlapping airport pairs for the three LCC pairs during the peak-pandemic month in August 2020 (third row). Comparing

[8] The majority of the airports listed on this table also ranked atop in December 2018, except for VIE which became a new base for Wizz Air. And easyJet-Wizz Air had only 4 overlapping airport pairs in December 2018.

[9] The share of the total number of flights of the top 10 overlapping airport pairs relative to the total number of flights of all corresponding overlapping airport pairs. For instance, if this number is equal to 100, this means that there are no more than ten corresponding overlapping airport pairs.

easyJet-Wizz Air			Ryanair-easyJet			Wizz Air-Ryanair		
Average daily flight numbers on all overlapping airport pairs								
3.2			3.0			2.4		
Top 10 overlapping airport pairs in terms of average (av.) daily flight numbers								
Airport pair	Av.	GDP	Airport pair	Av.	GDP	Airport pair	Av.	GDP
BUD-LGW	5.8	26.6	MXP-CTA	16.4	22.9	DTM-KTW	7.2	6.8
LTN-LIS	5.3	22.9	MXP-PMO	10.2	24.8	CIA-OTP	6.1	29.4
LTN-KRK	5.1	7.1	STN-BFS	9.9	6.5	GDN-NYO	5.4	11.6
BUD-BSL	3.9	31.0	MXP-SUF	9.4	13.8	LTN-KRK	4.8	7.1
LTN-PRG	3.8	13.0	BCN-LTN	7.8	34.9	BGY-OTP	4.8	13.9
LTN-OPO	2.3	15.2	BCN-SXF	7.4	30.0	VIE-FCO	4.8	52.1
VIE-NAP	2.1	31.6	STN-PRG	7.1	15.5	BUD-CRL	4.7	23.2
LTN-TFS	1.5	12.1	ALC-LGW	6.3	23.2	BUD-BCN	4.5	86.7
BSL-WAW	1.4	36.3	MXP-BRI	6.2	26.4	CRL-OTP	4.5	7.9
LTN-GNB	0.7	17.2	ALC-MAN	5.5	25.1	BUD-SXF	4.3	15.8
Averages	3.2	21.3	Averages	8.6	22.3	Averages	5.1	25.5
% to total^	100	N/A	% to total^	26.8	N/A	% to total^	31.8	N/A

Table 2: Average flight numbers on overlapping airport pairs in December 2019.

those numbers with the corresponding pre-Covid-19 average numbers in Table 2 (third row, too) reveals that the average flight numbers associated with the overlap easyJet-Wizz Air substantially increased, the average flight numbers on the overlap Ryanair-easyJet remained unchanged, and the average flight numbers on the overlap Wizz Air-Ryanair decreased.

Recall the strong increase in the overlap in terms of airport pair numbers associated with easyJet-Wizz Air in the peak-pandemic month (illustrated by Figure 2). This increase reduced the relative importance of the top ten overlapping airport pairs in the sense that their share (last row) was reduced by more than one third from 100 percent (Table 2) to 57 percent (Table 3). Similar effects although less pronounced can be observed for the other two overlaps as well.

An overlapping airport pair is considered as newly operated in the peak month of the Covid-19 pandemic period if it had never been operated in the pre-Covid 19 period. Table 4 lists new entrant and incumbent LCCs in each LCC pair in August 2020.

The network overlap Wizz Air-Ryanair had only one of the new top ten overlapping airport pairs, VIE-MXP, entered by Ryanair in August 2020. All others of the new top ten overlapping airport pairs had been, however, entered by Wizz Air and with relatively low number of flights, which are shown in Table 4. This explains the decrease in the associated average number of flights. Wizz Air opened its Austrian base at Vienna International Airport in June 2018 and after only one and a half years of operations, the airline allocated its seventh aircraft to the Austrian capital. This explains why all the airport pairs shown in the third and fourth columns of Table 4 involved Vienna airport.

The network overlap easyJet-Wizz Air had seven of the top ten airport pairs entered by Wizz Air whereas none entered by easyJet. Most of the newly operated airport pairs involved

easyJet-Wizz Air			Ryanair-easyJet			Wizz Air-Ryanair		
Average daily flight numbers on all overlapping airport pairs								
3.6			3.0			2.0		
Top 10 overlapping airport pairs in terms of average (av.) daily flight numbers								
Airport pair	Av.	GDP	Airport pair	Av.	GDP	Airport pair	Av.	GDP
LTN-AGP	8.0	14.9	MXP-CTA	12.5	22.9	VIE-FCO	5.9	52.1
LTN-PMI	7.7	13.8	MXP-PMO	9.2	24.8	VIE-MXP	5.7	21.0
LTN-FAO	7.0	8.3	LTN-AGP	7.9	14.9	VIE-CRL	5.0	13.9
LTN-MXP	6.7	13.9	MXP-SUF	7.2	13.8	CIA-OTP	4.8	29.4
LTN-LIS	6.7	22.9	LTN-FAO	7.2	8.3	VIE-ATH	4.6	13.4
MXP-IBZ	6.4	10.3	MAN-ALC	6.9	25.1	DTM-KTW	4.5	6.8
MXP-MAH	5.9	7.2	MAN-PMI	6.5	21.4	VIE-PMI	4.5	20.5
LTN-SPU	5.3	5.5	CTA-VCE	6.3	23.2	LTN-KRK	4.2	7.1
LTN-KRK	3.9	7.1	MAN-AGP	5.9	23.2	LTN-AGP	4.1	14.9
MXP-LIS	3.9	43.0	PMI-TXL	5.9	59.3	VIE-CGN	4.0	32.5
Averages	6.2	14.7	Averages	7.6	23.7	Averages	4.7	21.2
% to total	57.0	N/A	% to total	23.0	N/A	% to total	24.0	N/A

Table 3: Average flight numbers on overlapping airport pairs for the peak-pandemic month, August 2020.

Incumbent	easyJet	Ryanair	Wizz Air
New entrant	Wizz Air	Wizz Air	Ryanair
Airport pairs	LTN-AGP	VIE-CRL	VIE-MXP
	LTN-PMI	VIE-PMI	
	LTN-FAO	VIE-CGN	
	LTN-MXP		
	MXP-IBZ		
	MXP-MAH		
	MXP-LIS		

Table 4: New entrant and incumbent LCCs in August 2020.

leisure destinations in Spain and Portugal as August 2020 was the holiday season. All top ten peak-pandemic month airport pairs associated with the network overlap Ryanair-easyJet were already operated pre-Covid-19. Altogether, this clearly indicates that Wizz Air was the driving force for the increase in network overlaps and head-to-head competition among the three LCCs during the Covid-19 pandemic period.

Many FSCs received direct stated aids whereas this is not the case for the three LCCs discussed during the study period. Therefore, Wizz Air's network strategy was unlikely related to direct state aid payments.

2.5 Airfare Impact of Network Overlaps

This Subchapter uses a difference-in-differences analysis in its "canonical format" with two periods and one treatment, which separates control and treatment groups to estimate how incumbents respond to the entry of new rivals in terms of their posted airfares.[10] The posted airfares have been collected from RDC aviation intelligence.[11] RDC scrapes airfares from the airlines' online booking platforms six months, three months, one month, and one week prior to the travel date.

2.5.1 Data selection and descriptive statistics

An airline is considered a new entrant if it starts continuously operating an airport/city pair which it had not operated before. In October 2019, Ryanair started operating 19 OD airport pairs in which Wizz Air was the incumbent. The Table in the Appendix C lists the 19 airport pairs. The associated increase in network overlaps is visible in Figures 2, 3, and 4 as was highlighted before. According to our dataset, other months with entries exist but with much fewer instances of only four or fewer entries. Concentrating on October 2019, a difference-in-differences analysis is conducted with 19 OD airport pairs in the treatment group and 572 OD airport pairs in the control group which were operated by Wizz Air and not by Ryanair during the whole sample period.

For each airport pair and month, there are four categories of posted airfares. RDC provides the information about airfares which were posted six months, three months, one month, and one week prior to the travel date. Table 5 displays the numbers of posted airfare observations in the control and treatment groups. The 19 OD airport pairs in the treatment group involved 1,257 airfare observations for the period before the entry of Ryanair and 949 airfare observations for the period after the entry of Ryanair. The 572 OD airport pairs in the control group involved 35,833 observations for the period before the entry of Ryanair and 27,798 observations

[10]Relatively recent studies found that deviating from the canonical format by considering more than two periods and treatments can cause many complications (for example, Chaisemartin and D'Haultfœuille, 2020; and Callaway and Sant'Anna, 2021. Those complications are not a concern for us because we use the canonical format.

[11]RDC collects airfares based on scheduled flights independent of whether they have been operated as scheduled or canceled whereas Flightradar24 only contains operated flights. The use of RDC data implies that, in the treatment group, observations are included although they might involve canceled flights.

	Before	After	Total
Control:	35,833	27,798	63,631
Treatment:	1,257	949	2,206
Total:	37,090	28,747	65,837

Table 5: Numbers of posted airfare observations in the control and treatment groups.

for the subsequent period. The total number of posted airfare observations included in the difference-in-differences analyses is given by 65,837.[12]

Figure 5 displays the Wizz Air airfare changes in terms of the four airfare categories in the control (blue lines) and treatment (red lines) groups during the sample period. The entry period October 2019 is indicated by dashed vertical lines. The parallel trend assumption is required for the difference-in-differences analysis to reach valid results. Figure 5 indicates that the control and treatment groups exhibit similar trends both before and after the entry period of October 2019. The parallel trend assumption will be further discussed in the summaries.

2.5.2 DiD estimations

Let i denote an airport pair in month t. The DiD regression model can be written as

$$Airfare_{it} = \beta_0 + \delta_0 Entry_i + \delta_1 Period_t + \delta_2 Entry_i \times Period_t \, (+ODpair_i + Month_t) + \varepsilon_{it} \quad (1)$$

The explained variable, $Airfare_{it}$, is the (Wizz Air's) airfare on the OD airport pair i in month t. $Entry_i$ is a binary treatment variable which indicates whether one OD airport pair has been entered by another LCC or not. $Period_t$ is a binary period variable. In our case, it is 0 before October 2019, and 1 after October 2019. $Entry_i \times Period_t$ is the DiD term which is used to capture the difference between group (control and treatment) differences before and after the treatment to derive pure treatment effect. $ODpair_i$ captures the OD airport pair fixed effect and $Month_t$ captures the month fixed effect. Both terms are in brackets because the regression has been implemented with and without fixed effects. And ε_{it} is the random error.

The following analysis[13] proceeds in two steps. The first part concentrates on the pooled airfare data whereas the second part considers each airfare category separately. Pooling the airfare data produces significant estimation results for the pre-Covid-19 period and the entire

[12] Multiplying the total number of routes in terms of OD airport pairs involved in the difference-in-differences analyses by 4 and then by 35 which captures the number of posted airfare observations per month and the number of months across the sample period, respectively, yields a total number of 82,740 posted airfare observations. The total number of observations mentioned in Table 5 is 65,873, which is a lower value. There are two explanations for this. The first is related to changes in the number of routes operated by Wizz Air. October 2019 is typically a peak month. The lower number of routes operated by Wizz Air during other months than the peak month reduces the actual number of observations by 11,932. The second reason is related to missing values in the RDC database which amounts to 4,935 observations. The distribution of missing values seems random and they do not seem to affect the estimation results.

[13] All estimations were implemented in STATA with "didregress" or "diff" commands.

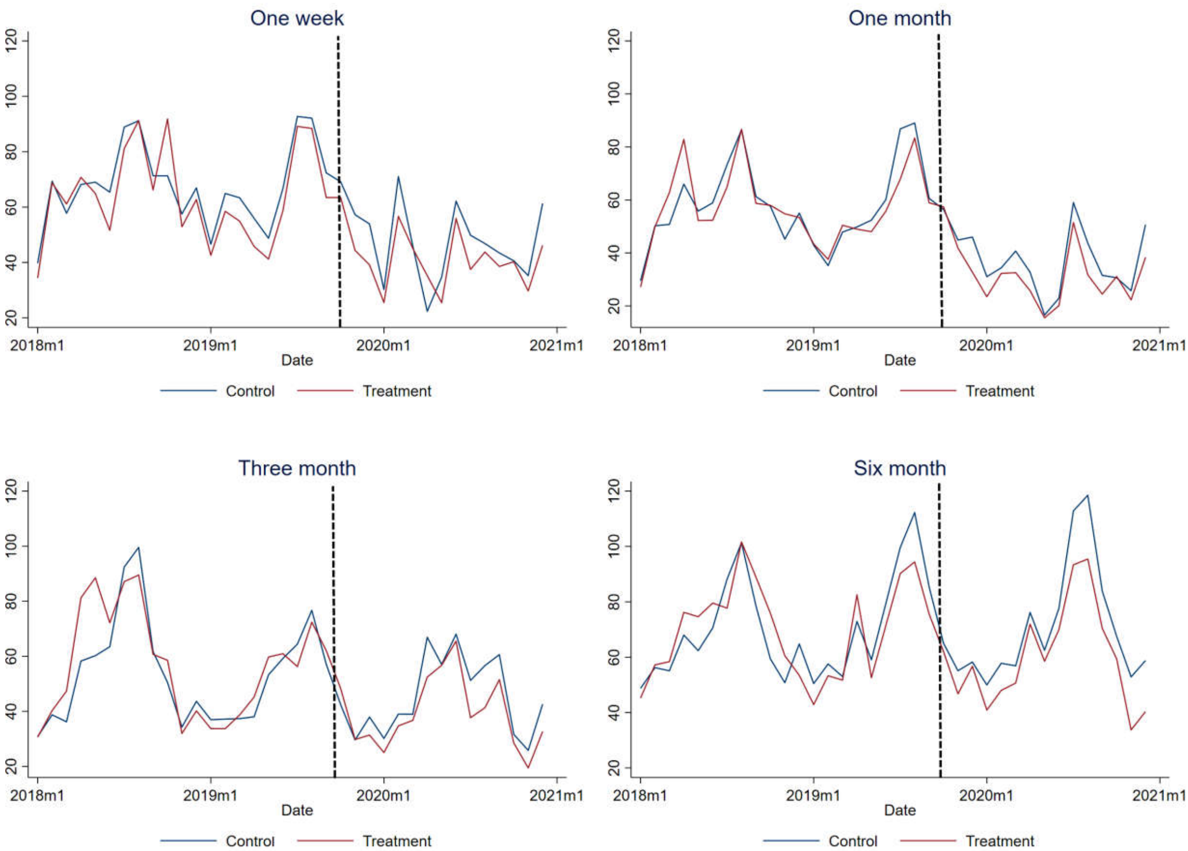

Figure 5: Wizz air's airfares before and after the entry of Ryanair.

FE	Baseline (Before entry) Control	Treat.	Diff	Follow-up (After entry) Control	Treat.	Diff	DiD	R^2
				Before Covid-19				
Without	62.6	61.7	-0.9	51.2	46.2	-5.0**	-4.1	0.01
With#	46.6	24.5	-22.0	50.0	23.8	-26.3	-4.2**	0.56
				Before and during Covid-19				
Without	62.6	61.7	-0.9	50.7	43.6	-7.1***	-6.2***	0.03
With#	29.3	77.9	48.6***	32.1	75.3	43.1***	-5.5***	0.48

*** p<0.01; ** p<0.05; * p<0.1

#Route and month fixed effects are included.

Table 6: Pooled airfare difference-in-differences regressions.

sample period. This allows identifying the effect of the Covid-19 period by comparing the estimation results.

The estimation results based on the pooled airfare data are displayed in Table 6. The estimation results are derived without and with route and month fixed effects. The top panel displays the results for the period before Covid-19. Without fixed effects the differences between the airfares in the control and treatment groups are significantly different from each other only in the period after entry whereas these differences are insignificant before and after entry when fixed effects are used. The coefficient estimate associated with the difference-in-differences term, DiD, is equal to -4.2 and significant when fixed effects are used. The coefficient estimate is of similar magnitude but not significant when fixed effects are not used.

The bottom panel displays the results for the periods before and during Covid-19. Without fixed effects the differences between the airfares in the control and treatment groups are significantly different from each other only in the period after entry whereas the differences are significant and positive before and after entry when fixed effects are used. This indicates that Ryanair entered the routes associated with relatively high airfares across the sample period. This is consistent with the average geometric means of airport pairs in the treatment and control groups given by 25.7 billion Euros and 20.4 billion Euros, respectively; thus, the treatment group is associated with relatively high demand in terms of GDP relative to the control group. The coefficient estimates associated with the DiD terms are equal to -6.2 and -5.5 and significant without and with fixed effects, respectively.

These estimations reveal that the coefficient estimates associated with the DiD terms are lower for the top panel than for the bottom panel (in absolute values). This indicates that network overlaps had a stronger effect on airfares during than before the Covid-19 period. This seems reasonable considering the overcapacity available during the Covid-19 period.

Table 7 displays the estimation results for each airfare category. These estimations are based on the observations from the entire sample period meaning that the analysis does not distinguish between the pre-Covid-19 and the Covid-19 pandemic periods. The estimation results are again derived without and with route and month fixed effects. The top panel displays the results without fixed effects and the bottom panel displays the results with fixed

Airfare	Baseline (Before Entry) Control	Treat.	Diff	Follow-up (After Entry) Control	Treat.	Diff	DiD	R^2
				Without fixed effects				
Six M.	72.3	71.0	-1.3	71.0	61.0	-10.0***	-8.7**	0.00
Three M.	54.4	56.8	2.4	45.7	40.1	-5.6***	-8.1***	0.02
One M.	58.6	57.3	-1.3	37.9	32.4	-5.5***	-4.2*	0.11
One W.	67.9	63.9	-4.0**	50.0	42.5	-7.5***	-3.5	0.08
				With fixed effects#				
Six M.	24.1	30.3	6.2	39.0	39.6	0.6	-5.6***	0.70
Three M.	29.3	66.2	36.9	25.4	55.2	29.9	-7.0***	0.64
One M.	48.8	65.5	16.7	24.0	36.6	12.6	-4.1**	0.62
One W.	33.8	81.5	47.7***	29.4	72.8	43.4***	-4.3**	0.60

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

#Route and month fixed effects are included.

