The EU-U.S. Open Skies Agreement: An Empirical Analysis of the Effects on Competition

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Preface

This master thesis is written as the ending part of our master's degree in business administration, carried out at the School of Business and Law at University of Agder, Kristiansand, 2020.

Through our work we have learned a lot and challenged ourselves in various ways. The work has been demanding, with uncertainties and difficulties. We decided to write about a demanding topic by using a methodology that we did not have a lot of prerequisites about. The procompetitive effects of the EU-U.S. Open Skies Agreement have been interesting to dig deeper into and we have surely broadened our knowledge about the transatlantic airline market and the competition in the aviation industry.

We want to thank our supervisor, Associate Professor Daniel Göller, for his comments, critical questions and help. Enduring our questions, his comments have been valuable for our thesis.

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Abstract

The transatlantic airline market is a significant part of the aviation industry. In 2008, the EU – U.S. Open Skies Agreement was implemented to liberalize this market. The aim of the agreement was to impose more competition on the transatlantic market.

The objective of this thesis is to analyze the procompetitive effects of the EU – U.S. Open Skies Agreement to investigate if it has fulfilled its aim. Using quarterly time series data from 1998 to 2018, this thesis analyzes the effect of the agreement on passenger traffic on three interhub routes, and the number of U.S. destinations offered from three EU airports. Through Johansen's three-step procedure, two VEC models are formulated to empirically test these procompetitive effects of the agreement. The results show that the agreement did *not* have a significant impact on the passenger traffic on any of the interhub routes, meaning that passenger traffic has not increased because of the agreement. Considering the U.S. destinations offered, the results show that the agreement *did* have a significant and positive impact on all three EU airports, meaning that the agreement has led to an increase in U.S. destinations offered.

These results indicate that the agreement struggles to influence markets where airline alliances have high market shares. Since the agreement also provides possibilities of antitrust immunity for these alliances, an ambiguity problem of the agreement may arise. Instead of entering these markets, new entrants may choose to operate different destinations. This will in turn increase the number of U.S. destinations offered.

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1 Introduction

1.1 Background

The transatlantic market is a significant part of the airline market. Traditionally, this market was highly regulated by bilateral agreements negotiated between the U.S. and sovereign states of Europe. However, in 2008, the EU – U.S. Open Skies Agreement was established to deregulate or "liberalize" this market. The aim of this agreement was to bring more competition into the market, and it laid the foundation of entrance to this segment by Low-Cost Carriers (Button, 2009, p. 64). At the same time, the agreement also opens for airline alliances to enjoy antitrust immunity. Concerns have been expressed that these alliances may reduce the procompetitive effects that was intended from the EU – U.S. Open Skies Agreement on certain types of routes where these alliances have a high market share (Brueckner, 2001, pp. 1476-1477).

1.2 Aim of the thesis

The aim of this thesis is to investigate the effects of the Open Skies Agreement on the competition in the transatlantic airline market. There are several markers of competition, such as lower prices, higher quality, and increased quantity. Higher quality is difficult to measure, and not necessarily applicable for the airline industry. The reason is that low-cost carriers (LCCs) have in recent years increased competition in the aviation industry. However, these airlines are known to offer a low level of quality. Thus, the quality level may not necessarily increase due to more competition in the airline market. The price level is generally a good marker of competition, as prices typically decrease with higher competition. However, getting access to price data for the transatlantic market is difficult. This point was also made by Pitfield (2009), where he discusses the expected outcomes of the agreement and the potential challenges on how to measure them (Pitfield, 2009, p. 308). Another good marker of competition is increased quantity level. Because the agreement allows for all EU-established airlines to operate between the EU and any point in the U.S., the number of transatlantic airlines is likely to increase (European Union, 2016). This is expected to lead to more passenger traffic and more U.S. destinations. Thus, we use passenger traffic and the number of U.S. destinations offered as our markers of competition.

1.3 Thesis contribution

As we present in this thesis, multiple researchers have considered the effects of deregulations in the airline industry. Pitfield (2007) conjectures that the Open Skies Agreement, hereafter referred to as the OSA, will not result in a significant growth in traffic. The reason is that the fluctuations in traffic volumes are mostly explained by other influences besides alliance formation and deregulations (Pitfield, 2007, p. 203). Furthermore, Button (2009) argues that the impacts are that many more can fly cheaper, greater variety of service and more jobs in the extended air transportation value chain (Button, 2009, p. 59)

Morandi, Malighetti, Peleari, and Redondi (2014) compares transatlantic traffic before and after the implementation of the OSA. They find that the agreement did not increase either passenger traffic or the number of destinations. Rather, they surprisingly found a negative effect (Morandi, Malighetti, Paleari, & Redondi, 2014, p. 324). This result is interesting for our research. However, because the OSA was implemented at the same time as the global financial crisis, they are effectively comparing numbers before and after the recession. As we can see, relatively little research has examined procompetitive effects of the OSA using time series models. Thus, our thesis compliments the existing literature on the topic by performing a times series analysis. We also use a longer timespan to capture a potential late response to the agreement because of the financial crisis that happened at the same time as the implementation of the agreement.

The main objective of the OSA was to impose more competition on the market. Thus, this research is also an investigation of whether or not the OSA fulfills it purpose of bringing more competition in the transatlantic airline market, by increasing the number of passengers and U.S. destinations offered. (European Commission & United States Department of Transportation, 2010, p. 2). By doing an empirically analysis, we contribute to the existing literature by examining quarterly data in the time period from 1998-2018, analyzing the procompetitive effects of the OSA.

Based upon the above-mentioned aim and contribution of the thesis, the following research question is formulated:

What are the effects of the EU-U.S. Open Skies Agreement on passenger traffic and the number of U.S. destinations offered in the transatlantic market?

Three route segments are considered in this thesis. We consider route segments between the EU and U.S. that is sufficiently large enough to analyze and illustrate fluctuations in traffic volumes, number of destinations offered, as well as market share of the dominant airline alliance. Since we are considering fluctuations in Herfindahl-Hirschman Index, dominant airline alliance market share, traffic volumes and number of destinations offered, we need to focus on large enough airports[1] in the essence of competition and large traffic volumes. In this context we consider the three route segments:

1. CDG – JFK (Charles de Gaulle, Paris – John F. Kennedy airport, New York)
2. MAD – JFK (Madrid Barajas airport, Madrid – John F. Kennedy airport, New York)
3. LHR – BOS (London Heathrow, London – Boston Logan airport, Boston)

Our research shows that the OSA, had no significant impact on passenger traffic, while it shows that the OSA had a significant and positive impact on the number of U.S. destinations offered from CDG, MAD and LHR using Vector Error Correction Model (VECM). The intuition of this result is that the OSA has brought procompetitive effects in terms of more U.S. destinations offered, but not passenger traffic on the above routes. This could be because new airlines may find it more desirable to operate different routes than to enter routes where alliances have market power and potentially enjoy antitrust immunity. This result is interesting because it follows Pitfield's (2007) conclusion that the OSA will not result in significant growth in airline traffic. Furthermore, the result contradicts Morandi et al. (2014), since the OSA has had a positive impact on the number of U.S. destinations offered. It also illustrates a potential ambiguity problem of the OSA. On the one hand the aim of the agreement is to impose more competition on the transatlantic market. On the other hand, it gives the possibility of code sharing and antitrust immunity, which according to Brueckner (2001), may give anticompetitive results. Thus, there are forces pulling in opposite directions.

1.4 Structure of the thesis

We follow up the introduction by briefly explaining the major developments that has defined the structure of the transatlantic market in chapter 2. The literature review is presented in chapter 3. This provides an overview of the existing literature on the subject of airline competition and the effects of deregulations. Chapter 4 contains the theoretical framework on which we base our intuition and interpretation of our results. Next, in chapter 5, we describe our data, providing figures to better explain the developments over time.

[1] By this we mean routes with multiple carriers, both non-allied and in different airline alliances. These are often between airports with high demand, located close to big cities. This is to ensure more robust results. On routes with only a few carriers, smaller one-time events can cause significant changes in traffic levels. Hence, it is more likely that a relationship between the OSA and passenger traffic is actually caused by coincidence on smaller routes.

The methodology is explained in chapter 6. This chapter explains our variables in detail along with the statistical tests and their procedures used to determine the statistical model. Based on this chapter we develop and specify our statistical model in chapter 7.

The empirical analysis is conducted in chapter 8, along with the results and their interpretations. In chapter 9, we present a discussion of the economic interpretation of the results in the light of the existing literature. We also briefly discuss the ethical dilemma of increased air traffic levels and its environmental impact, along with the limitations and potential weaknesses of our empirical research. Lastly, the thesis is summarized in chapter 10 with concluding remarks.

2 Developments in transatlantic air traffic

2.1 Air traffic regulations

Traditionally, the regulatory framework of the airline industry was a set of bilateral agreements between sovereign states that controlled the international air services. This was also the case for the transatlantic market. According to the European Commission and United States Department of Transportation (2010), these agreements created little scope for competition. In 1992, the Department of Transportation (DOT) in the U.S. launched an initiative to negotiate "open skies" agreements. These agreements were signed by several European nations with the U.S. These would provide open entry on all routes, unrestricted capacity and frequency, open rights to introduce air service between any point in the U.S. and any point in their partner country, rights of airlines to price their products and services without government restrictions, and open for code sharing (European Commission & United States Department of Transportation, 2010, p. 10). However, these agreements were individually negotiated between the U.S. and member countries of the EU, and even these Open Skies bilateral agreements contained operational and financial restrictions (Cosmas, 2009, p. 15). Preexisting European bilateral agreements with the U.S. follows in table 1:

Country	Date of agreement
Netherlands	14.10.1992
Belgium	1.3.1995
Finland	24.3.1995
Denmark	26.4.1995
Norway	26.4.1995
Sweden	26.4.1995
Luxembourg	6.6.1995
Austria	14.6.1995
Czech Republic	8.12.1995
Germany	29.2.1996
Italy	11.11.1998
Portugal	22.12.1999
Malta	12.10.2000
Poland	31.5.2001
France	19.10.2001

Table 1: Preexisting bilateral agreements (Pitfield, 2009, p. 309).

In 2002, the EU laid the foundation for their initiative to liberalize the transatlantic airline market with the “open skies judgements” of the Court of Justice of the EU. Several member states had already entered with the U.S. in the Open Skies Agreements, but the new judgement meant that member states of the EU could not negotiate international air service agreements on their own. In 2003, the Council of the EU established a new legal framework for the air transport relationship between the EU and the rest of the world. Any bilateral agreement that were not in line with the 2002 judgement had to be revised to ensure that all EU airlines were on equal footing for flights from any member state of the EU to third countries (European Commission & United States Department of Transportation, 2010, pp. 10-11).

In 2008, possibly the most influential agreement in deregulating the transatlantic airline market, the EU – U.S. Air Transport Agreement, was established. Also known as the EU – U.S. Open Skies Agreement or OSA, this agreement introduced new commercial freedoms for EU and U.S. airlines, and a framework for regulatory cooperation in the field of transatlantic aviation. It replaced individual agreements and removed barriers for EU and U.S. airlines. A joint committee was created to deal with issues relating to the interpretation and application of the agreement and reviewing its implementation (European Commission & United States Department of Transportation, 2010, pp. 11-12). The agreement provided all EU-established airlines with a right to operate services to the U.S. from any point in the EU. This meant that low-cost carriers could more easily enter the market, as it was no longer just for the national airlines with governmental support, typically referred to as “flag carriers”. According to the European commission and the U.S. Department of Transportation (2010). the most immediate aim was to introduce more competition in the transatlantic market (European Commission & United States Department of Transportation, 2010, p. 12). However, there are still some regulatory boundaries, for instance one that is prohibiting EU and U.S. carriers from merging (European Union, 2016). Thus, simply merging instead of creating an alliance is not an option.

2.2 Strategic Alliances

A strategic alliance is when two or more firms share resources and activities to pursue a common strategy (Johnson, Whittington, Scholes, Angwin, & Regnér, 2017, p. 350). In the aviation industry, strategic alliances began to emerge in the 1990’s (Button, 2009, p. 66). Prior to this, airlines had started to organize their route network in a hub-and-spoke system. The idea was to have one main airport, around which the airline based its operations. In addition, airlines started with frequent flyers programs, which gave benefits to loyal customers to give the airline a competitive advantage. As multiple airlines started developing their hubs, airlines then began to coordinate their operations between the hubs of the airlines. The alliance members coordinated their schedules, giving the passengers a single-airline feeling to increase the convenience of the passengers. This was a major benefit for the airlines because they were able to increase their route network and capacity, without having to invest in additional resources (Brueckner, 2001, p. 1476). When airline alliances first started to appear, they were also partly a solution to overcome the restrictions in the international aviation industry. The international airline market was previously largely dominated by bilateral agreements, restricting the entrance of new airlines on certain routes. An airline alliance was a method to circumvent these regulations. More recently, the airline market has become less deregulated thanks to agreements such as the OSA. Yet, airline alliances still exist, and a large share of international airlines belong to one of the three major airline alliances. The reason is that it brings greater convenience for passengers when they can travel with coordinated flights by allied airlines rather than by two non-allied carriers (Brueckner, 2001, p. 1476). The alliances focused on in this thesis are the three major global airline alliances Star Alliance, Oneworld, and SkyTeam. The following table shows the three major international airline alliances and their member airlines. Airlines operating direct routes between the U.S. and Europe are written in bold letters.

Star Alliance, est. 1997	Oneworld, est. 1999	SkyTeam, est. 2000
Aegean	**American Airlines**	**Aeroflot**
Air Canada	**British Airways**	Aerolineas Argentinas
Air India	Cathay Pacific	**Aero Mexico**
Air New Zealand	**Finnair**	**Air Europa**
ANA	**Iberia**	**Air France**
Asiana Airlines	Japan Airlines	**Alitalia**
Austrian	Latam	China Airlines
Avianca	Malaysia Airlines	China Eastern
Brussels Airlines	Qantas	Czech Airlines
Copa Airlines	**Qatar**	**Delta**
Croatia Airlines	Royal Jordanian	Garuda Indonesia
Egypt Air	S7 Airlines	Kenya Airways
Ethiopian	Sri Lankan Airlines	**KLM**
Eva Air		Korean Air
LOT Polish Airlines		Middle East Airlines

Lufthansa		Saudia
SAS		Tarom
Shenzen Airlines		Vietnam Airlines
Singapore Airlines		Xiamen Air
South African Airways		
Swiss		
TAP Air Portugal		
Thai Airways		
Turkish Airlines		
United Airlines		

Table 2: International Airline alliances.

2.3 Antitrust immunity

The OSA provides possibilities of antitrust immunity for the development of airline alliances (European Commission, 2008). In most industries, firms operate under a set of antitrust laws, which enforces the prohibition of price-fixing agreements and ensure that the industries are competitive (Pepall, Richards, & Norman, 2014, p. 371). However, for many of the airlines within the three major international alliances, the U.S. Department of Justice has given them immunity from the U.S. antitrust laws (United States Department of Transportation, 2019). The immunization of airline alliances is controversial and has caused a lot of discussion. On the one side, the advocates for the immunization argues that it gives consumer benefits in terms of convenience and more destinations. Those against immunization argue that competition might be reduced, causing negative welfare effects (Gillespie & Richard, 2011, p. 1). A discussion paper from the Economic Analysis Group of the U.S. Department of Justice found evidence for loss of competition in non-stop transatlantic routes due to antitrust immunity (Gillespie & Richard, 2011, p. 20). The following table shows the alliances that enjoy antitrust immunity:

SkyTeam	Star Alliance	Oneworld	Other
Delta/ Air France-KLM/ Alitalia/ Czech/ Korean	United/ Air Canada/ Brussels/ Lufthansa/ Swiss/ Austrian/ SAS/ LOT/ TAP	American/ Lan Airlines/ Lan Peru**	SAS/ Icelandair
Delta/ Virgin Atlantic*/ Air France-KLM/ Alitalia	United/ Air New Zealand	American/ British Airways/ Iberia/ Finnair/ Royal Jordanian	Delta/ Virgin Australia

	United/ Asiana	American/ Japan Air Lines	
	United/ All Nippon Airways		
	United/ COPA		

Table 3: Alliances with antitrust immunity (United States Department of Transportation, 2019).
*Not a member of SkyTeam
**Affiliate of LAN but not a member of Oneworld

From table 3, we see that the dominant alliances on the three route segments considered enjoy antitrust immunity. That is, Delta and Air France-KLM on the CDG-JFK route, Iberia and American Airlines on the MAD-JFK route, and British Airways and American on the LHR-BOS route, all enjoy antitrust immunity.

3 Literature Review

One of the most recognized researchers on the subject of competition in the airline industry is Jan K. Brueckner[2]. Bruckner & Whalen (2000) study strategic alliances in the airline industry and identify two market types based on how passengers are affected by the alliances. The first market type is the interline market, which is where passengers are dependent on both alliance airlines. Here, the alliance members can offer greater convenience for the passengers by coordinating their schedules to resemble a "single-airline" travel. Also, because the major alliances may enjoy antitrust-immunity they can engage in cooperative pricing on trips where the passengers are dependent on both carriers to get from A to B. This interline benefit can create lower fares than by using two non-allied carriers. The reason is that they can internalize negative externalities from the coordinate's choice of sub fares, leading to lower overall fares. This will give increased traffic, which lowers the marginal cost and puts further downward pressure on fares. However, they also stress that alliances can cause anticompetitive behavior in some cases, where collusion can lead to higher fares which benefits the alliance (Brueckner & Whalen, 2000, p. 504). The situation in which anticompetitive effects may arise is in the so-called gateway-to-gateway or interhub market. That is a segment where both of the allied airlines operate between two allied hubs. Concerns have been made by regulators that collusive agreements in this segment results in higher fares for the passengers (Brueckner & Whalen, 2000, p. 505). This concern is of interest for our analysis as a large share of the EU – U.S. routes are interhub routes.

Brueckner and Whalen thus identify two separate passenger groups, who are affected differently by airline alliances. Interhub passengers suffer a loss by collusive pricing, while interline passengers get benefits in terms of cooperation in pricing and scheduling. Thus, there is a welfare tradeoff between the two passenger groups. Because the route segments considered in our thesis are interhub markets, we do not expect to see a significant positive impact of the OSA on passenger traffic, based on Brueckner and Whalen's intuition.

Brueckner (2001) revisits the above research question where he analyzes the effect of airline alliances on fares, traffic levels, and welfare (Brueckner, 2001, p. 1475). Brueckner emphasizes that there is still a rationale for airline alliances even though markets are getting more deregulated. According to Brueckner, alliances were traditionally formed to overcome

[2] Bruckner & Whalen addressed the competitional effects of airline alliances and the concerns regarding collusive behavior in 2000. They explain that the deregulations of the airline market spurred the formation of international airline alliances. This paper as well as later publications from Bruckner have been cited in much of the research that has been done on the subject (Brueckner & Whalen, 2000, p. 503).

operating restrictions due to individual bilateral agreements, which would limit the entry of new carriers on certain routes. With markets becoming more deregulated, this problem is getting easier to overcome. However, airline alliances also allow carriers to expand their operations without investing in additional resources. Again, Brueckner addresses that cooperation between airlines can make them function as a single airline creating benefits for the interline passengers. Again, for the interhub market they express the concern for collusive behavior and anti-competitive effects (Brueckner, 2001, pp. 1476-1477). The paper finds that cooperative pricing in the interline market creates downward pressure on fares which creates benefits. However, because competition in the interhub market is reduced, fares tend to raise in this segment. Brueckner also finds that the welfare effects typically rise following formation of an alliance, despite the harm to the interhub passengers. Thus, his paper gives evidence that the positive effects of airline alliances may outweigh the harmful effects (Brueckner, 2001, p. 1494).

Pitfiled (2007) investigates the effect of alliances on traffic levels, market shares and concentration levels on routes between European hubs and the U.S. His research covers the time period from 1990 – 2003 to study the effect from the introduction of airline alliances. Pitfield expects alliances to have a positive impact on traffic on a route as well as the shares of the alliance member. Furthermore, these effects will be stronger if the members operate hub-and-spoke systems based on both the origin and destination (Pitfield, 2007, p. 192). Pitfield uses data from the US Bureau of Transportation Statistics which is analyzed year by year, but the data is complex because capacity on the principal routes examined in the paper is changed by both the incumbent airlines and airlines leaving and entering the market, which causes traffic volumes to fluctuate. Autoregressive Integrated Moving Average Models (ARIMA) with Intervention Analysis is used in the analysis of this paper to identify both the size and the significance of influences on traffic by route. Pitfield analyzes transatlantic alliance routes to the U.S. from London Heathrow (LHR), Paris Charles de Gaulle (CDG), Amsterdam (AMS) and Frankfurt (FRA) along with minor complementary roles for London Gatwick (LGW) and Paris Orly (ORY) by looking at non-stop traffic. In the analysis, however, Pitfield uses time-series intervention analysis by route from FRA and CDG to different destinations in the U.S.

Putting all together, the concluding remarks from this paper suggests that fluctuations in traffic has more to do with the so-called “ceteris paribus” (meaning holding all other variables constant), which is an assumption that there are many other influences on traffic volumes and market shares besides alliance formation and development, e.g. focus on U.S. carriers on non-hub EU routes with smaller aircraft types, than with alliance formation and development. Further, Pitfield conjectures that the OSA will not result in a significant growth in traffic or increased competition (Pitfield, 2007, p. 203). This is a very interesting result for us as we can now analyze if the OSA has had any significant effect or not on the competition measured by traffic levels and destinations offered. Pitfield expresses his concern prior to the OSA. Thus, our thesis can further contribute to his discussion and test whether these concerns holds or not after the implementation of the OSA.

Button (2009) provides an overview of the economics of the transatlantic situation where he gives insights to the reasons behind its development. He explains how the transatlantic market has been changed by deregulations in both the U.S. and EU (Button, 2009, p. 59). The article explains the institutional background for international air transportation, different deregulations that have been implemented, different bilateral agreements, and the removal of economic regulations in both the U.S. and in the EU. Button also explains much of what have already been introduced in the articles mentioned above, but he focuses more on a broader overview with no explicit model or analysis. In the conclusion, Button argues that not everyone has gained from the deregulated international airline market. However, the negative effects have been far outweighed by the positive impacts. The results/impacts are that many more can fly cheaper, greater variety of service, more jobs in the extended air transportation value chain (Button, 2009, p. 70). The article concludes that the OSA would provide much of the same general outcome, and that the European Union would benefit by this agreement, although there may be additional gains in extending it to a full Open Aviation Area of the type found within the US and the EU.

Pitfield (2009) also provides an overview of the main features of the OSA and some of its consequences, one year after its implementation. His findings indicate that consumer choice has broadened due to supply side adjustments after the agreement (Pitfield, 2009, p. 308). According to Pitfield however, there is still a need for an analysis of impacts on fares, costs and passengers. The paper emphasizes some challenges related to the methodology of such studies. The first is the challenge of receiving the appropriate data. The next challenge is to choose a methodology in which we can single out the effect of the OSA (Pitfield, 2009, pp. 311-312). His points are relevant for our thesis. We address his encouragement to perform an empirical analysis on the effects on passengers. Furthermore, as described in chapter 5, the data needed is comprehensive, and as we will discuss in chapter 6, the methodology needed to measure the effect of the OSA requires extensive assessment and statistical testing. Pitfield also suggests that the transatlantic traffic from LHR is of particular interest to study. As around 40% of the transatlantic traffic from Europe came from LHR prior to the OSA, he indicates that the liberalization will significantly affect this airport (Pitfield, 2009, p. 309). Because of his regards, we have chosen LHR as one of the airports in the analysis. Surprisingly however, our data show that the OSA has had little impact on passenger traffic here.

Furthermore, Pitfield (2011) uses time series analysis to investigate the consequences of the OSA, after highlighting the main features of the agreement in the paper from 2009. This paper uses ARIMA modelling to empirically test the effect of the OSA on passenger traffic. Furthermore, he considers four U.S. routes offered from LHR. In none of the routes does he find any evidence of a significant impact on passenger traffic from the OSA (Pitfield, 2011, p. 186). There were found no boost or discontinuity in passenger numbers that could not be explained by aircraft size, airlines' choice of frequency or fare setting. Furthermore, Pitfield explains that a longer data series would be preferable to provide more observations to allow the impact of the OSA to emerge, as the result may be partially masked by the concurrent recession of the financial crisis (Pitfield, 2011, p. 195). This result is interesting in our case, as we focus on a larger data series such that the effect of the financial crisis will play a smaller role in our time series.

Morandi, Malighetti, Paleari, and Redondi (2014) presents an analysis of traffic levels and competition in the transatlantic market before and after the implementation of the OSA. Specifically, they investigate the impact of the OSA on competition between airlines, alliances, and hub airports. They also examine whether the agreement has led to increased choices for transatlantic travelers (Morandi et al., 2014, p. 305). Morandi et al. address that the EU and U.S. governments had expectations of procompetitive effects such as more competition, increased route offerings and lower fares from the OSA. Yet, few insights are available of the actual impact of the OSA (Morandi et al., 2014, pp. 308-309). Like Button (2009) their analysis does not use any advanced empirical models. Rather they compare 2007 data with 2010 data, and provide an overview of how the market has changed in terms of number of flights, seats offered, destinations, alliance market shares and concentration ratios (Morandi et al., 2014, pp. 310-321). Their results find that the number of routes offered declined after the implementation of the OSA. In addition, they argue that competition between transatlantic airlines actually decreased as a result fewer players and consolidation of market shares after the implementation of the OSA. They also observe that there is a lack of new entrants to routes with a predominant airline and enhanced coordination within alliances (Morandi et al., 2014, pp. 324-326). Their results are a big contrast to the above-mentioned results of Button (2009). Thus, there is a discussion about the actual effects of an agreement such as the OSA. Our research aims to contribute to this debate. We investigate much of the same elements as Morandi et al., through a more complex empirical framework, using time series models to test the effect of the OSA. We also use more observations, since simply comparing 2007 data and 2010 can lead to results affected by the global financial crisis. As mentioned, it is possible that the airline industry had not fully recovered from the downturn in the economy, and hence a late response to the OSA is likely.

