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Master Thesis

"The effect of strategic alliances on service quality: Evidence from airline codeshare agreements and on-time performance"

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A B S T R A C T

This research looks for a casual effect of strategic alliances on service quality while taking into account other factors such as market structure and firm sizes. We derive data from the US Department of Transportation (DOT) and restrict our research sample to only U.S. domestic flights. Because we consider the effect of codeshare agreements between all major airlines, in combination with the limitation of the on time performance dataset, we are forced to make use of a new and unique method for estimating the effect of strategic alliances on service quality. In this new method, we compare codeshared routes by non-codeshared routes by using a dummy variable that values one if more than 5% of all flights on a particular route for a specific quarter are defined as codeshared flights. The main finding of this thesis is that airlines operating on codeshared routes experience on average fewer and less long delays than on non-codeshared routes. This effect is stronger on more competitive routes.

Keywords: Airline service quality, codeshare agreements, airline competition, firm size

JEL classification: L13, L40, L93

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1. Introduction

Flight delays are a widespread issue in the airline industry and the most common reason for airline passengers to complain (Dresner & Xu, 1995). Delays are inconvenient for airlines as well. They could cause multiple unwanted scenes, varying from paying compensation costs to facing a reduction in passenger demand.

In this thesis, we consider strategic alliances as a potential factor that causes delays. The airline industry deals with an increased amount of strategic alliances since the 1990s, during this period, numerous airlines made so-called codeshare agreements (CSA) with each other. On the one hand, codeshared allied airlines have the advantage of removing problematic flights on codeshared markets. An airline in a CSA can easily transfer problematic flights on route A-B, without losing a destination, since it can still offer flights on route A-B by selling the tickets from its allied partner. On the other hand, competition authorities have shown their concern about the increasing number of CSA. They argue that CSA could be anti-competitive. After all, carriers in a CSA with each other could abuse their market power, leading to fewer incentives for optimising service quality.

Given the issues of on time performances (OTP) and the recent trend of CSA as a dominant feature in the domestic airline industry, an interesting research question is: how do strategic alliances affect partners' service quality? Answering this question would shed light on whether strategic alliances have made issues concerning service quality better or worse.

The current empirical literature about the causal relationship between strategic alliances and service quality is somewhat inconclusive, with some papers arguing that strategic partnerships lead to improvements in service quality (Hassin & Shy, 2004; Gayle & Thomas, 2015; Yimga, 2017). While others find the opposite effect (Yimga & Gayle, 2014), or even no effect at all (Goh & Uncles, 2003; Tiernan, 2008; Tsantoulis, 2008). A possible explanation for the mixed results is that including a proxy for strategic alliances controls for other underlying mechanisms than only cooperation, such as competition levels or firm sizes. Larger firms, operating on competitive routes, are perhaps more likely to enter CSA. When we consider for example all domestic CSA in the past decade, it seems that especially larger firms established CSA. Furthermore, CSA are maybe more likely to be established on competitive routes since CSA offers more efficiency and competitive benefits on this type of routes. Through these reasons, it may be unclear which underlying mechanism is dominant above the other. To deal with this issue appropriately, we provide a model in which the effects of strategic alliances, market structure and firm size on service quality are examined together in one model. The benefit of using this approach is that the results will show which underlying mechanisms actually affect service quality.

Analysing CSA usually works out fine for papers focusing on alliances and fares. However, within the service quality research area, working with CSA-data has some critical limitations. The most important one is that codeshared flights cannot be differentiated from non-codeshared flights in the on-time performance dataset. The literature often deals with this limitation by using a difference-in-difference strategy (Yimga, 2017; Gayle & Thomas, 2015). This strategy compares relative changes in OTP between specific allied firms and non-alliance firms before and after those specific firms agreed to ally. The relative change between these two comparisons is in a difference-in-difference strategy identified as the effect of CSA. Unfortunately, the difference-in-difference approach would not work out for our research since we also take into account the effect of firm sizes on service quality. When we would use a difference-in-difference strategy, we would be limited to consider only the impact of the firm sizes of the allied firms that are examined in the difference-in-difference strategy, leading to a low variation of the variable firm sizes in the dataset. To deal with the data-limitation mentioned above and to still answer our research question correctly, we focus on comparing codeshared routes with non-codeshared routes instead of comparing codeshared flights with non-codeshared flights. More specifically, we compare a route at a particular time when it is defined as a codeshared route to the same route at a particular time when it is defined as a non-codeshared route. We identify codeshared routes in the OTP-database by creating a dummy variable which values one if more than 5% of all flights on a particular market for a specific quarter are defined as codeshared flights.