Table 7: Difference-in-differences regressions for all airfare categories (Before and during Covid-19).

effects.

The results with respect to the differences between the airfares in the control and treatment groups as well as the DiD terms are largely consistent with the results in Table 6 which are associated with the pooled airfare regressions. The analysis of individual airfare categories, however, reveals that airfare pressure by market entry is stronger for airfares posted three and six months in advance relative to airfares posted closer to the actual departure times. This could be related to the available seat capacity which tends to be high long before departure time leading to relatively strong competition but tends to get lower closer to departure time potentially softening competition.

An analogue analysis based on city pair entries rather than airport pair entries revealed no statistically significant impact of network overlaps on posted airfares. One reason could be that the competitive effects of network overlaps is weaker if entry does not occur on the same airport pair but involves the use of adjacent airports. The treatment group involving city pairs and not airport pairs, that is, adjacent airports contained four or fewer city pairs. The small size of the treatment group could be another reason for the insignificant estimation results. For the overlaps between easyJet and Wizz Air, most of them were temporary and discontinued after some months.

2.6 Summary

The present Chapter used a large and detailed dataset involving information at the individual flight level. The objective was to analyze the change in the networks of the big three European LCCs Ryanair, easyJet and Wizz Air before and during the Covid-19 pandemic period. The results indicate that LCCs increasingly expanded their networks into markets that had already been served by incumbent LCCs and that the use of adjacent airports had been a substantial part of this change. The example of Ryanair and Wizz Air illustrated that overlap increases were associated with relatively low flight numbers. The example of Wizz Air showed that network overlaps reached up to 30 percent of the total LCC's network. Altogether, this indicates that European LCCs increasingly compete head-to-head among themselves.

A difference-in-differences analysis based on posted airfare information was used to estimate the airfare effect of head-to-head LCC competition on overlapping network parts. The posted airfares have been collected from RDC aviation intelligence. RDC provides the information about airfares which were posted six months, three months, one month, and one week prior to the travel date. Ryanair started operating 19 OD airport pairs in which Wizz Air was the incumbent in October 2019. The estimation results indicate that airfares posted by the incumbent are reduced by approximately six Euros, or ten percent of the average airfares, after the entry of a rival LCC. This indicates that the head-to-head LCC competition leads to substantive airfare reductions.

There are several avenues for future research which can be followed to test whether the airfare effects estimated in this study are generalizable to other competition scenarios. LCCs compete among each other but also with FSCs and their LCC subsidiaries. It would be useful to develop a more complete dataset involving a broader set of airlines to study the change in network overlaps for different types of airlines. Such an extended dataset would allow for various difference-in-difference-in-difference (triple difference) regressions of type discussed in, for example, Gruber (1994) and Olden and Møen (2020). The advantage of triple difference regressions is that they can be used to handle issues associated with the parallel-trend assumption. The above mentioned two research avenues have been attended to in the following Chapter.

Chapter 3: Dynamic Pricing and Competition: Evidence from the Airline Market

3.1 Introduction

Price dispersion and the importance of competition for prices are two salient features of the airline market that have attracted a lot of attention in the theoretical and empirical literature.[14] More recently, the effect of competition on dynamic pricing has come to the fore (Mantin and Koo, 2009; Gaggero and Piga, 2011; Escobari, 2012; Dai et al., 2014; Escobari and Jindapon, 2014; Chen, 2018; Escobari et al., 2019; Dana and Williams, 2022; Hortaçsu et al., 2021 and 2022; Luttman and Gaggero, 2022; Williams, 2022).

The present Chapter estimates the effect of competition on dynamic pricing in terms of intertemporal price dispersion for the European airline market, about one quarter of all flights worldwide (IATA, 2019). Price dispersion is measured by the difference in the levels of posted prices one week before departure time and one month or several months before departure time. The advantage of using posted prices is that prices refer to standardized services as opposed to transacted prices which, for example, may or may not include carry-on luggage.

This study has been arranged as follows. Subchapter 3.2 explains the data and provides descriptive analysis. Subchapter 3.3 introduces the econometric methodology. Subchapter 3.4 contains the empirical results. Subchapter 3.5 provides different sensitivity analyses. And Subchapter 3.6 briefly summarizes.

3.2 Data and Descriptive Analyses

3.2.1 Market characteristics

This Chapter employs RDC aviation intelligence information on monthly prices for flights between European airports that are posted one week, one month, three months and six months prior to the travel date for a period of three years, 2017-2019.[15] As will be argued in the following methodology Subchapter, under nonrestrictive assumptions, the posted prices reflect transacted prices in a way that allows us to analyze the causal effect of carrier entry and exit on market prices.

The dataset contains information about 15 of the largest airlines in Europe, of which 10 are FSCs (Air France/KLM, Aer Lingus, British Airways, Iberia, Austrian Airlines, Brussels Airlines, Lufthansa including its subsidiary Eurowings, Swiss International Air Lines, and Scandinavian Airlines) and 5 are LCCs (Norwegian Air Shuttle, Vueling, Ryanair, easyJet and Wizz Air). Lufthansa owns Austrian Airlines and Brussels Airlines and these airlines together with Eurowings will, therefore, be treated as one airline. Aer Lingus, British Airways, Iberia and

[14] For example, see Borenstein (1985), Borenstein and Rose (1994), Dana (1999 and 2001), Gerardi and Shapiro (2009), Orlov (2011), Cornia et al. (2012), and Sengupta and Wiggins (2014).

[15] RDC scrapes prices from multiple online booking platforms and reports the monthly average. We exclude a limited number of flights to or from Turkish airports, including Istanbul, as we do not have information about Turkish airlines, the largest Turkish airline.

Sample	Full		Effective	
	Mean	SE	Mean	SE
	Difference in log prices			
1 week vs 1 month	0.276	0.345	0.245	0.303
1 week vs 3 months	0.435	0.459	0.398	0.408
1 week vs 6 months	0.415	0.493	0.420	0.437
	Rival numbers			
Total	0.337	0.580	0.834	0.714
0	0.715	0.451	0.340	0.474
1	0.237	0.425	0.499	0.500
2	0.044	0.206	0.150	0.357
3	0.004	0.063	0.012	0.108
LCC rivals	0.186	0.420	0.388	0.552
0 LCC	0.826	0.379	0.644	0.479
1 LCC	0.162	0.369	0.324	0.468
2 LCCs	0.011	0.106	0.031	0.174
3 LCCs	0.0004	0.020	0.001	0.027
FSC rivals	0.151	0.382	0.446	0.563
0 FSC	0.857	0.350	0.589	0.492
1 FSC	0.134	0.341	0.378	0.485
2 FSCs	0.008	0.092	0.033	0.179
3 FSCs	0.0001	0.012	0.001	0.025
Observations	157,407		33,228	

Table 8: Summary statistics.

Vueling belong to the International Airlines Group (IAG) and will, therefore, be treated as one other airline.[16]

For each route, the number of rivals *in a specific month* is known, where the number of FSC as well as the number of LCC rivals are distinguished. This analysis aims to investigate the effect of competition on the monthly (dynamic) price charged by a carrier for a round trip. In total there are 157,407 observations for 5,622 routes in which 33,228 are effective samples with at least one change in the number of LCC and FSC rivals during our study period.[17]

Table 8 provides summary statistics about the difference in log prices depending on the time difference between departure and booking as well as the number of rivals. It shows, for example, that prices are approximately 44% lower three months to departure compared to bookings just before departure. It also shows that the number of rival competitors tends to be low, as the

[16] IAG is considered as a FSC group even though IAG owns slightly more than 90 percent of Vueling. IAG also owns a share of almost 5 percent of Norwegian Air Shuttle. Because this share is small, Norwegian Air Shuttle is considered as an independent competitor to the other carriers owned by IAG.

[17] For prices six months before departure, we have 19% fewer observations because prices were still not posted by airlines so early in advance.

average is only 0.34. The majority of the routes, about 70%, are monopoly routes (in a specific month), which is comparable to the share of monopoly routes found by others (for example, Burghouwt et al., 2015).[18] In less than 1% of the cases, there are at least three rivals. The distribution of the number of LCC rivals is almost identical to the distribution of the number of FSC rivals.

The econometric analyses will rely on methodologies that exploit changes over time in the number of competing rivals. In the majority of routes, there is no change in competition during the period of observation, and this is in particular true for the monopoly routes, so the *effective sample* is smaller and summary statistics are considerably different from the overall sample. The last two columns of Table 8 show the summary statistics for the effective sample. It appears that for this sample, the number of rivals is more than two times higher and equal to 0.83 and only 34% of the routes are monopoly routes. Price differences depending on the booking relative to departure times are almost identical for the full and the effective sample.

3.2.2 Posted versus transacted prices

This study follows a literature that uses information about monthly averages of posted prices of a standardized trip rather than transacted prices, as we do not have information about transacted prices for different booking times. This raises the question given which assumptions our estimates of competition on posted prices can be interpreted as causal effects on transacted prices at the time of booking.

The following two, nonrestrictive, assumptions are sufficient to guarantee this. First, one has to assume that there is a large number of transactions, such that during the time interval before departure (up to 6 months) there is at least one transaction at or close to the dates observed (one week before, one month before, three months before, six months before). Second, it is necessary to make the assumption that the average posted price calculated is not systematically correlated to changes in the number of rivals observed, so the error induced by this is random. For example, if it is the case that the average prices are calculated differently after entry of a rival, then the results are not causal. Although RDC does not provide information on how the monthly average is calculated, so cannot fully exclude this possibility, it is believed that this assumption is not unreasonable. To be more precise, it is also necessary to assume that the difference between log posted prices and log transacted prices can be interpreted as additive random error, given controls, i.e., a so-called classical random error. In other words, the analyses allow for systematic differences between log transacted prices and log posted prices which are captured by the controls. For example, it allows for the situation that transacted prices are systematically higher than posted prices for specific routes of certain carriers. Moreover, it also allows for idiosyncratic additive differences not correlated to entry or exit of carriers (Verbeek, 2008).

[18] These monopoly routes tend to be domestic within-country routes.

3.3 Empirical Methods

Our goal is to estimate the causal effect of competition on dynamic pricing patterns. Market entry or exit changes the number of rivals in the market and, thus, competition. The causal effect of changes in the number of rivals on the dynamic pricing patterns in the short and the long run is estimated by using an event study approach. This is followed by considering standard two-way fixed effects models which estimate the average causal short and long run effects of competition. Staggered two-way fixed effects estimations can be biased because of negative weights (for example, de Chaisemartin, 2020, and Callaway, 2021). A long difference approach is used to obtain an unbiased estimate of the long run effect of competition on dynamic pricing.

3.3.1 Event study

This Subchapter starts with an event study model in which we focus on the event of a change in competition. Such an event can be associated with the entry of a new rival or the exit of an existing rival. The entry of a new rival leads to an increase in competition in time whereas the exit of an existing rival leads to a reduction of competition in time. To increase the efficiency of the estimations, entry and exit events will be pooled together by reversing the time line for exit. This assumes that the incumbent carrier's response to the entry of a rival (competitor +1) is not distinguishable from the carrier's response to the exit of a rival (also competitor +1 in a *reversed* timeline), which is a plausible assumption.

Consider the entry of a rival. Let c denote the carrier, r denote the route, $t \in \{1, .., 36\}$ denote the month, and $T \in \{0, 1, 3, 6\}$ denote the duration to departure in months ($T = 0$ denotes one week before departure). Let P_{crt-T} denote the prices charged for flights booked T months in advance. We are interested in the effect of market entry on the logarithm of the prices booked one month, three months or six months in advance relative to the prices for flights booked one week in advance, P_{crt-0}/P_{crt-T} for $T \in \{1, 3, 6\}$. Consider a given route at month t where a rival enters at time $t + h$. In this case, the value of h indicates how many months before ($h < 0$) or how many months after ($h > 0$) period t entry occurs on route r. Let δ_{crk} denote a dummy variable which indicates whether entry happened k months away from month t, that is, $\delta_{crk} = 1$ if $k = h$ and zero otherwise. We assume a linear specification and include carrier-route fixed effects, D^T_{cr}, and months fixed effects, D^T_t. This leads to the specification for $T \in \{1, 3, 6\}$:

$$log\left(P_{crt-0}/P_{crt-T}\right) = \sum_{k=-24}^{-2} \beta^T_k \delta_{crk} + \sum_{k=0}^{24} \beta^T_k \delta_{crk} + D^T_{cr} + D^T_t + \varepsilon_{crt-T}, \tag{2}$$

with 24 leads and lags around the entry month h and where ε_{crt-T} denotes the random error.

To increase the efficiency of the estimations, entry and exit events are pooled together by changing the meaning of h for exit events as follows. Consider a given route r where a rival exits at time t. In the exit case, the value of h indicates how many months after ($h < 0$) or how many months before ($h > 0$) exit occurs on route r relative to period t. For the pooled dataset, the estimated coefficients β^T_k indicate the effect of an increase in competition which can be related to either the entry of a new rival or the absence of the exit of an existing rival.

We are particularly interested in the estimated coefficients β_k^T, which indicate the effect relative to one month before treatment, that is, $\delta_{crk} = 1$ for $k = -1$.[19] And use it as the reference for other coefficients in the event study. When we implement the event study, we will further distinguish between LCC and FSC competitors.

In our application, many routes are treated more than once, which creates a complication. So, for example, on a specific route, there will be entry in a certain month and an exit several months later. We will deal with this complication by focusing on the first entry or exit and then right-censor observations when the second event occurs.[20] Standard errors are clustered at the route level. In this way we allow not only for correlation of residuals between carriers on the same route, but also allow for correlation over time. The censoring reduces the efficiency of the estimations. More efficient two-way fixed effects regression will, therefore, be considered in a next step.

3.3.2 Two-way fixed effects

We are interested in the effect of the number of rivals, denoted by $N_{crt} \in \{0, 1, 2, 3\}$, on the price differences, $log\,(P_{crt-0}/P_{crt-T})$. We start with the specification

$$log\,(P_{crt-0}/P_{crt-T}) = \alpha^T N_{crt} + D_{cr}^T + D_t^T + \varepsilon_{crt-T}. \tag{3}$$

Our main interest is in the effect of the number of rivals on prices as captured by the coefficient α^T. Standard errors are, again, clustered at the route level.

The above specification assumes that the marginal effect of the number of rivals is the same for LCCs and FSCs. There is good evidence that LCCs can create strong competitive forces relative to FCCs (for example, Morrison, 2001 and Mason and Alamdari, 2007). The following specification distinguishes between the number of LCCs and FSCs,

$$log\,(P_{crt-0}/P_{crt-T}) = \alpha_1^T L_{crt} + \alpha_2^T F_{crt} + D_{cr}^T + D_t^T + \varepsilon_{crt-T}. \tag{4}$$

Our main interest is in the effect of the number of LCC rivals, denoted by $L_{crt} \in \{0, 1, 2, 3\}$, versus the number of FSC rivals, denoted by $F_{crt} \in \{0, 1, 2, 3\}$, on prices as captured by the coefficients α_1^T and α_2^T.

Finally, the above specifications assume that the marginal effect of the number of rivals is constant. Although convenient, this assumption is unlikely to hold, as one expects that the marginal effect would become smaller if the number of rivals increases. To capture this, we use flexible dummy specifications, in which we include two sets of dummies describing the number of LCC and FSC rivals, L^y and F^y, respectively, in which $y \in \{1, 2, 3\}$. With flexible dummies, the regression equation can be rewritten as

$$log\,(P_{crt-0}/P_{crt-T}) = \beta_1^T L_{crt}^1 + \beta_2^T L_{crt}^2 + \beta_3^T L_{crt}^3 + \beta_4^T F_{crt}^1 + \beta_5^T F_{crt}^2 + \beta_6^T F_{crt}^3 + D_{cr}^T + D_t^T + \varepsilon_{crt-T}. \tag{5}$$

[19] In our data, we do not know the exact moment of entry or exit but only the month of the event, so we have measurement error in the month of the event but not after that.

[20] Right censoring generates consistent estimates given the assumption that the second event was unexpected to the incumbent carriers or that the second event was expected, but the incumbent carriers did not adjust prices before the event. This assumption seems adequate as we have little evidence of adjusting prices before the first event.

The above equations are quite standard. Nevertheless, staggered adoption, that is, the number of rivals keeps changing across routes and periods can cause estimation problems. It recently has been understood that difference-in-differences estimates may be not informative on the average treatment effect in the case of staggered adoption (for example, De Chaisemartin and D'Haultfœuille, 2018 and 2020; Borusyak et al., 2021; Callaway and Sant'Anna, 2021). In our case, this is because the estimated coefficients are a weighted average of several difference-in-differences comparing changes in prices between consecutive time periods across different pairs of routes. De Chaisemartin and D'Haultfœuille (2020) show that this may imply negative weights because treated observations in earlier periods may function as controls for observations that are treated later. Amongst others, De Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021) have proposed alternative ways to handle the issue of staggered adoption and negative weights. In the present paper, we develop another way to overcome this issue, as explained in the next Subsubchapter.

3.3.3 Long differences

The estimation of long differences is, in principle, straightforward. Rather than focusing on the average treatment effect of changes in the number of rival carriers, which is aimed to be captured by the two-way fixed effect model, one focuses on a selection of observations from the beginning and the end of the sample period. Consider specification (3). This specification changes to:

$$\triangle log\left(P_{crt-0}/P_{crt-T}\right) = \alpha^T \triangle N_{crt} + D_{cr}^T + D_t^T + \varepsilon_{cr-T}, \tag{6}$$

where $\triangle X$ denotes $X_{t=36} - X_{t=1}$. This approach has several advantages.