Other researchers on the topic of EU-U.S. OSA such as Fu, Oum and Zhang (2010), Cristea, Hummels and Roberson (2012), and Alves and Forte (2015) have also analyzed the impact of the deregulation. They all conjecture that an open skies agreement leads to an increase in the number of airlines in the market. In turn, it leads to an increase in competition in the air transport market. Further, this increase will be followed with a decrease of market restrictions, which should cause a restructuring of the air transport market, allowing new airlines to enter the deregulated segments of the market. Already existing airlines will then, according to Fu et al. (2010), restructure and optimize their networks, becoming viable to operate routes between locations that were not available or possible before due to the small number of passengers for that route (Fu, Oum, & Zhang, 2010, p. 32). Intuitively, this restructuring will increase the competition in those market segments because of the increase of possible number of routes and destinations (Alves & Forte, 2015, p. 133). In turn, following a rational point of view, this increased competition will lead to more airlines in the market segment which will lead to more passengers travelling transatlantic. This will further be analyzed in the empirical analysis. According to Cristea et al. (2012) evidence is found from their estimation results that outbound air traffic is 60 percent higher in liberalized markets compared to other markets that are still regulated, however, they argue that passenger traffic have not significantly increased before 5 years into the new agreement (Cristea, Hummels, & Roberson, 2012, p. 5). One reason for this might be that people have to adapt to the new agreement and new potential airlines to travel with. Another explanation can be that the financial crisis may have had an impact. As we present in our thesis, we see that passenger traffic have increased comparing traffic numbers pre and post the OSA[3]. Thus, this

[3] Based on description of data in table 4.

is not a significant result. It only describes passenger data pre and post the OSA, not considering if the increase is due to the OSA. According to Alves & Forte (2015), it takes time to see the full effect of such an agreement as the OSA. Their empirical result indicates that after the implementation of the agreement, prices will be decreased, and consumer surplus will increase due to the effect of double marginalization (Alves & Forte, 2015, p. 133).

4 Theoretical framework

4.1 Competition

In almost any industry, competitiveness is often crucial to both stay in a market and to get the upper hand on the rivals in the market that a company operates in. We say that a market is purely or perfectly competitive if each player in the market assumes that the market price is independent of its own level of output. That is, each player can only sell its good at one price: the market price (Varian, 2010, p. 396). At the other end we have monopoly, where a single firm is the only supplier of a good or service. Because this firm is the only supplier, it can influence the price in this market because its choices alter the total supply (Pepall et al., 2014, pp. 24-25). Perfect competition is viewed as positive, while monopoly is often judged negatively. The reason is that perfect competition is said to be efficient. By efficient means that it is impossible to find a small change in the allocation of capital, labor, goods, or services that may improve the well-being of one individual without harming others. To measure the efficiency, one use consumer surplus and producer surplus. Consumer surplus is the difference between the consumer's maximum willingness to pay and the amount the consumer actually pays. Similarly, producer surplus is the difference between the amount the seller receives and the cost of producing it. Because perfectly competitive firms take market prices as given, price equals marginal revenue. As a result, the price is set equal to marginal cost. This implies that this market is efficient because it maximizes the sum of producer and consumer surplus (total surplus). Monopoly on the other hand does not yield an efficient outcome. The reason is that the firm produces less and charges a higher price. This reduces consumer surplus. The monopolist's gain is less than the consumer's loss, resulting in lower total welfare (Pepall et al., 2014, pp. 28-31).

In the airline industry a healthy level of competition is important to maintain the best services for the lowest possible price. However, it does not always ensure the stability of an industry. To understand the competition in this industry it is crucial to understand what drives the competition. In the airline industry, typical drivers of competition are quality and cost. The airline can either focus on a cost leadership strategy or offer differentiation in terms of better quality (Johnson et al., 2017, p. 211 & 215).

Normally an airline has a combination of high fixed- and low variable costs, and they attempt to spread their fixed costs across many units (e.g., tickets). This will then create an incentive for the airline to grow very large, so they can spread these costs out on the number of tickets, hence, passengers. We then have economies of scale and the result is a few very large companies dominating the industry (Wolla & Backus, 2018, p. 3).

Competition can be divided into different market structures. As discussed, two outer points are perfect competition and monopoly. Often however, markets tend to lie somewhere in between these two. Examples of these are oligopoly, which is classified more towards monopoly, and monopolistic competition, which is classified more towards perfect competition. Wolla and Backus (2018) summarize these market structures in figure 1 below (Wolla & Backus, 2018, p. 2). As seen in the figure, an oligopoly moves towards perfect competition as the number of firms increases.

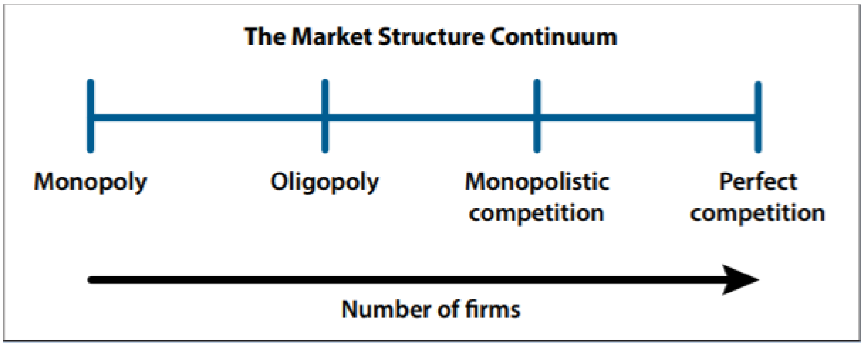

Figure 1: The Market Structure Continuum. From "The Economics Of Flying: How Competitive Are The Friendly Skies?," by A.S. Wolla and C. Backus, 2018, Federal Reserve Bank of St. Louis, p. 2.

4.2 Oligopolistic competition

Oligopoly is a market structure which is dominated by a few large producers or suppliers of a homogenous or differentiated product or service. In that sense, the airline industry can be characterized as an oligopoly. Often there are number of competitors in the market, but not so many that they have negligible effect on price (Varian, 2010, p. 497). Generally, when there are between three to six companies that have almost all market share, we can be sure it refers to an oligopolistic industry (McConnel, Brue, & Flynn, 2009, p. 229). As we will present in 5.2, every route segment considered possess a high Herfindahl-Hirschman index, indicating that the much of the total market share belongs to only a few firms. Hence, it indicates that the market is oligopolistic. Although the main service of airlines, air transportation from A to B, is the same regardless of airline, they differ in service levels across the world. Price strategies are also different between airlines with focus on comfort and service and LCCs. It is therefore unreasonable to expect one grand model for oligopolistic competition since many different behavior patterns can be observed in the real world (Varian, 2010, p. 497).

In this industry, the companies dominate the market with a high market share. New entrants are faced with strong barriers, including high startup costs and economies of scale. This allows larger companies to produce more output at even lower average costs. Sometimes firms collude to maintain their high prices (Wolla & Backus, 2018, p. 2). As mentioned previously, collusion is often prohibited via antitrust laws. However, the OSA gives the possibility of antitrust immunity to some airline alliances. From a consumer perspective this can lead to complications in several ways. When there are fewer companies in the market it means that the competition is less fierce, and the bigger airlines can raise their prices more easily without the threat of losing a lot of customers. Further, because of the high startup costs and the strong entry barriers it can be tough to enter an oligopolistic industry, although new entrants have greater potential gains from entering a less-competitive market (Wolla & Backus, 2018, p. 3).

4.3 Cournot competition

In general, there exists three prominent models of oligopolistic competition: Cournot, Bertrand and Stackelberg. As mentioned, our marker of competition is increased quantity in the form of passenger traffic and number of U.S. destinations offered. This rules out the Bertrand model, since it considers price as the strategic variable. The difference between the Cournot and Stackelberg model is the timing. In the Cournot model, all firms select their output quantity simultaneously (Pepall et al., 2014, pp. 222-223). The Stackelberg model is a two-stage game, in which one firm (the market leader) chooses its output quantity first. The other firms (followers) then select their quantity after observing the market leader's choice (Pepall et al., 2014, p. 265). According to Alves and Forte (2015), the appropriate theoretical model for interpretation of the OSA is the Cournot model.

Put simply, the Cournot best response of each firm when there are N firms, is to choose an output equal to $q^* = \frac{(A-c)}{2B} - \frac{(N-1)q*}{2}$. The Nash equilibrium quantity for each firm is then $q^* = \frac{(A-c)}{(N+1)B}$. This gives a total industry output of $Q^* = \frac{N(A-c)}{(N+1)B}$, and a market price of $P^* = \frac{A}{(N+1)} + \frac{N}{(N+1)}$c (Pepall et al., 2014, pp. 228-229).

The above equations of the Cournot-Nash equilibrium illustrate that the output increases as the number of firms increases, and the price decreases. In other words, they illustrate the dynamics of the market structure continuum in figure 1. Since the OSA allows for EU airlines to operate between any point in the EU to the U.S. and vice versa, it opens for new airlines to enter the transatlantic market and for existing airlines to expand their transatlantic route network. With more players in the transatlantic market, the N will increase, and in theory, increase the output and lower the price of transatlantic air travel. This is in line with the aim of the agreement and the expectations of the governments. Alves and Forte (2015) conclude that the Cournot model is an appropriate model to measure the impact of the OSA. However, the Cournot model fails to catch some important aspects of the competition in the airline market. As mentioned in section 4.1, the competition in this industry is multi-dimensional. This means that there are several drivers of the competition. The Cournot model assumes that the products or services offered by the competing firms are perfect substitutes (Pepall et al., 2014, p. 223). In theory the idea of perfect substitution in the airline industry may be reasonable since the same "core" service, air transportation from A to B, is offered regardless of airline. Being able to offer the same core service, but at a significantly reduced price, is indeed one of the key elements behind the formation of LCCs. In reality however, different air travel offerings are most likely not perfect substitutes. First of all, airlines themselves are offering different services by typically separating between economy, business and first class. There are also significant differences between airlines with a high-quality focus and airlines offering cheaper no-frills tickets. Other differences are related to convenience in terms of departure times, additional services, frequent flyer programs, code-sharing agreements, etc.

Thus, although the Cournot model is recognized as a sufficient model to interpret the impact of the OSA by Alves and Forte (2015), the assumption of perfect substitution may be unrealistic. As a consequence it lacks the ability to capture the multi-dimensional competition in the market. However, it still provides an explanation of the market dynamics one might expect after the introduction of the OSA. It also shows that the expectations from the U.S. and EU governments are anchored in the economic theory. This thesis empirically tests whether the aim of the agreement and the Cournot prediction of higher output in terms of passenger traffic and the number of destinations holds.

4.4 Market Concentration and the Herfindahl-Hirschman Index

A common measure of market concentration is the Herfindahl-Hirschman Index (HHI). It is a measure often used to examine competition and the impact of mergers and alliances on market share and competition. The index is given by:

$HHI = S_1^2 + S_2^2 + S_3^2 + \cdots + S_n^2 = \sum_{i=1}^{N} S_i^2$, where S_i^2 represents the squared market share of airline i (Pepall et al., 2014, p. 49).

In section 5.2, we calculate the HHI quarterly using market shares which we calculate from the traffic figures from the DOT T-100 database for the non-stop direct segment. By doing this, we can examine the trend in the market concentration for the time period of the study. One advantage of the HHI is that it reflects the combined influence on both unequal firm sizes and the concentration of activity in a few large firms. That is, instead of just reflecting a single point on the concentration curve, the HHI tells something about the shape of the curve. (Pepall et al., 2014, p. 49). In this matter, concentration curves are a useful illustrative device that permits one to get a sense of how industry production is allocated across firms from a visual inspection. It is called a concentration curve because it describes the extent of concentrated output of just a few firms (Pepall et al., 2014, pp. 47-48).

4.5 Brueckner's model of airline network structure

Brueckner (2001) presents the following model of a network for airlines. The figure is used to illustrate the two-firm case (Brueckner, 2001, p. 1479).

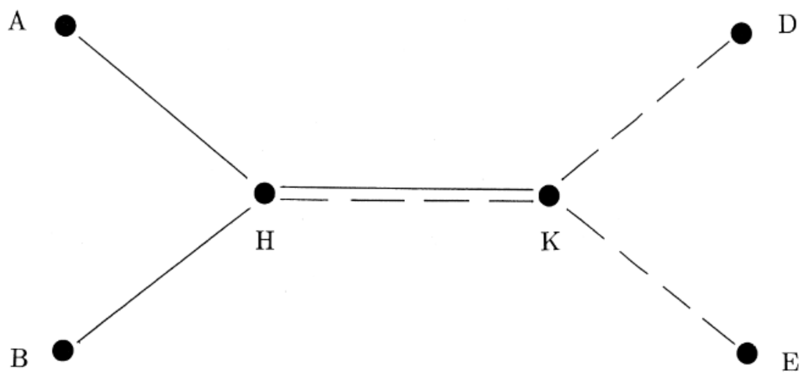

Figure 2: Network Structure. From "The economics of international codesharing: an analysis of airline alliances," by J.K. Brueckner, 2001, International Journal of Industrial Organization, 19, p. 1479.

In Figure 2, airline 1 operates at hub H, with domestic routes to A and B and international route to K. K is the hub for airline 2, with domestic routes to D and E and international route to H (Brueckner, 2001, pp. 1479-1480). In the context of our analysis, H represents a hub for a U.S. carrier while K represents the hub for a European carrier. The segment H – K, thus illustrates the transatlantic market. A and B are destinations in the U.S. while D and E are destinations in the EU. The model illustrates one of the benefits of an airline alliance. If the two airlines are cooperating, airline 1 can expand its capacity with destinations D and E without investing in additional resources. Airline 2 will then operate the flights to D and E, and the two allied airlines will share the profits from A to D, A to E, etc. This strategy also makes it convenient for passengers if the two airlines are cooperating in their scheduling, giving a single-airline feeling. This illustrates a competitional aspect that the Cournot model fails to catch. These kind of routes, where the passengers are dependent on both carriers, are typically referred to as interline trips (Brueckner, 2001, p. 1477). The opposite, where both carriers operate (H – K segment), is referred to as the gateway-to-gateway, or interhub market. The concern about antitrust immunity has been raised around the latter. The concern is that the two airlines in the interhub market engage in collusive conduct to increase their market share and to lower the competition. One thing to notice in this model is the possibility of fare arbitrage. For instance, if $p_{AH} + p_{HB} < p_{AB}$, then a passenger in the AB market would benefit of purchasing two round-trip tickets, one from A to H and one from H to B instead of purchasing a direct AB round-trip ticket (Brueckner, 2001, p. 1481). By symmetry we can have $p_{DK} + p_{KE} < p_{DE}$ in the case of airline 2.

4.6 The EU – U.S. Open Skies Agreement's regulatory impact

The OSA allowed EU airlines to operate flights to the U.S. from any airport in the EU, and U.S. airlines to operate flights to the EU. In addition EU and U.S. airlines can operate routes beyond the EU and the U.S. without restrictions on number of flights or type of aircraft. The agreement also allows for free pricing for the airlines. At the same time, the agreement opens for unlimited code-sharing and opportunities for EU carriers to provide aircrafts with crew to U.S. airlines on international routes (European Union, 2016). The access to unlimited code-sharing has raised concerns regarding possible collusive or anti-competitive behavior. As Brueckner pointed out, this can indeed be beneficial to the consumers on routes where they are dependent on both carriers. However, on routes where both carriers operate, like the transatlantic market, it may result in a reduction of the procompetitive effects of the agreement. The specific terms or "freedom rights" that was given by the 2008 OSA were according to the European Union (2016) the following:

3rd freedom rights: the right to put down traffic coming from the home country of the carrier

4th freedom rights: the right to take on traffic destined for the home country of the carrier

5th freedom rights: the right to put down and take on traffic coming from or going to a non-EU country

7th freedom rights: the right of transporting traffic between the territory of the granting country and any non-EU country. This does not require the service to connect to or be an extension of any service to/from the home country of the carrier (European Union, 2016).

Some member countries of the EU already had bilateral agreements with the U.S., introduced in table 1. These agreements would let EU airlines fly to any point in the U.S. without restrictions, but only from their home countries. In other countries, such as the UK, air services were restricted to a certain weekly frequency or a certain number of airlines. This significantly reduced the scope for competition in these markets (European Commission, 2008). The new agreement in 2008, would put each member country of the EU on equal footing by providing a uniform agreement for the whole of the EU, in addition to some non-EU members such as Norway (European Commission, 2008). The fact that there were no longer restrictions on prices and number of airlines on each route made it possible for LCCs to enter the transatlantic market. The agreement was first signed 30. April 2007, but was not operational until the year after, 30th March 2008. This first agreement lasted until 25th March 2010 before the second phase of the agreement was agreed through eight rounds of negotiations which built upon the success of the signed EU-U.S. OSA of 2007. The negotiations on phase 2 began just 60 days after the OSA entered into force. The negotiations took a long time which could indicate that the parties struggled to reach an agreement. Thus, one might expect airlines to wait until the negotiations were finished and the OSA was further cemented before changing their operations or entering the market. Cristea, Hummels, and Roberson (2012) also pointed out that one would not expect airlines to immediately change their behavior in response to the OSA. The second phase was more focused on the environment, agreeing on a close collaboration on environmental matters. The goal was to reduce the cost of climate change for consumers and measures in the aviation industry. Both U.S. and EU also committed to have close cooperation with each other in terms of “green” technologies, air traffic management innovation, fuels and to address the climate change impact of international air services (European Commission, 2010). The second phase also focused on increasing the transparency of the cooperation between the competition authorities concerning transatlantic airline alliances. It created a link between the first phase of the agreement by creating additional opportunities of both sides of the market by deepening the cooperation on issues that were of common interest in the industry. (European Commission, 2010)

5 Data

5.1 Data collection

This thesis uses secondary data to empirically test the effect of the OSA on passenger traffic and the number of U.S. destinations offered. Our primary source of data is the T-100 database created by the U.S. Bureau of Transportation Statistics. The dataset T-100 international segment (all carriers) contains data on the international non-stop segment reported by both U.S. and foreign air carriers. The dataset provides information on airline, origin, destination, departures, and passengers transported when at least one point of service is in the United States or one of its territories. The data ranges from 1990 to 2019. However, the 2019 data ends in August (U.S. Bureau of Transportation Statistics, 2019). From the dataset, we have downloaded data on traffic levels in terms of number of passengers carried by each airline in the market segment and number of destinations offered from the three airports in EU considered, namely Charles de Gaulle (CDG) in Paris, Madrid Barajas (MAD) in Madrid, and Heathrow (LHR) in London. This data has been used to calculate the market share for airline alliances, which have used to identify the dominant alliance. This is again used to determine the market concentration, measured by the Herfindahl-Hirschman Index. The market share is calculated based on the number of passengers carried. That is, alliance i's passenger traffic divided by the total passenger traffic each quarter. To distinguish between airlines of different alliances, in addition to non-allied and allied airlines, we used table 2 as our main tool.

Since we want to control for the effect of the GDP level on passenger levels, we are additionally using data from the Federal Reserve Bank of St. Louis on the average of real GDP from the U.S. and the EU as a control variable, which is further explained in the description of data. We are not using the average real GDP of the specific country on each route and the U.S. as a control variable. The reason for this is that we instead use the average real GDP of EU and U.S. since we want to capture Brueckner's network structure model. That is, it is possible to travel from another place in EU e.g. ARN (Arlanda, Stochholm) to CDG and then JFK in the U.S. with an allied partner. Then, not only France's GDP will explain the demand, but also Sweden's GDP.

According to the Federal Reserve bank of St. Louis, real GDP for the EU is retrieved from Eurostat, where GDP is at market prices in millions of 2010 euros, seasonally adjusted. They set GDP equal to the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products (Eurostat, 2020).

5.2 Description of data

From the data retrieved from the T-100 database, we present the development of passenger traffic, the number of U.S. destinations offered, market share of the dominant airline alliances, market concentration, and the real GDP on our three route segments considered.

Seasonal fluctuations in the offer and demand of air transport is a natural and frequent phenomenon, as it is affected by higher demand by tourists in the third quarter during the summer months. The demand for tourist destinations makes the demand for the other quarters relative smaller. We therefore witness a fluctuation in passenger traffic on the route segments we consider, which can describe the trend less obvious and making the pattern of an upward trend less visible. Seasonality is a form of non-stationarity which can lead to spurious correlations if the variables are correlated due to the seasonal fluctuations and not necessarily a causal relationship (Brooks, 2014, p. 694). In our thesis, we deal with the challenges of seasonality through the vector error correction model (VECM) since the VECM uses first differenced variables. As seen in Appendix A, the first-differenced variables appear to be stationary. This is supported by the Augmented-Dickey Fuller test for the first-differenced variables in table 7.2, 8.2, and 9.2.

5.2.1 Charles de Gaulle – John F. Kennedy International Airport

This route segment is a very busy transatlantic route with a high volume of passenger traffic along with a high level of market share of the dominant airline alliance.

5.2.1.1 Passenger Growth – CDG - JFK

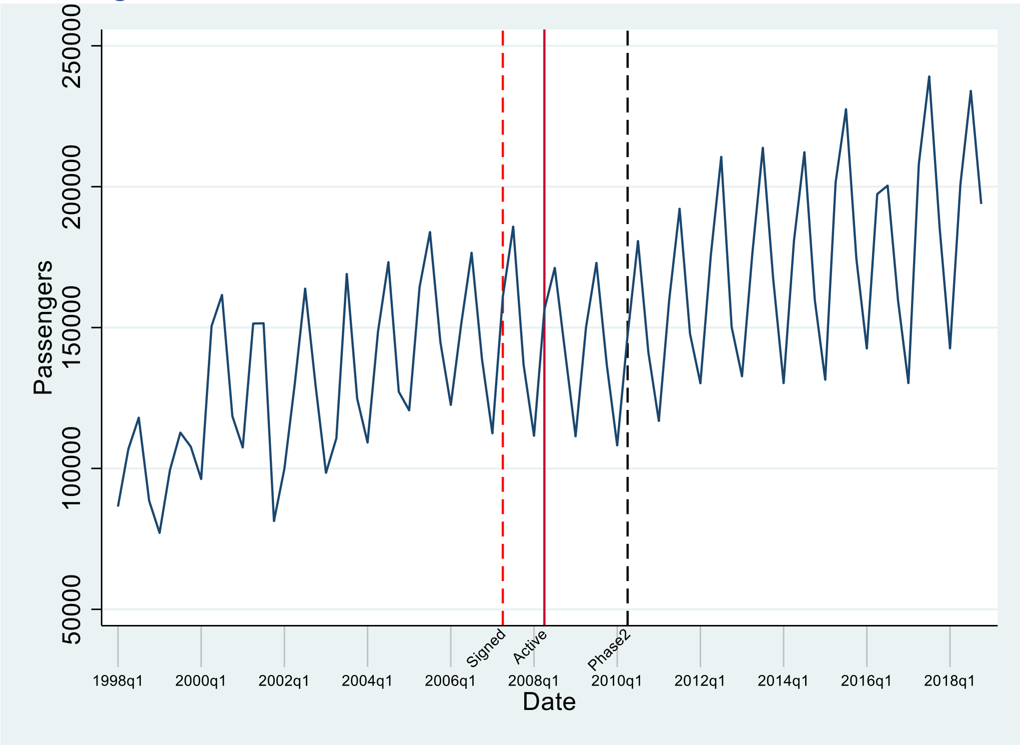

Figure 3.1: Passenger growth CDG – JFK, quarterly

Figure 3.1 shows graphically that it is an increasing trend in the number of passengers. That is, the number of passengers travelling from Charles de Gaulle to John F. Kennedy Airport has been increasing since the year 2000. The red, dotted vertical line indicates the signing of the OSA. It does not appear to have affected the number of passengers. The graph does not indicate that the incumbent airlines changed their behavior in terms of quantity in the anticipation of the OSA entering into force. The solid red line indicates the OSA entering into force and will in the empirical analysis be referred to as implementation of the agreement. The OSA does not appear to have had an immediate impact of passenger traffic when it was first signed. However, after the second phase was agreed in the second quarter of 2010, indicated by the black, dotted line, it appears to be an increasing trend in passenger traffic.

5.2.1.2 Dominant Alliance Share – CDG - JFK

As previous research has pointed at concerns towards alliances reducing the procompetitive effects of the OSA and that it may affect the output. Thus, we want to investigate the development of airline alliances on the route segment and see whether it has changed after the implementation of the OSA. The following graph illustrates the development of the market share of the dominant alliance SkyTeam on this route segment, since the alliance was created in June 2000.

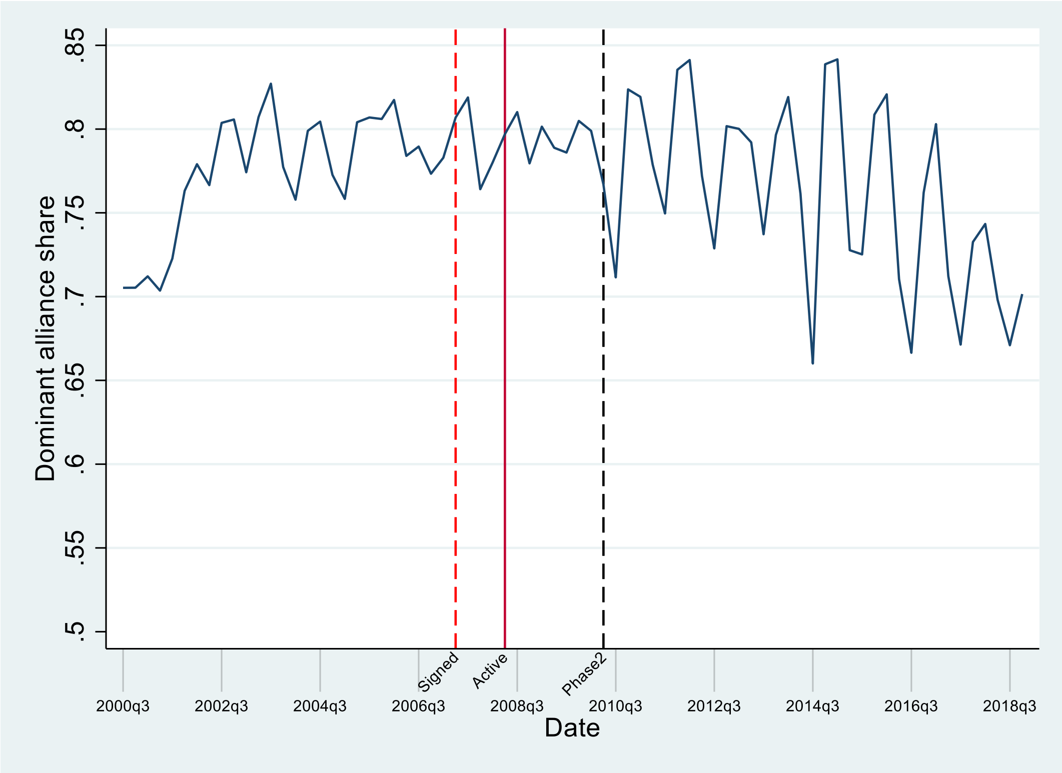

Figure 3.2: Market share of the dominant alliance CDG – JFK, quarterly

From figure 3.2, we observe that the market share of SkyTeam increased quite rapidly in the first two years after the alliance was established in 2000. Their market share leveled off around 2003. The signing of the OSA in 2007 does not appear to have had an impact on the alliance market share in anticipation of the agreement entering into force. That is, SkyTeam did not increase their market share to further deter entry. SkyTeam's market share has decreased since the OSA entered into force inn 2008. However, we see that the change has been only minor. Despite that the non-allied carrier XL Airways entered the market in 2009, SkyTeam appeared to maintain their market share level on the route segment. In 2016, the LCC Norwegian Air Shuttle also entered the market. This event appears to have had a negative impact on SkyTeam's market share. In 2018, they carried more passengers on the route than Air France's alliance partner Delta. All in all, however, the changes appear to be only minor and SkyTeam have been able to continue to have a high market share on this route segment. With XL Airways ceasing operations in 2019, they are likely to strengthen their strong position.

5.2.1.3 Herfindahl-Hirschman Index – CDG - JFK

One would expect that the formation of the SkyTeam alliance and the establishment of the OSA to have an impact on the market concentration. As mentioned in the theory section, a common measure for market concentration is the Herfindahl-Hirschman Index (HHI). The following graph shows the development in market concentration since 1998.

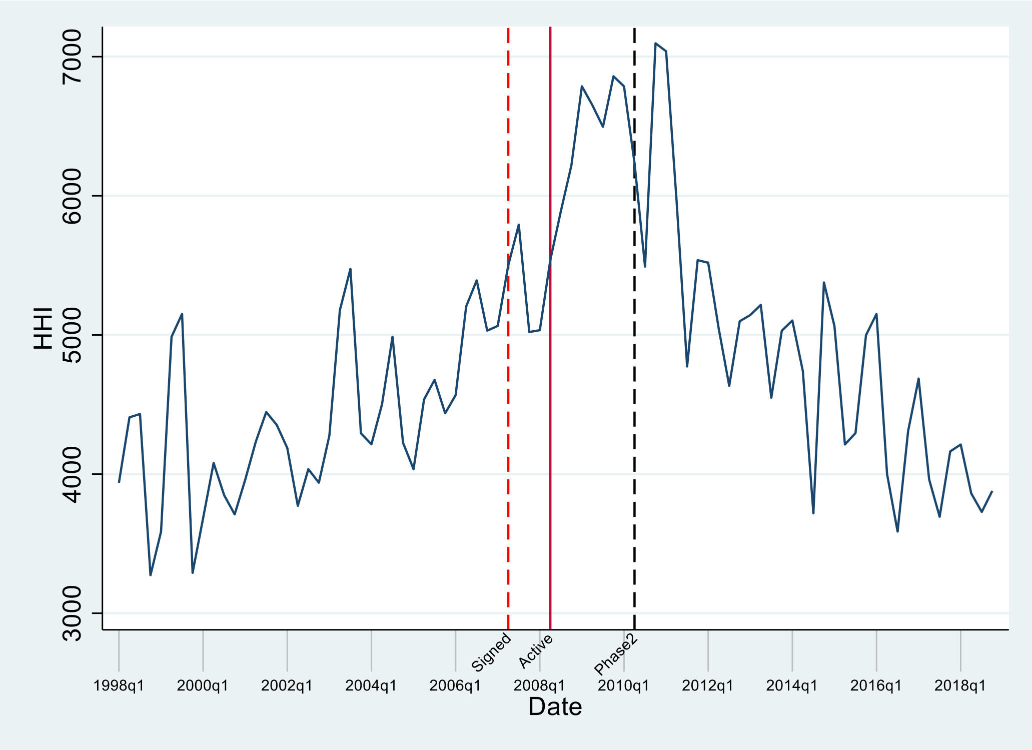

Figure 3.3: Herfindahl-Hirschman Index CDG – JFK, quarterly

Figure 3.3 shows that it appears to be an upward trend in market concentration after the SkyTeam alliance was created. Furthermore, the OSA does not appear to have an immediate effect on the market concentration, measured by the HHI. In fact, the HHI continues to increase after the OSA enters into force, and phase 2 is signed. From around 2011 however, the market concentration is decreasing. This late reaction may be due to a significant decrease in passenger traffic on this route by alliance partner Delta during the global financial crisis. It also took some time before XL Airways' passenger traffic became relatively large. Thus, during the financial crisis, the vast majority of passengers on this route were carried by either Air France or American Airlines. This will give a high market concentration. After the financial crisis, the passenger numbers of XL Airways and Delta started to increase again, giving lower market concentration. Thus, the peak in market concentration during the financial crisis appears to be explained by Delta's very limited operation in this period.

5.2.1.4 Number of destinations – CDG

To detect the presence of increased competition after the OSA, it can be helpful to look at the number of destinations offered from the airports considered to the transatlantic market.

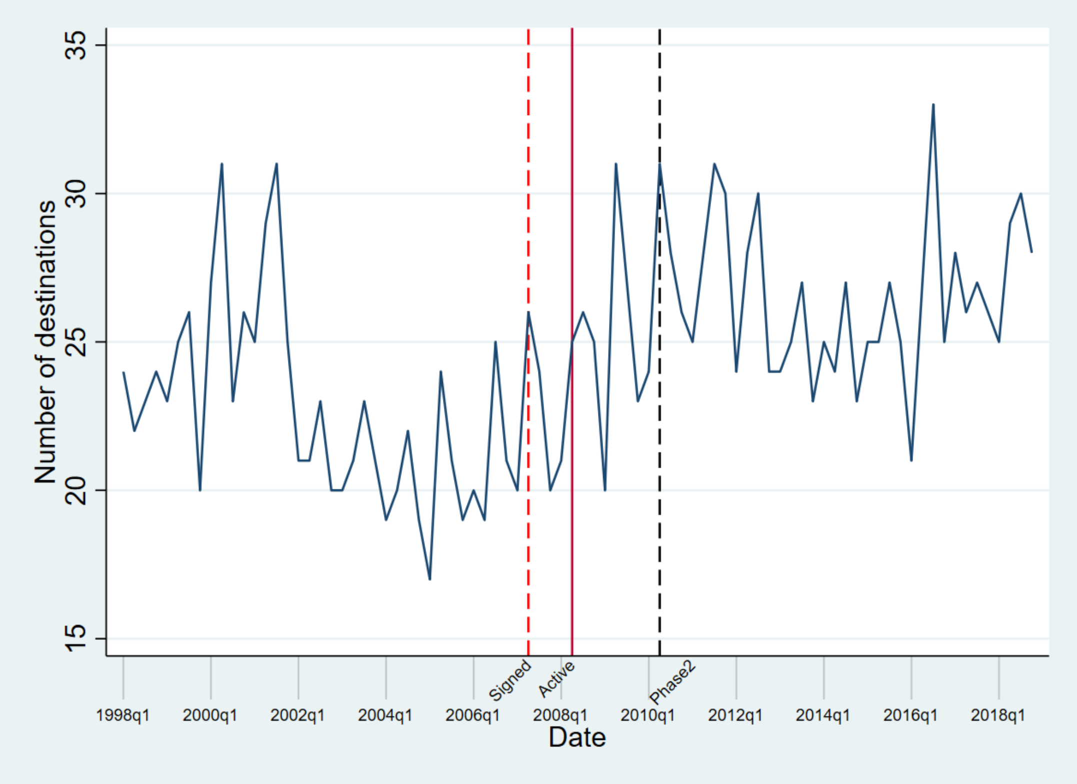

Figure 3.4: Number of destinations, CDG, quarterly

As we can observe, the number of U.S. destinations offered from CDG has to some extent fluctuated. However, the pattern is not constant so seasonality does not seem to be any issue because the fluctuations are not by the same quarterly intervals. We observe that the number of U.S. destinations increases drastically after the signing and implementation of, before it stabilizes itself after the second phase of OSA. This is a crude way to analyze the impact of the OSA, and it will be more thoroughly examined in the empirical analysis. However, it is a good way to get an overview of the data and its development.

5.2.2 Madrid Barajas International Airport – John F. Kennedy International Airport

Madrid Barajas international airport is the main international airport serving Madrid in Spain. It is dominated mainly by the airline alliance Oneworld but has in recent time been introduced to more airlines, causing market concentration to decrease which we will describe even further in figure 4.3.

5.2.2.1 Passenger Growth – MAD-JFK

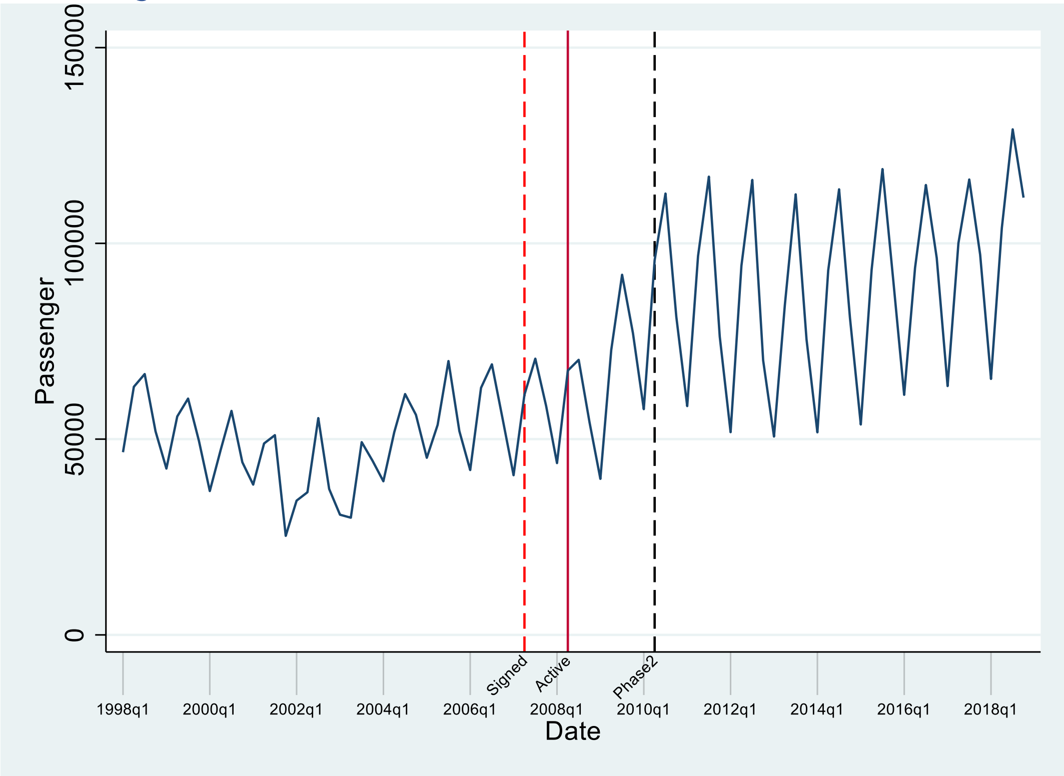

Figure 4.1: Passenger growth MAD – JFK, quarterly

This figure shows that it appears to be an overall positive trend in number of passengers as in the previous route analyzed. That is, the number of passengers between Madrid Barajas international airport and John F. Kennedy has been increasing overall from the year 1998. However, as it is seen from the figure, there was a stagnation in total passengers in the years between 1999-2002 before the growth began again. An explanation of this fascinating result may be the attacks of 9/11 in 2001, shocking the airline market and leading to a decrease in transatlantic air traffic measured by number of passengers. The signing of OSA does not appear to have had any immediate effect on passenger growth. The implementation of the OSA indicates, however, that passenger traffic increased compared to previous years, here described as active. This trend appears to strengthen in phase 2. Furthermore, although the growth in passenger traffic looks to be more significant than the route segment CDG-JFK, it must be noted that the value from the y-axis is quite different on the two similar graphs. As it can be seen, first graph for CDG-JFK ranges from 5000-25000, while for MAD-JFK it ranges from 0-15000. This might be misleading by first sight.

5.2.2.2 Dominant Alliance Share – MAD-JFK

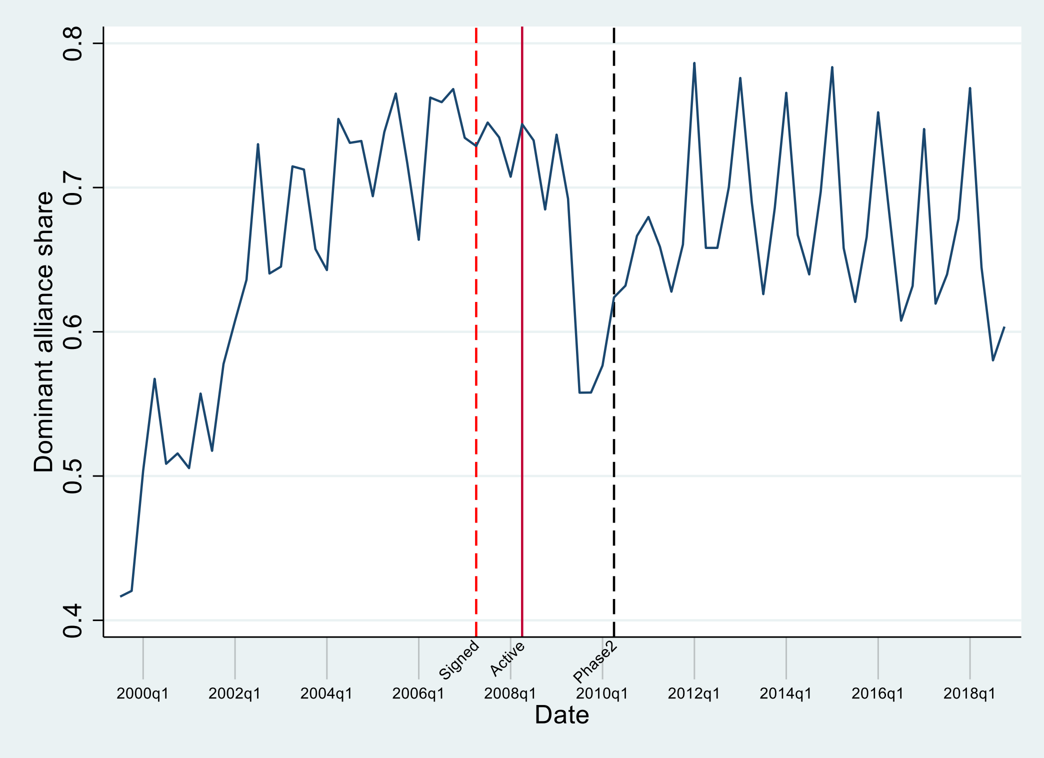

Figure 4.2: Market share of dominant alliance MAD – JFK, quarterly

Figure 4.2 describes the changes of the market share for Oneworld as the dominant alliance on this route segment. We can see that the dominant market share grew a lot after 2000. This appears to be a result of American Airlines acquiring the non-allied carrier Trans World Airlines (TWA) in 2001. Before this year they operated as competitors, making the dominant market share much lower than after the acquiring. After implementation of the OSA we can see that the market share decreases quite a lot before increasing again after phase 2. Immediately, one would believe that this was caused by the OSA. However, the increase appears from the introduction of an additional Oneworld member, American Airlines, carrying almost as many passengers as Delta, which is part of SkyTeam. This introduction increased the market share for Oneworld. Furthermore, in 2018 we can see from the figure that the dominant market share appears to decrease. The explanation for this may come from more passenger traveled for Air Europa, which is part of SkyTeam, but also for the introduction of the LCC, Norwegian Air Shuttle in the third quarter of 2018.

5.2.2.3 Herfindahl-Hirschman Index – MAD-JFK

One would expect that the formation of Oneworld and the deregulation of the OSA to influence the market concentration at this route segment. As described previously, this is measured through the Herfindahl Hirschman Index (HHI) and can be interpreted in figure 4.3 below.

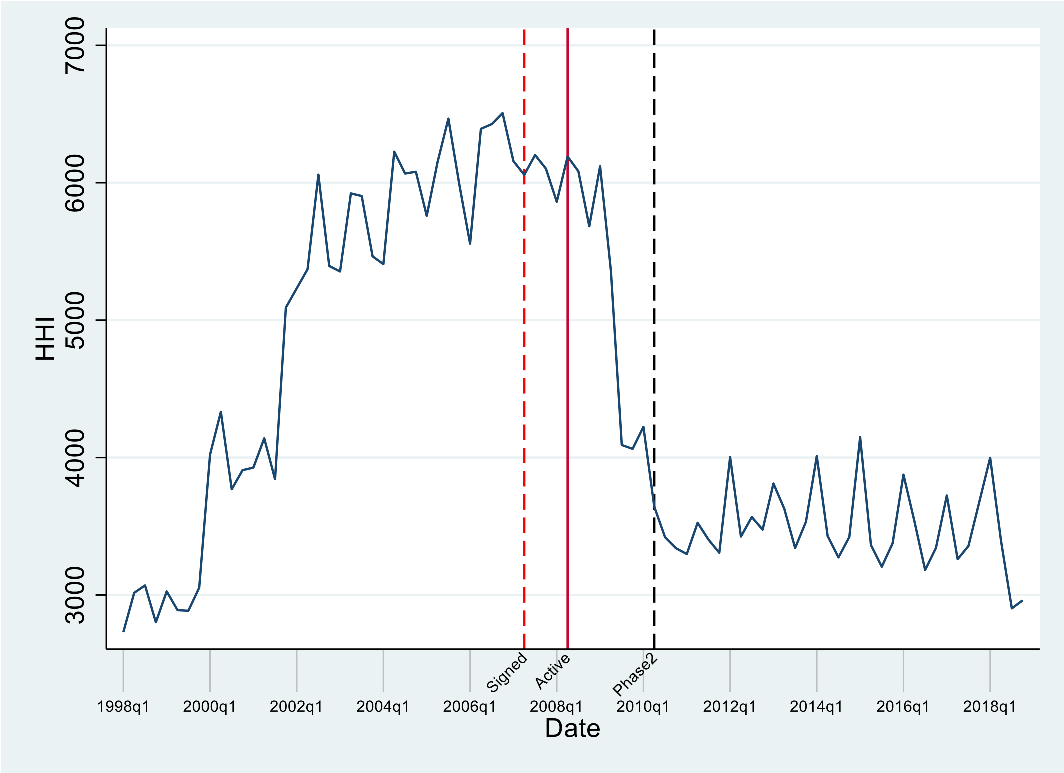

Figure 4.3: Herfindahl-Hirschman Index MAD – JFK, quarterly

After the creation of Oneworld the market concentration appears to have an upward trend until the implementation of the OSA. From this point the market concentration decreases quite a lot before it stabilizes itself from 2011 until beginning of 2018. The OSA appears to have a significant effect on market concentration which is an interesting result. As it is seen from figure 4.2, the dominant alliance market share decreased a lot in the years after the implementation of OSA until 2011 before it stabilized. The same can be seen in this figure where market concentration stabilizes itself to a quite low level of under 4000, while it had levels of approximately 6000 before the implementation of the OSA. It appears that the reason for this is that the route segment went from having only two airline carriers in the market, to introducing Air Europa and American Airlines splitting the passengers into four different airline carriers, hence, the market concentration decreased. Passengers had now the possibility to choose from different airline carriers, which could also be an effect on growth in passenger traffic.

5.2.2.4 *Number of destinations – MAD*

We also explain the developments of number of destinations offered from MAD to the U.S. in figure 4.4 below.

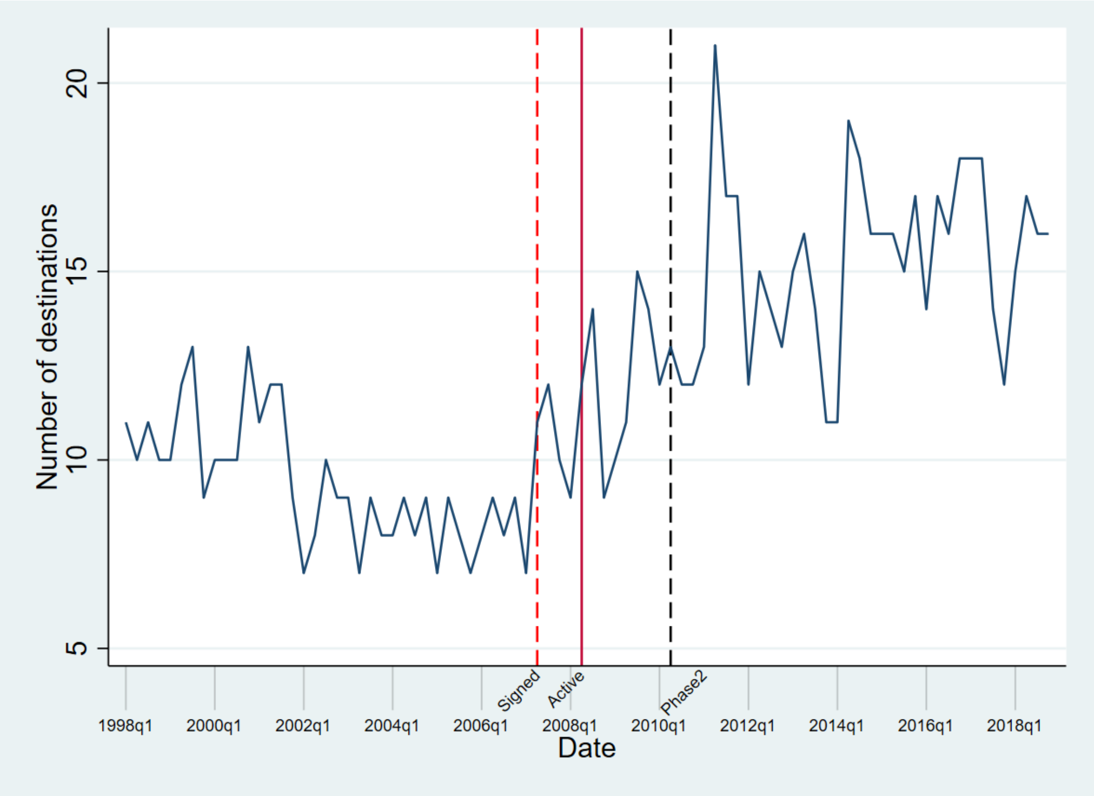

Figure 4.4: Number of destinations, MAD, quarterly

It is obvious that number of destinations offered have increased after both the signing, implementation, and the second phase of the OSA. This visual assessment strongly suggests that the OSA has had an impact on the number of destinations, by that, also competition on this specific airport. If this result is based solely on the OSA or if it is only a contribution to the increase in destinations, will be interesting to further analyze empirically.

5.2.3 London Heathrow – Boston Logan International Airport

London Heathrow Airport is one of the world's busiest airports measured by international passenger traffic and the busiest in Europe in 2018 according to Statista (Statista, 2020). British Airways and American Airlines are the main alliances serving this route. British Airways has its main hub in Heathrow while American Airlines operates with its hub in Boston, hence, we have an interhub route segment.

5.2.3.1 Passenger Growth – LHR-BOS

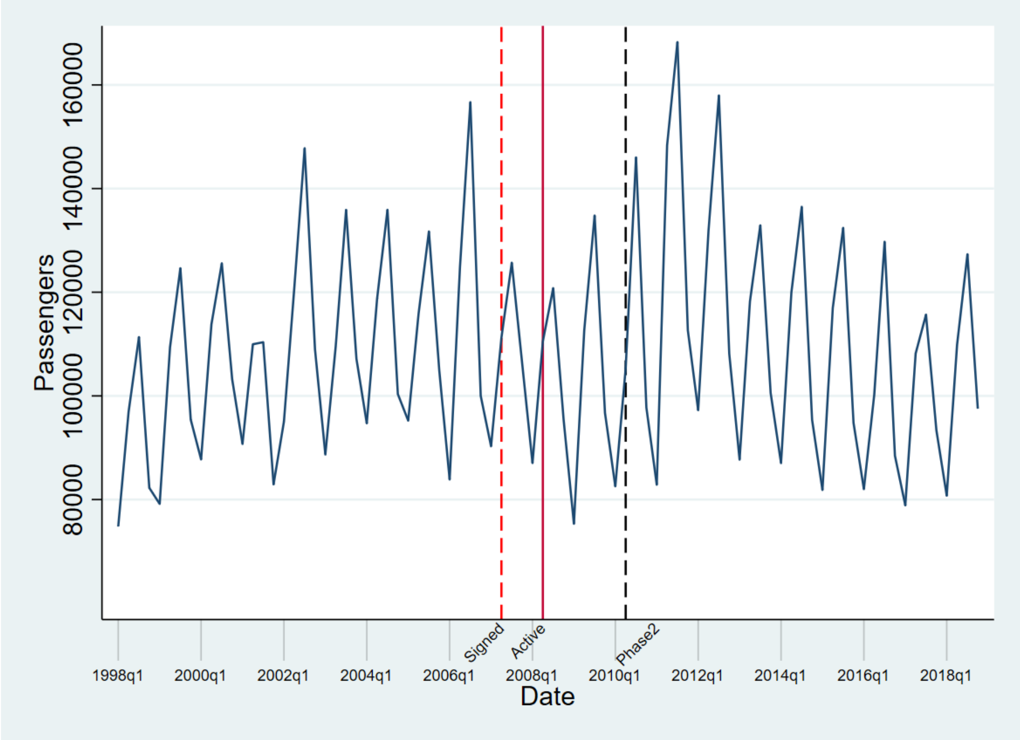

Figure 5.1: Passenger growth LHR – BOS, quarterly

From figure 5.1 we observe a lot of seasonal fluctuations of passenger travelling in this route segment. By an overall view of the graph, we can see that neither the signing, implementation, nor the second phase of the OSA appear to have had an immediate effect on the number of passengers carried. Passenger traffic does not seem to increase but looks to be stationary along the timespan. As Heathrow is such a large airport, it has operational constraints, environmental capacity and economic capacity that needs to be taken care of in order to increase growth of passengers travelled. There are also other competing airports in London, such as Gatwick, Stansted, London City, Luton and Southend which can lead to constraints in terms of passenger growth. The environmental constraints at Heathrow are related to noise and land use, which affect runway capacity by restricting the use of runways to achieve maximal operational capacity. All these constraints makes it hard for Heathrow to increase passenger growth, compared to the two other route segments considered (Janic, 2004, pp. 7-8). As this route is an interhub market, British Airlines and American Airlines dominate the market. However, Virgin Atlantic and Delta Airlines do also operate in this route segment along with United Airlines. These airlines carried the majority of passengers in our timespan.