The main econometric advantage is that, by construction, treatment is not staggered, because the treatment happens between the first and the last month of the observation period. The second advantage is that it captures the long-term effect, which addresses two important issues.[21] First, as is well known, standard two-way fixed effect approaches ignore anticipation effects. It is plausible that airlines start to reduce prices if they expect a competitor to enter a market. Consider the scenario in which a carrier gradually moves into a market by first starting to serve the endpoint airports of a market before moving into the market itself. Serving the endpoint airports is considered as a measure for the threat of entry determinant of ticket prices in many studies (for example, Morrison, 2001; Goolsbee and Syverson, 2008; Brueckner et al., 2013; Shrago, 2022). In such scenarios, one may underestimate the competitive pressure of actual entry on prices. Second, it may be the case that incumbent airlines that are confronted with a new competitor react differently in the short and long run. For example, the incumbent expects that passengers are temporarily willing to pay a premium for its service, e.g., because of brand loyalty that may have been induced by frequent flyer points. Another example is related to the possibility of so-called predatory pricing behavior and involves an aggressive price reduction with the goal to quickly drive the new entrant out of the market (for example, Forsyth et al., 2018).

[21] In our context, long term is defined by maximally three years and the average time before entry or exit is 18 months and the average time after entry or exit is also 18 months.

Although using the long difference approach has substantial econometric advantages and useful economic implications in the sense that it identifies long-term price effects of entry, it has one important disadvantage. It will lead to a strong decrease in efficiency.[22] This inefficiency is even enhanced because the first and the last month of our data refer to January and December, which are months with fewer flights. Fundamentally, we improve by combining an annual averaging approach with a long difference. Let $\bar{X}_y$ refer to the average taken over the observations in year y and redefine $\triangle X$ as $\bar{X}_3 - \bar{X}_1$. In this case, we do not use the first month, but the average over the first year of the observation period as the first observation. Similarly, as the last observation, we do not use the last month, but the average over the last year of the observation period. As one expects, we then find strong increases in efficiency, but somewhat smaller effects (in absolute value) as we have reduced the time interval which defines the long run.

3.4 Econometric Results

This Subchapter demonstrates that an increase in competition changes price dynamics in the sense that there is a causal negative effect of competition on the differences in log prices charged far in advance relative to one week before departure. We start with an event study which supports the subsequent econometric analyses, then the two-way fixed effects estimation, followed by long differences. We also examine the potential heterogeneity between entries/exits by LCCs and FSCs.

3.4.1 Event study

Figure 6 shows nine event studies to the effect of entry and exit on price dynamics as measured by the difference between log prices charged one week and one month (first column), three months (second column) and six months (third column) months in advance, $log\,(P_{crt-0}/P_{crt-T})$ for $T \in \{1, 3, 6\}$, for LCC and FSC entries/exits combined (first row), only FSC entries/exits (second row), or only LCC entries/exits (third row).

The event study plots indicate the existence of a causal effect of entries and exits on pricing dynamics. The yellow vertical line in the event study plots indicates the treatment period. Consider the left-hand side of the vertical line. This side refers to periods with low competition, that is, before either the entry of a new rival or after the exit of an existing rival. In this part of the event study plots, almost all coefficient estimates are insignificant which is consistent with the notion of the absence of a pre-trend for all three price difference categories, that is, for all $T \in \{1, 3, 6\}$. Consider the right-hand side of the vertical line. This side refers to periods with high competition, that is, after either entry of a new rival or before the exit of an existing rival. Many of the coefficient estimates are negative and significant on this side of the event plots. The plots show a clear discontinuity because most negative coefficient estimates are close to the treatment period. This strongly indicates that entries and exits are the causes for the changes in the pricing dynamics. Comparing the plots in the three columns further indicates that the

[22] In our application, the number of observations reduces by a factor of 18, suggesting that standard errors tend to increase by a factor of approximately $18^{0.5} \approx 4.2$. This is also what we find in the application.

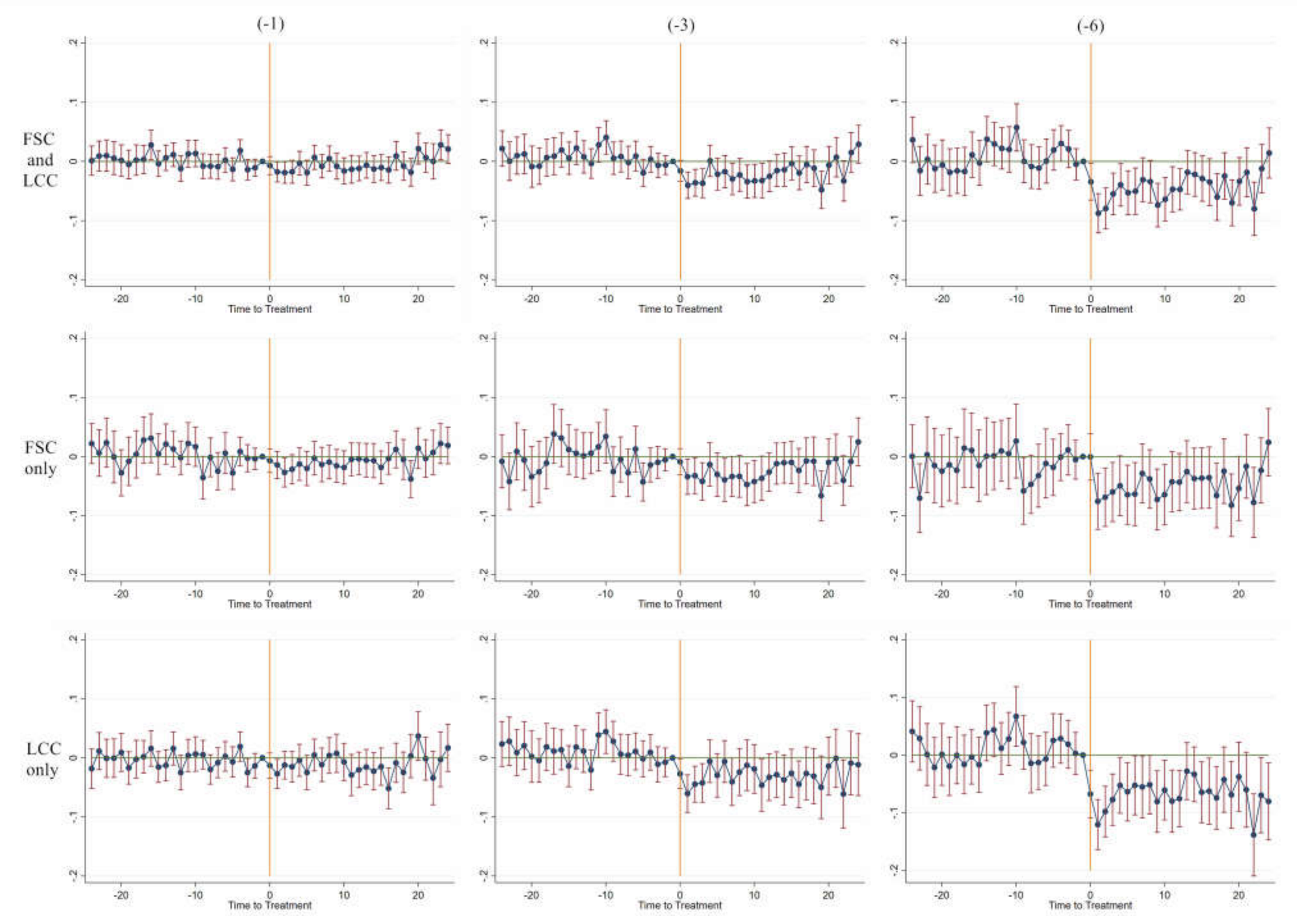

Figure 6: Event studies to the effect of entry and exit on price dynamics as measured by the difference between log prices charged one week and one month (first column), three months (second column) and six months (third column) in advance, $log\,(P_{crt-0}/P_{crt-T})$ for $T \in \{1, 3, 6\}$, for LCC and FSC entries/exits combined (first row), only FSC entries/exits (second row), or only LCC entries/exits (third row). The vertical lines denote the 95% confidence bands.

causal effects are stronger for price differences associated with the bookings made three ($T = 3$) and six months ($T = 6$) in advance relative to the price differences associate with the bookings made one month ($T = 1$) in advance.

Figure 7 illustrates the absence of pre-trends for both entry and exit observations which indicates that the pooling of entry and exit observations does not distort the analysis. More specifically, the figure depicts the event study to the effect of entry and exit on price dynamics as measured by the difference between log prices charged one week and three months in advance, $log\,(P_{crt-0}/P_{crt-3})$, for pooled entry and exit observations (left), only entry observations (middle), and only exit observations (right, with a reversed timeline). Almost all coefficients on the left hand sides of the vertical lines in the middle and right plots are insignificant indicating the absence of pre-trends. Corresponding figures associated with $T = 1$ and $T = 6$ show similar patterns, thus, omitted.

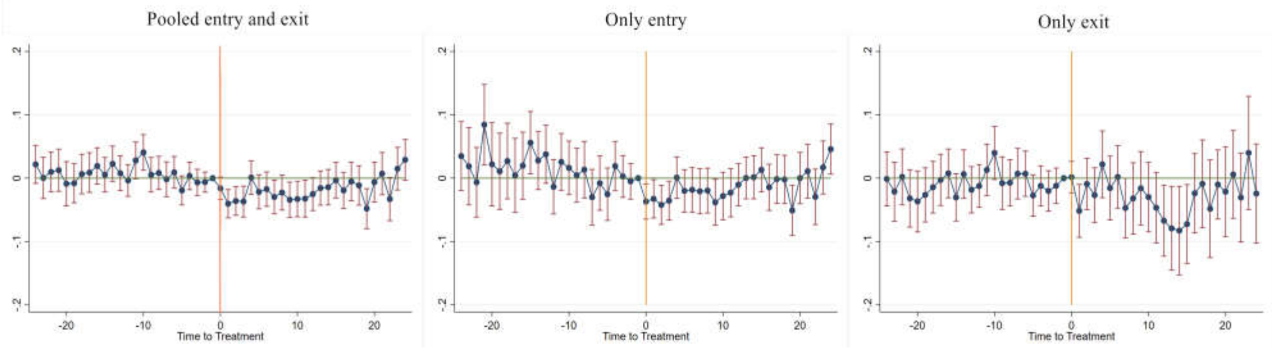

Figure 7: Event study to the effect of entry and exit on price dynamics as measured by the difference between log prices charged one week and three months in advance, $log\left(P_{crt-0}/P_{crt-3}\right)$, for pooled entry and exit observations (left), only entry observations (middle), and only exit observations (right). The vertical lines denote the 95% confidence bands.

3.4.2 Two-way fixed effects

The event study established the causal effect of competition on the pricing dynamics. This part discusses the results of the more efficient two-way fixed effect regressions using specifications (3)-(5) shown in Table 9 columns (a)-(c), respectively.

Consider the results in (a). They clearly show the negative effect of competition on price differences and, more importantly, that competition has a strong effect on dynamic pricing. For example, the marginal effect of rivals on prices three months before departure are about 4.1% lower than one week before departure. The effect of LCC rivals, shown in (b), appears to be even stronger with a marginal effect of -4.8%. The effects of competition on dynamic pricing become even stronger when we focus on price differences associated with bookings six months before departure, but weaker when we focus on the effect of competition on prices differences booked one month before departure. We formally test between the two marginal effects for LCCs and FSCs. The results are shown in Table 10. Considering the 5% level of significance, the results show that LCCs have a significantly stronger effect on price differences only for fares booked six months before departure. When we allow for non-constant marginal effects in (c), these results are confirmed. The results indicate that the marginal effect tends to be diminishing over time for FSCs but not necessarily for LCCs.

To interpret our results, we can partly rely on a literature which emphasizes the importance of changes in the composition of arriving customers over time to departure (Williams, 2022). Arguably, changes over time to departure in the elasticity of demand is required to rationalize airfare pricing patterns (McAfee and Te Velde, 2006). The effect of competition on price differences is diminishing when booking time is far away from departure. The reason may be that leisure travelers often book air tickets much in advance and if the travel cost is too high, for a particular destination, they can choose to travel to other destinations. Thus, the competition is not only on that route, but most likely in the regional market constituting a buyer's market suppressing price markups for tickets sold long in advance. But business travelers often book air tickets closer to their traveling dates with relatively higher values and fixed destinations.

	(a)			(b)			(c)		
	(−1)	(−3)	(−6)	(−1)	(−3)	(−6)	(−1)	(−3)	(−6)
Rivals	−0.015***	−0.041***	−0.066***						
	(0.004)	(0.006)	(0.008)						
LCC rivals				−0.011*	−0.048***	−0.089***			
				(0.006)	(0.009)	(0.011)			
FSC rivals				−0.018***	−0.033***	−0.041***			
				(0.006)	(0.008)	(0.010)			
1LCC rival							−0.013**	−0.052***	−0.098***
							(0.006)	(0.009)	(0.012)
2LCC rivals							−0.012	−0.077***	−0.134***
							(0.017)	(0.029)	(0.033)
3LCC rivals							0.050	−0.081	−0.243*
							(0.094)	(0.102)	(0.138)
1FSC rival							−0.016**	−0.031***	−0.039***
							(0.006)	(0.009)	(0.011)
2FSC rivals							−0.055***	−0.089***	−0.101***
							(0.015)	(0.024)	(0.026)
3FSC rivals							−0.148***	−0.126***	−0.149***
							(0.043)	(0.034)	(0.057)
No. of Obs.	155,363	155,363	125,123	155,363	155,363	125,123	155,363	155,363	125,123

***$p < 0.01$,** $p < 0.05$,* $p < 0.1$; Controls include carrier-route, destination-month and carrier-month fixed effects. Standard errors in parentheses are clustered at route levels.

Table 9: Baseline results for pricing dynamics.

	$T = 1$	$T = 3$	$T = 6$
		Linear	
LCC = FSC	0.354	0.218	0.002
		Non-linear	
1 LCC rival = 1 FSC rival	0.749	0.093	0.0003
2 LCC rivals = 2 FSC rivals	0.056	0.740	0.438
3 LCC rivals = 3 FSC rivals	0.053	0.679	0.530

Table 10: F-test results.

	(a)			(b)		
	(−1)	(−3)	(−6)	(−1)	(−3)	(−6)
			January 2017 vs December 2019			
Rivals	0.012	-0.068^{***}	-0.096^{*}			
	(0.018)	(0.023)	(0.054)			
LCC rivals				−0.020	-0.145^{***}	-0.191^{**}
				(0.029)	(0.037)	(0.085)
FSC rivals				0.040^{*}	0.002	−0.024
				(0.024)	(0.031)	(0.069)
Observations	4,544	4,544	1,740	4,544	4,544	1,740
			Annual average prices of 2017 vs 2019			
Rivals	−0.006	-0.036^{***}	-0.047^{***}			
	(0.010)	(0.013)	(0.015)			
LCC rivals				−0.016	-0.055^{***}	-0.093^{***}
				(0.012)	(0.017)	(0.019)
FSC rivals				0.010	−0.002	0.032
				(0.015)	(0.019)	(0.025)
Observations	9,466	9,466	8,720	9,466	9,466	8,720

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Controls include carrier-route, destination-month and carrier-month fixed effects. Standard errors in parentheses are clustered at route levels.

Table 11: Long-term effect of competition on pricing dynamics.

Thus, the competition is only on that route and with a strong demand constituting a seller's market with high price markups for tickets sold close to departure time leaving more room for en-route competition to suppress prices.[23]

3.4.3 Long differences

We aim to improve on the previous results by exploiting the identification of long-term variation between treated routes and non-treated routes. As discussed above, we do so in two ways: the first specification uses observations only for the first month and the last month of observation period whereas the second specification uses annual averages for the first and the last year only.

The results of the two specifications are displayed in Table 11. They are largely consistent for the two specifications although, as expected, the second specification is more efficient than the first one. They show that LCC competition reduces intertemporal price dispersion in the long term whereas this is not true for FSCs. The lack of a long-term effect by full-service carriers may be due to the existence of frequent flyer programs which soften competition a while after the entry of a new rival (for example, Borenstein, 1992). The results further show that the long-term effect of LCCs is strongest for prices charged far in advance.

[23] Kaplan et al. (2019) use a similar line of reasoning in their analysis of price dispersion in retail markets.

3.5 Difficulty in Measuring Rival Numbers

This Subchapter presents a range of sensitivity analyses with respect to the measurement error in counting rivals. There are two sources for measurement errors. First, our analysis relies on information from the largest carriers in Europe, but we exclude information on a few smaller rivals in the European domestic market. Second, we treat destinations located in multi-airport regions (see Appendix A) similar to destinations which are not located in multi-airport regions.

To partially deal with the first issue, we have excluded a limited number of flights to or from Turkish airports, including Istanbul, as we do not have information about Turkish airlines. This may cause a small bias if the missing rivals enter or leave certain routes during the period of observation. If the moment of entry and leaving of these unobserved rivals is random with respect to the changes in competition observed in our data, then we should have a small downward bias in our estimation of the competition effects because the marginal effect of rival numbers tends to be diminishing. The downward bias may be larger if there is a negative relationship between the entry and exit behavior of unobserved and observed rivals. If this relationship is positive, we may have an overestimate of the competition effect.

To further address the first issue, we have done two sensitivity analyses. The results are shown in the first two panels of Table 12. Both of these analyses create additional measurement error. First, we have added 891 flights to Turkish airports, which creates measurement error, as we miss important carriers of these airports. It appears that this does not affect our results. Second, we also have done a sensitivity analysis in which we treat observed changes in competition by the largest carrier in Europe, Ryanair as unobserved, hence we revised all observations in which Ryanair is a competing rival and we exclude all prices for flights of Ryanair. In total we exclude about 50,000 observations, roughly 1/3 of our dataset, whereas for almost 12,000 observations, we have measurement error in the number of rivals. It appears that causing substantial measurement error in the data by excluding changes in competition caused by Ryanair hardly affects the results.