5.2.3.2 Dominant Alliance Share – LHR-BOS

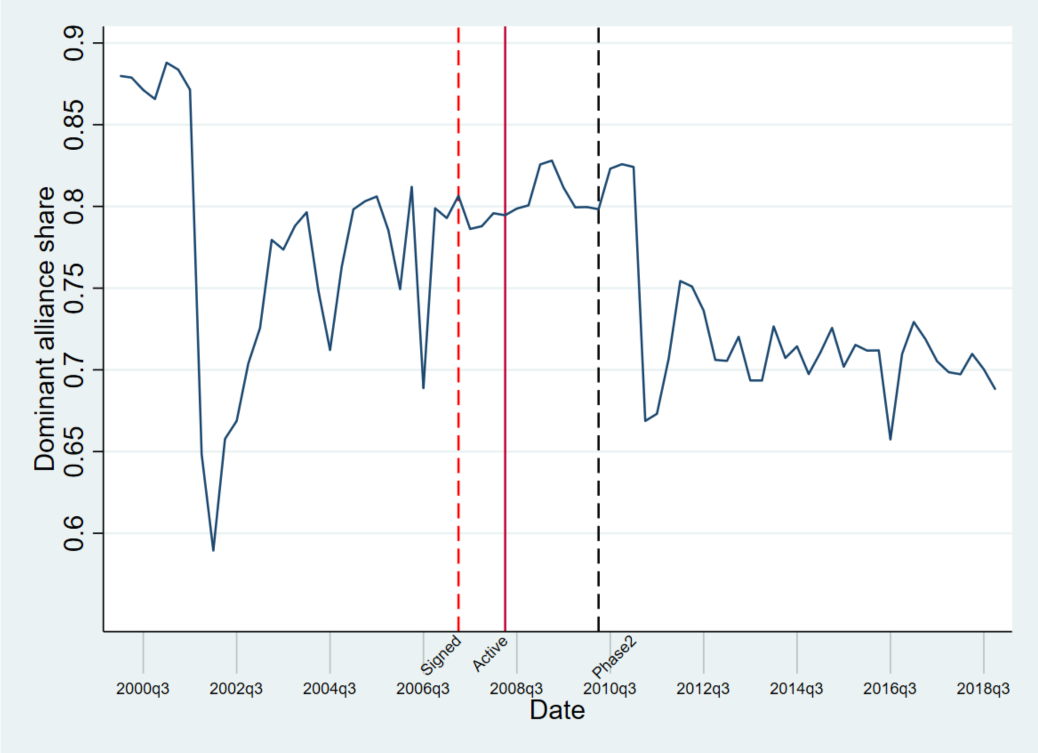

Figure 5.2: Market share of dominant alliance LHR – BOS, quarterly

The dominant alliance on the route LHR-BOS is Oneworld. Furthermore, we have Star Alliance with United Airlines, SkyTeam with Delta and non-allied airlines with Virgin Atlantic being the biggest non-allied carrier on this specific route. From figure 5.2 we observe that the route segment is clearly dominated by Oneworld in 2000, but in 2002 we have a low point of approximately 0,59 or 59% market share to Oneworld. By observing the data, the reason for this appears to be the introduction of Virgin Atlantic. From the figure, we observe that the introduction of the OSA and the implementation of the OSA does not seem to have any significant effect on the dominant market share of Oneworld. However, after the second phase of the OSA we can see a strong reduction on the graph. This may be a coincidence, or that the second phase have a stronger effect than the first phase. Again, it may also be a late response due to the financial crisis.

5.2.3.3 Herfindahl-Hirschman Index – LHR-BOS

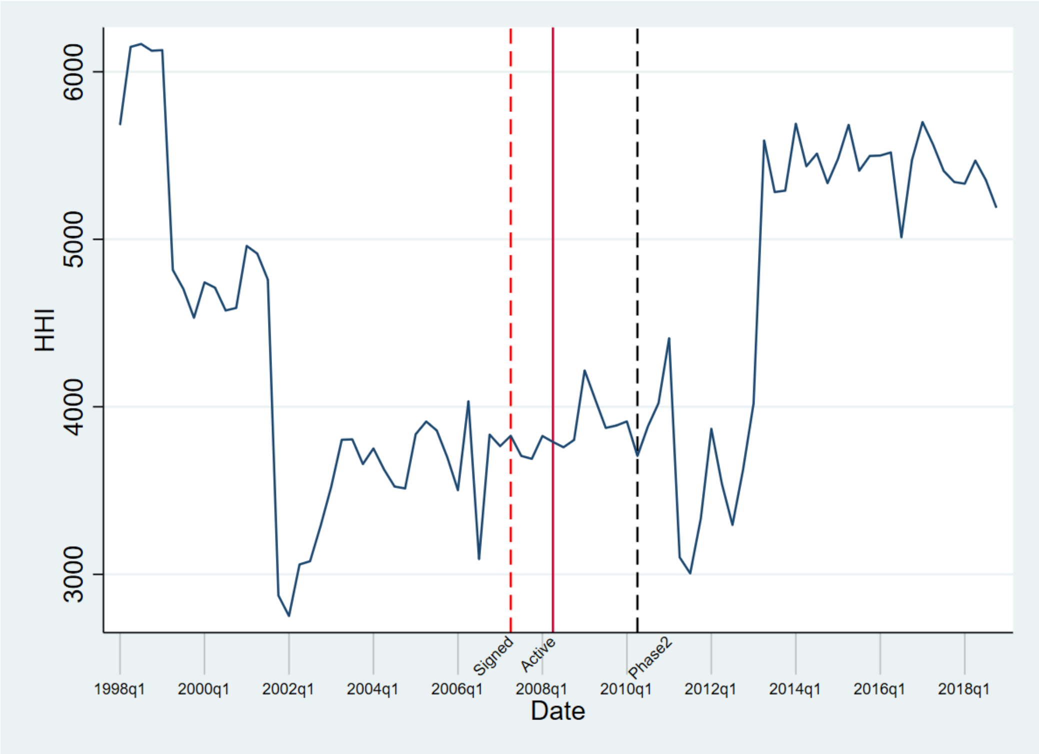

Figure 5.3: Herfindahl – Hirschman Index LHR-BOS, quarterly

Figure 5.3 shows that the HHI decreases dramatically from 1998 to 2002 before increasing again when the OSA is signed and the first phase becomes active. By observing this graph, it appears that the signing and implementation of the first phase does not influence the HHI. However, after the initiation of the second phase in 2010, the index increases drastically. This can be explained by fewer airlines flying on this route segment. From the data it can be observed that British Airlines increased significantly in passengers traveled, while American Airlines stopped flying from Heathrow to Boston, leading to a great increase in the HHI in figure 5.3. That is, the market becomes more concentrated with British airways as the most leading airline. This fluctuations in data induces that effects on HHI may have little to do directly with the OSA.

5.2.3.4 Number of destinations – LHR

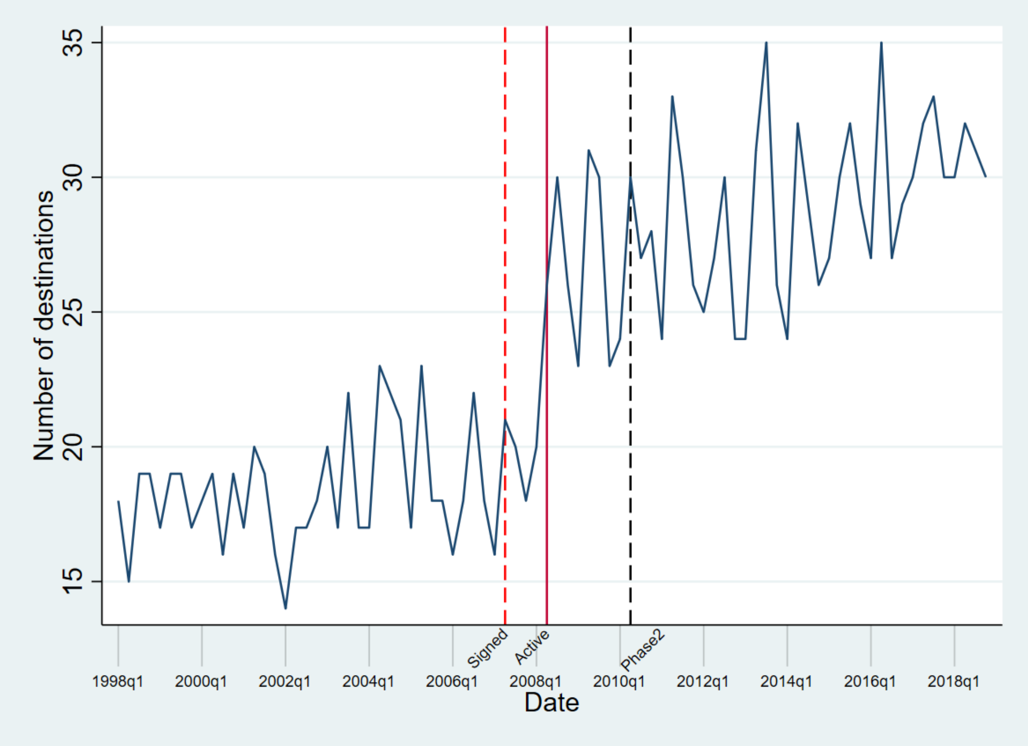

Figure 5.4: Number of destinations, LHR, quarterly

From this figure we observe a structural break in the number of destinations offered from the LHR airport. Number of destinations has very clearly increased after the implementation of the OSA. This is an interesting result, as it describes evidence of increased routes from LHR in the transatlantic market. This can again introduce more competition in the transatlantic airline industry, making more carriers able to fly transatlantic with fewer restrictions. This will further be analyzed so that we can determine if this increase is in fact due to the OSA.

5.3 Real GDP development

The real GDP variable used in this thesis is an average between the real GDP of the U.S. and the EU (28 countries). By doing this, we get to include both sides of the market, as the majority of the passengers in this market are likely to be of American or European origin. The GDP data for both the U.S. and EU was gathered from the database of the federal reserve bank of St.Louis. Since European real GDP was reported in euros it had to be converted into dollars. The data was in chained 2010 euros. To convert it into dollar amounts, we therefore used the 2010 rate of purchasing power parity (PPP). The PPP is taken from the database of OECD. According to them, PPPs are rates of currency conversion that try to equalize the purchasing power of different currencies. It does so by eliminating the differences in price levels between the countries (OECD Data, 2020).

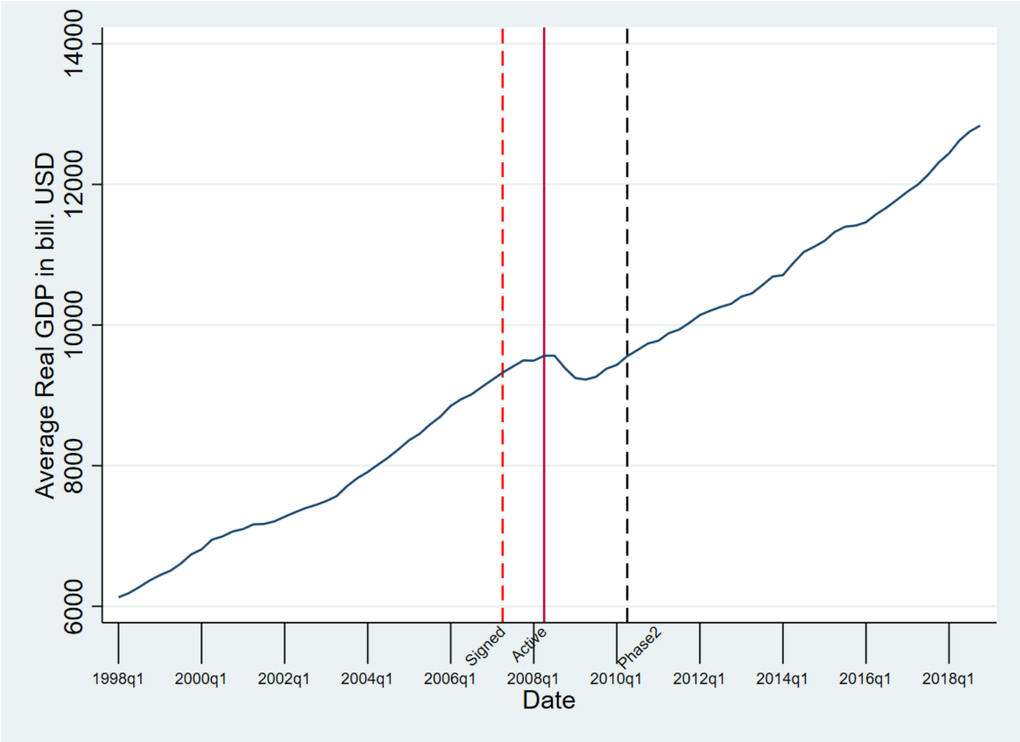

Figure 6: Average real GDP between the U.S. and EU in billion U.S. Dollars.

From Figure 6, we observe that the average real GDP has been increasing. The exception is the period between 2008 and 2009, which was the period of the global financial crisis. We see that the financial crisis happened around the same time as the OSA entered into force. As mentioned, a late response to the OSA in terms of passenger traffic or U.S. destinations offered may be explained by the decrease in the real GDP. After the crisis, the real GDP was increasing again, and appears to be increasing at a steady rate around the time of the signing of the second phase of the OSA. Besides a downturn during the financial crisis, it appears to have been a positive trend in the real GDP for our period of research.

5.4 Comparison of passenger traffic, real GDP, and destinations

It is first and foremost important to detect if there has been any change in passenger traffic and destinations pre and post the OSA. This is the same approach that is used by Morandi et al. (2014). As described in the previous graphs of passenger growth of our three segments, we can see that passenger growth appears to be present, however, they are quite different in volumes. To get a broader overview of passenger traffic, we can compare the numbers of passenger traffic pre and post the OSA for our three segments on average quarterly. This will show the differences more clearly.

Route segment	Avg. quarterly passengers pre OSA	Avg. quarterly passengers post OSA	Percent change
CDG – JFK	143 525	185 722	29,40%
MAD – JFK	49 693	85 450	71,09%
LHR – BOS	118 803	120 557	1,48%

Table 4: Summary of passenger traffic pre and post OSA

Table 4 shows the differences in average quarterly passenger traffic pre and post the OSA. We observe that the average number of passengers carried is larger for the period with the OSA for all of the segments, however, we observe that LHR-BOS have quite small increase compared to the other two routes. Passenger traffic has increased the most in the route segment CDG-JFK in numbers. However, the percentage change have been largest on MAD-JFK. An interesting part is that LHR-BOS have such small increase. As descried briefly earlier, this is likely due to constraints at the Heathrow airport, but also because JFK is a bigger airport compared to Boston and therefore have a greater potential of growing in number of passengers. This is of course a crude way to analyze the impact of the OSA, but it demonstrates that there has been an increase in passenger traffic after the OSA for all the three routes, although the increase for LHR is only minor. Further empirical analysis will investigate whether the increase in passenger traffic can be attributed to the OSA, or if it is mostly due to the overall economic conditions measured by the real GDP.

This can be compared with average real GDP pre OSA and post OSA for the three route segments. This is to compare the percentage change of passengers to the change in real GDP and number of destinations offered. As previously described, we use the same average real GDP for all our route segments.

Time period	Average real GPD growth
Pre OSA	1,09%
Post OSA	0,72%

Table 5: Average GDP pre and post OSA

As we mentioned earlier, the late response of higher traffic levels may be due to the financial crisis and the reduced growth of real GDP. From this table we see that the average real GDP growth has in fact been reduced. Comparing this GDP growth to growth of passengers in table 4 above and number of destinations offered in table 6 below, we observe that average real GDP growth are reduced post OSA. This is the opposite of passenger growth and destinations, where we observe an increase in the same period.

Route segment	Avg. quarterly U.S. destinations pre OSA	Avg. quarterly U.S. destinations post OSA	Percent change
CDG	25	29	16%
MAD	10	16	60%
LHR	20	31	55%

Table 6: Summary of destinations offered pre and post OSA

In table 6 above, we observe that number of U.S. destinations have increased in all airports considered. By percentage change, we can see that MAD have increased the most, as it did in the growth of passengers. Furthermore, by only looking at the increase in number of U.S. destinations, we see that LHR have increased by 9 more destinations compared to 6 more for MAD. However, the percentage change is not that significant because of a higher base in the pre period of OSA. Although we saw that number of passengers from LHR did not increase by the same level as the other routes on the route to BOS, we observe, on the contrary, that number of destinations have increased the most from this airport. Following figure 5.4, the reason for this increase appears to be explained by the OSA and its effect of more competition in the market, leading to increased number of U.S. destinations offered.

6 Methodology

As described in the previous chapter, we use secondary data retrieved from the U.S. Bureau of Transportation Statistics. This is raw data that we retrieve directly from the source and, so it needs to be coded specifically for our research in order to answer our research question. Furthermore, it is important that we define the right scale type for our data analysis. Since we are going to do an empirical analysis based on time series with traffic numbers, market share values from alliances and number of destinations, we would classify it as ratio scale[4] (Sekaran & Bougie, 2016, p. 279).

To best describe the effects of the OSA, the choice of the appropriate statistical model for our empirical analysis is important. According to Sekaran & Bougie (2016), this largely depends on the number of independent and dependent variables that we are examining and the scale of our variables. Furthermore, since we are examining multiple variable relationships, we use a multivariate statistical technique in our statistical model to capture any effect on passenger traffic and destinations offered (Sekaran & Bougie, 2016, p. 302). Since we are going to analyze effects over time, we would classify our data in a time series before we analyze it. As introduced in the data collection section, the T-100 database is a very common resource in analyzing effects of passenger traffic levels and number of destinations, which is the strategic variables that we are investigating.

6.1 Unit of analysis

The unit of analysis refers to the level of aggregation of the data that we have retrieved during our data analysis. In our case this is the procompetitive effects which is measured by the traffic level and the number of destinations offered. These are again measured by individuals travelling transatlantic in our segments and number of destinations offered from the three EU airports to the U.S. It is important that we state our unit of analysis because the data collection methods, sample size and even the variables included in the framework may be determined by the individual analysis level (Sekaran & Bougie, 2016, pp. 102-103). In our case it is best to use a time series approach study, because we will analyze data by measuring the OSA through time by a dummy variable and other control variables. We use a multivariate time series approach since we consider models for the stochastic process of several series simultaneously to improve our forecasts (Verbeek, 2004, p. 309). This dummy variable considers the implementation of the OSA, also referred to as the first phase in the

[4] Ratio scale is a measurement scale that has an absolute zero origin, and hence indicates not only the magnitude, but also the proportion, of the differences (Sekaran & Bougie, 2016, p. 395).

description of data. This is to see if the agreement had any significant impact on the traffic levels and destinations offered at our timespan. Another way to do this would be to simply focus on two time periods before and after the agreement to look at the effect, however, time series regression depicts the development better by including the implementation of the OSA as a dummy variable.

6.2 Variables

The dependent variable is the variable we want to examine. We want to examine the variation in the dependent variable given a change in the independent variables (Sekaran & Bougie, 2016, p. 73). The two dependent variables are the number of passengers carried in each of the EU – U.S. non-stop route segments considered, and the number of U.S. destinations offered from the three airports considered in the EU. From the theory section above, we know that the output, which in this case is the available seats for passengers and number of U.S. destinations, is expected to increase as the market becomes more competitive. Thus, if competition increases in the transatlantic market due to the deregulation of the OSA, one would expect the passenger traffic and U.S. destinations to increase. These variables are then considered to capture two procompetitive effects from the OSA.

Independent variables are the variables that are expected to influence the dependent variables in either a positive or a negative way (Sekaran & Bougie, 2016, p. 74). Our first independent variable is the market share of the dominant alliance in each route segment. The dominant alliance is here defined as the alliance with the highest market share out of the three major global alliances mentioned earlier. This is included to capture the effect of airline alliances on expected passenger traffic and the number of U.S. destinations offered. Based on Brueckner's (2001) findings, we expect the market share of the dominant alliance to influence both passenger traffic and U.S. destinations. Typically, the dominant alliance is the alliance of the two airlines serving the interhub market. For instance, on the CDG – JFK route segment Air France and Delta are the largest carriers in terms of passengers. They both belong to the SkyTeam alliance and the segment is an interhub because Delta use JFK as their main transatlantic hub, while CDG serves as Air France's main hub. Air France – KLM and Delta also enjoy antitrust immunity (United States Department of Transportation, 2019). Based on the theory section above, collusion between firms to give them market power may have a negative effect on competition. Higher market power increases their ability to restrict output and charge higher prices. Thus, one would expect that alliances with a high market share would have a negative impact on passenger traffic and the number of U.S. of destinations.

Furthermore, as we will analyze the effect on both passenger traffic and number of destinations offered, the market share of the dominant alliance will be different for the two dependent variables. When analyzing the number of destinations offered, the first independent variable will be the market share of the dominant alliance from one of the airports considered to the U.S, e.g. CDG – U.S. For all airports considered, the alliance which is dominant for passenger traffic will still be the same dominant alliance when considering number of destinations.

To capture the effect of the OSA on passenger traffic and destinations offered, we have included a dummy variable in our analysis. Dummy variables are binary variables often included to see the effects of an event on the dependent variable (Wooldridge, 2013, p. 359). The event we want to capture is the OSA. Previously, we identified three stages of the OSA. However, as we noted in section 4.2, there was little evidence of any reaction from the incumbent airlines shortly after the signing of the OSA in 2007. We are able to see some changes from the OSA becoming active in 2008, which became clearer from 2010, as the second phase was agreed. Thus, to capture the effect of the OSA on passenger traffic and the number of destinations, we use a dummy variable that takes the value 0 from 1998 to the OSA entering into force in 2008, and 1 from it entering into force to the end of our sample period. That way, we capture the portion of our sample period where the OSA is active and are able to see if there are any significant differences in traffic levels and destinations with one dummy variable. One may also consider using two dummies to capture the effect of each stage of the OSA. However, if we do this, we encounter problems with collinearity. To avoid collinearity issues, we use only one dummy variable to capture the effect of the OSA.

As Pitfield pointed out in his paper, fluctuations in traffic may have more to do with the so-called "ceteris paribus" effects, which is that there are many other influences on traffic volumes besides alliances (Pitfield, 2007, p. 201). Because of his remarks, we have included the real GDP as an additional independent variable. This additional variable is included to capture the effect of the underlying economic conditions on passenger traffic and the number of destinations offered in the transatlantic airline market. The reason is that one would expect the demand for passenger traffic to correlate with the real GDP. The reasoning is simple. When GDP is high, people will have more disposable income and are more willing to travel. By the same principle, when GDP is low, consumers have less disposable income causing less demand for air travel. The same goes for number of destinations offered in the market. When GDP is high/low, it will affect the carriers to fly to more/fewer destinations. We are interested in seeing whether the OSA and the alliance market share will have a significant effect on the expected passenger traffic and destinations offered even with the real GDP in the model. Real GDP is also an important variable in this research of the OSA because the agreement entered into force at the same time as the global financial crisis was harming both the U.S. and the European economy. Thus, a late change in the passenger traffic on transatlantic route may be explained by the then ongoing financial crisis.

6.3 Time series

Since we are studying multiple route segments and are looking at how passenger numbers are affected by the variables introduced earlier over time, we are clearly facing time series data. Before going into the analysis, it is important to know exactly what time series data is and what we need to consider before analyzing the time series regression.

Time series data is data that has temporal ordering. A sequence of random variables indexed by time is called a stochastic process or time series process. When we collect the time series dataset on air traffic, we obtain one possible outcome of the stochastic process. Furthermore, we can only use one regression because we cannot go back in time and start the process again. If we did, we would generally obtain a different realization for the stochastic process. Thus, we think of time series data as the outcome of random variables. The sample size for a time series is set to the number of time periods over which we observe the variables of interest (Wooldridge, 2013, pp. 345, 346). In our case, the sample size is 84 quarters in the period from 1998-2018.

6.4 Stationarity

When predicting and analyzing the effect of the OSA in the time series, there are several complex points that need to be considered before we can run the regression directly. Multiple facets can be at play simultaneously. One of the main features that needs to be considered to predict the model using time series data is stationarity. In order to state anything about the effect or result of the regression, it is critical that the forecasting model works well. Most of the data collected in research tends to follow a trend. This means that the data follows a non-stationary trend. If this applies, the data needs to be transformed into stationary data, which will be further discussed. Analyzing non-stationary time series will lead to results that is not applicable and will represent the data poorly (Manuca & Savit, 1996, p. 134). Assessing the stationarity is the starting point of a time series analysis. Based on the results from the stationarity testing, we select the model and method that should be used for the specific time series (Shrestha & Bhatta, 2018, p. 88).

A stationary time series means that the statistical properties such as the mean, variance and covariance do not change over time. When these hold, predictions in the analysis can be done and the results will represent the data better (Wooldridge, 2013, pp. 381-382). Generally speaking, we can separate between three types of stationarity: strict stationarity, trend stationarity, and difference stationarity. Strict stationarity is typically what one refers to as stationarity. It is when the time series has a mean, variance and covariance that are not a function of time. Trend stationarity is when the mean trend is deterministic. We can estimate this trend and remove it from the data. The result is a residual series that is a stationary stochastic process (Wooldridge, 2013, p. 396). Difference stationarity is when the mean trend is stochastic. If a series is difference stationary, we can difference the series d times, and get a stationary stochastic process (Verbeek, 2004, p. 270).

Making the variables stationary is crucial when we are estimating or testing. When variables are non-stationary and not fluctuating around a constant mean, they may cause an arbitrary high R-squared, highly autocorrelated errors, and falsely significant regressors. This occurs because the two series are spuriously related due to the fact that they are both trended, and not necessarily because there exists a causal relationship between them. Such regressions are referred to as spurious regressions (Verbeek, 2004, p. 313).

6.4.1 Unit Root

Consider the simple one-lagged autoregressive (AR(1)) model: $y_t = \rho y_{t-1} + e_t$. Many economic time series are characterized with $\rho = 1$. Then the model can be written as $y_t = y_{t-1} + e_t$. The process described by this equation is called a random walk. This is a process where y at time t is found by starting at the previous value, y_{t-1}, and adding a zero mean random variable that is independent of y_{t-1}. A random walk is a special case of a unit root process. It is called a unit root from the fact that $\rho = 1$ in the AR(1) model. The key feature of a unit root process is that the y of today is highly correlated with y in the future and past y. Such models are called persistent. One important aspect of persistence is autocovariances. Autocovariances are the covariances between y_t and its previous values y_{t-k}. In general, the joint distribution of all values of y_t is characterized by these autocovariance (Verbeek, 2004, p. 257). Another aspect is autocorrelations. Autocorrelations are correlations between y_t and its previous values y_{t-k}. The autocorrelations considered as a function of k is referred to as the autocorrelation function (ACF). This plays a major role in modelling dependencies among observations, as it characterizes the process describing the evolution of covariances between y_t and its previous values y_t over time. The ACF can help determining the extent to which on value is correlated to a previous value, and thus the length and strength of the memory of the process (Verbeek, 2004, p. 259). One thing to note is that a series can be persistent and not trending, but often a persistent series contains a trend. One such model is a random walk with a drift: $y_t = \alpha + \rho y_{t-1} + e_t$. This model is very similar to the above model, but we include the parameter α. This is included to represent the drift term. According to this type of series, the value of y at time t is found from adding a constant(α) and a random noise (e_t) to the previous value (y_{t-1}). A random walk with a drift is an example of a unit root because it is an AR(1) process with $\rho = 1$. The difference is that is has an intercept. If a time series has a unit root, it shows a systematic pattern, which can cause problems when making predictions (Wooldridge, 2013, pp. 393-395). We use the concept of unit roots when we are assessing the stationarity of the variables. As described in 5.4.3 and 5.4.4, we can use statistical tests to detect the presence of a unit root.

6.4.2 Differencing and integration order

A common method to transform non-stationary variables into stationary variables is the method of differencing. This is a method to remove the temporal dependence of the time series. Differencing can help to stabilize the mean of a time series and eliminate the trend and seasonality. To put it simply, differencing is performed by subtracting the previous observation of the variable from the current observation. Mathematically, the process can be described in the following way:

$$\Delta y_t = y_t - y_{t-1}$$

The number of times a variable needs to be differenced in order to become stationary, determines the variable's order of integration (Wooldridge, 2013, p. 396). As mentioned, a series of differences (d) can transform the non-stationary time series into a stationary one. If non-stationary time series becomes stationary by taking the first difference, it is said to be of integration order 1. More generally, if the non-stationary time series becomes stationary after differencing it d times, it is said to be of integration order d. This process is denoted I(d), where d is the order of integration (Baffes, 1997, p. 69). Knowing the order of integration is critical when we are selecting our statistical test. As we will describe in more detail in 5.5, the variables may be cointegrated if they are I(1). Thus, if we have that the variables are I(1), we might have a long-term relationship between the variables.

6.4.3 Dickey Fuller and Augmented Dickey-Fuller test

The Dickey-Fuller test is a statistical method to test for the presence of a unit root in a time series (Dickey & Fuller, 1979). Consider the following autoregressive model:

$$y_t = \alpha + \rho y_{t-1} + e_t,\ t = 1,2, \ldots,$$

If y_t follows the above model, it is said to have a unit root if $\rho = 1$. From this, we get the following null hypothesis:

$$H_0 \colon \rho = 1$$

That is, the null hypothesis is that y_t has a unit root. A convenient way to carry out the test of a unit root is to subtract y_{t-1} on both sides of the equation above and define $\theta = \rho - 1$. We then get:

$$\Delta y_t = \alpha + \theta y_{t-1} + e_t$$

The null hypothesis is then $H_0 \colon \theta = 0$. The issue with this is that under the null, the time series is of order I(1). Dickey and Fuller showed that the t-statistic for the null hypothesis does not have a t-distribution. Although we cannot use the usual critical value, we can use the t-statistic for $\hat{\theta}$ in the above equation[5]. The reason is that appropriate asymptotic critical values have been tabulated over time, from Dickey and Fuller's original work in 1979. This test is what is referred to as the Dickey-Fuller (DF) test for a unit root. The critical values tabulated by Dickey and Fuller are used in the way that we reject the null hypothesis $H_0 \colon \theta = 0$ when $t_{\hat{\theta}} < c$, where c is a negative value from the tabulated critical values (Wooldridge, 2013, pp. 639-641). The Dickey-Fuller test generally takes three forms:

1) $\Delta y_t = \theta y_{t-1} + e_t$
2) $\Delta y_t = \alpha + \theta y_{t-1} + e_t$
3) $\Delta y_t = \alpha + \beta t + \theta y_{t-1} + e_t$

The first version is a "simple" test for a unit root in the sense that it does not include a time trend or a constant. This version may be unrealistic for economic data. The second version includes a constant (α) and is used for series with a drift, while the third version includes a time trend (βt) (Baltagi, 2011, p. 380).

[5] $\hat{\theta}$ is the estimate of θ.

The Dickey-Fuller test has been extended to be able to test for unit root in more complex models. This extended version is referred to as the augmented Dickey Fuller (ADF) test. This is done by including an additional term in the above equation:

$$\Delta y_t = \alpha + \theta y_{t-1} + \sum_{i=1}^{\rho} \gamma_i \Delta y_{t-1} + e_t$$

Where $|\gamma_i| > 1$, which ensures that Δy_t follows a stable AR(1) model under the null hypothesis. The augmented version allows us to add ρ lags to Δy_t to account for the dynamics in the process. Again we carry out the t-test on $\hat{\theta},$ and the same decision criteria is used (Wooldridge, 2013, pp. 641-642). The test can be used to determine how many times the variable needs to be differenced to become stationary. If we cannot reject the null hypothesis of a unit root, we can perform the same test with the first-difference of the variable. If we then can reject the null hypothesis, we know that the variable can be transformed to stationary by taking the first difference. We then typically say that the variable is non-stationary in levels, but stationary in differences. The variable is then of integration order of 1, or I(1). If we still cannot reject the null hypothesis, we repeat the process.

6.4.4 KPSS test

Another common unit root test is the KPSS test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). As opposed to the ADF test, the null hypothesis is here that the series is trend stationary and the alternative hypothesis is non-stationarity – or better – a unit root series (Hadri & Rao, 2009, p. 1187). The model can be interpreted as follows, where Kwiaitkowsky et al (1992) assume that the series can be decomposed into the sum of a deterministic trend, a random walk and a stationary error:

$$y_t = \xi t + r_t + \epsilon_t$$

Here, r_t is a random walk with $r_t = r_{t-1} + u_t$ where u_t are independent and identically distributed random variables $N(0, \sigma_u^2)$. Under the null hypothesis, $\sigma_u^2 = 0$, indicating that the variance is equal to 0, the initial value r_0 is treated as fixed unknown and act as an intercept. Furthermore, the ϵ_t is assumed to be stationary, under the null hypothesis y_t is trend stationary. If we have that $\xi t = 0$, y_t will be stationary around a level (Kwiatkowski et al., 1992, p. 162). To get a broader picture, we can categorize the hypotheses in an easier way as follows:

H_0: The series is trend stationary

H_a: The series has a unit root (series is non-stationary)

In order to test these hypotheses, one uses the one-sided lagrange multiplier (LM) test statistics for the test. If the LM statistic is greater than the critical value, then the null hypothesis is rejected, hence, the series is non-stationary. If the LM statistic is lower, we have the opposite result with a stationary time series (Kwiatkowski et al., 1992, pp. 162-163). If we fail to reject the null hypothesis, we have evidence that the series is trend stationary. Recall from section 5.4 that trend stationarity is when the mean trend is deterministic, that we can remove this trend from the data once we have estimated it. The result is a residual series that is a stationary stochastic process. A disadvantage for KPSS, however, is that it has a high rate of type 1 errors. A way to deal with this disadvantage is to combine this KPSS test with an ADF test, described above. If the result from both tests suggest that the time series is stationary, then we have a stronger case of stationarity.

6.5 Cointegration

The concept of cointegration was formally treated by Engle and Granger (1987). They discuss whether a meaningful regression can be performed when variables are I(1) (Engle & Granger, 1987, p. 251). The general rule is that using non-stationary variables when estimating, will lead to spurious results. The exception to this rule is when the variables have the same stochastic trend in common. This means that if the variables are integrated of order I(1) and share the same stochastic trend, there exists a linear relationship between them that is integrated of order I(0). When that is the case, the variables are said to be cointegrated (Verbeek, 2004, pp. 314-315). Thus, if we find our variables to be non-stationary, we need to make sure that they are integrated of order I(1) and test whether they are cointegrated so that we can determine if there exists a relationship between them.

6.5.1 Engle & Granger 2-step approach

Engle and Granger proposed a two-step approach to modelling non-stationary and cointegrated variables. The first step is to make sure all variables are I(1) and cointegrated. To test whether the variables are cointegrated, we can use the Engle-Granger test. The null hypothesis of this test is that there is no cointegration. If the null hypothesis is true, we are running a spurious regression. The test compares the t-statistic with an asymptotic critical value. If the t-statistic is below the critical value, we reject the null hypothesis. When this is the case, we say that we have evidence that the variables are cointegrated (Wooldridge, 2013, pp. 646-648). When this is done, we can use OLS to estimate the cointegrating regression.

From this regression, we store the residuals, and test if they are I(0), by performing an ADF test as described above. If the residuals are indeed I(0), we proceed to the second step.

In the second step, we use the stationary residuals we obtained from the first step in the error correction model (ECM). The intuition behind this model is that variables of integration order I(1) have a long-run relationship, and that there is some force that is pulling the equilibrium error towards zero. The ECM describes how the variables behave in the short-run consistent with a long-run cointegrating relationship (Verbeek, 2004, p. 318).

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2(\hat{u}_{t-1}) + v_t$$

Where $\hat{u}_{t-1} = y_{t-1} - \beta_0 - \beta_1 x_{t-1} = y_{t-1} - \hat{y}_{t-1}$

The stationary linear combination of non-stationary variables is referred to as the cointegrating vector. Any linear transformation of the cointegrating vector will also be a cointegrating vector. Since all variables in this model are stationary, it is now valid to interpret the parameters (Brooks, 2014, p. 378).

One of the weaknesses of Engle & Granger's 2-step approach is that it can at most find one cointegrating relationship, even though there might be multiple cointegrating relationship. Because we have multiple variables, we may also have multiple cointegrating relationship (Brooks, 2014, p. 379). A method that is able to find more than one cointegrating relationships is the Johansen 3-step approach. Hence, this is the model we will use in our analysis.

6.5.2 Johansen's 3-step approach

The first step of Johansen's approach is to estimate the vector autoregressive (VAR) model. The VAR model describes the evolution of multiple variables from their common history (Verbeek, 2004, p. 322). A VAR is a systems regression, meaning that there is more than one independent variable. The structure is that each variable is a linear function of past lags of itself and past lags of the other variables. We can write the VAR model of order p (VAR(p))in the following way:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

Where y_t is a vector of variables, A_i is a matrix of coefficients, and u_t is a vector of random error terms (Lütkepohl, 2005, p. 13).

Once we have estimated the above VAR model with potentially non-stationary variables, the next step we need to perform is to test whether we have any cointegrating relationships between the variables. We do this by using the Johansen test for cointegration. To perform the test, we first need to write the above equation as a vector error correction model (VECM) of the form:

$$\Delta y_t = \Pi_{t-p} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{p-1} \Delta y_{t-(p-1)} + u_t$$

Where $\Pi_{t-p} = (\sum_{i=1}^{\rho} A_i) - I_g$ and $\Gamma_i = (\sum_{j=1}^{i} A_j) - I_g$

This VAR has g variables in first-difference form on the left-hand side and $p - 1$ lags of the differences on the right-hand side. The Johansen test can be affected by the lag length selected for the VECM. Thus, it is important to find the optimal lag length for the analysis (Brooks, 2014, p. 386). This will be described in detail in section 6.5.3. The Johansen test can be viewed as an examination of the Π matrix. This matrix may be interpreted as a long-run coefficient matrix, since in equilibrium, all Δy_{t-i} will be zero. If we set the error terms to their expected value of zero, it will give $\Pi y_{t-p} = 0$. The test for cointegration between the variables is done by looking at the rank of the Π matrix via its eigenvalues. The rank of the matrix is equal to the number of eigenvalues that are significantly different from zero. The eigenvalues are denoted by λ_i and must be less than one in absolute values. If the rank of the Π matrix is not significantly different from zero, the variables are not cointegrated. The Johansen test considers two test statistics:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i)$$

and

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$$

Where r is the number of cointegrated vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated value of the ith ordered eigenvalue of the Π matrix. An eigenvalue that is significantly different from zero, indicates that the cointegration vector is significant.

λ_{trace} is a joint test that test the null hypothesis that the number of cointegration vectors is less than or equal to r, against the alternative hypothesis that there are more than r cointegration vectors.

λ_{max} conducts separate tests on each eigenvalue. It tests the null hypothesis that the number of cointegration vectors is r against the alternative hypothesis that the number if cointegration vectors is r+1 (Brooks, 2014, p. 387).

The decision rule for both test statistics is that we reject the null hypothesis if the test statistic is greater than the critical value found from Johansen's table. The testing is conducted sequentially. This means that if we reject first the null hypothesis, that r=0, we can conclude that the variables are cointegrated, but we do not know how many cointegration vectors that exist. Thus, the process is continued until we no longer can reject the null (Brooks, 2014, p. 388). Both test statistics have the same power of indicating if there is a cointegration relationship between the variables. However, the method of maximum-eigenvalue statistic, λ_{max}, is used less often than the trace statistic method because no solution to the multiple-testing problem has yet been found (StataCorp, 2019, pp. 904-906). That is, the trace statistic is today judged most reliable.

Once we have performed the Johansen test for cointegration and concluded that there exists one or more cointegrations between our variables, we move forwards to the third step, which is estimating the vector error correction model. The VECM is an extension to the VAR model explained above. The VECM includes first difference terms and a cointegrating variable. The model can be written as:

$$\Delta y_t = \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{p-1} \Delta y_{t-(p-1)} + \Pi y_{t-1} + u_t$$

Where Πy_{t-1} represents the error-correction component and explains the long-term relationship (Lütkepohl, 2005, pp. 247-248).

6.5.3 Lag-order selection criterions

Generally, there are two methods in selecting the lag order in VAR models. It can either be a sequence of likelihood ratio tests or a likelihood-based information criterion (Nielsen, 2006, p. 93). The information criterions are a useful instrument to determine the optimal lag order in different VAR models. In our case, these selection criterions will help us to determine how many lags we should interpret in our model in the empirical analysis.

We will now introduce these methods, explaining the sequence of likelihood ratio and the four information criterions and their formulas. For the likelihood ratio test, three approaches are available. However, we focus on the first approach, namely the log likelihood ratio test.

This log likelihood (LL) for a VAR was introduced by Hamilton and can be further defined below (Hamilton, 1994, pp. 295-296). Here, the likelihood log (LL) can be written as:

$$LL = -\left(\frac{T}{2}\right)\{\ln(|\hat{\Sigma}|) + Kln(2\pi) + K\},$$

where T is the number of observations, K denotes number of equations, and $\hat{\Sigma}$ is the maximum likelihood estimate of [$u_t u_t'$], where u_t is a K x 1 vector of disturbances. With the LL, we may estimate the likelihood ratio (LR), by letting LL(j) be the value of the LL with j number of lags which produces the LR statistic for lag order j (Hamilton, 1994, pp. 295-296):

$$LR(j) = 2[LL(j) - LL(j-1)]$$

The four information criterions considered are the final prediction error (FPE), Akaike's information criterion (AIC), Schwartz's Bayesian information criterion (SBIC) and the Hannan and Quinn information criterion (HQIC). FPE is the model-order statistic that may be presented as (Lütkepohl, 2005, p. 147):

$$FPE = |\Sigma_u|\left(\frac{T + K_{p+1}}{T - K_{p-1}}\right)^K$$

Considering the other three information criterions, we observe similarity, but they are computed by including a constant term from the LL. They may be written as:

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T}$$

$$SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T}t_p$$

$$HBIC = -2\left(\frac{LL}{T}\right) + \frac{2\ln[\ln(T)]}{T}t_p$$

Here, p is the number of lags and t_p is the total number of parameters considered in the model. These information criterions are computed and the lag-length that has the lowest value are suggested by the corresponding information criterion. The optimal lag-length are chosen to be the lag-length that has the highest number of suggestions. A reasonable strategy is to estimate a VAR model for different values of p and then select it based on Akaike or Schwartz information criteria described above (Verbeek, 2004, p. 324). For VECM one should select number of lags based on the same information criteria as for a VAR model. Normally SBIC is good for explanatory modelling, while Akaike should be used if the model is intended for forecasting (Winker & Maringer, 2004, pp. 4-6). When selecting the lag length based on these information criterions, the model may suffer from autocorrelation. It is therefore important that we choose enough lags to get a more robust model.

7 Model selection

7.1 Model selection

We are performing a multivariate statistical analysis since we are analyzing how the OSA, dominant alliance market share, and real GDP influence passenger traffic and the number of destinations offered. We can write the linear models as:

Model 1: $lnPassengers_t = \beta_0 + \beta_1 lnAllianceRoute_t + \beta_2 OSA_t + \beta_3 lnGDP_t + e_t$

Model 2: $lnDestinations_t = \beta_0 + \beta_1 lnAllianceUSdest_t + \beta_2 OSA_t + \beta_3 lnGDP_t + e_t$

We must use different variables for the dominant alliance market share for the two linear models. When we look at the passenger traffic, we observe the development at a specific transatlantic route. Hence, the dominant alliance market share has to be route specific as well. In model 2, we use the dominant alliance between a specific European airport and the U.S. as a whole, since we are observing the developments in the number of U.S. destinations offered. Also note that we use the natural logarithm of the variables. When we have the natural logarithm on both sides, the coefficients can be interpreted as elasticities. That way, we can see how a 1% change in independent variable affects the expected dependent variable.

7.2 VAR model

As mentioned in 6.5.2, the first step of Johansen's approach is to estimate the VAR(p) model. We use the notation presented in section 6.5.2 and select the lags using the selection criterions presented in 6.5.3 to select the optimal lag length. The selection criterions give an optimal lag length of p, which varies across our two models in the three route segments. We develop the following models, where the model for lnPassengers is referred to as model 1, and the model for lnDestinations as model 2:

$$lnPassengers_t = A_0 + \sum_{i=1}^{p} A_i\, lnPassengers_{t-i} + \sum_{i=j}^{p} A_j\, lnAllianceRoute_{t-j} + \sum_{k=1}^{p} A_k\, lnGDP_{t-k} + A_m OSA_t + u_t$$

$$lnDestinations_t = A_0 + \sum_{i=1}^{p} A_i\, lnDestinations_{t-i} + \sum_{i=j}^{p} A_j\, lnAllianceUSdest_{t-j} + \sum_{k=1}^{p} A_k\, lnGDP_{t-k} + A_m OSA_t + u_t$$

As mentioned, the notation is similar to what we presented in 6.2.2. The difference is that we use the operator $\sum$ to shorten it. The operator is used to denote the lag levels of the different variables. This is not used in front of the dummy variable for the OSA, because we must treat this variable as exogenous[6] since this only indicates the presence or absence of the OSA (Jiang & Liu, 2011, p. 973).

7.3 VEC model

Once the VAR(p) model is developed, the next step is to test whether the variables are cointegrated by using Johansen's test for cointegration. If we can conclude that there is one or more cointegrating relationship, we will develop and estimate a VEC model. Since the VEC model contains first-differenced terms of the VAR model, the lag length will be one period shorter, i.e. the VECM has lag order $p-1$. Then, we can develop the VECM which we will estimate in the empirical analysis. Again, the model for lnPassengers is referred to as model 1 and the model for lnDestinations as model 2.

$$\Delta lnPassengers_t = A_0 + \sum_{i=1}^{p-1} A_i \, \Delta lnPassengers_{t-i} + \sum_{j=1}^{p-1} A_j \, \Delta lnAllianceRoute_{t-j} + \sum_{k=1}^{p-1} A_k \, \Delta lnGDP_{t-k} + A_m OSA_t + \rho\mu_{t-1} + u_t$$

$$\Delta lnDestinations_t = A_0 + \sum_{i=1}^{p-1} A_i \, \Delta lnDestinations_{t-i} + \sum_{j=1}^{p-1} A_j \, \Delta lnAllianceUSdest_{t-j} + \sum_{k=1}^{p-1} A_k \, \Delta lnGDP_{t-k} + A_m OSA_t + \rho\mu_{t-1} + u_t$$

As we can see from the equations, the VECM is similar to the VAR. The difference is that the VECM contains first-differenced terms and an error correction component ($\rho\mu_{t-1}$). Again, we treat the dummy for the OSA as exogenous.

Now that we have described the data, methodology and specified the model, we proceed with the empirical analysis in which we perform the statistical tests and present our results.

[6] A variable that exerts an influence on the cause-and-effect relationship between two variables and are uncorrelated with the error term (Sekaran & Bougie, 2016, p. 391).

8 Empirical analysis

8.1 Stationarity Assessment

Assessing the stationarity of a time series is often recognized as the starting point of a time series analysis. As mentioned in the methodology section, we can use unit root tests to assess the stationarity of each variable. We want to determine whether the variables are stationary or not, and what order of integration they are.

If the unit root tests give significant evidence that all variables are of integration order I(0), one can use traditional methods such as OLS and VAR. However, this is considered to be unrealistic in economic time series (Shrestha & Bhatta, 2018, p. 71). If the variables are non-stationary, we perform the unit root test for the first differenced variable to determine whether it is of integration order I(1). If we find the variables to be I(1), we can proceed with the Johansen test for cointegration. We will now perform a stationarity assessment of the variables. We will start with a visual assessment followed by unit root tests for each of the variables and determine the order of integration.

8.1.1 CDG-JFK stationarity assessment

We perform the visual assessment for the route segment by presenting time series plots for each of the variables:

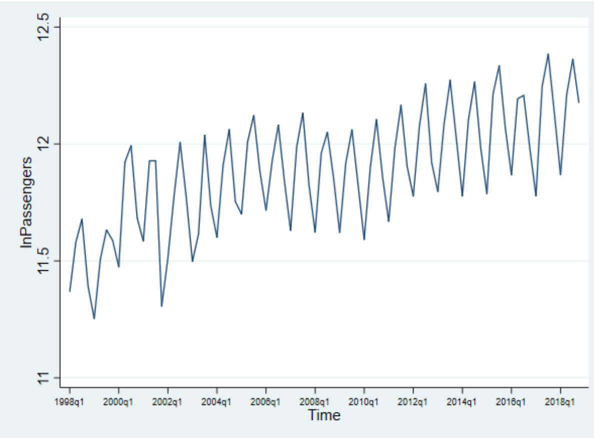

Figure 7.1: LnPassengers, CDG-JFK, quarterly

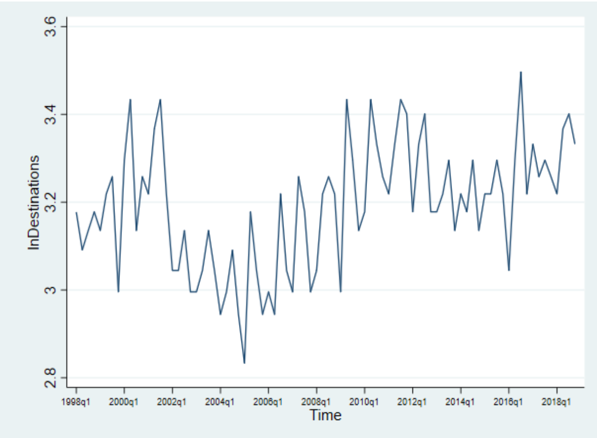

Figure 7.2: LnDestinations, CDG, quarterly

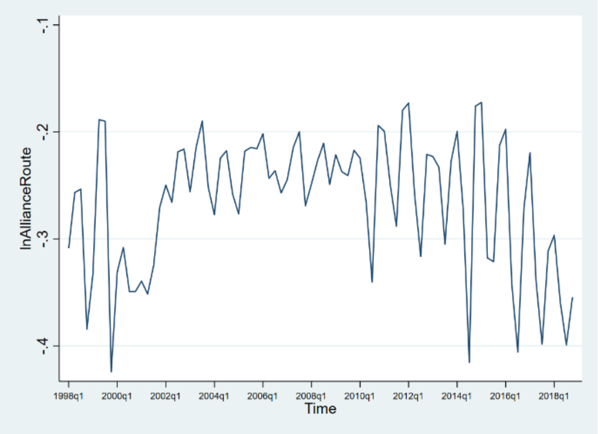

Figure 7.3: LnAllianceRoute, CDG-JFK, quarterly

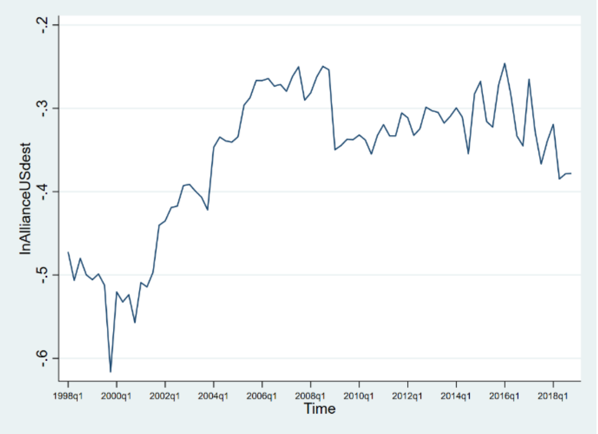

Figure 7.4: LnAllianceUSdest, CDG, quarterly

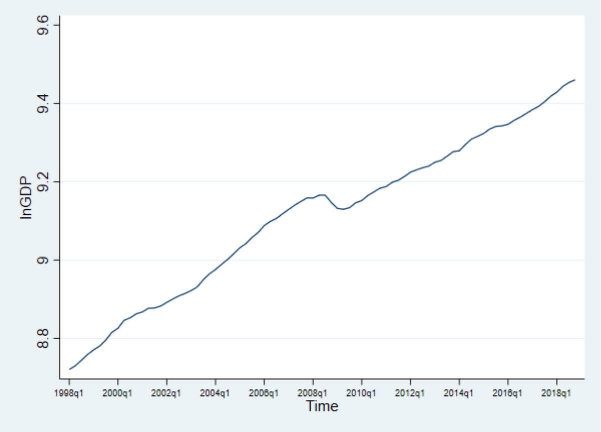

Figure 7.5: LnGDP, average of U.S. and EU.

From the graph of lnPassengers, we observe that there appears to be an upward trend. That is, there appears that the mean is increasing with time. For lnDestinations the trend is less obvious. However, it appears to be increasing somewhat from around the time of the signing of the OSA through the next five years or so. The natural logarithm of the market share of the dominant alliance does not appear to have a clear trend on the route CDG-JFK. For the dominant alliance on U.S. destinations however, there appears to be an upward trend until approximately 2009 before it stabilizes and decreases towards 2018. LnGDP appears to be increasing with time, with the exception of the period around the global financial crisis. These plots are of course a very crude way to analyze stationarity, but it gives an overview of how the variables have developed with time. Next, we will go through more formal statistical methods to assess the stationarity as described in the methodology.

We begin with the KPSS test. The test was described in the methodology section, and we had the following null hypothesis for the test:

H_0: The series is trend stationary

H_1: The series has a unit root (series is non-stationary)

The test statistics from the KPSS test are listed in the table below. The second part of the table, provides an overall conclusion of whether or not to reject the null hypothesis of trend stationarity.

10% critical value: 0.119 5% critical value: 0.146 1% critical value: 0.216	**Test statistic at lag order**			
Variable	**0**	**1**	**2**	**3**
LnPassengers	0.0668	0.0602	0.0976	0.137*
LnDestinations	0.391***	0.284***	0.244***	0.204**
LnAllianceRoute	0.615***	0.453***	0.438***	0.391***
LnAllianceUSdest	1.142***	0.763***	0.534***	0.415***
LnGDP	1.190***	0.606***	0.414***	0.319***

Variable	**lnPassengers**	**lnDestinations**	**lnAllianceRoute**	**lnAllianceUSdest**	**lnGDP**
Result	Do not reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0

Table 7.1 KPSS test CDG-JFK. 1%*** significance level, 5%** significance level, 10%* significance

The results from the KPSS test show that for four of the five variables, we reject the null hypothesis that the series is trend stationary. This provides evidence for a trend in these time series. What is perhaps surprising is that we do not reject the null hypothesis for lnPassengers, despite the time series plot giving indication of a trend. As we discussed in the methodology however, this gives evidence that the trend we observe in the plot is deterministic.