Destinations in multi-airport regions involve a set of adjacent airports which potentially are considered as substitutes by passengers. Not capturing the changes in rival numbers on competing airport pairs is a source for measurement error. The results in the third panel of Table 12 are obtained after excluding all observations involving multi-airport regions. In total, eliminating multi-airport regions means that 74,795 observations are excluded. Again, the results are robust in the sense that estimation results are hardly changed. Altogether, this shows that the measurement error in counting rivals is not affecting our main results.

3.6 Summary

This Chapter studies incumbent airlines' responses to competitions on the same route. A large price dataset by RDC intelligence which includes monthly prices on intra-Europe aviation routes operated by the top ten European FSCs and top five European LCCs has been utilized. prices are posted prices one week, one month, three months and six months to departure, which allows us to capture booking time as an important determinate. Event studies, panel data two-way fixed effects, as well as long differences models are applied.

	(a)			(b)		
	(-1)	(-3)	(-6)	(-1)	(-3)	(-6)
			Add in Turkish airports and observations			
Rivals	-0.015^{***}	-0.041^{***}	-0.066^{***}			
	(0.004)	(0.006)	(0.008)			
LCC rivals				-0.011^{*}	-0.048^{***}	-0.089^{***}
				(0.006)	(0.009)	(0.011)
FSC rivals				-0.018^{***}	-0.033^{***}	-0.042^{***}
				(0.006)	(0.008)	(0.010)
Observations	156,194	156,194	125,705	156,194	156,194	125,705
			Eliminate Ryanair			
Rivals	-0.015^{***}	-0.042^{***}	-0.061^{***}			
	(0.005)	(0.007)	(0.009)			
LCC rivals				-0.015^{*}	-0.057^{***}	-0.088^{***}
				(0.009)	(0.013)	(0.017)
FSC rivals				-0.015^{***}	-0.033^{***}	-0.043^{***}
				(0.006)	(0.009)	(0.011)
Observations	104,922	104,922	80,058	104,922	104,922	80,058
			Eliminate multi-airport regions			
Rivals	-0.019^{***}	-0.055^{***}	-0.076^{***}			
	(0.006)	(0.009)	(0.011)			
LCC rivals				-0.009	-0.056^{***}	-0.089^{***}
				(0.008)	(0.013)	(0.017)
FSC rivals				-0.029^{***}	-0.053^{***}	-0.062^{***}
				(0.009)	(0.013)	(0.015)
Observations	80,541	80,541	64,448	80,541	80,541	64,448

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Controls include carrier-route, destination-month and carrier-month fixed effects. Standard errors in parentheses are clustered at route levels.

Table 12: Addressing the difficulty in measuring rival numbers.

This Chapter demonstrates that the increase in airline competitions causes reductions in intertemporal price dispersion, that competition mainly benefits late bookers, and that low-cost carrier competition has a lasting effect on pricing dynamics whereas full-service carrier competition does not. These results are consistent with a dynamic price competition models in which firms have market power and the composition of arriving customers changes over time to departure, that is, passengers who book just before departure are less price elastic than those who book several months before (for example, Williams, 2022). The existence of frequent flyer programs could be the reason for the lack of long-term effects created by full-service carrier competition (for example, Borenstein, 1992). Future research avenues include the consideration of heterogenous passengers, and the possible use of utility-based regression models.

Chapter 4: The Success of Gulf Carriers Explained: The Case of the Australia-UK Airway

4.1 Introduction

Market entry has received great attention in the economics literature (Geisel et al., 1993; Karakaya and Stahl, 1989), particularly for markets that traditionally were regulated such as the airline industry, which will be the focus of this study. There is general consensus that new entrants have non-negligible effects on prices, revenues, quality supply and social welfare (for example, Karakaya and Stahl, 1989; Geisel et al., 1993). This explains why governments tend to be in favour of new entrants. In the US aviation market, nowadays 30% of the whole market is covered by Low-Cost Carriers. National governments are however much less in support of foreign entrants by granting them liberties to operate between two countries via their homeland country (the "sixth freedom" of the Chicago Convention) and even to operate domestic flights within non-homeland countries (the "seventh freedom" or cabotage right). In Europe, the full deregulation was implemented in 1997 after three airline policy "packages" were approved in 1988, 1990 and 1993. Since 2006, the European Union (EU) has concluded so called "horizontal agreements" with a few African countries and countries in the Middle East such as the United Arab Emirates (UAE). For instance, the agreement with UAE allows European and Gulf carriers such as Emirates and Etihad to fly between the UAE and any EU member state since 2007. The EU/US Open Skies agreement became operational in 2008.[24] Arguably, increased competition by foreign competitors is good for domestic consumers, but not necessarily for domestic airlines (Dresner et al., 2015). This is particularly obvious in the international airline market. In this market, for many years, most national governments did not allow international companies from entering their domestic market (cabotage right). Many national governments still provide substantial subsidies to domestic companies (for example, through favorable loans, by providing grandfather rights, fiscal treatment, by subsidizing specific airports), which recently has become clear during the Covid crisis in which the International Air Transport Association (IATA) highlighted that there was a long tail of weaker airlines with negative economic profit even before Covid-19 (IATA, 2020).

So, not surprisingly, one of the most hotly-debated markets in the world is the *international* aviation market. Here, we focus on the *long-distance* international market. This market is o particular interest because, in this market, Low-Cost Carriers are more or less absent whil with the Gulf carriers such as Emirates, Etihad, and Qatar Airways, new players have entere the market and quickly gained market shares. For instance, in the Australia-UK markets th Gulf carriers' shares in terms of passenger volumes increased from 5% in 2002 to 35% in 2012.

The airway between Australia and the UK witnessed over 8 million travelers during 2002 and 2012. It is also one of the longest airway on earth with a great circle distance no shorte than 11,000 kilometers, which bore no direct flights before 2018. Aviation researches have discussed many domestic markets (Wang, Zhang and Zhang, 2018) and short-distant internation markets (Wang et al., 2020) but were seldom related to long-distant international markets (Choi

[24] Czerny and Lang (2019) provide an overview over airline privatization and deregulation policies worldwide.

et al., 2019). Some were related to the macro topology of international flight networks (Cheung et al., 2020 and Wong et al., 2019), but none has been related to the airway between Australia and the UK.

Australia-UK airway via the eastern hemisphere started from 1935 with several intermediate connects. In 2002, there were over 20 airlines operating this route. Gulf carriers, typically referring to the three major carriers, Qatar Airways, Emirates and Etihad Airlines, also entered this competition in 2002. Using a typical market entry strategy (Gudmundsson, 1998), they offered low airfares and a variety of flight options to air travelers to boost market shares, and also doubled daily flight frequencies per itinerary between 2002 and 2012 (this will be discussed in more detail in the descriptive analyses). This brought up serious concerns from multiple parties about distorted competitions as debated at the 2015 European Aviation Conference and in Douglas (2019). Dresner et al. (2015) also reported small but statistically significant traffic loses and fare reductions for U.S. carriers in the U.S. aviation markets due to the entry of Gulf carriers. After all, Gulf carriers have innate advantages based in the middle east, a crucial transfer stop from Australia to the UK. And they offer close substitutes to other carriers, which may cause excessive competition in homogeneous product markets and lead to social inefficiency.

At this point, research questions of this study become clear: what were the influences from the entry of Gulf carriers on the airfares and consumer surplus, how did demand and consumer preferences shift in the Australia-UK, and how did marginal cost and profit change in this market?

This study presents four different logit/nested logit models of the aviation markets between Australia and the UK during 2002 and 2012. Estimations are done from the demand-side and the supply-side. One unique and novel itinerary dataset with detailed transfer information from Sabre Airport Data Intelligence (ADI) database is applied. Its virtues lie in the containment of detailed airfares in each itinerary and information of operating airlines on each flight segment. Flight frequencies are customized from Official Aviation Guides (OAG).

This study finds that significant changes in air travelers' preferences, as well as changes in consumer surplus, happened during 2002 and 2012 after the entry of Gulf carriers. Demand-side estimations show that air travelers became less sensitive to airfares, became more in favor of one-connect and high-frequency flights, and became less price-elastic. On the other hand, products provided by the Gulf carriers and the incumbents were getting more and more homogeneous to each other, which seems to confirm the concerns from the above: Gulf carriers had been providing close substitutes to do excessive competition against incumbents. However, consumer surplus analyses show that the entry of Gulf carriers had an overall positive effect on average consumer surplus. Supply-side estimations show that across all flights and also for multi stop flights, the marginal cost increased from the first to the second period and decreased from the second to the third period while the marginal cost of one stop flights decreased across all three periods. Gulf carriers were the main drivers for the drop in the marginal cost for one stop flights. Markups and Lerner Indexes substantially increased leading to higher profits for almost all airlines across all periods.

4.2 Literature

4.2.1 Market entry and airline market

Recently, Industrial Organization researches about market entry focus on peer-to-peer lodging firms such as Airbnb. Roma, Panniello and Nigro (2019) examined how the emergence of sharing economy platforms influenced incumbents' price responses, and they found that the price effects depended on the type of the incumbents (low/medium-end versus high-end hotels), accommodation period (weekend versus weekdays), and the type of consumers. Zach, Nicolau and Sharma (2020) analyzed the differentiated efforts of four incumbent lodging firms to compete with Airbnb and they found that incumbent firms did not seize quickly on the peer-to-peer market segment.

A strand of literature is related to new entry into the aviation market. External entry threats, especially High-Speed Rail (HSR) to the aviation industry, have been under the spotlight since the Shinkansen came into existence in Japan in 1964. Yang and Zhang (2012) investigated the competition between airlines assumed to maximize profit and HSR assumed to maximize a weighted sum of profit and social welfare. They showed that welfare in the HSR system was higher under price discrimination than under uniform pricing. Ma et al. (2019a) found that both airfare and air travel demand decreased significantly after the entry of the HSR. Then, Ma et el. (2020) used a difference-in-differences approach and found that the negative impact of high-speed rail on airfares gradually weakened after airline mergers. The entry effects can be reciprocal. Wang, Jiang and Zhang (2021) studied the effects of airline entry on HSR. They found that the entry of airlines reduced frequencies of HSR services, and improved social welfare in most cases.

Internal entry threats, especially Low-Cost Carriers (LCCs) to incumbent airlines, have also been a hot topic since the launch of Pacific Southwest Airlines in 1949. Morrison (2001) quantified and econometrically analyzed the actual, adjacent and potential competition effects of Southwest Airlines. And the estimated savings were 12.9 billion USD in which Southwest's low airfares were directly responsible for 3.4 billion. Zhang, Wang and Fu (2017) investigated air transport services in regional Australia. They found that the presence of leading airlines, increased LCC services and direct international services contributed positively to the expansion of local markets. Zhang et al. (2014) measured Chinese airlines' market power by using the Lerner index. They found that the existence of parallel HSR and LCCs services dramatically impacted the market power of dominant airlines in China. Wang, Zhang and Zhang (2018) investigated the effects of policy, ownership and LCC competition on airline pricing and air travel demand in China and India. They found that the presence of an LCC on a route had the effect of reducing the airfare and stimulating the demand for air travel in India, and that the absolute value of the price elasticity of the Indian market was much larger than that in the Chinese market probably due to high LCC penetration rates in India. Ma et al. (2019b) studied the Australian domestic airline market's price competition and price wars. They found that an increase in the major airlines' capacity was the main cause of price cuts and price wars, and despite the antitrust authorities' dislike of the Duopoly market structure, competition could remain strong in the Australian domestic market. Using the global airport connectivity index proposed by Cheung, Wong and Zhang (2020), Wong et al. (2019) discovered there was a trend of shifting airport choices from lower-tier to upper-tier airports for LCCs.

To the best of our knowledge, this paper is the first paper to analyze the long-distance aviation markets between Australia and the UK. And also the first paper about Gulf carriers' entry into these markets. Gulf carriers provided homogeneous products compared to incumbents. And they contributed to the increase of the per passenger consumer surplus in the markets.

4.2.2 Nested logit model

This paper uses an instrumented nested logit model, which belongs to the family of discrete choice models. Discrete choice models were pioneered by McFadden (1973) by including micro-characteristics of products in the utility function and relaxing the independence of irrelevant alternatives axiom in logit models. Several variants, for example, the Dogit model (Gaudry and Dagenais, 1979) with income effect, the Parameterized Logit Captivity model (Swait and Ben-Akiva, 1987) with random utility constraints, the C-Logit model (Cascetta, Nuzzolo, Russo and Vitetta, 1996) for path-overlapping problems, came into existence with specific applications. Anderson, Palma and Thisse (1989) showed that various approaches of discrete models could be reconciled under certain conditions. See Garrow (2010) for a review of the history of discrete choice models and their applications in the aviation industry.

Theoretically, the most closely related model is Berry (1994), which proposed estimation by "inverting" the market-share equation to find the implied mean levels of utility for each good for both logit and nested logit models. In the spirit of Berry (1994), Berry, Levinsohn, and Pakes (1995) invented the BLP model which allowed for variable slope coefficients to capture differentiated household income and consumer preferences. They also used an "inverted" market-share contraction mapping to do the estimation. Nevo (2000a) provided a practical computation guide for the estimation process of the BLP models, and Nevo (2000b, 2001) used such models to measure market power and merger evaluation in the ready-to-eat cereal industry. The above papers set a theoretical baseline for empirical researches later.

Recent empirical researches are listed as follows. Berry and Jia (2010) set a blueprint of random coefficient nested logit model designed for the airline industry, and provided instruments for endogeneity issues about airfares, frequencies and nesting parameters. Choi et al. (2019) applied a multinomial logit model to estimate air travelers' utility function from choosing different transfer airports in an origin-destination market. Wang et al. (2020) studied the entry pattern of LCCs in New Zealand and their impacts on domestic and trans-Tasman markets linking Australia and New Zealand using a probit model. Bontemps, Remmy and Wei (2022) estimated a structural (nested logit) model of the domestic U.S. airline market to analyze the effect of the recent merger between American Airlines and US Airways.

This paper is not to have innovations over the above literature but to apply instrumented nested logit model to a long-distance air travel market. Theoretical foundations are from Berry (1994) who showed how to use log-transformed market share to turn nested logit model into a linear form so that ordinary two-stage linear estimation can be loaded.

4.2.3 Handling endogeneity

There are three types of endogeneities in this paper: airfares, nesting parameters and flight frequencies. Instruments used in Berry and Jia (2010) and Bontemps, Remmy and Wei (2022) have been all tested and selected to derive the best solution.

Berry and Jia (2010) used route-level characteristics: the percentage of rival routes that offer direct flights, the average distance of rival routes, the number of rival routes and the number of all carriers. These instruments have all been tested but are either not significant or had limited impacts on the explained market shares. Product-level characteristics are more favorable in the long-distance markets rather than route-level. To handle airfare endogeneity, Berry and Jia (2010) used the fitted values of the 25th and 75th quantiles of airfares on a given route, which are proved effective and thus, adopted in this study.

Bontemps, Remmy and Wei (2022) used functions of rival firm product attributes: the percentage of rival products that are direct flights, the total number of rival products, the percentage of direct flights in a market, the number of competitors, and a dummy indicating whether a market is a monopoly or not. These instruments serve well in this paper because most of them are on the product-level. To handle nesting parameter endogeneity simply and effectively, the percentage of one-connect products of rival airlines within a certain market is adopted in this study.

As a common practice in aviation research, hub information for airports involved in a certain flight leg is used as the instrument for flight frequencies on the leg.

4.3 The Model

An instrumented nested logit model is used to model the demand side. This follows Berry (1990), Berry and Jia (2010) and Bontemps, Remmy and Wei (2022) in their modeling of the passenger demand side in aviation markets.

Markets are given by pairs of origin and destination regions and indicated by subscript g. Products are grouped in inside and outside products where each group forms one nest. The inside products involve flights from a region in Australia to a region in the UK whereas the outside products involve all other activities such as flying from Australia to places other than the UK or not flying at all. For each market, products (whenever products are mentioned in the following, we mean inside products) in a market are defined by a unique combination of the origin and destination regions, connecting airports, ticketing carrier and the binned fare and indicated by subscript j. The utility of passenger i consuming product j in market g is modeled as

$$u_{ijg} = x_{jg}\beta - \alpha p_{jg} + \xi_{jg} + v_{ijg}(\lambda) + \lambda\eta_{ijg} \tag{7}$$

where x_{jg} is a vector of product attributes, p_{jg} is the product price bin, ξ_{jg} represents unobserved product attributes such as ticket restrictions and departure times. The parameters to be estimated are given by the marginal disutility of a price α, the vector of the taste for attributes β, and the nested logit parameter λ. Let ε_{ijg} denote the unobserved idiosyncratic taste shock of consumer i for product j in market g with $\varepsilon_{ijg} = v_{ijg}(\lambda) + \lambda\eta_{ijg}$ and assume that it follows a Gumbel distribution with mode 0 (or any other type I extreme value distribution).

The nested logit parameter λ varies between 0 and 1 and governs the substitution between the two nests. If λ approaches 1, there is no substitution within the nests and the model reduces to the multinomial logit form whereas if λ approaches 0, all substitution happens within the nests. Letting $j = 0$ indicate the outside product, the utility of purchasing the outside product is normalized as $u_{i0g} = \eta_{i0g}$ where η_{i0g} is, across consumers, an independently and identically distributed logit error.

Let P_{ijg} denote the probability that passenger i chooses product j in market g, which is equal to the probability of u_{ijg} being the largest within market g. Letting J_g denote the set of products in market g and the "mean utility" in (7), $x_{jg}\beta - \alpha p_{jg} + \xi_{jg}$, be denoted by δ_{jg}, this probability can be written as

$$\begin{aligned} P_{ijg} &= \Pr\left(u_{ijg} > u_{ikg} \quad \forall k, j \in J_g : k \neq j\right) && \text{(8a)} \\ &= \Pr\left(\delta_{jg} - \delta_{kg} \geq \varepsilon_{ikg} - \varepsilon_{ijg} \quad \forall k, j \in J_g : k \neq j\right). && \text{(8b)} \end{aligned}$$

Consider $\lambda \in (0, 1)$. In this case, the within-market share of product j in market g, denoted by $s_{j|g}$, represents the share of passengers choosing product j relative to all passengers flying in market g and can be written as

$$s_{j|g}\left(x_g, p_g, \xi_g\right) = \frac{\exp\left(\delta_{jg}/\lambda\right)}{\sum_{k\in J_g}\exp\left(\delta_{kg}/\lambda\right)} \quad \forall k, j \in J_g. \tag{9}$$

The corresponding share of people flying in market g denoted by s_g can be written as

$$s_g\left(x_g, p_g, \xi_g\right) = \frac{\left(\sum_{j\in J_g}\exp\left(\delta_{jg}/\lambda\right)\right)^{\lambda}}{1 + \left(\sum_{j\in J_g}\exp\left(\delta_{jg}/\lambda\right)\right)^{\lambda}} \tag{10}$$

whereas the share of passengers choosing product j in market g can be written as $s_{jg} = s_g \cdot s_{j|g}$ and the share of individuals in market g who do not fly between Australia and the UK can be written as $s_{0g} = 1 - s_g$. Berry (1994) demonstrated that the shares in (9) to (10) can be used to derive the following linear regression model:

$$\ln\frac{s_{jg}}{s_{0g}} = x_{jg}\beta - \alpha p_{jg} + (1-\lambda)\ln s_{j|g} + \xi_{jg}. \tag{11}$$

A higher value of the demand-side unobservables, ξ_{jg}, implies a higher demand for product j in market g, which will typically translates into higher prices, p_{jg}, and higher within-market shares, $s_{j|g}$. These relationships cause endogeneity problems, which will be addressed by employing 2SLS regressions. The instrument set should include exogenous variables that help to predict prices and within-market shares.

4.4 Data

The main data source is the Sabre Airport Data Intelligence (ADI) database, which includes origin-destination market information including origin and destination airports, connecting airports, marketing carriers, segment carriers, passenger numbers, and airfares[25]. This database

[25] In the case of return tickets, the airfares associated with the itinerary in one direction are weighted by the share of the corresponding itinerary's flight distance relative to the total flight distance of the inbound and outbound itineraries.

retrieves data from computer reservation systems and booking computations. It does not include direct bookings from airline websites. Direct bookings are especially relevant for low cost carriers but less so for full service carriers. The latter is the relevant category in this study because it considers long-distance markets which is a domain of full service carriers. Another data source is OAG, which provides detailed information about airline flight schedules and therefore be used to retrieve information about flight frequencies. Population information was retrieved from the Eurostat database. Information about the airport hub status and inflation rates was retrieved from various websites.

4.4.1 Sample selection

The Sabre ADI dataset available to us provides itinerary information for up to two connecting airports for the flight parts from Australia to the UK whereas the itinerary information for the flight parts from the UK to Australia are not included in the dataset. The dataset contains yearly information for the years from 2002 to 2012. In the beginning of this period, in 2002, Gulf carriers including Emirates, Etihad Airlines and Qatar Airways had a small market share whereas they gained a substantial market share until the end of this period in 2012. For this reason, this period is highly suitable for studying the impact of the entry of Gulf carriers on the market. Before data cleanse, the pooled dataset included 108,310 observations and 8,389,897 passengers. The airfares are de-inflated to the USD values in 2002. Inflation rates are retrieved from officialdata.org (see Appendix D).

The dataset was cleansed to eliminate less reasonable observations. This included observations with airfares lower than 400USD and higher than 5,000USD, observations with itineraries involving extreme flight distances of over 20,000 kilometers, and observations for which information about connecting airports and segment airlines are entirely missing. Airlines were included in the sample only if they were active in every year of the sample period from 2002 to 2012. The cleansed data sample includes 31 airlines who accounted for slightly more than 98% of the original total passenger number. In total, 18,576 observations involving 564,757 passengers are deleted by this cleansing process, which reduces the original total passenger number by approximately 6.7%.

4.4.2 The growing importance of Gulf carriers

Figure 8 displays annual total passenger numbers (in 1,000) and the percentages of passengers served by Gulf carriers between 2002 and 2012. The figure shows that there were no big changes in the annual passenger numbers during this period except in 2008 when Terminal 5 opened at London Heathrow. The figure further shows that the share of passengers served by Gulf carriers increased more than sixfold during this time with a share of approximately 5% in 2002 increasing to a share of approximately 32% in 2012.

To increase the number of observations per period, observations in periods 2002-2005, 2006-2008 and 2009-2012 are pooled together. Table 13 lists the top 10 airlines in the Australia-UK market by passenger numbers in these three periods. Emirates went from position 6 in 2002-2004, to position 2 in 2006-2008, and position 1 in 2009-2012. In 2009-2012 also Etihad entered

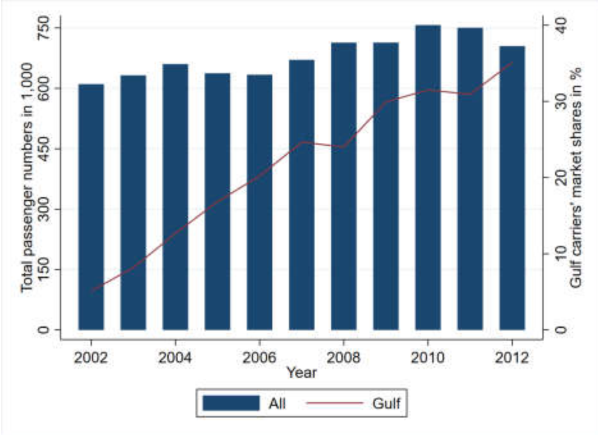

Figure 8: Passenger numbers and percentage of passengers served by Gulf carriers (Source: Sabre ADI and authors' calculations).

2002-2005		2006-2008		2009-2012	
Airline	Passengers	Airline	Passengers	Airline	Passengers
Qantas	134,997	Qantas	162,517	Emirates	167,775
Singapore Airlines	108,765	Emirates	141,143	Qantas	131,296
British Airways	77,787	Singapore Airlines	101,748	Singapore Airlines	101,213
Malaysia Airlines	77,025	British Airways	51,370	British Airways	59,444
Japan Airlines	69,508	Malaysia Airlines	49,776	Etihad Airways	51,966
Emirates	68,461	Cathay Pacific	46,692	Cathay Pacific	51,689
Cathay Pacific	39,121	Royal Brunei Airlines	20,157	Malaysia Airlines	50,163
Royal Brunei Airlines	19,012	Virgin Atlantic	19,836	Royal Brunei Airlines	25,987
Thai Airways	9,545	Japan Airlines	17,386	Virgin Atlantic	23,774
Korean Air	8,549	Thai Airways	14,661	Thai Airways	14,317

Table 13: (Qatar ranked no.11 in the third period) Top 10 airlines in the Australia-UK aviation market by average annual passenger numbers (Source: Sabre ADI and authors' calculations).

top ten on position 5. Qatar Airways reached position 11 in 2009-2012.

Markets are given by pairs of origin and destination regions in Australia and the UK, respectively. The UK regions are based on the NUTS1 classification which distinguishes 12 regions. Guernsey, Isle of Man and Jersey are 3 more regions because they are considered as leisure destinations leading to a total sum of 15 UK regions. The Australian regions are based on the territories classification which distinguishes eight territories. These classifications give a total number of 120 markets. The Australian territories and the UK NUTS1 regions and their airports are listed in Appendix E.

The left part of Figure 9 illustrates the development of Gulf carrier market shares. This part shows that the number of markets in which Gulf carriers had substantial market shares grew substantially over the span of the three periods. For instance, there were around 40 markets in which Gulf carriers had less than 10% market shares in the period 2002-2005 whereas the corresponding number of markets dropped to only 14 markets in the period 2009-2012. The

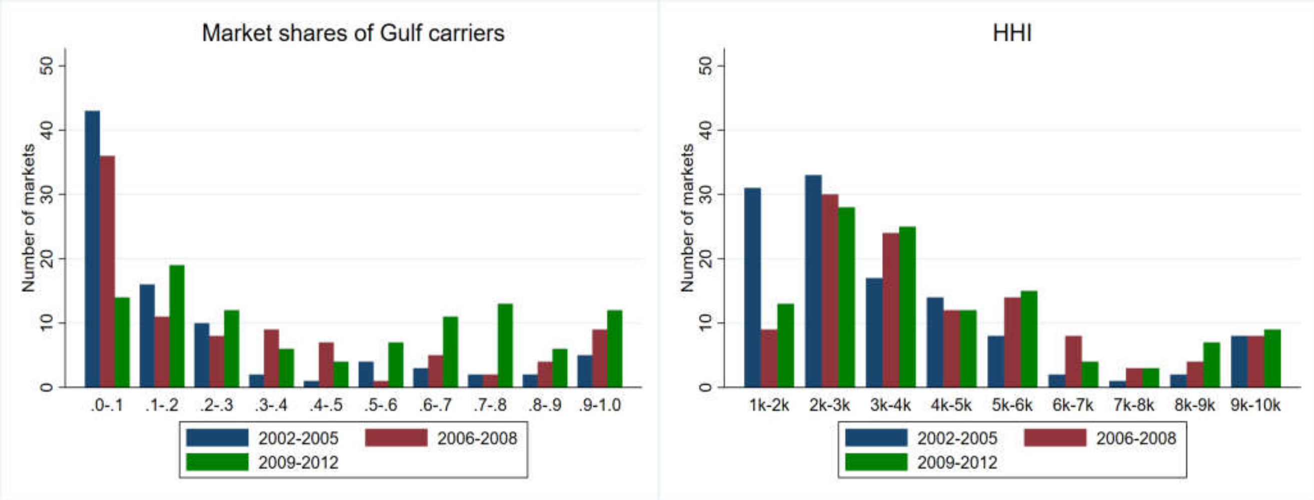

Figure 9: Gulf carrier market shares (left) and HHIs (right).

right part of Figure 9 illustrates the development of HHIs during the same time span. This part illustrates that markets have become more concentrated over time. One might expect that the penetration of existing markets by new market players would be associated with less concentrated markets. This cannot be observed here. For instance, there were around 60 markets with an HHI below 3K in 2002-2005 whereas the corresponding number of markets dropped to only 40 markets in the period 2009-2012.

Table 14 shows the top 10 origin territory-destination NUTS1 region pairs in terms of passenger numbers in the three periods. The dominating market by far is the one involving London and New South Wales covering flights from Sydney airport to London Heathrow airport. The biggest increases in passenger numbers can be observed for the markets from Victoria and Western Australia to London. Gulf carriers contributed to these growth numbers. The passenger shares of Gulf carriers for itineraries from Melbourne airport in Victoria to London Heathrow and itineraries from Perth airport in Western Australia to London Heathrow increased from 10% to 30% and from 0% to 25%, respectively, between 2002 and 2012.

Table 15 distinguishes between one-stop and multi-stop itineraries in which multi-stop flights involve a minimum of two stops. The table illustrates that many more passengers choose one-stop connections over multi-stop connections. It further shows that Gulf carriers expanded passenger numbers mainly in the area of one-stop connections. Somewhat surprisingly, average airfares for one-stop and multi-stop connections are not so different from each other for both Gulf and other carriers and they increased over time for Gulf carriers whereas they have increased or decreased over time for other carriers. This is consistent with the growth in market concentration as measured by the HHIs. Figure 10 further illustrates that airfares have been more dispersed for Gulf carriers than for other carriers. Naturally, many more markets can be served by multi-stop connections than by one-stop connections, which is true for both Gulf and other carriers. Still, Gulf carriers have an advantage in the sense that the geographical position of their base airports allows them to enter many more one-stop markets relative to other carriers. The number of one-stop markets served by Gulf carriers substantially increased

Origin region (Territory)	Destination region (NUTS1)	2002-2005	2006-2008	2009-2012
New South Wales	London	186,870	177,202	206,915
Queensland	London	98,851	90,633	99,872
Victoria	London	82,149	97,311	117,018
Western Australia	London	74,720	81,446	85,060
South Australia	London	25,459	27,072	31,013
New South Wales	North West England	22,766	23,051	22,957
Western Australia	North West England	21,396	24,415	19,943
Queensland	North West England	15,350	17,096	16,047
Victoria	North West England	12,720	13,770	15,524
New South Wales	Scotland	11,619	12,655	11,560

Table 14: Top 10 markets by average annual passenger numbers (Source: Sabre ADI and authors' calculations).

	2002-2005		2006-2008		2009-2012	
	Gulf	Others	Gulf	Others	Gulf	Others
One stop						
Passengers	33,305	400,509	94,553	386,240	172,980	379,429
Airfares	854	1,017	953	1,130	1,135	1,059
Markets	20	17	24	14	30	15
Observations	226	1,398	272	1,091	448	1,191
Multi stop						
Passengers	35,156	166,077	60,310	131,437	59,890	119,122
Airfares	936	987	949	1,105	1,044	992
Markets	88	116	94	110	106	114
Observations	2,271	21,118	3,134	15,991	6,612	18,335

Table 15: Descriptive statistics of Gulf carriers and other carriers (annual averages, and airfares are weighted by passenger numbers) (Source: Sabre ADI and authors' calculations).

whereas the number of one-stop markets served by other carriers slightly decreased across the three periods.

4.4.3 Regression variables

Table 16 reports the summary statistics of the variables used for the regressions. The top panel displays the mean and standard deviation of the variables needed to create the left-hand side variable in (11). The mean values of the product share variable, s_{jg}, and the market share variable, s_g, decreased. The decrease in s_g indicates that flying between Australia and the UK became less attractive over time in the sense that the share of the individuals who fly to other parts of the world or do not fly increased over time. Consistent with these developments, the ratio s_{jg}/s_{0g} decreased over time, and this observation will be reconsidered in Chapter 4.5.2 in which frequency information is integrated into the analysis.

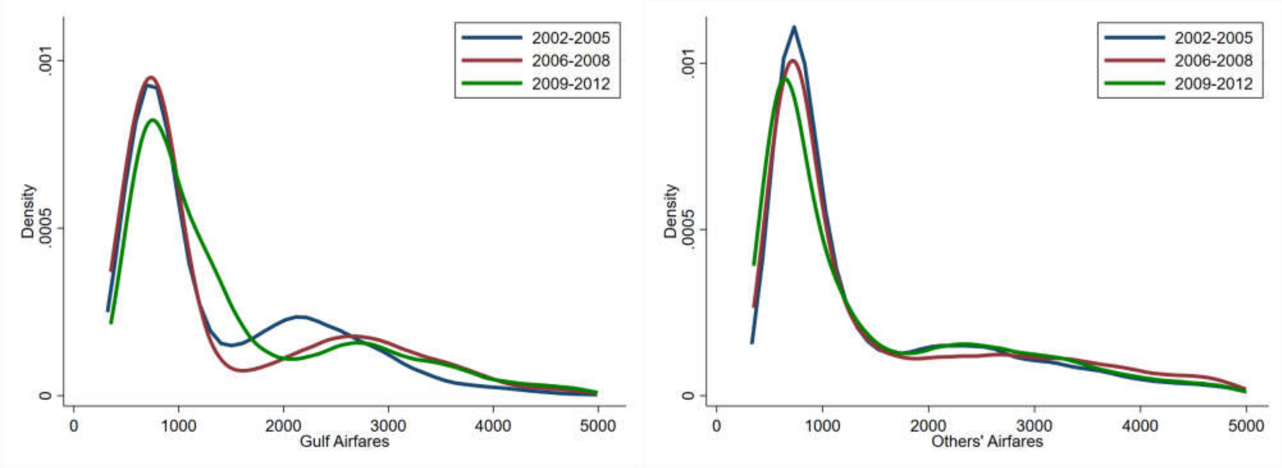

Figure 10: Airfare dispersion for Gulf carriers (left) and for others (right).

The second panel lists the regressors describing the product characteristics. A product is defined by the airfare bin, the number of connecting airports and the ticketing carrier. Airfare bins involve steps of 100US for airfares less than 1,000 USD and steps of 200 USD for airfares exceeding 1,000 USD (see Appendix F for some different price bin settings). The mean value of the airfare bins increased in the latter two periods relative to the first period which indicates an increase in price dispersion as measured by the number of airfare bins in the high airfare range. The share of products with two or more stops remained remarkably constant across the three periods. Consistent with the analysis in the previous Subchapter, the presence of Gulf carriers as measured by their share in the number of products has substantially increased over the sample period. Different from, for example, Berry and Jia (2010) and Bontemps, Remmy and Wei (2022), flight distance is not included as a regressor variable because all flights all itineraries are long distance in the Australia-UK market.

Apparent from Figure 8, the opening of Terminal 5 at London Heathrow in 2008 affected the demand. To capture this, the third panel in Table 16 includes two dummy variables for the period 2006-2008. These dummies are equal to one if either London Heathrow was the destination airport, $T5D_{jg}$, or London Heathrow was used for transfer, $T5T_{jg}$, in 2008 and these dummies were set to zero otherwise. The mean values demonstrate that many more products were affected by the opening which included London Heathrow as a destination airport than as a transfer airport.

The bottom panel lists instrumental variables. Following Berry and Jia (2010), the fitted values of the 30th and 70th quantiles of airfares, p_{jg}_30 and p_{jg}_70 are used as the instruments for airfare bins. In the quantiles regressions, airfares are regressed on the log-transformed populations of origin and destination regions, hub status of origin and destination airports, multi-stop dummy, airline dummies and whether the destinations belong to the three tourism islands of the UK. A market with a good mix of one-stop and multi-stop connections can be considered more differentiated than a market where the majority of flights are either one-stop or multi-stop. The ratio of one-stop products of rival airlines at the market level, $OneStopShare_{jg}$, is the instrumental variable associated with the within-market share.