Moving forwards, we also apply the ADF test. Because the visual assessment show that there appears to be a trend in most of our variables, we perform the ADF test with a trend. We also include lags to the test, chosen according to the lag order selection criteria described in the methodology section. Recall from the methodology section that we had the following null hypothesis for the ADF test:

H_0: The series has a unit root

The results of the tests are summarized in the following table:

ADF level, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
LnPassengers	-2.739	0.2203
LnDestinations	-1.551	0.8109
LnAllianceRoute	-1.134	0.9232
LnAllianceUSdest	-0.405	0.9867
LnGDP	-2.482	0.3372
ADF first differences, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
D.lnPassengers	-6.589	0.0000
D.lnDestinations	-7.812	0.0000
D.lnAllianceRoute	-6.928	0.0000
D.lnAllianceUSdest	-3.712	0.0216
D.lnGDP	-3.740	0.0199

Table 7.2: ADF test CDG – JFK

The test shows that we cannot reject the null hypothesis of a unit root for any of the variables at level. This provides evidence of a unit root. In other words, none of the variables appear to be I(0). However, we notice that lnPassengers appears to be a borderline case as whether or not we reject the null hypothesis depends on the number of lags we include in the test. With 3 lags included, we cannot significantly reject the null hypothesis. The next step is to take the first difference of the variables and run the test again. If we then reject the null hypothesis, we have evidence that the variable is I(1). If not, we repeat the exercise until we reject the null hypothesis. The procedure yields the following result for the order of integration:

Variable	**lnPassengers**	**lnDestinations**	**lnAllianceRoute**	**lnAllianceUSdest**	**lnGDP**
Result	I(1)	I(1)	I(1)	I(1)	I(1)

Table 7.3: Order of integration CDG – JFK

8.1.2 MAD-JFK stationarity assessment

We follow the same procedure as with the CDG – JFK route segment to assess the stationarity in the time series. We begin by presenting the time series plots of the variables.

Since the variable for real GDP is the same as in the previous route segment, we do not present this plot again.

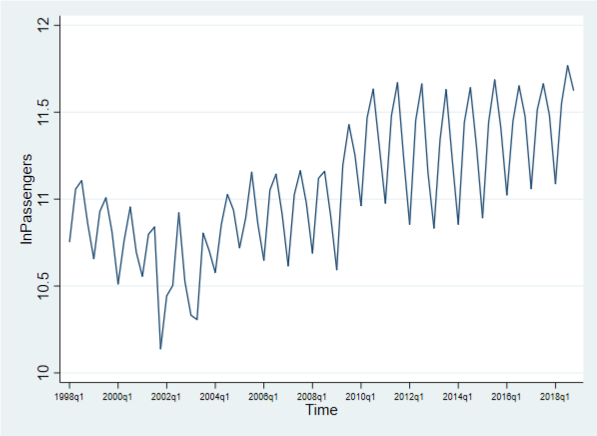

Figure 8.1: LnPassengers, MAD-JFK, quarterly

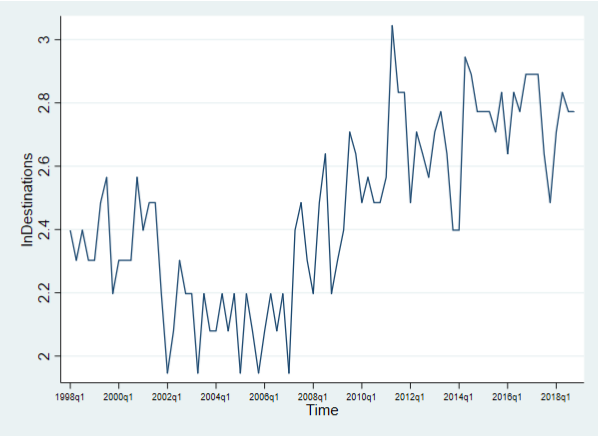

Figure 8.2: LnDestinations, MAD, quarterly

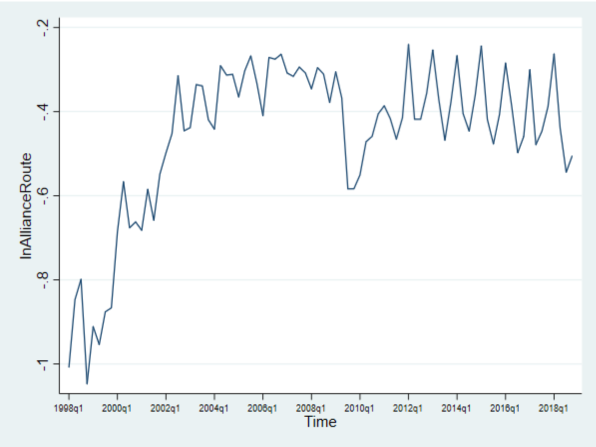

Figure 8.3: LnAllianceRoute, MAD-JFK, quarterly

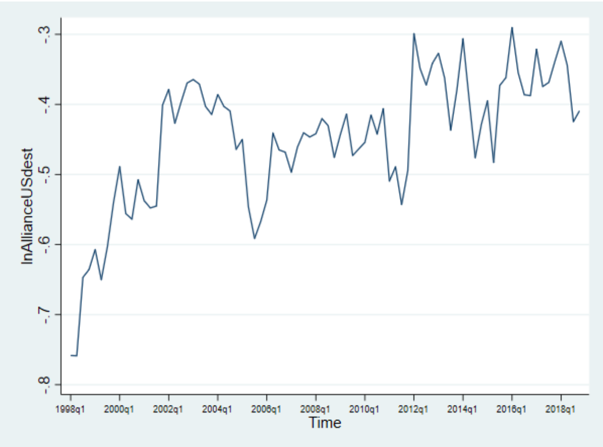

Figure 8.4: LnAllianceUSdest, MAD, quarterly

The time series graph for lnPassengers indicates that there is an upward trend in passenger traffic. The graph for lnDestinations shows that the number of destinations from MAD increased quite rapidly from around the time of the implementation of the OSA. We observe that the market share of the dominant alliance grew rapidly in the beginning of the 2000's. After this however, it appears to be relatively stable.

When we interpret the formal tests, we once again start with the KPSS test for trend stationarity. Below we have summarized the KPSS test results.

10% critical value: 0.119 5% critical value: 0.146 1% critical value: 0.216	**Test statistic at lag order**			
Variable	**0**	**1**	**2**	**3**

LnPassengers	0.177**	0.142*	0.164**	0.168**
LnDestinations	0.701***	0.445***	0.347***	0.291***
LnAllianceRoute	1.210***	0.682***	0.494***	0.390***
LnAllianceUSdest	0.345***	0.207**	0.160**	0.135*
LnGDP	1.190***	0.606***	0.414***	0319***

Variable	**lnPassengers**	**lnDestinations**	**lnAllianceRoute**	**lnAllianceUSdest**	**lnGDP**
Result	Reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0

Table 8.1 KPSS test MAD-JFK. 1%*** significance level, 5%** significance level, 10%* significance

Table 8.1 shows that we can reject the null hypothesis that the variable is trend stationary for all of the variables and at every lag order at the 5% level, except lnPassengers at lag order 1. Because we have evidence that most of the variables are not trend stationary, we once again include a trend in the ADF test. The results of the ADF tests are summarized in the following table:

ADF level, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
LnPassengers	-3.000	0.1320
LnDestinations	-2.067	0.5643
LnAllianceRoute	-2.293	0.4377
LnAllianceUSdest	-3.167	0.0911
LnGDP	-2.482	0.3372
ADF first differences, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
D.lnPassengers	-4.147	0.0054
D.lnDestinations	-7.156	0.0000
D.lnAllianceRoute	-4.572	0.0011
D.lnAllianceUSdest	-5.047	0.0002
D.lnGDP	-3.740	0.0199

Table 8.2: ADF test MAD – JFK

The results in table 8.2 are similar to those of the CDG – JFK route segment. We cannot significantly reject the null hypothesis that there exists a unit root for any of the variables. When we fail to reject the null hypothesis, it gives support to the alternative hypothesis of a unit root. Next, we must determine what order of integration each variable is. Based on the

ADF test of the first differenced variables, we can conclude on the following order of integration for the variables:

Variable	lnPassengers	lnDestinations	lnAllianceRoute	lnAllianceUSdest	lnGDP
Result	I(1)	I(1)	I(1)	I(1)	I(1)

Table 8.3: Order of integration MAD – JFK

We see that the results from the tests are very similar to those from the CDG – JFK route segment. When we perform the ADF test with the first difference, we can reject the null hypothesis of a unit root.

8.1.3 LHR-BOS stationarity assessment

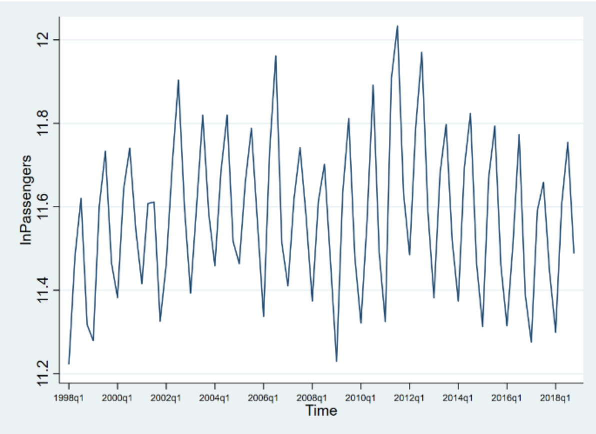

Figure 9.1: LnPassengers, LHR-BOS, quarterly

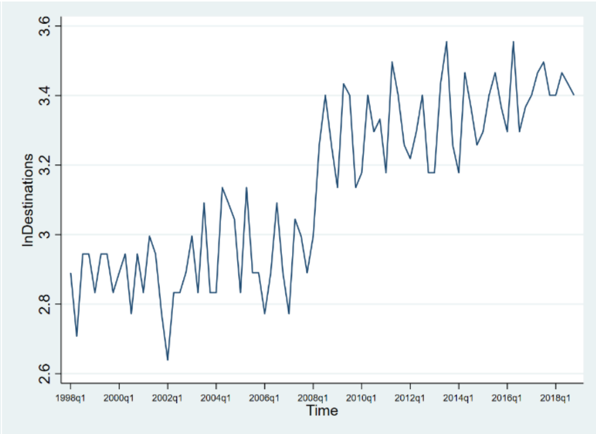

Figure 9.2: LnDestinations, LHR, quarterly

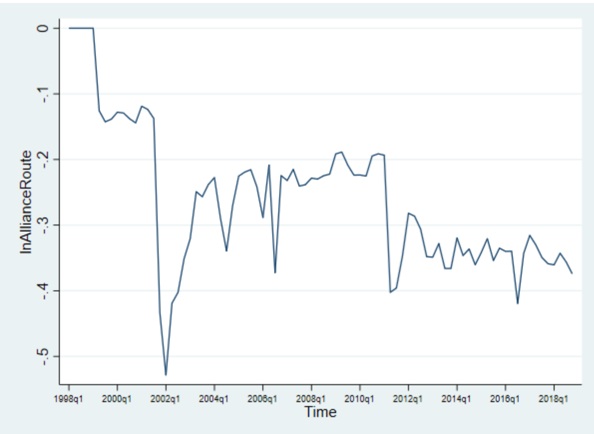

Figure 9.3: LnAllianceRoute, LHR-BOS, quarterly

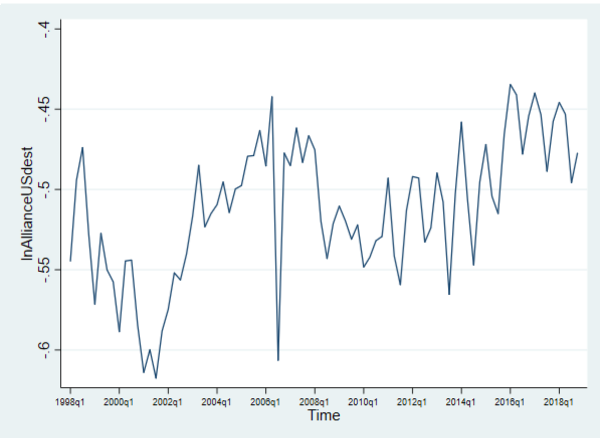

Figure 9.4: LnAllianceUSdest, LHR, quarterly

The graph for lnPassenger does not show signs of a trend. Like for the other routes however, there appears to be seasonal fluctuations, which can cause it to be non-stationary. For lnDestinations, there appears almost to be a structural break around the time of the OSA entering into force. There appears to have been a rapid increase in the number of destinations offered from LHR, further followed by a positive trend. For lnAllianceRoute we observer that the market share of the dominant alliance appears to have decreased during the period. Although it has decreased, there is no obvious negative trend in lnAllianceRoute. For lnAllianceUSdest we observe fluctuating levels, which does not appear to follow a specific trend.

The following table summarizes the results of the KPSS tests:

10% critical value: 0.119 5% critical value: 0.146 1% critical value: 0.216	**Test statistic at lag order**			
Variable	**0**	**1**	**2**	**3**
LnPassengers	0.127*	0.113	0.177**	0.226***
LnDestinations	0.219***	0.174**	0.161**	0.142*
LnAllianceRoute	0.361***	0.207**	0.155**	0.130*
LnAllianceUSdest	0.255***	0.171**	0.138*	0.117*
LnGDP	1.190***	0.606***	0.414***	0319***

Variable	**lnPassengers**	**lnDestinations**	**lnAllianceRoute**	**lnAllianceUSdest**	**lnGDP**
Result	Do not reject H_0	Reject H_0	Reject H_0	Reject H_0	Reject H_0

Table 9.1 KPSS test LHR-BOS. 1%*** significance level, 5%** significance level, 10%* significance

Table 9.1 shows we cannot reject the null hypothesis of trend stationarity for lnPassengers at lag order 0 and 1. For lnAllianceUSdest we observe that we can only reject the null hypotheses at the 10% level at lag order 2 and 3. This is also the case for lnDestinations and lnAllianceRoute at lag order 3. For all other, we can reject the null hypothesis at the 5% level. Rejecting the null hypothesis gives evidence of non-stationarity. Although this is the case for most of the variables, the results are somewhat less clear than in the previous two route segments. Next, we move to the ADF test to see if this provides clearer evidence. The test results are summarized in the following table:

ADF level, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
LnPassengers	-2.869	0.1729
LnDestinations	-2.359	0.4019
LnAllianceRoute	-3.701	0.0223
LnAllianceUSdest	-2.495	0.3305
LnGDP	-2.482	0.3372

ADF first differences, with trend. Lags selected according to selection criterions		
Variable	**Test statistic**	**P-value**
D.lnPassengers	-6.589	0.0000
D.lnDestinations	-6.907	0.0000
D.lnAllianceRoute	-9.427	0.0000
D.lnAllianceUSdest	-5.455	0.0000
D.lnGDP	-3.740	0.0199

Table 9.2: ADF test LHR-BOS

From Table 9.2, we observe that we can reject the null hypothesis of a unit root for lnAllianceRoute. This is the only variable in the analysis where this is the case. From figure 9.3 we observe that the values are decreasing over time. This is the only plot where we observe this development. Recall that the rationale behind including a trend term in the ADF test is that the majority of the series show evidence of a positive trend. Since lnAllianceRoute for LHR does not have a positive trend, we rerun the ADF test without a trend term and constant. When we exclude this, it indicates that the series is a random walk without a drift under the null hypothesis. We can no longer reject the null hypothesis of a unit root with this version of the test. Thus, we have evidence that the variable is non-stationary. We still have evidence that the first difference is stationary. Thus, we have evidence that lnAllianceRoute is also I(1). For the other variables, we have significant evidence of non-stationarity at levels and stationarity at first differences when a trend is included. We can summarize the order of integration of each variable below:

Variable	**lnPassengers**	**lnDestinations**	**lnAllianceRoute**	**lnAllianceUSdest**	**lnGDP**
Result	I(1)	I(1)	I(1)	I(1)	I(1)

Table 9.3: Order of integration LHR-BOS

8.2 Johansen test for cointegration

Now that we have evidence of non-stationary variables that are integrated of order one, we proceed with the Johansen test for cointegration. We perform the test for each model at every route segment.

8.2.1 CDG-JFK Johansen test

Hypotheses		**Model (1), $p = 5$**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.2508	43.4727	42.44	22.8141	25.54
$r \leq 1$	$r = 2$	0.1995	20.6586*	25.32	17.5641	18.96
$r \leq 2$	$r = 3$	0.0384	3.0945	12.25	3.0945	12.52

Table 10.1: Johansen test for cointegration in model(1), CDG-JFK

From table 10.1, we observe that the test statistic λ_{trace} exceeds the critical value, while λ_{max} test statistic is lower than the critical value. Based upon our explanation in the methodology section, we can reject the null hypotheses of $r = 0$ since the test statistic λ_{trace} exceed the critical value. However, we fail to reject the null hypothesis $r \leq 1$ because neither of the test statistics exceed their respective critical value. As the Johansen test method accepts the first r for which the null hypothesis cannot be rejected, we accept that r=1(StataCorp, 2019, p. 852). This indicates that the variables are cointegrated and that there exists a long-run relationship between them.

Hypotheses		**Model (2), $p = 1$**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.51119	72.2188	29.68	59.4106	20.97
$r \leq 1$	$r = 2$	0.13630	12.8082*	15.41	12.1619	14.07
$r \leq 2$	$r = 3$	0.00776	0.6430	3.76	0.6463	3.76

Table 10.2: Johansen test for cointegration in model(2), CDG-JFK

From table 10.2, we observe the same result as the previous table. For both the test statistic λ_{trace} and λ_{max} we can reject the null hypothesis $r = 0$. We fail to reject the null hypothesis $r \leq 1$ since neither of the test statistics exceed their respective critical value. As previously, we accept that r=1. We achieve the result of cointegrated variables, that there exists a long-run relationship between the variables in model (2).

8.2.2 MAD-JFK Johansen test

Hypotheses		**Model (1), p =5**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.3077	47.2731	42.44	29.0466	25.54
$r \leq 1$	$r = 2$	0.1196	18.2265*	25.32	10.0595	18.96
$r \leq 2$	$r = 3$	0.0982	8.1671	12.25	8.1671	12.52

Table 11.1: Johansen test for cointegration in model(1), MAD-JFK

Based upon the same intuition and explanations above on the route CDG-FJK, we get λ_{trace} and λ_{max} with test statistics higher than their respective critical value. Hence, we can reject the null hypothesis $r = 0$, but cannot reject with $r \leq 1$. This indicates that the variables are cointegrated and there exist a long-run relationship between them in model (1) of MAD-JFK, observed from table 11.1 above.

Hypotheses		**Model (2), $p = 1$**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.3431	54.0436	29.68	34.9178	20.97
$r \leq 1$	$r = 2$	0.1906	19.1258	15.41	17.5480	14.07
$r \leq 2$	$r = 3$	0.0188	1.5778*	3.76	1.5778	3.76

Table 11.2: Johansen test for cointegration in model(2), MAD-JFK

Unlike the previous tables of cointegration relationship, table 11.2 in model (2) of MAD-JFK shows that we get can reject the null hypothesis for $r = 0$ and for $r \leq 1$. Furthermore, we fail to reject the null hypothesis of $r \leq 2$, since neither of the test statistics exceeds the critical value at this point. Hence, we have that the variables have 2 cointegration equations, indicating 2 long-run relationships between the variables in this model.

8.2.3 LHR-BOS Johansen test

Hypotheses		**Model (1), p =4**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.2782	48.1676	42.44	26.0823	25.54
$r \leq 1$	$r = 2$	0.1653	22.0854*	25.32	14.4551	18.96
$r \leq 2$	$r = 3$	0.0910	7.6303	12.25	7.6303	12.52

Table 12.1: Johansen test for cointegration in model(1), LHR-BOS

From table 12.1 we observe that we can reject the null hypothesis of $r = 0$, but we fail to reject the null with $r \leq 1$. This can be concluded since the test statistic λ_{trace} and λ_{max} exceeds the critical value when the null hypothesis is $r = 0$. This indicates a long-run relationship between the variables in model (1) of the route segment LHR-BOS.

Hypotheses		**Model (2), p =5**				
H_0	H_A	Eigenvalue	λ_{trace}	5% Critical value	λ_{max}	5% Critical value
$r = 0$	$r = 1$	0.4052	64.4239	29.68	41.0430	20.97
$r \leq 1$	$r = 2$	0.2556	23.3810	15.41	23.3132	14.07
$r \leq 2$	$r = 3$	0.0009	0.06770*	3.76	0.0677	3.76

Table 12.2: Johansen test for cointegration in model(2), LHR-BOS

As we observed in table 11.2 on the route segment MAD-JFK, we observe the same result and follow the same explanation in table 12.2 above. We reject the null hypothesis for $r = 0$ and for $r \leq 1$. We fail to reject the null hypothesis of $r \leq 2$. This indicates that we in model (2) of route segment LHR-BOS have 2 cointegration equations, indicating 2 long-run relationships between the variables.

8.3 VECM results

Now that we have evidence that there exists at least one cointegrating relationship between the variables, we can estimate the VEC model. We use the same number of lags as the underlying VAR model, which was also used in the Johansen test for cointegration.

8.3.1 CDG-JFK VECM results

Variables	Δ lnPassengers	P-values
$\Delta lnPassengers_{t-1}$	0.2517	0.204
$\Delta lnPassengers_{t-2}$	-0.1281	0.449
$\Delta lnPassengers_{t-3}$	-0.1648	0.192
$\Delta lnPassengers_{t-4}$	0.3916***	0.001
$\Delta lnAllianceRoute_{t-1}$	0.0947	0.741
$\Delta lnAllianceRoute_{t-2}$	0.2038	0.476
$\Delta lnAllianceRoute_{t-3}$	0.2115	0.460
$\Delta lnAllianceRoute_{t-4}$	0.2146	0.420
$\Delta lnGDP_{t-1}$	0.4579	0.844
$\Delta lnGDP_{t-2}$	0.8588	0.741
$\Delta lnGDP_{t-3}$	4.1347	0.111
$\Delta lnGDP_{t-4}$	-1.1268	0.642
OSA(dummy)	**-0.0077**	**0.765**
Error correction	-0.8702***	0.000
Intercept	0.0009	0.980
Cointegrating equation	**Coefficient**	**P-values**
$lnPassengers$	1	
$lnAllianceRoute$	-0.0073	0.983
$lnGDP$	-0.8385***	0.000
Intercept	-4.2135	

Table 13.1: VECM results for model (1), CDG-JFK. 1%*** significance level, 5%** significance level, 10%* significance

The first part of table 13.1 contains the estimates of the short-run parameters along with their respective p-value. The output of the calculations indicates that the dummy for the OSA has a non-significant negative impact on passenger traffic. This provides evidence that the OSA has not led to increased passenger traffic on this route segment. The error correction coefficient is the adjustment parameter for the model and explains the rate at which the model adjusts itself towards its long-run equilibrium. In table 13.1, we see that the error correction parameter is negative and significant at 1% level. It suggests that a deviation from the long-run equilibrium is rapidly corrected for at a speed of 87.02 %.

The second part of table 13.1 contains the estimates of the parameters in the cointegrating vector along with their p-values. To interpret the results of the long-run coefficients, we need to reverse the signs (Sanchez & Zavarce, 2012). The results indicate the following cointegrating equation:

$$lnPassengers - 0.0073lnAllianceRoute - 0.8385lnGDP - 4.2135$$

lnPassengers is then described as:

$$lnPassengers = 0.0073lnAllianceRoute + 0.8385lnGDP + 4.2135$$

Hence, the output shows that in the long-run there is a positive impact of the real GDP on the number of passengers carried in this route segment. The coefficient is statistically significant at the 1% level. The results also indicate that the market share of the dominant alliance on the CDG-JFK route segment has a non-significant impact on the passenger traffic in the long-run. Since we have a large p-value, it indicates that the passenger traffic level has a relatively low impact by the dominant market share of this route segment.

Next, we interpret the results of the VEC model for model(2) in the following table, following the same procedure as in model(1) in table 13.1.

Variables	Δ lnDestinations	P-values
OSA(dummy)	**0.1398*** **	**0.000**
Error correction	-0.9296***	0.000
Intercept	-0.0004	0.983
Cointegrating equation	**Coefficient**	**P-values**
$lnDestinations$	1	
$lnAllianceUSdest$	1.1750***	0.000
$lnGDP$	-0.3247**	0.021
Intercept	-0.2656	

Table 13.2: VECM results for model (2), CDG-JFK. 1%*** significance level, 5%** significance level, 10%* significance

The output of the first part of table 13.2 indicates that the coefficient for dummy variable for the OSA is positive and significant at the 1% level. Thus, the OSA has had a positive impact on the number of U.S. destinations offered from CDG. This differs from the result above where we found that the OSA did not have a significant impact on the passenger traffic between CDG-JFK. This is in line with Brueckner's theory (2001) since CDG-JFK is an interhub market. Since the OSA gives airlines the opportunity to operate between any two points in the U.S. and EU, we expect that new airlines want to operate different U.S. routes from CDG that are less competitive. Hence, the OSA will give an increase in the number of destinations offered, but not necessarily passenger traffic on interhub markets.

The adjustment parameter is negative and statistically significant at the 1% level. This indicates that a deviation from the equilibrium value is corrected for at a convergence speed of 92.96%. In the second part of table 13.2, we see that there is a negative relationship between the market share of the dominant alliance and the number of destinations offered. This is statistically significant at the 1% level. It is also a positive relationship between the real GDP and the number of destinations offered, which is significant at the 5% level. The positive relationship between the real GDP and the number of destinations is expected, because higher GDP gives the consumers higher disposable income, which results in higher demand for air travel, and hence demand for new destinations. The negative long-run relationship between the market share of the dominant alliance and the number of U.S. destinations offered from CDG may be because the new airlines do not want to operate from CDG to the U.S. if the dominant alliance serves much of this market. As Button (2009) mentions, the allied airlines may have easier and cheaper access to resources on CDG, advantages in slot times, etc. Then, non-allied carriers may find it unprofitable or undesirable to operate U.S. destinations from CDG.

8.3.2 MAD-JFK VECM results

Variables	Δ lnPassengers	P-values
$\Delta lnPassengers_{t-1}$	-0.3068**	0.028
$\Delta lnPassengers_{t-2}$	-0.4363***	0.001
$\Delta lnPassengers_{t-3}$	-0.4278***	0.000
$\Delta lnPassengers_{t-4}$	0.4413***	0.000
$\Delta lnAllianceRoute_{t-1}$	0.0879	0.704
$\Delta lnAllianceRoute_{t-2}$	-0.1210	0.593
$\Delta lnAllianceRoute_{t-3}$	0.0058	0.979
$\Delta lnAllianceRoute_{t-4}$	-0.0675	0.745
$\Delta lnGDP_{t-1}$	4.8953	0.141
$\Delta lnGDP_{t-2}$	-1.0661	0.762
$\Delta lnGDP_{t-3}$	2.5917	0.462
$\Delta lnGDP_{t-4}$	-6.9101**	0.034
OSA(dummy)	**0.1215**	**0.1115**
Error correction	-0.2171	0.075*
Intercept	0.0016	0.977
Cointegrating equation	**Coefficient**	**P-values**
$lnPassengers$	1	
$lnAllianceRoute$	0.6591**	0.022
$lnGDP$	-5.8467***	0.000
Trend	0.0435	0.000
Intercept	41.1289	

Table 14.1: VECM results for model (1), MAD-JFK. 1%*** significance level, 5%** significance level, 10%* significance

As in the other output tables from 8.3.1, table 14.1 represents the short-run and the long-run estimates we got from constructing the VECM. The first part indicates that the coefficient for the dummy variable for the OSA is positive, but non-significant. To explain this, we revisit the paper of Pitfield (2007) where he explained that the growth of passengers had more to do with ceteris paribus effect[7]. This result indicates that there is no short-run effect of the OSA on passenger traffic on MAD-JFK in our time period and follows the same explanation as presented from Brueckner (2001) in previous table. The adjustment parameter is negative and statistically significant at 7,5% level. This indicates that a deviation from the equilibrium value is corrected for at a convergence speed of 21.71%.