Variables	2002-2005 Mean	SD	2006-2008 Mean	SD	2009-2012 Mean	SD
s_{jg}	0.0000258	0.000177	0.0000232	0.000169	0.0000238	0.000166
s_g	0.0108	0.0133	0.0103	0.0125	0.00912	0.0113
p_{jg} (in 100USD)	14.92	10.63	15.92	11.79	15.71	11.18
$MultiStop_{jg}$	0.94	0.25	0.93	0.25	0.94	0.24
Qantas	0.19	0.39	0.18	0.38	0.16	0.37
British Airways	0.15	0.35	0.13	0.34	0.12	0.32
Singapore Airlines	0.12	0.32	0.09	0.29	0.07	0.26
Cathay Pacific	0.06	0.24	0.05	0.21	0.04	0.20
Japan Airlines	0.04	0.19	0.02	0.14	0.01	0.09
Royal Brunei Airlines	0.03	0.17	0.02	0.15	0.01	0.10
Virgin Atlantic	0.01	0.09	0.02	0.16	0.02	0.15
Gulf carriers	0.10	0.30	0.17	0.37	0.27	0.44
Other carriers	0.23	0.42	0.26	0.44	0.25	0.43
$T5D_{jg}$	-	-	0.11	0.31	-	-
$T5T_{jg}$	-	-	0.06	0.24	-	-
p_{jg}_30 (in 100USD)	7.66	1.28	7.38	1.13	7.45	1.64
p_{jg}_70 (in 100USD)	16.04	3.93	17.70	4.49	17.90	4.30
$OneStopShare_{jg}$	0.06	0.08	0.06	0.08	0.06	0.08
Observations		25,013		20,488		26,586

Table 16: Summary statistics.

	p_{jg}			$\ln s_{j\|g}$		
	2002-2005	2006-2008	2009-2012	2002-2005	2006-2008	2009-2012
			Logit			
p_{jg}_30	0.44***	0.31**	0.57***			
p_{jg}_70	0.42***	0.37***	0.38***			
			Nested Logit			
p_{jg}_30	0.49***	0.34***	0.61***	0.17***	0.11***	0.21***
p_{jg}_70	0.35***	0.34***	0.33***	-0.21***	-0.13***	-0.14***
$OneStopShare_{jg}$	4.54***	4.05***	4.27***	-18.49***	-19.27***	-19.25***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: First-stage regression results.

4.5 Demand-side Estimations

4.5.1 Without flight frequency data

Passenger demands are affected by airfares, the number of connections, carrier dummies and, in the intermediate period 2006-2008, the London Heathrow Terminal 5 dummies. The consumers' utility should be decreasing in the airfares and the number of connections. It seems reasonable to assume that the opening of Terminal 5 and its new facilities would increase the utility of both origin-destination and transfer passengers. Tables 17 and 18 show the first- and second-stage results, respectively, for Logit and Nested Logit models.

First, consider the results associated with the Logit model. The corresponding first-stage coefficients of the fitted quantile airfare values p_30 and p_70 with respect to p_{jg} in Table 17 are significant and have positive signs. The sums of these two coefficients are close to one in each period. This means that a change in these quantile values is associated with a change in the average airfare in the same direction and approximately the same amount.

Consider the second-stage Logit regression results in Table 18. The estimations indicate that passengers became less price sensitive over the three periods. The price coefficients decreased in absolute values from 0.274, over 0.181 to 0.147 in the periods 2002-2005, 2006-2008 and 2009-2012, respectively, and this decrease was associated with a decrease in the corresponding average (own) price elasticities, shown in the bottom panel, which in absolute values went down from 4.094, to 2.879, and to 2.303, respectively.[26] The estimation results further indicate that the passengers' utility from one-stop connections relative to multi-stop connections and the connection semi-elasticities have increased across these time periods.[27]

Figure 9 indicated that markets have become more concentrated across the three time periods whereas Table 15 showed that this development was associated with the Gulf carriers' expansion into one-stop markets and airfare increases by Gulf carriers. The increase in the passengers' demand for one-stop connections and the passengers' reduced price sensitivity reveals

[26] For the Logit model, the own price elasticity can be written as $-\alpha\,(1 - s_{jg})\,p_{jg}$ (for example, Bontemps, 2021).

[27] The connection semi-elasticities can be written as $\beta \cdot (1 - s_g)$. Given that the values of s_g are close to zero, the multi-stop coefficients are good approximations for the mean connection semi-elasticities.

the demand-side fundamentals underlying these developments.

The Terminal 5 Dummies, $T5D_{jg}$ and $T5T_{jg}$, indicate that the opening of the new facilities in London Heathrow increased the passenger utilities and especially the utilities of transfer passengers in 2008. The coefficients of the carrier dummies are largely consistent with the carrier rankings in Table 13 and reflect the increasing popularity of Gulf carrier relative to the other carriers turning from negative to positive coefficients across time. The signs of the year dummies are all positive in the periods 2002-2005 and 2009-2012. Correcting for the London Heathrow Terminal 5 utility effect in 2008, a similar dynamic can be asserted for the intermediate period 2006-2008.

Second, consider the results associated with the Nested Logit model. There are two first-stage regressions where one is associated with the endogenous airfare variable, p_{jg}, and the other is associated with the within market share variable, $\ln s_{j|g}$. Consider the first-stage regression associated with p_{jg}. The outcome of the first-stage coefficients of the fitted quantile airfare values p_30 and p_70 with respect to p_{jg} are robust compared to those associated with the Logit regression. The coefficient of $OneStopShare_{jg}$ is positive as one-stop flights are more expensive compared to multi-stop flights involving two or more than two stops. Consider the second first-stage regression associated with $\ln s_{j|g}$. Whereas the sum of the coefficients for the fitted quantile airfare values approximately sum to one when they are associated with p_{jg}, they approximately sum to zero when they are associated with $\ln s_{j|g}$. This is mutually consistent because an increase in the fitted quantile airfares is associated with a change in the average airfares by the same amount which leaves the relative airfares across the different products within a market and, therefore, also within-market shares unchanged. The coefficient of $OneStopShare_{jg}$ is negative which reflects the passengers' strong preference for one-stop over multi-stop flights.

The second-stage Nested Logit regression results are remarkably robust compared to the results associated with the Logit regression so that all the insights that could be derived from the Logit regression also hold for the Nested Logit regression.[28] One slight difference can be observed for the London Heathrow Terminal coefficients which indicate that both origin-destination and transfer passengers similarly appreciated the new terminal facilities. Another difference is the presence of the within-market share variable. The difference between one and the value of the coefficients associated with the within-market shares is an estimate for the nesting parameter λ. According to the estimations, the nesting parameter decreased from 0.920 in the first period to 0.856 in the second period and to 0.844 in the last period. This suggests that the products within the nest which contains all flights from Australia to the UK became closer substitutes. One explanation for this results could be the increased market concentration measured by the HHI as highlighted in Figure 9.

4.5.2 With flight frequency data

The above analyses considered airfares and the number of stops as determinants for passenger utilities. Another determinant of utilities are the scheduled flight times which determine

[28]For the Nested Logit model, the own price elasticity can be written as $-\frac{\alpha}{\lambda}\left(\left(1-(1-\lambda)\,s_{j|g}\right)-\lambda s_{jg}\right)p_{jg}$.

Table 18: Second-stage regression results for the Logit and Nested Logit models.

	Logit			Nested Logit		
	2002-2005	2006-2008	2009-2012	2002-2005	2006-2008	2009-2012
$\ln s_{j\|g}$				0.080***	0.144***	0.156***
				(0.015)	(0.011)	(0.008)
p_{jg} (in 100USD)	-0.274***	-0.181***	-0.147***	-0.194***	-0.084***	-0.051***
	(0.019)	(0.014)	(0.010)	(0.021)	(0.013)	(0.009)
$MultiStop_{jg}$	-2.741***	-2.763***	-3.210***	-2.467***	-2.349***	-2.694***
	(0.117)	(0.101)	(0.082)	(0.107)	(0.084)	(0.071)
$T5D_{jg}$		0.628***			0.768***	
		(0.082)			(0.054)	
$T5T_{jg}$		0.996***			0.800***	
		(0.081)			(0.055)	
Qantas	0.249***	0.682***	1.148***	0.242***	0.507***	0.707***
	(0.082)	(0.078)	(0.075)	(0.063)	(0.054)	(0.061)
Singapore Airlines	-0.098	0.299***	0.333***	-0.047	0.112*	0.106*
	(0.084)	(0.089)	(0.076)	(0.066)	(0.062)	(0.057)
British Airways	0.080	0.141*	0.487***	0.109*	0.133***	0.333***
	(0.084)	(0.078)	(0.066)	(0.065)	(0.051)	(0.049)
Cathay Pacific	0.141	0.459***	0.566***	0.129*	0.240***	0.320***
	(0.096)	(0.108)	(0.090)	(0.075)	(0.076)	(0.067)
Japan Airlines	0.157	-0.163	-0.101	0.167*	-0.088	-0.012
	(0.122)	(0.135)	(0.149)	(0.096)	(0.097)	(0.117)
Royal Brunei Airlines	-0.203	0.909***	0.571**	0.049	0.669***	0.609***
	(0.127)	(0.130)	(0.140)	(0.112)	(0.097)	(0.113)
Virgin Atlantic	-0.952***	0.066	0.406***	-0.830***	0.057	0.339***
	(0.276)	(0.136)	(0.108)	(0.207)	(0.091)	(0.082)
Gulf Carriers	-0.275***	0.275***	0.755***	-0.190***	0.212***	0.381***
	(0.091)	(0.073)	(0.061)	(0.073)	(0.049)	(0.051)
Others	-1.281***	-0.552***	-0.148***	-0.973***	-0.314***	-0.175***
	(0.086)	(0.066)	(0.054)	(0.089)	(0.048)	(0.041)
Year 2003/7/10	0.137**	-0.040	0.094**	0.112**	-0.043	0.029
	(0.056)	(0.043)	(0.037)	(0.044)	(0.028)	(0.027)
Year 2004/8/11	0.469***	-0.389***	0.315***	0.345***	-0.432***	0.122***
	(0.065)	(0.050)	(0.041)	(0.055)	(0.033)	(0.031)
Year 2005/12	0.427***		0.361***	0.284***		0.055
	(0.071)		(0.049)	(0.060)		(0.039)
Constant	-6.550***	-8.048***	-8.758***	-7.441***	-8.843***	-9.210***
	(0.360)	(0.276)	(0.167)	(0.325)	(0.203)	(0.126)
Elasticity	-4.094	-2.879	-2.303	-5.105	-3.380	-2.096
J statistic	58.381	30.783	102.969	68.804	25.459	57.030

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

schedule delay cost representing the disutility of flying at other times than the most preferred travel times (Douglas and Miller, 1974). Schedule delays can be captured by the consideration of flight frequencies because passengers will find it easier to travel at their preferred flight times if airlines increase their flight frequencies on the corresponding flight segments.

Flights from Australia to the UK can be associated with two or more than two stops and collecting the relevant information for the large set of relevant flight segments is challenging. To capture flight frequencies, the OAG database is used to identify the frequencies on flight segments which connect Australian airports with the first connecting airports outside Australia (outbound frequencies) and the frequencies on flight segments which connect the last connecting airports outside the UK in the ADI database with UK airports (inbound frequencies).[29] This flight frequency information is then used to calculate the daily average outbound and inbound frequencies per itinerary denoted by $outFreq_{jg}$ and $inFreq_{jg}$, respectively. Consider the following example with one Australian origin territory with airports A and B. Assume that the outbound flight segments from these two Australian airports are using the same connecting airport C outside Australia and that the total number of daily flights on these two flight segments is given by four (for instance, three flights from A to C and one flight from B to C). In this example, the average daily outbound flight frequency of itineraries involving this Australian territory and this connecting airport outside Australia would be equal to two. Average daily inbound frequencies per itinerary are calculated analogously.

Figure 11 displays the development of the daily average outbound (left) and inbound (right) frequencies during the sample period from 2002 to 2012 for Gulf carriers (blue solid lines) and other carriers (red dashed lines). The figure illustrates that average daily frequencies are higher for the inbound flight segments relative to the outbound flight segments. This is intuitive given the importance of the UK for global aviation markets. The figure further illustrates that the average daily frequencies of other carriers remained almost unchanged across the sample period whereas the Gulf carriers' frequencies increased over time and even surpassed the other carriers' frequency values from 2009 onwards.

Recall the regression model (11) containing the demand-side unobservables, ξ_{jg}. A higher value of these unobservables imply a higher demand for product j in market g, which will typically translates into higher flight frequencies and, thus, higher values of $outFreq_{jg}$ and $inFreq_{jg}$ causing endogeneity problems. To address these endogeneity problems, the instrument set is complemented by two new instrumental variables which should be exogenous and predict flight frequencies. In this study, the involvement of hub airports in outbound and inbound flight segments, $outHub_{jg}$ and $inHub_{jg}$, are used as instruments for $outFreq_{jg}$ and $inFreq_{jg}$, respectively.[30] As daily average flight frequencies are associated with itineraries, the hub variables also have to be calculated on the basis of itineraries. Consider the example of the three airports A, B and C from above. Assume that airport A is a hub and airports B and C are not hubs.

[29] Some observations in the ADI database cannot be matched with the flights recorded in the OAG dataset. Deleting the unmatched observations reduces the passenger numbers by 79,000 representing approximately 1 percent of the passengers in the cleansed dataset. Furthermore, if there are more than two connections, inbound flight frequencies may not be accurately represented by our procedure.

[30] Hub airport information for each airline is retrieved from upgradedpoints.com.

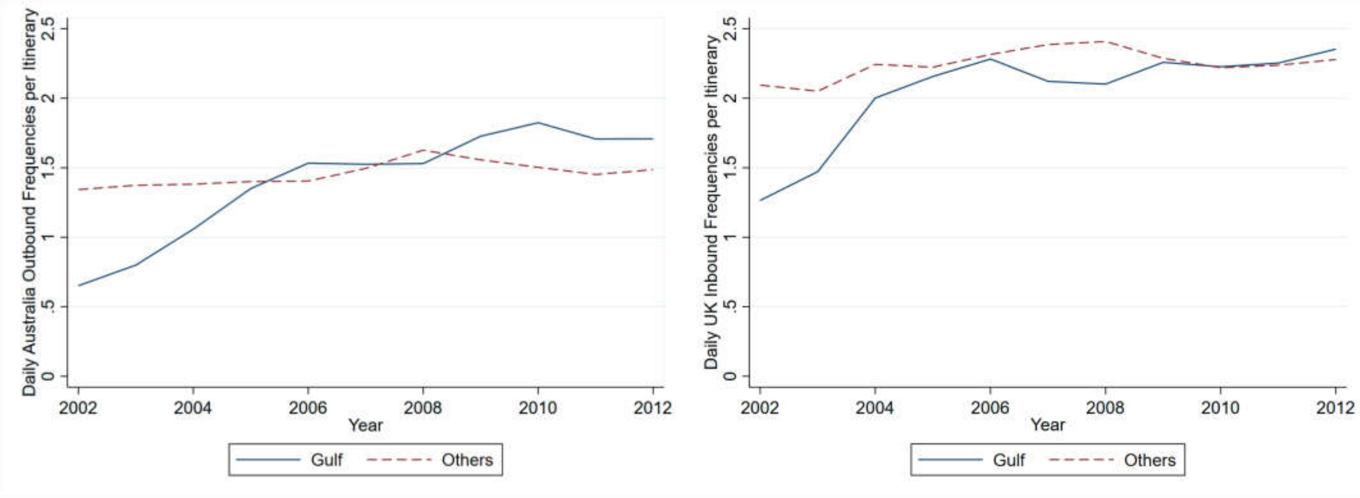

Figure 11: Daily average flight frequencies per itinerary for outbound (left) and inbound flights (right) by Gulf carriers and other carriers (Source: OAG and authors' calculations).

	2002-2005		2006-2008		2009-2012	
Variables	Mean	SD	Mean	SD	Mean	SD
$outFreq_{jg}$	1.40	0.72	1.55	0.79	1.60	0.82
$inFreq_{jg}$	2.33	1.85	2.51	1.84	2.41	1.75
$outHub_{jg}$	0.78	0.39	0.79	0.39	0.80	0.39
$inHub_{jg}$	0.67	0.47	0.69	0.46	0.68	0.47
Observations	22,442		18,335		23,626	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Summary statistics for the new variables added to the regressions capturing flight frequencies.

In this case, the outbound hub variable would take value of one half because there are two outbound flight segments and only one of them involves at least one hub airport whereas the other flight segment involves zero hub airports.

Table 19 displays the summary statistics for the frequency and hub variables. Consistent with Figure 11, the daily average outbound frequencies have lower mean values than the daily average inbound frequencies. The mean values of the hub variables associated with outbound flight segments are higher than the mean values of the hub variables associated with the inbound flight segments. One reason for the difference in the mean values is caused by the classification of Singapore as a non-hub airport for airlines other than Singapore Airlines, for instance, Singapore was used by Qantas for stopovers for flights from Australia to the UK by the time but was not counted as a hub for Qantas.

First, consider the regression results associated with the Logit model. There are three first-stage regressions where one is associated with the endogenous airfare variable, p_{jg}, and the other two are associated with the endogenous outbound and inbound flight frequencies, $outFreq_{jg}$ and $inFreq_{jg}$. The first-stage regression results associated with the airfare variable are largely consistent with the previous first-stage regression results displayed in Table 17. The complete set of first-stage regression results are relegated in Appendix G.