The second part of table 14.1 contains the estimates of the parameters in the cointegrated vector along with their p-values. We follow the same interpretation as we did in table 13,1, reversing the signs to evaluate the impact of our variables on passenger traffic. The long-run output indicates that there is a positive impact of the real GDP on the number of passengers at this route segment as well. The coefficient is statistically significant at the 1% level. The result also indicates that the market share of the dominant alliance has a negative and significant impact on passenger traffic at 5% significance level[8].

Variables	Δ lnDestinations	P-values
OSA(dummy)	**0.2748*** **	**0.000**
Error correction 1	-0.5469***	0.000
Error correction 2	-0.1116	0.659
Intercept	-0.0001	0.997
Cointegrating equation 1	**Coefficient**	**P-values**
$lnDestinations$	1	
$lnGDP$	0.1299	0.625
Intercept	-0.3800	
Cointegrating equation 2	**Coefficient**	**P-values**
$lnAllianceUSdest$	1	
$lnGDP$	-0.2553*	0.086
Intercept	2.7585	

Table 14.2: VECM results for model (2), MAD-JFK. 1%*** significance level, 5%** significance level, 10%* significance

In the first part of table 14.2 we see that the coefficient for the dummy variable representing the OSA is positive and statistically significant at the 1% level. This indicates that the OSA has had a positive impact on the number of U.S. destinations offered from MAD, which is the same result that got from CDG. Since this model has two cointegrating relationships, we also have two adjustment parameters. The first one is negative and statistically significant at the 1% level. The second is also negative, but not statistically significant.

[7] Recall Pitfield (2007) from literature review, where he explains that there are many other influences on traffic volumes. Pitfield conjectures that the OSA will not result in a significant growth in traffic or increased competition.

[8] Follows the intuition described in section 6.2, where this independent variable would be expected to have a negative impact on passenger traffic based on Brueckner (2001).

From the second part of table 14.2, we get the following cointegrating equations:

$$lnDestinations = -0.1299 lnGDP + 0.38$$

$$lnAllianceUSdest = 0.2553 lnGDP - 2.7585$$

However, since the second adjustment parameter is non-significant, the second cointegration equation is not assumed to have a long-term causality (StataCorp, 2019, pp. 854-856). The first cointegration equation on the other hand is assumed to have a long-term causality since the first adjustment parameter is significant. We see that the real GDP does not significantly contribute to the explanation of the number of destinations offered from CDG in this case. The result is surprising because as we see in figure 4.4, the number of U.S. destinations offered from MAD has increased significantly, while the real GDP has also increased as seen in figure 6. However, the increase in destinations happened rather suddenly after the OSA. During the same period, the real GDP was decreasing because of the global financial crisis.

8.3.3 LHR-BOS VECM results

Variables	Δ lnPassengers	P-values
$\Delta lnPassengers_{t-1}$	-0.3181***	0.006
$\Delta lnPassengers_{t-2}$	-0.8456***	0.000
$\Delta lnPassengers_{t-3}$	-0.4388***	0.000
$\Delta lnAllianceRoute_{t-1}$	0.0672	0.676
$\Delta lnAllianceRoute_{t-2}$	-0.5240***	0.001
$\Delta lnAllianceRoute_{t-3}$	-0.4152**	0.012
$\Delta lnGDP_{t-1}$	2.4343	0.196
$\Delta lnGDP_{t-2}$	-2.3747	0.250
$\Delta lnGDP_{t-3}$	2.7798	0.152
OSA(dummy)	**0.0256**	**0.267**
Error correction	-0.1986***	0.008
Intercept	-0.0134	0.616
Cointegrating equation	**Coefficient**	**P-values**
$lnPassengers$	1	
$lnAllianceRoute$	-0.7838	0.128
$lnGDP$	0.2105	0.623
Intercept	-13.5890	

Table 15.1: VECM results for model (1), LHR-BOS. 1%*** significance level, 5%** significance level, 10%* significance

The output of the first part of table 15.1 indicates that the coefficient for the OSA is positive and non-significant. The interpretation of this result follows the same explanation as in table 13.1 and 14.1. We observe that there is no short-term effect of the OSA on passenger traffic on the route segment LHR-BOS in the time period considered. In the short-run, only its own lagged values and the alliance market share at lags 2 and 3, appear to significantly impact passenger traffic. The adjustment parameter is negative and statistically significant at 1%

level. Furthermore, this indicates that a deviation from the equilibrium value is corrected for at a convergence speed of 19,86% according to table 15.1.

The second part of the table follows the same interpretation as we did in the previous tables from the VECM results of 8.3. The long-run output indicates that there is a negative impact of real GDP on passenger traffic, meaning that number of passengers decreases when the real GDP increases in this route segment. This is the opposite result of the other two route segments described, however, it is non-significant. This means that we cannot say with certainty that an increase in real GDP will negatively influence the number of passengers travelled on this route. The reason why we observe a contradictory result compared to the other routes, may be described by the description of our data. In figure 5.1 we observed that passenger traffic actually had a decreasing trend from around 2011 until 2018, while GDP increased in this period. This development of passenger traffic may be due to the different constraints and competitive environment around LHR, as described in section 5.2.3.1.

The output also indicates a long-run positive impact of the dominant alliance market share in this route which is non-significant. We observe in our time period that the dominant alliance share has decreased in figure 5.2, while passenger traffic also decreased. This makes our model indicate that there is a positive impact. The reason may instead be due to the competitional constraints from other airports described in section 5.2.3.1.

Variables	**Δ lnDestinations**	**P-values**
$\Delta lnDestinations_{t-1}$	-0.1591	0.358
$\Delta lnDestinations_{t-2}$	-0.3569**	0.030
$\Delta lnDestinations_{t-3}$	-0.2726*	0.057
$\Delta lnDestinations_{t-4}$	-0.1423	0.199
$\Delta lnAllianceUSdest_{t-1}$	-0.1591	0.358
$\Delta lnAllianceUSdest_{t-2}$	-0.3569**	0.030
$\Delta lnAllianceUSdest_{t-3}$	-0.5411	0.256
$\Delta lnAllianceUSdest_{t-4}$	-0.2190	0.600
$\Delta lnGDP_{t-1}$	-3.4847	0.179
$\Delta lnGDP_{t-2}$	2.1912	0.403
$\Delta lnGDP_{t-3}$	-2.0703	0.431
$\Delta lnGDP_{t-4}$	5.1540**	0.028
OSA(dummy)	**0.3761*** **	**0.000**
Error correction 1	-0.8313***	0.000
Error correction 2	1.4333***	0.007
Intercept	0.0003	0.993
Cointegrating equation 1	**Coefficient**	**P-values**
$lnDestinations$	1	
$lnGDP$	-0.3415***	0.003
Intercept	0.1581	

Cointegrating equation 2	Coefficient	P-values
$lnAllianceUSdest$	1	
$lnGDP$	-0.2954***	0.000
Intercept	3.1718	

Table 15.2: VECM results for model (2), LHR-BOS. 1%*** significance level, 5%** significance level, 10%* significance

The first part of table 15.2 indicates that the coefficient for the dummy variable representing the OSA is positive and statistically significant at the 1% level. Thus, there is significant evidence that the OSA has had a positive impact on the number of U.S. destinations offered from LHR. This is the same result that we got from CDG and MAD. What is different from the two previous airports, is that the number of U.S. destinations from LHR has increased despite having competing airports in relatively close proximity. The increase in U.S. destinations can be seen in figure 5.4 and happens suddenly after the OSA. Although LHR has close competitors, it still has the advantage of their closeness to the city of London and the fact that it is the largest in terms of passengers. Thus, it is still an attractive airport for airlines to serve. Since the OSA allows for new airlines to operate between this popular airport and any point in the U.S., the number of U.S. destinations increase.

The first part of the table also shows that both adjustment parameters are statistically significant at the 1% level. The first adjustment parameter is negative and the second is positive. Because only the first adjustment parameter is both negative and statistically significant, only the first cointegrating equation is assumed to have a long-run causality. From this we see that the coefficient for real GDP is positive and statistically significant at the 1% level. Thus, the long-run model suggests that there is a positive relationship between the real GDP and the number of U.S. destinations offered from LHR. This is expected based on the macroeconomic theory explained in 8.3.1.

8.4 Model diagnostics

Now that we have estimated the VEC models, we perform diagnostic tests to assess the validity of each model. We perform the Lagrange-multiplier test to test for residual autocorrelation and the Jarque Bera test to test for normality in residuals. To perform estimation and inference in the VECM, it is necessary that there is no autocorrelation in the residuals. Although one can derive many of the asymptotic properties without the assumption of normally distributed residuals because parameter estimates may still be consistent, the assumption is still often tested (StataCorp, 2019, pp. 858-860).

CDG - JFK Lagrange-multiplier test				
	Model 1		Model 2	
Lag	Chi-square	P-value	Chi-square	P-value
1	7.9599	0.538	14.2062	0.115
2	14.2188	0.115	15.3336	0.082
Jarque Bera test for normality				
Variable	Model 1		Model 2	
	Chi-square	P-value	Chi-square	P-value
lnPassengers	1.987	0.370	—	—
lnAllianceRoute	0.597	0.742	—	—
lnDestinations	—	—	1.641	0.440
lnAllianceUSdest	—	—	32.132	0.000
lnGDP	137.405	0.0000	75.427	0.000

Table 16.1: Model diagnostics, CDG-JFK

The first part of the table contains the chi-square statistics from the LM test along with their corresponding p-values. The null hypothesis of the test is that no autocorrelation is present at lag order. For both models and for both lag orders, we fail to reject this null hypothesis. Therefore, we have evidence that both models are free of the problem of residual autocorrelation. The second part of the table contains the chi-square statistics with their p-values from the Jarque Bera test. The null hypothesis is that the residuals of the variables are normally distributed. For model 1, we see that the only variable that carries the problem of normality is lnGDP. For lnPassengers and lnAllianceRoute, we fail to reject the null hypothesis of normally distributed residuals. In model 2, lnDestinations is the only variable for which we fail to reject the null hypothesis. Thus, both lnAllianceUSdest and lnGDP appear to carry the problem of normality.

MAD – JFK Lagrange-multiplier test				
	Model 1		Model 2	
Lag	Chi-square	P-value	Chi-square	P-value
1	4.0172	0.910	15.6238	0.075
2	8.1540	0.519	11.8746	0.220
Jarque Bera test for normality				
	Model 1		Model 2	
Variable	Chi-square	P-value	Chi-square	P-value
lnPassengers	31.778	0.000	—	—
lnAllianceRoute	0.728	0.695	—	—
lnDestinations	—	—	0.520	0.771
lnAllianceUSdest	—	—	0.346	0.841
lnGDP	66.735	0.000	21.952	0.000

Table 16.2: Model diagnostics, MAD-JFK

Following the same procedure as in table 16.1, we observe from table 16.2 that there appears to be no problem of residual autocorrelation. Based on the Jarque Bera test for model 1, we observe that lnPassengers and lnGDP have a normality problem. Thus, we reject the null hypothesis. In model 2, the only variable that appears to have a normality problem is lnGDP. This is the only variable where we can reject the null hypothesis.

LHR – BOS **Lagrange-multiplier test**				
	Model 1		Model 2	
Lag	Chi-square	P-value	Chi-square	P-value
1	5.1709	0.819	8.7557	0.460
2	8.1855	0.516	7.8067	0.554
Jarque Bera test for normality				
	Model 1		Model 2	
Variable	Chi-square	P-value	Chi-square	P-value
lnPassengers	15.239	0.001	—	—
lnAllianceRoute	244.184	0.000	—	—
lnDestinations	—	—	1.683	0.431
lnAllianceUSdest	—	—	21.316	0.000
lnGDP	64.548	0.000	6.131	0.047

Table 16.3: Model diagnostics, LHR-BOS

There appears to be no problem of autocorrelation for either of the models on this route. From the Jarque Bera test, we reject the null hypothesis of normality for all variables in model 1, indicating that this model has a normality problem. In model 2, we fail to reject the null hypothesis for lnDestinations at the 5% level, and lnGDP at the 1% level. However, there is significant evidence of a normality problem for the variable lnAllianceUSdest.

Based on these diagnostic tests, we observe normality problems in some variables. These are further pointed out and considered in our discussion below.

9 Discussion

9.1 Discussion

We have used time series analysis to investigate the impact of the OSA on both passenger traffic and the number of U.S. destinations offered. The choice of the route segments for the analysis of passenger traffic is based on Brueckner's (2001) result, that airline alliances are likely to bring negative competitive effects in interhub markets (Brueckner, 2001, pp. 1476-1478). The route segments CDG-JFK, MAD-JFK, and LHR-BOS are all interhub markets, where the origin airport serves as a hub for one of the alliance members, and the destination airport serves as a hub for the other alliance member. By using this kind of market, we examine whether the agreement is influential enough to bring procompetitive effects even in markets where alliances have significant market power. Since we investigate three markets, our conclusions are more valid and reliable than focusing on a single route. It helps preventing the conclusion from being drawn by coincidence. To investigate the effect of the OSA on the number of destinations, we have used the number of U.S. destinations offered from the three EU airports CDG, MAD, and LHR. These are airports where traditionally the national flag carrier offered a large share of the transatlantic flights. We wanted to investigate whether entrance of new airlines after the OSA have increased the competition in the form of more destinations after the introduction of the OSA.

According to the European Commission, the aim of the OSA was to introduce more competition in the transatlantic market (European Union, 2016). We have used passenger traffic and the number of U.S. destinations to measure the procompetitive effects. Our analyses show that the OSA does not appear to have a significant effect on the passenger traffic in the three route segments considered. This is in line with Brueckner's (2001) theory that these markets can bring anticompetitive effects since airline alliances have a relatively high market share and, in our case, enjoy antitrust immunity. Thus, it appears that it is challenging for the OSA to have a significant positive effect on passenger traffic in these interhub markets. For the number of U.S. destinations offered from CDG, MAD, and LHR our analyses show that the OSA has had a significant positive effect. Thus, it appears that although the passenger traffic on interhub routes have not significantly increased as an effect of the OSA, there has been a procompetitive effect in the form of increased number of U.S. destinations offered. This supports our intuition that the OSA have opened for new carriers to enter the transatlantic market. Hence, number of destinations have increased. Based on economic theory of competition, entering a market such as an interhub market may not be attractive since the alliance members have high market power and may even enjoy antitrust immunity. This means that competition will be fierce for the new entrant or they may be deterred from entering all together. Thus, for the new entrants, operating routes that are less concentrated may be more preferable. The OSA allows the new carriers to operate such routes, as it allows EU airlines to operate between any two points between the EU and U.S.

Based upon self-intuition and Pitfield (2011), we expected the real GDP to have a positive relationship between passenger traffic and destinations. Our results indicate that the real GDP did have a significant positive relationship on both passenger traffic and U.S. destinations in our markets, except on passenger traffic between LHR and BOS. The reason why we observe this contradicting result on the last route segment, is that passenger traffic did not increase significantly after the implementation of the OSA. This follows the overview presented in table 4 and what we discussed under our results of table 15.1, in terms of increased number of destinations offered, in the empirical analysis. By having a higher real GDP and hence more disposable income, people would be more willing to travel, causing higher demand for passenger tickets and increasing number of destinations offered.

Morandi et al. (2014), found that the OSA had a negative impact on the number of EU – U.S. connections. This is in great contrast to our results. For all EU hubs considered in the analysis, we find that the OSA had a significant positive impact on the number of U.S. destinations offered. Morandi et al. explain that this could be due to the lack of new entry (Morandi et al., 2014, p. 326). Recall that they study a time period that is largely affected by the global financial crisis. Hence, expanding their route network was likely undesirable for airlines during this downturn in the economy due to less demand. In fact, our descriptive presentation of the data shows that the market share of the dominant alliance at CDG-JFK and LHR-BOS does not decrease until after 2010. This suggests that a response to the OSA was delayed, possibly due to the recession.

Throughout this thesis, we have viewed increased competition in the form of more destinations and passenger traffic as positive. This is based on the economic theory of efficiency presented in the theory section of the thesis, and the fact that the aim of the OSA was to impose more competition on the transatlantic market. From the theoretical economic perspective, we know that more competition may provide consumers with more options due to increased quantity, which again may result in lower prices and higher consumer welfare. In recent years however, a contradictory view has developed. Concerns have been raised regarding the environmental impact of the increasing aviation activity. This means that our thesis faces an ethical dilemma where there is a tradeoff between consumer welfare and environmental concerns. Although our thesis is an economic research which is theoretical by nature, it is important to address this conflict as it illustrates that the OSA does not only bring economic benefits but may also cause negative externalities.

9.2 Limitations

Throughout this thesis, we have faced problems and limitations to our model selection that deserves to be mentioned. We will mention the most predominant weaknesses and limitations in terms of our model selection.

The data available from the T-100 database contained the number of passengers for each airline on a given route and the destinations served by each airline from a given airport. Thus, the analysis required us to manually count the number destinations and calculate the market shares and HHI. We also had to calculate the average GDP between the EU and U.S., which included converting euros into dollars using purchasing power parity. This work is not only time consuming, but manual calculations will always be a potential source of error.

Through our work with the empirical analysis, we observed that the significance and model adequacy vary across different lag lengths and trend terms. Suggested lags varied across our route segments and models, and we decided to choose the number of lags that was necessary to make our model robust. These decisions were however based on the selection criterions described in the methodology. We mainly base our choice of whether to include a trend term or not on the KPSS test together with the model diagnostic tests. For most cases, we found no evidence of a deterministic trend in the KPSS tests. Thus, we did not include a trend term in the model. This also resulted in the best results with respect to the assumption of autocorrelation. The exception was model 1 in the MAD-JFK route segment, where we got an autocorrelation problem. The problem was corrected for by including a trend term. However, this indicates that the model adequacy may be dependent on the choice of lag length and the interpretation of the trend.

As discussed in our VECM results, the Jarque Bera test suggests that we face normality problems in some of the variables. This may indicate model deficiencies, such as structural breaks. It is normal that this test may indicate non-normality with small data samples and suggests a limitation of our model selection. Although it is a limitation, non-normality will not have implications on the validity of the VECM as the diagnostic test for autocorrelation is far more important in this model. Furthermore, in appendix B, we see that the normality plots of the residuals from each model suggests no large deviations from the normality assumption.

As mentioned, structural breaks and shocks may be a reason for the non-normality we observe. The airline market is prone to suffer from shocks like the attacks of 9/11, the global financial crisis, and most recently, the covid-19 pandemic. Our model may fail to single out the effect of these kind of shocks. Thus, for further research it would be interesting to examine how these shocks have impacted the passenger traffic and the number of destinations offered, and whether they affect the procompetitive effects of the OSA.

By using the same approach as our thesis, it would also be interesting to analyze the same effects on other route segments, and possibly compare interhub and non-interhub route segments. This to see whether the OSA has affected the two market types differently or not.

10 Conclusion

The aim of this thesis was to analyze the effects of the OSA on passenger traffic and the number of U.S. destinations offered. We can now answer the following research question that we previously defined:

What are the effects of the EU-U.S. Open Skies Agreement on passenger traffic and the number of U.S. destinations offered in the transatlantic market?

Our research shows that the OSA has had no significant impact on the passenger traffic on three interhub routes. This indicates that the OSA did not result in a significant growth in passenger traffic in terms of number of passengers. This also follows Pitfield's (2011) findings. He found that any change in passenger traffic had more to with the "ceteris paribus" effect. This thesis also shows that there is a significant long-run relationship between the real GDP and passenger traffic for two of the three route segments considered. Thus, we can draw a similar conclusion as Pitfield (2011), that the growth in passenger traffic has more to do with the overall economic conditions. Since passenger traffic did not increase in these interhub markets, it also supports Brueckner's (2001) concerns regarding collusive agreements. Although the market share of the dominant alliances has decreased with time, the impact of the OSA has still been limited on these interhub markets. Based on these findings and the above discussion of this thesis, a potential drawback of the OSA may be that it provides possibilities for antitrust immunity for alliance members, while aiming to impose increased competition in the transatlantic market.

Our findings show that the OSA did have a significant and positive impact on the number of U.S. destinations offered from CDG, MAD and LHR. This is contradictory to the results of Morandi et al. (2014). They identified the lack of entry by new airlines as the main reason for their result. However, we consider a larger timespan after the implementation of the OSA. Our data suggests that the response to the OSA was not immediate, possibly due to the financial crisis. Although the OSA did not have a significant effect on passenger traffic in the interhub markets we considered, we can conclude that it has brought procompetitive effects in terms of more U.S. destinations offered from CDG, MAD, and LHR.

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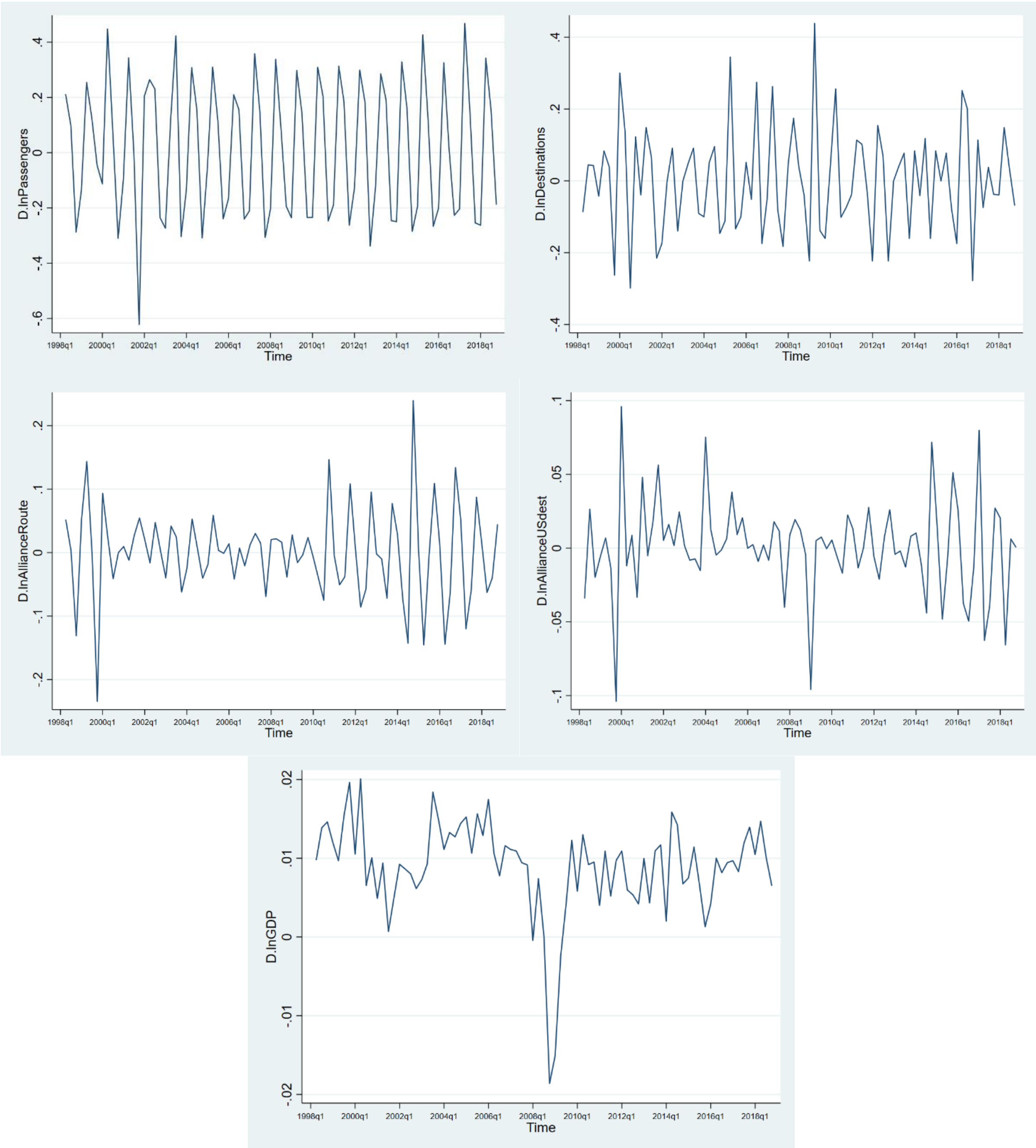
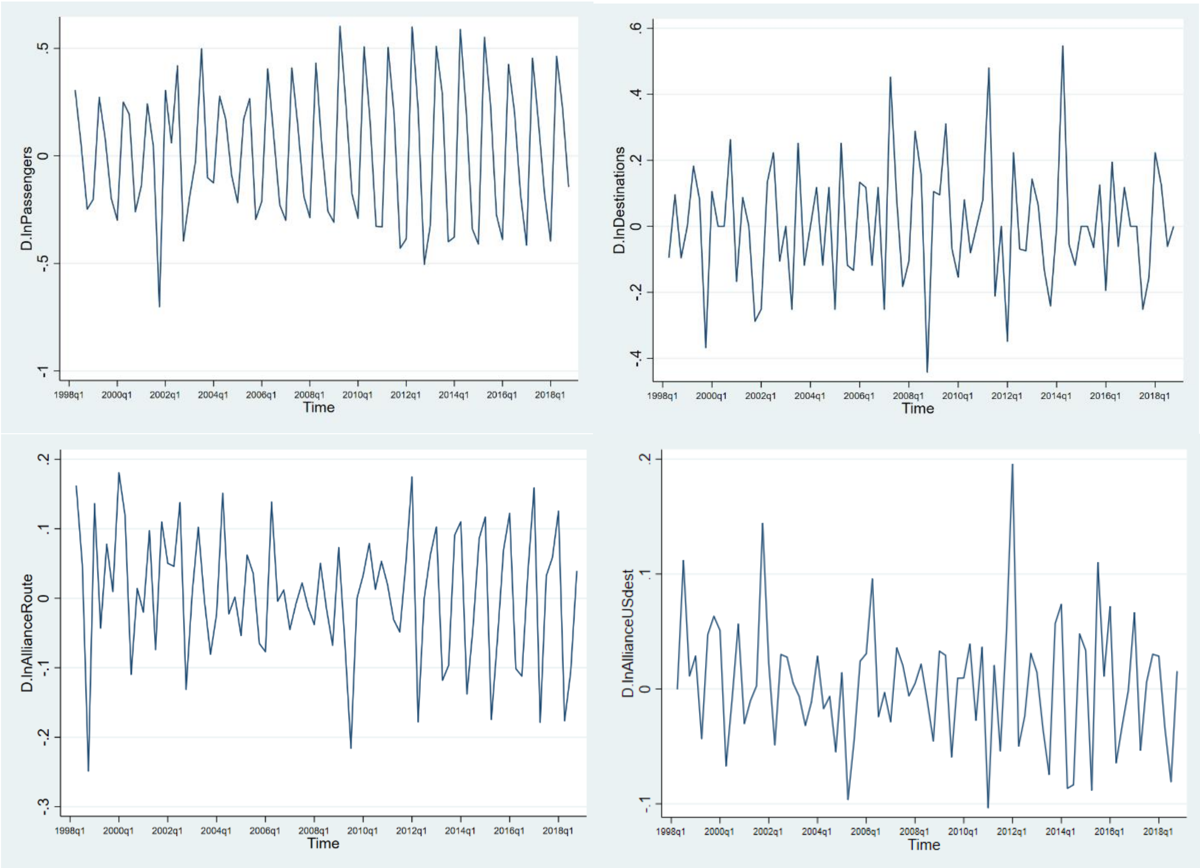
Appendices