Consider the second-stage Logit regression results in Table 20. The corresponding second-stage coefficients of the Logit regression results with consideration of flight frequencies are broadly consistent in Table 18 without flight frequencies. The coefficient of Australian outbound frequencies, $outFreq_{jg}$, can be positive or negative. This is because it not only represents the convenience to fly outside of Australia, but also represents part of the relative utility to choose not to fly to the UK but to other countries. The coefficient of the UK inbound frequencies, $inFreq_{jg}$, on the other hand, can only be positive because the destination is constrained to the UK. A clear increase in the coefficients of the UK inbound flight frequencies can be observed, and the coefficients of the Australia outbound flight frequencies are fluctuating and all negative. Air travelers preferred to choose high-frequency flights because this gives them more freedom to decide when to fly and less transit time. One slight difference can be observed for the increased (own) price elasticities compared to the other models.

Second, consider the results associated with the Nested Logit model where p_{jg}, $outFreq_{jg}$, $inFreq_{jg}$ and $\ln s_{j|g}$ are endogenous. There are four first-stage regressions where one is associated with the endogenous airfare variable, p_{jg}, two are associated with the outbound and inbound flight frequencies, $outFreq_{jg}$ and $inFreq_{jg}$, and the last one is associated with the within market share variable, $\ln s_{j|g}$ (again, see Appendix G). The analyses below focus on the first-stage regression associated with $outFreq_{jg}$ and $inFreq_{jg}$ with respect to $OneStopShare_{jg}$, and the first-stage regression associated with $\ln s_{j|g}$ with respect to $outHub_{jg}$ and $inHub_{jg}$ because other regression results are robust compared with the other three models.

Consider the first-stage regression associated with $outFreq_{jg}$ and $inFreq_{jg}$ with respect to $OneStopShare_{jg}$. $OneStopShare_{jg}$ has limited negative or insignificant effects on $outFreq_{jg}$ but relatively strong and positive effects on $inFreq_{jg}$. This is because $outFreq_{jg}$ counts in not only flights destined to the UK but also to other countries, and $inFreq_{jg}$ only counts in flights destined to the UK. On the other hand, The coefficient of $OneStopShare_{jg}$ is positive associated with $inFreq_{jg}$ which reflects the convenience of one-stop flights relative to multi-stop flights. Consider the first-stage regression associated with $\ln s_{j|g}$ with respect to $outHub_{jg}$ and $inHub_{jg}$. The sum of the coefficients for $outHub_{jg}$ and $inHub_{jg}$ approximately sum to zero, as well as the sum of the coefficients for p_30 and p_70. The reason for the latter, as discussed before, is because an increase in the fitted quantile airfares is associated with a change in the average airfares by the same amount which leaves the within-market shares unchanged. This explanation can also be applied to the involvement of hub airports.

The second-stage Nested Logit regression results are remarkably robust compared to the results associated with other Logit/Nested Logit settings in this and the previous Subchapters and for smaller or larger price bins as shown in the Appendix F. The Nested Logit model with flight frequencies is favorable in the sense that it is associated with the smallest Hansen J statistic among all the models.

Let CS_g denote the average consumer surplus across market g's population, which can be

Table 20: Second-stage regression results with frequencies.

	Logit			Nested Logit		
	2002-2005	2006-2008	2009-2012	2002-2005	2006-2008	2009-2012
$\ln s_{j\|g}$				0.177***	0.269***	0.395***
				(0.013)	(0.013)	(0.011)
p_{jg}	-0.245***	-0.234***	-0.257***	-0.117***	-0.049***	-0.018*
	(0.024)	(0.021)	(0.021)	(0.018)	(0.013)	(0.010)
$MultiStop_{jg}$	-2.542***	-2.932***	-3.813***	-2.174***	-2.173***	-2.507***
	(0.132)	(0.135)	(0.136)	(0.091)	(0.081)	(0.066)
$T5D_{jg}$		0.447***			0.740***	
		(0.114)			(0.056)	
$T5T_{jg}$		0.856***			0.525***	
		(0.114)			(0.058)	
$outFreq_{jg}$	-1.607***	-1.560***	-1.508***	-1.136***	-1.127***	-1.289***
	(0.138)	(0.155)	(0.155)	(0.088)	(0.074)	(0.067)
$inFreq_{jg}$	0.226***	0.387***	0.731***	0.235***	0.335***	0.588***
	(0.039)	(0.053)	(0.062)	(0.023)	(0.023)	(0.026)
Qantas	0.429***	1.180***	2.214***	0.394***	0.751***	0.833***
	(0.083)	(0.129)	(0.173)	(0.053)	(0.062)	(0.080)
Singapore Airlines	1.272***	2.172***	2.542***	0.960***	1.313***	1.543***
	(0.144)	(0.220)	(0.247)	(0.092)	(0.109)	(0.111)
British Airways	-0.093	0.301**	1.228***	0.092	0.290***	0.592***
	(0.093)	(0.123)	(0.146)	(0.062)	(0.060)	(0.070)
Cathay Pacific	0.109	1.101***	1.590***	0.106	0.500***	0.799***
	(0.100)	(0.160)	(0.188)	(0.065)	(0.087)	(0.092)
Japan Airlines	0.009	0.203	-0.125	0.116	0.275*	-0.015
	(0.125)	(0.262)	(0.255)	(0.083)	(0.160)	(0.142)
Royal Brunei Airlines	-1.260***	0.276	0.815***	-0.232	0.299**	1.046***
	(0.199)	(0.244)	(0.270)	(0.154)	(0.128)	(0.138)
Virgin Atlantic	-0.762***	0.297	1.074***	-0.448***	0.307***	0.626***
	(0.270)	(0.196)	(0.184)	(0.162)	(0.094)	(0.090)
Gulf Carriers	-0.747***	0.651***	1.804***	-0.429***	0.443***	0.601***
	(0.097)	(0.105)	(0.140)	(0.066)	(0.053)	(0.067)
Others	-1.354***	-0.787***	-0.308***	-0.813***	-0.329***	-0.295***
	(0.101)	(0.099)	(0.096)	(0.072)	(0.052)	(0.055)
Year 2003/07/10	0.169***	0.130**	0.262***	0.128***	0.067**	0.104***
	(0.059)	(0.060)	(0.065)	(0.038)	(0.030)	(0.031)
Year 2004/08/11	0.471***	0.010	0.525***	0.267***	-0.179***	0.071**
	(0.069)	(0.082)	(0.074)	(0.046)	(0.039)	(0.035)
Year 2005/12	0.493***		0.600***	0.240***		-0.065
	(0.074)		(0.089)	(0.050)		(0.043)
Constant	-5.486***	-6.050***	-6.625***	-7.178***	-8.045***	-7.580***
	(0.403)	(0.404)	(0.333)	(0.286)	(0.219)	(0.150)
Elasticity	-3.729	-3.773	-4.099	-5.14	-3.370	-1.97
J Statistic	33.362	21.686	63.101	14.660	6.796	4.282

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	2002-2005	2006-2008	2009-2012
Average consumer surplus	0.018	0.044	0.117
Period-to-period change		+144.4%	+165.9%

Table 21: Average consumer surplus at the market level.

calculated as

$$CS_g = \frac{1}{\alpha} \ln \left[1 + \left(\sum_{j \in J_g} \exp\left(\delta_{jg}/\lambda\right) \right)^{\lambda} \right] \tag{12}$$

as was shown by Small and Rosen (1981). The right-hand side includes the familiar log-sum term appearing in the denominator of equation (10) normalized by α. Table 21 displays average values of CS_g across all markets for all three periods based on the parameter estimates derived from Nested Logit model with flight frequencies. The table shows that the average consumer surplus values increased across time despite the increase in market concentration and average airfares shown in Figure 9 and Table 15.

4.6 Supply-side Estimations

In each market, airlines are assumed to play a Nash-Bertrand pricing game. Omitting the product characteristics included in x_g and demand-side unobservables ξ_g, the market share of product j in market g is simply written as $s_{jg}(p_g)$ in the following, which highlights its dependence on airfares. Let $\digamma_g$ denote the set of airlines and J_{fg} denote the set of products offered by airline f in market g with $\cup_{f \in \digamma_g} J_{fg} = J_g$. The size of market g is denoted by M_g and the marginal cost of product j in market g is denoted by mc_{jg}. Letting Π_{fg} denote the profit of airline f in market g and assuming constant marginal costs, the profit of airline f can be written as

$$\Pi_{fg}(p_g) = M_g \sum_{j \in J_{fg}} \left(p_{jg} - mc_{jg}\right) s_{jg}\left(p_g\right). \tag{13}$$

The first-order conditions for the best responses in terms of airfares are given by $\frac{\partial \Pi_{fg}}{\partial p_{jg}} = 0$, which can be written as

$$s_{jg}\left(p_g\right) + \sum_{k \in J_{fg}} \left(p_{kg} - mc_{kg}\right) \frac{\partial s_{kg}\left(p_g\right)}{\partial p_{jg}} = 0 \tag{14}$$

for all $j \in J_{fg}$ and $f \in \digamma_g$. In the case of the nested logit model, the derivatives in the second term on the left-hand side of the equation, can be written as

$$\frac{\partial s_{jg}}{\partial p_{jg}} = -\frac{\alpha}{\lambda} s_{jg} \left(\left(1 - (1-\lambda) s_{j|g}\right) - \lambda s_{jg} \right) \tag{15}$$

and

$$\frac{\partial s_{jg}}{\partial p_{kg}} = \frac{\alpha}{\lambda} s_{jg} \left(\left(1 - (1-\lambda) s_{j|g}\right) - \lambda s_{kg} \right) \tag{16}$$

with $k \neq j$ (for example, Bontemps et al. 2021).

The following explains how the first-order conditions can be used to infer the marginal cost of the products in market g. Let p_{fg} denote the set of airline f's airfares in market g and $\mathbf{S}_{fg}$ the column vector collecting all market shares of airline f's products. The latter can be written as

$$\mathbf{S}_{fg}(p_{fg}) = \begin{pmatrix} s_{jg}(p_{fg}) \\ s_{kg}(p_{fg}) \\ \vdots \end{pmatrix} \text{ with } \left(J_{S_{fg}}\right)^T = \begin{pmatrix} \frac{\partial s_{jg}}{\partial p_{jg}} & \frac{\partial s_{kg}}{\partial p_{jg}} & \cdots \\ \frac{\partial s_{jg}}{\partial p_{kg}} & \ddots & \\ \vdots & & \end{pmatrix} \text{ for } j,k,\ldots \in J_{fg} \text{ and } k \neq j,\ldots, \tag{17}$$

where $\left(J_{S_{fg}}\right)^T$ is the transpose of the Jacobian matrix of $\mathbf{S}_{fg}(p_{fg})$. Let $\mathbf{MC}_{fg}$ denote the column vector collecting the marginal costs of airline f's products, which can be written as

$$\mathbf{MC}_{fg} = \begin{pmatrix} mc_{jg} \\ mc_{kg} \\ \vdots \end{pmatrix} \text{ for } j,k,\ldots \in J_{fg} \text{ and } k \neq j,\ldots \tag{18}$$

and $\mathbf{P}_{fg} = p_{fg}^T$. The first-order conditions for the best responses of all airlines in market g can be used to derive the column vector collecting the marginal cost of all products in market g as follows

$$\begin{pmatrix} \mathbf{MC}_{mg} \\ \mathbf{MC}_{ng} \\ \vdots \end{pmatrix} = \begin{pmatrix} \mathbf{P}_{mg} \\ \mathbf{P}_{ng} \\ \vdots \end{pmatrix} - \begin{pmatrix} \left(J_{S_{mg}}\right)^T & & \\ & \left(J_{S_{ng}}\right)^T & \\ & & \ddots \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{S}_{mg} \\ \mathbf{S}_{ng} \\ \vdots \end{pmatrix} \tag{19}$$

for $m,n,\ldots \in \mathcal{F}_g$ and $n \neq m,\ldots$. The airfares collected in $\mathbf{P}_{fg}$ are directly included in the dataset. The dataset can be used to calculate the market shares $\mathbf{S}_{fg}$ and the demand side estimation results can be used to calculate the derivatives of market shares with respect to airfares entering $\left(J_{S_{fg}}\right)^T$ for all $f \in \mathcal{F}_g$. Using this information, the marginal costs for each product in each market can be calculated based on equation (19). The results are summarized in Table 22.

Table 22 consists of three panels each associated with one of the three periods 2002-2005, 2006-2008 and 2009-2012. The second column to the right, profit, displays the average annual profit. The remaining columns display average marginal cost, average markup, average Lerner Index, and average airfares where averages are at the product level. The values are displayed for all flights, one stop and multi stop flights, and for different airlines or groups of airlines.

Consider the marginal cost. Across all flights and also for multi stop flights, the marginal cost increased from the first to the second period and decreased from the second to the third period. An explanation for the high marginal cost in the second period could be jet fuel prices which peaked in 2008. One stop flights show a different pattern because the marginal cost decreased across all three periods with the biggest decrease in the third period. Considering the marginal cost developments by airline reveals that Gulf carriers were the main drivers for the drop in the marginal cost for one stop flights. Table 23 separately displays the marginal cost of Gulf carriers for one stop and multi stop flights. It reveals a decrease in the marginal cost of one stop flights across all three periods with a sharp drop in the third period whereas the marginal cost of multi stop flights slightly increased across all three periods. The sharp drop in the Gulf

Table 22: Profits breakdown (in 100USD).

	Marginal Cost	Markup	Lerner Index	Profit	Airfare
			2002-2005		
All Flights	14.45	0.76	9%	2,786,549	15.21
One Stop Flights	16.93	1.59	16%	2,118,887	18.52
Multi Stop Flights	14.27	0.69	9%	667,662	14.96
Qantas	15.42	0.55	8%	596,685	15.97
Singapore Airlines	15.17	0.62	8%	522,804	15.79
British Airways	15.39	0.49	7%	318,739	15.88
Cathay Pacific	15.47	0.94	9%	163,968	16.41
Japan Airlines	14.33	1.14	11%	323,359	15.47
Royal Brunei Airlines	11.83	0.94	9%	60,021	12.77
Virgin Atlantic	17.41	0.95	10%	9,457	18.36
Gulf Carriers	13.97	0.71	9%	311,471	14.68
Others	12.24	1.07	13%	116,707	13.31
			2006-2008		
All Flights	15.03	1.09	15%	6,360,568	16.12
One Stop Flights	15.74	3.66	36%	4,987,903	19.40
Multi Stop Flights	14.98	0.89	13%	1,372,665	15.87
Qantas	16.50	0.73	12%	1,573,086	17.23
Singapore Airlines	16.80	1.11	13%	1,130,740	17.91
British Airways	16.02	0.63	9%	380,257	16.65
Cathay Pacific	17.08	1.33	15%	443,965	18.41
Japan Airlines	14.12	2.13	20%	95,616	16.25
Royal Brunei Airlines	16.42	1.58	13%	159,924	18.00
Virgin Atlantic	14.99	1.65	22%	184,198	16.64
Gulf Carriers	14.75	0.90	12%	1,587,988	15.65
Others	12.56	1.51	20%	326,281	14.07
			2009-2012		
All Flights	14.18	1.74	26%	15,503,451	15.92
One Stop Flights	9.42	9.83	100%	12,678,768	19.25
Multi Stop Flights	14.53	1.15	21%	2,824,682	15.68
Qantas	16.52	1.09	19%	2,624,984	17.61
Singapore Airlines	14.43	2.03	33%	2,491,313	16.46
British Airways	15.02	0.97	20%	1,069,432	15.99
Cathay Pacific	14.12	2.29	34%	1,113,089	16.41
Japan Airlines	10.10	3.94	41%	47,817	14.04
Royal Brunei Airlines	11.22	2.38	30%	590,547	13.60
Virgin Atlantic	12.41	2.54	41%	493,254	14.95
Gulf Carriers	14.85	1.60	21%	5,216,000	16.45
Others	12.12	2.45	33%	784,549	14.57

	2002-2005	2006-2008	2009-2012
One Stop Flights	12.36	11.32	4.57
Multi Stop Flights	14.15	15.08	15.63

Table 23: Gulf carriers' marginal cost (in 100USD).

carriers' marginal cost for one stop flights is not obvious from Table 22 because the marginal cost associated with Gulf carriers is around average across all airlines in all three periods. The explanation is related to the number of products which are much higher for multi stop flights than for one stop flights. The airline specific marginal cost displayed in Table 22 lump one stop and multi stop flights together, and the relatively large number of multi stop products means that changes in the marginal cost associated with one stop flight products are not easily visible when averages are calculated at the product level. Consider the markups, Lerner indexes and profits. Table 22 shows that markups and Lerner Indexes substantially increased leading to higher profits for almost all airlines across all periods and categories. This is, again, consistent with the growth in market concentration as measured by the HHIs displayed in Figure 9.

The marginal cost function for product j can be specified as

$$mc_{jg} = w_{jg}\gamma + \zeta_{jg} \tag{20}$$

where w_{jg} is a vector of marginal cost shifters, γ is a vector of marginal cost parameters to be estimated and ζ_{jg} is an unobserved cost shock. The values of the left-hand side variables are calculated by using the results of the demand-side estimations and equation (19). Marginal cost shifters include the number of connections $OneStop_{jg}$, hub variables $outHub_{jg}$ and $inHub_{jg}$, and airline and year dummies. Ordinary least squares can be used to estimate the marginal cost parameters in Equation (20). The estimation results are summarized in Table 24.

The parameter estimates associated with the one stop variable indicate that one stop flights became less costly relative to multi stop flights across time. This is consistent with the decrease in the marginal cost of one stop flights shown in Tables 22 and 23. The parameter estimates associated with the hub variables are all positive or insignificant. Bontemps et al. (2022) mention that hub airports can cause higher coordination and management fees. This line of reasoning could be applied here. The rest of estimates associated with airline and year dummies are consistent with the corresponding results displayed in Tables 22 and 23.

4.7 Summary

This study uses a large panel dataset covering the time between 2002 and 2012 to empirically analyze the markets for long-distance flights between Australia and the UK. The sample period covers the time in which Gulf carriers (Emirates, Etihad, and Qatar) increased their overall market share in terms of passenger numbers sixfold and grew from niche to dominant players in these markets. The study consists of three parts: a descriptive part, demand-side estimations and supply-side estimations.

	Marginal Cost (in 100USD)		
	2002-2005	2006-2008	2009-2012
$OneStop_{jg}$	2.863***	1.271***	-3.306***
	(0.320)	(0.420)	(0.447)
$outHub_{jg}$	0.083	0.898***	2.949***
	(0.232)	(0.294)	(0.293)
$inHub_{jg}$	0.870***	0.721**	0.272
	(0.220)	(0.295)	(0.298)
Qantas	1.291***	3.469***	6.971***
	(0.352)	(0.496)	(0.534)
Singapore Airlines	0.303	2.934***	4.280***
	(0.328)	(0.482)	(0.549)
British Airways	0.714**	2.694***	6.164***
	(0.334)	(0.468)	(0.509)
Cathay Pacific	0.624	3.198***	3.916***
	(0.388)	(0.561)	(0.619)
Japan Airlines	-0.461	0.397	0.573
	(0.448)	(1.027)	(1.213)
Royal Brunei Airlines	-3.153***	2.550***	0.666
	(0.657)	(0.869)	(1.254)
Virgin Atlantic	1.561*	1.825**	4.150***
	(0.814)	(0.713)	(0.754)
Gulf Carriers	-5.564***	-3.767***	-2.729***
	(0.369)	(0.454)	(0.460)
Others	-2.473***	-1.072***	1.954***
	(0.300)	(0.421)	(0.464)
Gulf×One stop	-5.063***	-5.513***	-8.423***
	(0.855)	(0.929)	(0.847)
Year 2003/7/10	0.408*	0.307	0.977***
	(0.211)	(0.237)	(0.275)
Year 2004/8/11	1.700***	0.672***	1.966***
	(0.211)	(0.237)	(0.273)
Year 2005/12	1.931***		3.009***
	(0.213)		(0.270)
Constant	12.829***	11.866***	5.886***
	(0.379)	(0.514)	(0.548)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Marginal cost estimations.

The descriptive analysis revealed that Gulf carriers successfully expanded passenger numbers mainly in the area of one-stop connections. Average airfares for one-stop and multi-stop connections are not so different from each other for both Gulf and other carriers, and they increased over time for Gulf carriers whereas they have increased or decreased over time for other carriers. This is consistent with the growth in market concentration as measured by the HHIs. The demand-side estimations involved instrumented logit and nested logit regression models with and without frequency variables. The estimation results were largely consistent across the different demand-side model specifications. The results indicate that passengers became less price sensitive, displayed a stronger preference for flights with fewer stops and connections with higher flight frequencies, and that average consumer surplus increased during the sample period. The demand-side estimation results based on the nested logit regression model with frequencies are used to infer markups, marginal costs and Lerner indexes at the product level. These inferred variables all increased across the sample period implying airline profit increases. In the last period, a sharp drop in the marginal cost of one-stop flights could be inferred which was largely driven by Gulf carriers. Supply-side estimations indicate that multi stop flights became more costly relative to one stop flights across time and that the involvement of hub airports increases marginal cost. Future studies could involve random coefficient models to capture heterogenous passenger preferences. Counterfactual analysis comparing social welfare with and without Gulf carriers can also be added.

Chapter 5: Conclusions

This dissertation consists of three empirical studies on the assessment of airline competition among LCCs and FSCs. Chapter 2 and 3 focus on airline competitions within Europe and their corresponding airfare impacts, and Chapter 4 focus on Gulf carriers' entry strategies in the Australia-UK aviation markets and corresponding changes in airfares, consumer surpluses and passengers' preferences.

Chapter 2 arose from Zhang et al. (2022a). The objective was to analyze the change in the networks of the big three European LCCs Ryanair, easyJet and Wizz Air before and during the Covid-19 pandemic period. The results indicate that LCCs increasingly expanded their networks into markets that had already been served by incumbent LCCs and that the use of adjacent airports had been a substantial part of this change. A difference-in-differences analysis based on posted airfare information was used to estimate the airfare effect of head-to-head LCC competition on overlapping network parts. The estimation results indicate that airfares posted by the incumbent are reduced by approximately six Euros, or ten percent of the average airfares, after the entry of a rival LCC. This indicates that the head-to-head LCC competition leads to substantive airfare reductions.

Chapter 3 arose from Zhang et al. (2022b) and is a subsequent study to Chapter 2. Chapter 3 extends Chapter 2 by considering FSCs and LCCs competition on a much larger dataset. It concentrates on the top ten European full-service carriers and the top five European low-cost carriers. Event studies, panel data two-way fixed effects, as well as long differences models are applied. The event study establishes a causal effect of competition on pricing dynamics by showing that intertemporal price dispersion is reduced by competition. The more efficient two-way fixed effects regressions show that the effects of competition on dynamic pricing are stronger when we focus on price differences associated with flights booked far in advance and weaker for flights booked closer to departure times. The intuition is that competition drives down prices but prices booked early in advance are on average substantially lower and therefore the effect implies a reduction in intertemporal price discrimination which mainly benefits late bookers. They further show that the effect of competition is diminishing in the number of rivals in the case of full-service carriers whereas it is constant in the case of low-cost carriers. Finally, the long-difference approach shows that low-cost carrier competition has a lasting effect on pricing dynamics whereas full-service carrier competition has not.

Chapter 4 arose from Zhang et al. (2022c) and studies aviation markets from Australia to the UK. It revealed that Gulf carriers successfully expanded passenger numbers mainly in the area of one-stop connections. Average airfares for one-stop and multi-stop connections are not so different from each other for both Gulf and other carriers, and they increased over time for Gulf carriers whereas they have increased or decreased over time for other carriers. The demand-side estimation results indicate that passengers became less price sensitive, displayed a stronger preference for flights with fewer stops and connections with higher flight frequencies, and that average consumer surplus increased during the sample period from 2002 to 2012. The supply-side estimation results indicate all airline profits increased. In the last period from 2009 to 2012, a sharp drop in the marginal cost of one-stop flights could be inferred which was largely driven by Gulf carriers.

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Appendix

A Multi-airport regions

The following table lists 16 multi-airport regions located in the European Union (including the UK airports). The selection is based on the origin/destination cities information provided by Flightradar24. Cities with more than one airport are considered multi-airport regions.

Multi-airport regions[31].

Regions	Airports	Regions	Airports
Belfast	BFS	Madrid	MAD
	BHD		TOJ
Berlin	BER	Milan	BGY
	SXF		LIN
	TXL		MXP
Brussels	BRU	Murcia	MJV
	CRL		RMU
Bucharest	BBU	Paris	BVA
	OTP		CDG
Frankfurt	FRA		LBG
	HHN		ORY
	QEF		XCR
Hamburg	HAM	Rome	CIA
	XFW		FCO
London[32]	BQH	Stockholm	ARN
	LGW		NYO
	LHR		VST
	LTN	Tenerife	TFN
	STN		TFS
Lyon	LYN	Warsaw	WAW
	LYS		WMI

[31]Some airports, for example, Biggin Hill Airport, Torrejon Air Base and Le Bourget Airport, have been deleted from the dataset during the data cleanse process because none of the three LCCs considered in this study operated more than 12 flights per year at these airports.

[32] Flightradar24 associates SEN airport with Southend and not London (even though SEN is called London Southend Airport). Adding SEN airport to the London multi-airport region would slightly increase the overlap between Ryanair and easyJet by one or two city pairs per month whereas the overlap in terms of airport pairs would not be affected by this change in classification. The network overlaps involving Wizz Air would also not be affected by this reclassification.

B Airport pairs served by LCCs

Peak numbers of airport pairs served by easyJet, Ryanair and Wizz Air in 2018, 2019 and 2020.

	easyJet	Ryanair	Wizz Air
2018	804	1,768	364
2019	878	1,828	407
2020	657	1,590	452

C Ryanair new entry

19 airport pairs entered by Ryanair in October 2019.

BCN-RIX	BUD-OPO	DTM-KTW	NYO-VIE
BOD-BUD	BVA-POZ	EIN-VIE	OTP-PSA
BUD-CTA	BVA-SOF	GDN-GOT	SKG-VIE
BUD-GOT	CGN-KTW	GDN-HAM	TFS-VIE
BUD-LIS	CTA-KTW	KRK-LTN	

D USD inflation rates

USD inflation rates (2002 as USD1.0).

Year	Inflated Values
2002	1.000
2003	1.019
2004	1.053
2005	1.088
2006	1.116
2007	1.161
2008	1.163
2009	1.194
2010	1.212
2011	1.248
2012	1.269

E Regions and corresponding airports

Australian territories and corresponding airports

New South Wales (37): ABX, ARM, BEO, BHQ, BHS, BNK, BRK, CAZ, CFS, DBO, DGE, GFF, GFN, GLI, IVR, KPS, LBH, LDH, LHG, LSY, MIM, MRZ, MTL, MYA, NAA, NRA, NTL, OAG, OOM, PKE, PQQ, SYD, TMW, TRO, WGA, WOL, WWY
Queensland (56): ABG, BCI, BDB, BFC, BKP, BKQ, BLS, BLT, BMP, BNE, BUC, CNS, CTL, CTN, DBY, DKI, DRN, DYA, EMD, GIC, GLM, GLT, GOO, HID, HTI, HVB, ISA, JCK, KWM, LRE, LUT, LZR, MBH, MCY, MET, MKY, MLV, MOV, NTN, OBA, OOL, PPP, RMA, ROK, SCG, SFP, SGO, STH, THG, TSV, TWB, TXR, WAZ, WEI, WIN, ZBL
Northern Territory (14): AMX, ANZ, ASP, AYQ, DRW, GOV, GTE, HMG, KCS, LEL, LIB, MCV, MGT, TCA
South Australia (13): ADL, CED, CPD, DLK, GSN, INM, KGC, MGB, NUR, OLP, PLO, PUG, WYA
Western Australia (31): ALH, BIW, BME, CVQ, DCN, DRB, EPR, GET, GLY, KAX, KGI, KNX, KTA, LDW, LEA, LER, LGE, MGV, MJK, PBO, PER, PHE, PRD, RVT, SSK, TEF, TPR, WIT, WND, WRW, ZNE
Australian Capital Territory (1): CBR
Tasmania (7): BWT, DPO, HBA, HIS, KNS, LST, SRN
Victoria (9): AVV, BLN, BXG, KRA, LTB, MEL, MQL, PTJ, RBS

British NUTS1 and corresponding airports

Scotland (21): ABZ, ADX, BEB, BRR, CAL, COL, CRN, CSA, DND, EDI, GLA, ILY, INV, KOI, LSI, OBN, PIK, SYY, TRE, WIC, ZGG
London (10): BQH, HEN, LCY, LHR, LON, QQK, QQP, QQS, QQU, QQW
East Midlands (England) (4): EMA, NQT, WTN, XNM
East of England (4): CBG, LTN, NWI, STN
Northern Ireland (3): BFS, BHD, LDY
North East (England) (2): MME, NCL
North West (England) (4): BLK, LPL, MAN, QQM
West Midlands (England) (2): BHX, QQN
South East (England) (6): ABB, FAB, LGW, OXF, PME, SOU
South West (England) (5): BOH, BRS, EXT, NQY, PLH
Wales (1): CWL
Yorkshire and the Humber (3): HUY, LBA, QQY
Guernsey (2): ACI, GCI
Isle of man (1): IOM
Jersey (1): JER

F Smaller and larger price bins

In this robustness check on price bins. We test smaller and bigger price bins.

For smaller bins: 50 USD per bin for tickets between 400 USD and 1000 USD, 100 USD for tickets between 1000 USD and 2000 USD, and 200 USD for tickets above 2000 USD; and for bigger bins: 200 USD per bin for all tickets.

Second-stage regression results with different price bins.

	Smaller bins			Bigger bins		
	2002-2005	2006-2008	2009-2012	2002-2005	2006-2008	2009-2012
$\ln s_{j\|g}$	0.180***	0.271***	0.393***	0.192***	0.273***	0.397***
	(0.012)	(0.012)	(0.010)	(0.013)	(0.014)	(0.011)
p_{jg}	-0.112***	-0.045***	-0.013	-0.083***	-0.041***	-0.013*
	(0.017)	(0.012)	(0.009)	(0.013)	(0.010)	(0.007)
$MultiStop_{jg}$	-2.198***	-2.125***	-2.497***	-2.161***	-2.189***	-2.501***
	(0.090)	(0.078)	(0.064)	(0.088)	(0.080)	(0.064)
$T5D_{jg}$		0.678***			0.757***	
		(0.052)			(0.059)	
$T5T_{jg}$		0.499***			0.561***	
		(0.052)			(0.065)	
$outFreq_{jg}$	-1.056***	-1.046***	-1.276***	-1.172***	-1.177***	-1.279***
	(0.083)	(0.070)	(0.065)	(0.093)	(0.078)	(0.069)
$inFreq_{jg}$	0.222***	0.332***	0.600***	0.276***	0.340***	0.571***
	(0.022)	(0.022)	(0.026)	(0.024)	(0.025)	(0.026)
Qantas	0.304***	0.688***	0.790***	0.361***	0.781***	0.840***
	(0.049)	(0.055)	(0.073)	(0.055)	(0.065)	(0.082)
Singapore Airlines	0.862***	1.223***	1.512***	0.949***	1.378***	1.533***
	(0.087)	(0.102)	(0.106)	(0.097)	(0.115)	(0.114)
British Airways	0.037	0.257***	0.545***	0.109*	0.339***	0.609***
	(0.058)	(0.056)	(0.063)	(0.064)	(0.065)	(0.074)
Cathay Pacific	0.080	0.404***	0.726***	0.124*	0.558***	0.843***
	(0.060)	(0.080)	(0.086)	(0.067)	(0.092)	(0.096)
Japan Airlines	0.111	0.299**	-0.021	0.132	0.325*	-0.011
	(0.077)	(0.152)	(0.140)	(0.085)	(0.169)	(0.149)
Royal Brunei Airlines	-0.228	0.344***	0.998***	-0.117	0.336**	1.068***
	(0.145)	(0.122)	(0.128)	(0.156)	(0.135)	(0.145)
Virgin Atlantic	-0.456***	0.275***	0.602***	-0.461***	0.334***	0.647***
	(0.152)	(0.088)	(0.082)	(0.156)	(0.100)	(0.096)
Gulf Carriers	-0.423***	0.388***	0.548***	-0.414***	0.512***	0.613***
	(0.063)	(0.050)	(0.062)	(0.070)	(0.057)	(0.071)
Others	-0.766***	-0.324***	-0.337***	-0.877***	-0.332***	-0.255***
	(0.067)	(0.048)	(0.052)	(0.083)	(0.057)	(0.058)
Year 2003/07/10	0.120***	0.053*	0.117***	0.122***	0.068**	0.106***
	(0.035)	(0.028)	(0.029)	(0.039)	(0.031)	(0.032)
Year 2004/08/11	0.255***	-0.170***	0.064*	0.289***	-0.202***	0.068*
	(0.043)	(0.037)	(0.033)	(0.050)	(0.041)	(0.037)
Year 2005/12	0.228***		-0.065	0.239***		-0.095**
	(0.046)		(0.040)	(0.051)		(0.048)
Constant	-7.377***	-8.303***	-7.779***	-7.073***	-7.788***	-7.460***
	(0.272)	(0.203)	(0.143)	(0.284)	(0.226)	(0.156)
Elasticity	-4.766	-2.979	-1.306	-5.499	-3.972	-2.093
J Statistic	12.856	0.684	0.668	27.829	0.364	6.200

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

G First-stage regression results

	2002-2005	2006-2008	2009-2012	2002-2005	2006-2008	2009-2012
		p_{jg}			$\ln s_{j\|g}$	
			Logit			
p_{jg}_30	0.44***	0.21	0.66***			
p_{jg}_70	0.38***	0.39***	0.37***			
$outHub_{jg}$	-0.42*	-0.35	0.68***			
$inHub_{jg}$	0.50**	0.24	0.96***			
			Nested Logit			
p_{jg}_30	0.49***	0.24	0.69***	0.17***	0.20***	0.20***
p_{jg}_70	0.33***	0.36***	0.33***	-0.21***	-0.16***	-0.15***
$outHub_{jg}$	-0.40*	-0.33	0.70***	-0.62***	-0.67***	-0.75***
$inHub_{jg}$	0.47**	0.20	0.90***	0.50***	0.54***	0.45***
$OneStopShare_{jg}$	3.81***	3.43**	3.52***	-17.90***	-18.16***	-17.35***
		$outFreq_{jg}$			$inFreq_{jg}$	
			Logit			
p_{jg}_30	-0.04***	-0.02***	-0.05***	-0.08***	-0.10***	-0.10***
p_{jg}_70	0.03***	0.01***	-0.00	0.11***	0.07***	0.07***
$outHub_{jg}$	0.45***	0.53***	0.42***	-0.014	0.19***	0.032
$inHub_{jg}$	-0.13***	-0.04**	0.13***	1.51***	1.42***	1.44***
			Nested Logit			
p_{jg}_30	-0.05***	-0.02**	-0.05***	-0.03*	-0.03	-0.04***
p_{jg}_70	0.04***	0.01***	-0.00	0.02***	0.01**	0.01***
$outHub_{jg}$	0.45***	0.53***	0.42***	0.020	0.24***	0.068**
$inHub_{jg}$	-0.13***	-0.04***	0.13***	1.45***	1.35***	1.34***
$OneStopShare_{jg}$	-0.20***	0.28***	0.010	6.24***	6.50***	5.95***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First-stage regression results with frequencies.