Appendix A: First-differenced time series plots

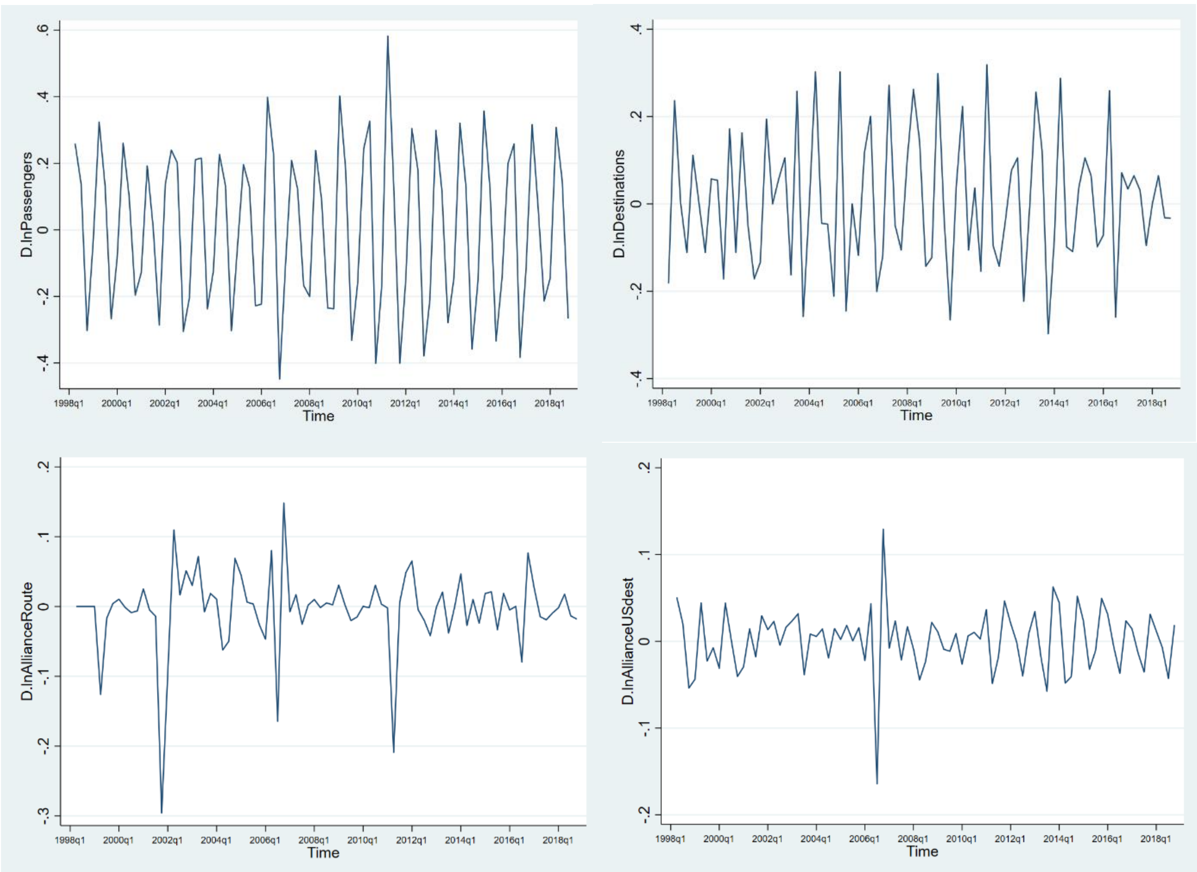
CDG-JFK



MAD-JFK

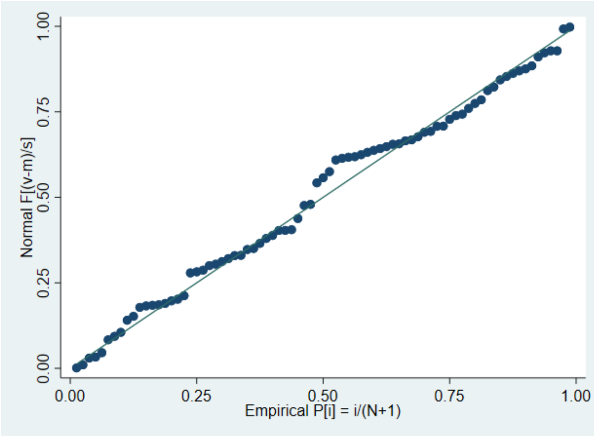


LHR-BOS

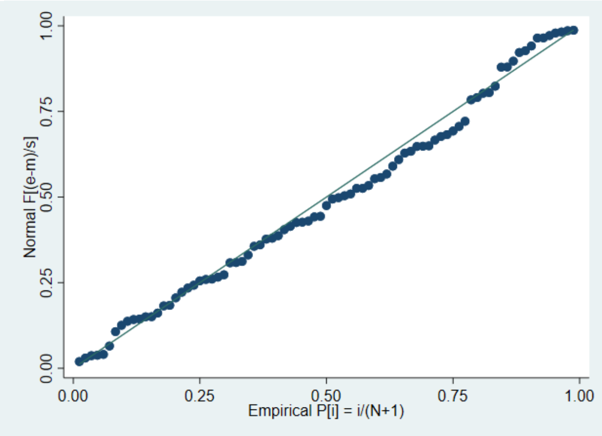


Appendix B: Normality plots

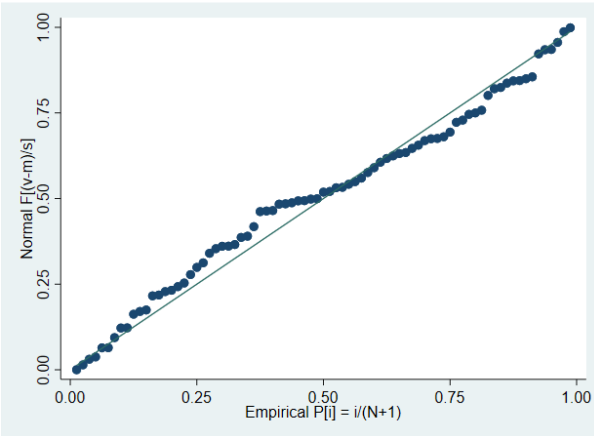
CDG-JFK, model (1):



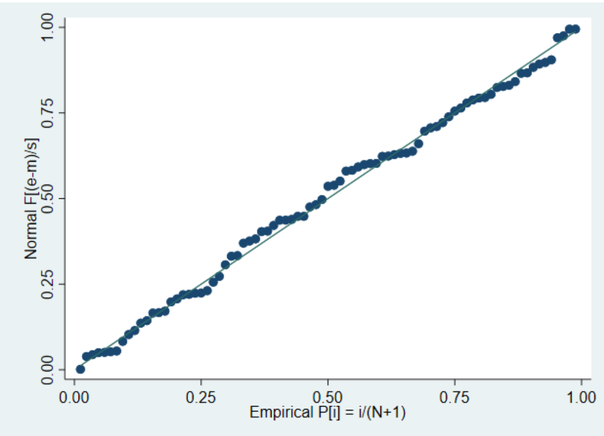
CDG model (2):



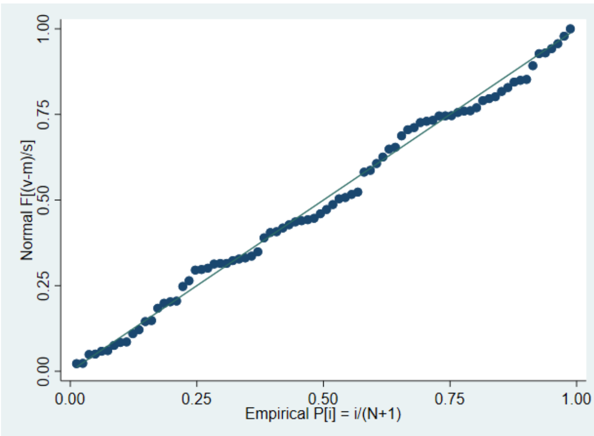
MAD-JFK, model (1):



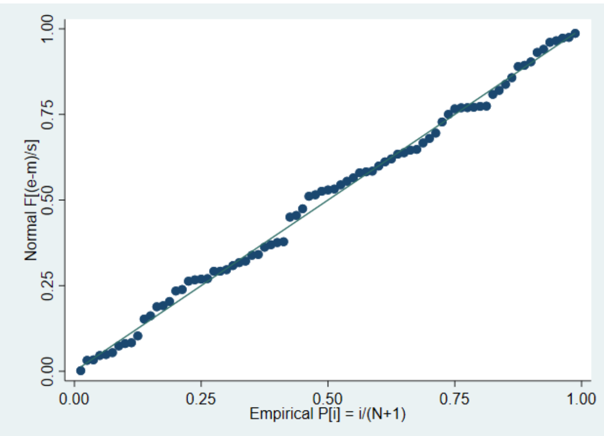
MAD model (2):



LHR-BOS, model (1):



LHR model (2):



Appendix C: Stata do-file

```
/* Master thesis do-file */

/* Declare time series */
gen qdate = quarterly(Date,"YQ") //quarterly data//
format qdate %tq
tsset qdate

/* Generate variables */
        // log variables //
gen lnPassengers = ln(Passengers)
gen lnDestinations = ln(Destinations)
gen lnAllianceRoute = ln(AllianceRoute)
gen lnAllianceUSdest = ln(AllianceUSdest)
gen lnGDP = ln(AvgGDP)
        // Dummy //
gen OSA =0
replace OSA = 1 if tin(2008q2,2018q4)

/* Time series plots */
tsline lnPassengers
tsline lnDestinations
tsline lnAllianceRoute
tsline lnAllianceUSdest
tsline lnGDP
tsline HHI

/* KPSS test */
kpss lnPassengers
kpss lnDestinations
kpss lnAllianceRoute
kpss lnAllianceUSdest
kpss lnGDP

/* Lag order selection for indiv. variables */
varsoc lnPassengers
varsoc lnDestinations
varsoc lnAllianceRoute
varsoc lnAllianceUSdest
varsoc lnGDP

/* Augmented Dickey-Fuller (ADF) test */
dfuller lnPassengers, lags(#) trend // # = no. of lags from varsoc //
dfuller lnDestinations, lags(#) trend // # = no. of lags from varsoc //
dfuller lnAllianceRoute, lags(#) trend // # = no. of lags from varsoc //
dfuller lnAllianceUSdest, lags(#) trend // # = no. of lags from varsoc //
dfuller lnGDP, lags(#) trend // # = no. of lags from varsoc //
 //ADF for first-differences//
dfuller D1.lnPassengers, lags(#) trend // # = no. of lags from varsoc //
dfuller D1.lnDestinations, lags(#) trend // # = no. of lags from varsoc //
dfuller D1.lnAllianceRoute, lags(#) trend // # = no. of lags from varsoc //
dfuller D1.lnAllianceUSdest, lags(#) trend // # = no. of lags from varsoc //
dfuller D1.lnGDP, lags(#) trend // # = no. of lags from varsoc //
```

```
/* Lag order selection for models */
varsoc lnPassengers lnAllianceRoute lnGDP, exog(OSA) maxlag(5) // treating OSA as exogenous //
varsoc lnDestinations lnAllianceUSdest lnGDP, exog(OSA) maxlag(5) // treating OSA as exogenous //

/* Johansen cointegration test */
vecrank lnPassengers lnAllianceRoute lnGDP, lags(#) si(OSA) max // treating OSA as exogenous //
vecrank lnDestinations lnAllianceUSdest lnGDP, lags(#) si(OSA) max // treating OSA as exogenous //

/* Vector error correction model (VECM) */
vec lnPassengers lnAllianceRoute lnGDP, lags(#) si(OSA) rank(#) // treating OSA as exogenous //
vec lnDestinations lnAllianceUSdest lnGDP, lags(#) si(OSA) rank(#) // treating OSA as exogenous //

/* Model diagnostics */
veclmar, mlag(#) // test for autocorrelation //
vecnorm, jbera // Jarque-Bera test for normality //
predict e, res // residuals model(1) //
predict v, res //residuals model(2) //
pnorm e // normality plot model(1) //
pnorm v // normality plot model(2) //
```

Appendix D: Reflection note 1
Nyhus, Espen

Main findings

This master thesis has been an empirical research of the effects of the 2008 EU – U.S. Open Skies Agreement (OSA) on the competition in the transatlantic airline market. There are many different markers of competition in the airline industry, but we focused on increased quantity. More specifically, passenger traffic and the number of U.S. destinations offered from EU airports. The thesis takes a time series approach to empirically test effect of the OSA. Included in the model are also variables to measure the effect of the real GDP and the market share of the dominant alliance. The reason is that the service level in the transatlantic market is likely to affected by the overall economic conditions, and the market power of the dominant alliance. The research required considerable processing of the data. The data on the passenger traffic and the number of U.S. destinations was relatively easily accessible from the U.S. department of transportation's database. From the data we had to identify every airline, and the alliance to which they belong. Then we were able to find the dominant alliance, and their market share. This process was repeated for every route segment. Once the data was gathered, we assessed the stationarity of every variable and reached the conclusion that there was evidence of non-stationary variables. These variable were integrated of order I(1) and cointegrated based on the Johansen cointegration test. On the basis of these results, we found that a vector error correction model (VECM) was the most appropriate time series model. With this model, we find the short-run impact of the OSA, real GDP, and the market share of the dominant alliance, in addition the long-run relationship between passenger traffic and the number of U.S. destinations offered. The results show the OSA did not have a significant impact on the passenger traffic on the routes considered. This means that the OSA has not brought procompetitive effects in the form of increased passenger traffic on these interhub routes. The results are in line with Brueckner's (2001) theory that airline alliances may cause anticompetitive effects. However, the results showed that the OSA did have a positive and significant effect on the number of U.S. destinations offered. Thus, although it has not caused passenger traffic to increase on the interhub routes, it has created procompetitive effects in the form of more destinations. This may indicate that new airlines may choose to operate different routes, than entering the routes where the alliance members have a large market share. In addition, the OSA makes it easier for existing airlines to expand their route networks with new destinations.

International

The airline industry is international by nature, and our research reflects this by looking at how an international deregulation agreement affects the passenger traffic and the number U.S. destinations offered from large European airports. It is not only international deregulations and economic laws that affect the airline market. We include a variable that is an average of the European and the American GDP to capture the overall economic condition. That way, the international economy is directly included in our research. For many of the markets considered, we found that the average GDP level contributed significantly to the explanation of the passenger traffic and the number of destinations. Thus, international trends and shocks in the economy has an effect on the demand for air travel. For instance, for all markets in our research, passenger traffic did not increase during the global financial crisis. In addition, there may be international shocks that affects the airline industry such as the attacks of 9/11, "Brexit" and the recent covid-19 pandemic.

Because of the international nature of the airline industry, the research on the subject also spans across the world. Thus, our thesis is a contribution to a international field of research on competition and market dynamics in the airline industry. This makes our thesis also of interest internationally.

Innovation

Innovation is a key concept in the aviation industry and it has in many ways been decisive in how airlines compete. Much of the competition is due to innovations in technology as well as innovations in organizational structure, cost-savings, etc. Our thesis mentions that one of the early and significant innovations to the international airline market, was the hub-and-spoke system that was developed in the 1990's. This was a new way of organizing an airline to improve efficiency, expand its reach and save costs. Then in the early 2000's, airlines began to cooperate operations between their respective hubs. This coordination of activity was very much the beginning of the formation of airline alliances. Our thesis incorporates airline alliances by including it as a variable in our long-run models. The airlines and airline alliances also started with "frequent flyer programs", which provides benefits to frequent customer in order to improve customer loyalty. More recently, we have seen the introduction of low-cost carriers (LCCs) to the international airline market, including the transatlantic market. This innovating take on air travel, typically includes airlines offering "no-frills" tickets at a low price, and charging extra for additional services. LCCs often operate one or a few fuel-efficient aircraft types, to reduce maintenance and operating costs. This caused pressure on existing airlines since the new airlines could offer the same core product, travel from a to b, but at a significantly lower cost. This is one of the key aspects of our thesis, because the OSA opens up for LCCs to enter the transatlantic market. Hence, we expected passenger traffic and the number of destinations to increase as an effect of the OSA.

Innovation is not only an important aspect in our topic, but it is also central for our methodology. Modelling with non-stationary variables is an innovation to time series analysis, and the field has witnessed a lot of improvements in recent time. Engle and Granger (1987), recognized that a long run relationship between non-stationary variables may exist. They developed a two-step approach to sufficiently make estimations with non-stationary variables. However, numerous weaknesses were identified to this approach, where one of the most important one was that it can at most examine one cointegrating relationship. In reality however, and as we saw in our thesis, multiple cointegrating relationships may exist. This issue was solved by Johansen (1992), where he allows for more than one cointegrating relationship to be analyzed. The result was an error correction model based on the vector autoregressive model (VAR), called vector error correction model (VECM). This is the methodology that we use in our thesis. Thus, our research compliments a relatively new field of time series research. In addition, we are using an extension to the VECM by including an exogenous dummy variable. Although there has been multiple research with this approach, we found little empirical research on the aviation industry using this methodology.

<u>Responsibility</u>

Our thesis touches upon the subject of collusive behavior between firms. This is a subject that has caused a lot of debate, but the general take is that collusion is not allowed. This is protected by antitrust laws. However, our thesis mentions that the OSA allows for immunity from these antitrust laws. This creates a potential ambiguity problem with the agreement, because it may create anticompetitive behavior, whilst the aim of the agreement was to impose more competition. It also creates an ethical concern, because the anticompetitive effects of a collusive agreements can harm consumer welfare, and prevent markets from becoming efficient.

Another ethical dilemma that arises in our thesis, is between the economic welfare theory and environmental policy. On the one hand economic theory views increased competition as positive because it increases consumer welfare by increasing the quantity offered, which in turn lowers the price. On the other hand, increased air traffic has raised concerns due to its environmental impact. Environmental matters have received increased attention in recent years, and many industries have experienced increased pressure to operate sustainable and responsible. The aviation industry is no exception. Although, aircrafts have become more fuel efficient and environmental friendly, it still imposes negative externalities. Since our thesis is an economic research and is based on theoretical principles, increased passenger traffic is viewed as positive. In addition, we are testing to see if the agreement fulfills its aim of imposing more competition on the market. However, it is important to emphasize that the increased competition in the airline industry also creates negative externalities.

Conclusion

This reflection note has discussed our master thesis with respect to the three concepts international, innovation and responsibility. The airline industry is international by nature and is prone to suffer from international shocks and disturbances. This means that the empirical research on the field also spans across countries. Innovation is a key aspect in gaining a competitive advantage in the airline industry, and our thesis mentions some of the innovations that has defined much of the market dynamics. The methodology of the research itself is also contributing to a relatively recent method of analyzing time series data. From what we experienced, little of the previous literature on the aviation industry has taken this scientific approach. Our thesis also addresses an ethical dilemma that arises. From the economic welfare theory, increased competition is viewed as positive because the markets are getting more efficient. Recently however, increased concerns have been made about the environmental impact of air travel. Increased passenger traffic and number of U.S. destinations will thus not only increase total welfare, but also bring negative externalities.

Kristiansand, 31.May 2020

Espen Nyhus

Appendix E: Reflection note 2

Mossestad, Jonas

This reflection note presents the objective and findings of the master thesis we have written. In addition to this, it is written to create a link to the three themes of internationalization, innovation, and responsibility to the topic we have worked on. Internationalization, innovation, and responsibility are key concepts in the School of Business and Law's mission statement and strategy and are therefore important to consider when evaluating our work in this reflection note. Along with the master thesis, these key concepts have also been highly emphasized in the learning outcomes for the whole study program of business administration at the University of Agder and are therefore natural to consider at the ending part of our master program.

<u>Main findings</u>

This thesis had the objective to analyze the procompetitive effects of the EU – U.S. Open Skies Agreement to investigate if it has fulfilled its aim. We have investigated this by using quarterly times series data to analyze the effect of the agreement on passenger traffic and number of U.S. destinations offered on three interhub routes. By using advanced econometrics and time series data, we found that the agreement has *not* had any significant impact on passenger traffic on our unit of analysis on any of the considered interhub routes. This means that our findings suggest that passenger traffic have not increased because of the EU – U.S. Open Skies Agreement. We also found that the U.S. destinations offered *have* increased because of the EU – U.S. Open Skies Agreement positively and significantly on all the unit of analysis considered. This further means that our findings suggest that the U.S. destinations offered have increased because of the agreement. It is important to highlight that we have only considered interhub routes and therefore must consider this when evaluating our results. This is further discussed in our discussion of the thesis. We have also mentioned that it would be of interest to consider other routes that are not interhub routes, to see if the agreement has changed the competition, hence, passenger traffic and U.S. destinations offered, differently.

Although there have been several researchers considering the topic of bilateral agreements, airline alliances and the broad topic of the airline industry as a whole, there have been few researchers considering advanced econometrics and time series regression in their discussions of procompetitive effects. This made us more interested. We also wanted to use our knowledge from Industrial Organization and econometric courses in practice to broaden our understanding in a practical study.

International

The concept of internationalization have a direct connection with our topic of an empirical analysis of the effects on competition, regarding the EU – U.S. Open Skies Agreement of 2008. The airline industry we consider in our thesis are international by nature, especially since we consider the computational effects of the transatlantic airline market regarding the agreement of 2008. By considering airports and markets that operate all over the globe, our thesis contributes to the concept of internationalization in terms of international behavior in passenger traffic and airline industry competition by analyzing three different airline segments operating in France, Spain and England. These airports and route segments may react to the concept of internationalization, as more and more passengers travel from one country to another.

In our thesis we have introduced several well-known researchers on the topic of the airline industry. Pitfield, Bruckener, Button, etc. These researchers have also highlighted that this industry is of interest to several countries all over the globe. That is, it is naturally of interest internationally, considering competitive effects that can influence other countries as well as the countries where the airports originate. Since the topic is naturally of international interest, there will be many actors that can react to our suggested findings in the literature, making our contribution more relevant for other researchers. By considering the airline industry and relevant time series approaches in our analysis, we believe that other researchers can benefit from our study worldwide.

Innovation

Innovation is a concept that drives much of the competition in the airline industry today. Therefore, it is also a highly relevant concept in our master thesis. An airline can choose to operate in different ways by either considering a hub-and-spoke model, enjoying antitrust immunity, operate in an alliance, non-alliance or operate as a low-cost carrier (LCC). All these approaches to operate, needs to be looked upon as different innovations in this market. This reflects the competition differently according to what type of innovation strategy the airline focuses on. For example, the entrance of low-cost carriers in the airline market has increased the competitiveness of the airline industry, causing high specialization to segments and differentiate from their competitors. This innovation strategy has caused a redefinition of their business models, simplifying their organization, and focusing only on their profitable strengths. With such measures, companies would emphasize upon innovation as their way to add value to the company.

Although our topic is highly related to innovation, we have not been that innovative in collecting data directly from the airports or route segments considered, because it is very restricted and hard to get hands on. For that reason, we used the T-100 database from the U.S. department of transportation, which offered data from 1990-2019. This way of attracting data may have ways of improvements. However, since much of the data are collected by private companies, it costs a lot to obtain and will therefore be expensive to buy. To improve this collecting of data, a possibility would be to hand out questionnaires to the relevant airports. That way, we could attract data directly from the source, which we could further analyze. However, we would most likely have had a problem of too little data and low hit-rate on our questionnaires because of the COVID-19 pandemic. Furthermore, we would most likely not have retrieved the same detailed data and not nearly as much data. This would again have made our analysis hard to conduct, because of the need for a lot of data on a long time period.

We believe that our methodology by using Johansen's three-step procedure and formulating two VEC models to empirically test the procompetitive effects, have explored other ways to conduct a thorough analysis for this well-known industry. Previously researchers have not implemented the same approach as we have, to analyze the procompetitive effects. Indeed, other time series approaches have been conducted as we have discussed in the literature review, but not using VECM.

To implement and manage innovation processes in a complex international setting can be difficult to highlight in a master thesis. We believe we have managed this by including an econometric approach that we have not seen anybody else use in this international industry. We have also been critical, finetuning our work by asking for guidance from our supervisor along with thorough analyzing of other relevant papers.

Responsibility

When analyzing the procompetitive effects throughout this thesis, we have viewed increased competition in the form of more destinations and passenger traffic as positive. We believe that this is positive for the consumers, capturing higher consumer welfare. However, as we all know, the airline industry plays a huge role regarding environmental issues of increased emissions. This means that our thesis faces an ethical dilemma where there is a tradeoff between consumer welfare and environmental concerns. It is important for us to highlight that this thesis is an economic research, however, it is important to address this issue. As we discuss, this environmental issue has further been considered in phase 2 of the Open Skies Agreement. Because of collinearity issues, we decided to analyze the main agreement of the Open Skies Agreement to describe the effects of competition. Thus, it can be of interest to conduct a similar research by mainly considering the more environmentally friendly phase 2.

Another ethical dilemma for this topic is that the agreement allows alliance members to enjoy antitrust immunity. This means that the competition will be fierce for new entrants in the industry or may even deter them from entering. This may be a potential drawback of the agreement.

Conclusion

As I have discussed, all the three concepts of internationalization, innovation and responsibility are highly relevant in analyzing the transatlantic airline industry. Internationalization have been the most prominent concept of the three, as it is an international topic by nature. Furthermore, through my reflection, I have learned that innovation plays an important role by considering the different ways an airline can operate. The industry is also capable to quickly respond to consumer demands, providing innovative solutions to deliver either flexible tickets, better service, lower costs etc. Last, but not least, responsibility have become more important than ever in this industry. The industry faces ethical and environmental issues that needs to be considered. In our investigation, phase 2 of the agreement depicts some of these challenges. This phase would be an interesting agreement to analyze in the future, contributing to our results regarding to the environmental issues of high emissions in the industry.

Kristiansand, 31.May 2020

Jonas Mossestad

Jonas Mossestad