Our results will serve as supportive evidence concerning decisions to interfere (or not to interfere) further into strategic alliances. When for example strategic alliance negatively affects service quality on particular high competitive routes, competition boards could consider forbidding new partnerships between domestic airlines on competitive routes. Also, this thesis would be of interests for airline companies as well; our results will influence the way airlines companies assess collaboration opportunities. Our results could, for example, indicate whether it is more or less beneficial to collaborate with larger or smaller airlines.

Our research also provides additional insights that could be of scientific relevance. Previous literature has already shown the double effect of CSA on service quality. Yimga (2017) suggests that alliances improve OTP and that this effect is more abundant on routes where the alliance partners faced each other before the alliance. This finding implicates that efficiency effects outweigh competitive forces in general but even more on markets where the partners encountered each other before they became allies. To verify the results of Yimga, we take a broader view of possible factors that influence the impact of CSA on service quality. More specifically, we include an interaction term to control for CSA under different market structures. Including this moderator extends Yimga's research since he only managed for route level competition by estimating the direct effect of the number of airlines serving a route on service quality. The second extension to Yimga's research is that we also take into account the effect of firm sizes in general, as well as a moderator variable concerning CSA. Larger airlines probably exuberance fewer delays since they have more resources available to handle disruptive events. The idea for adding size also as a moderator stems from the research of van Reeven and Pennings (2016). They empirically proof that firm size acts as a moderator in the relation between multimarket contact (MMC) and service quality. Reeven and Pennings reason that the size of an airline determines if cooperation between two airlines is beneficial or not. We examine if this reasoning also applies for CSA.

The rest of this research is structured as follows: Section 2 contains our theoretical framework and empirical results of the past literature. Section 3 describes the hypotheses related to the research question. Section 4 describes the data and methods used. Section 5 discusses our empirical findings. Section 6 concludes and provides recommendations for further research. Finally, section 7 contains the appendices.

2. Theoretical Framework

This section provides some in-depth explanations about past literature related to service quality. The first paragraph focusses on service quality in general, followed in the second, third and fourth paragraph with a theoretical and empirical overview concerning service quality on the one hand and respectively strategic alliances, market structure and firm size on the other hand.

2.1 Service Quality

Airline companies often criticise that airline delays are behind their control, as in the case of extreme weather. However, in most circumstances, delayed flights are often clarified as a consequence of a trade-off between OTP and costs. OTP can namely be improved by proactively anticipating delays and investing in additional resources. When for example a storm is forecasted, an airline can choose to cancel a proportion of the flights during the storm, with the intention to use a relatively larger pool of resources, to make sure the remaining flights arrive on time. Another example of the trade-off between OTP and delays occurs when whether or not spare aeroplanes are scheduled to reduce delays caused by other delayed flights. Furthermore, when imminent delays occur, airlines can control which flights are affected. They can redeploy their assets and maintenance crew to flights where the consequences of delays are likely to be more expensive (Mazzeo, 2003). Another typical example of the trade-off between OTP and costs is ‘schedule padding’. Carriers could have an incentive to control for delays on paper by adjusting schedule times. Most of the time this is done by adding extra time to arrival time. Expected delays are automatically controlled for in this way. However, schedule padding also has a downside, when a plane is scheduled for ‘longer’ flights it has logically also a lower utilisation rate, leading to lower revenues. Therefore, schedule padding is in the end mainly a trade-off between fewer delays on paper and higher opportunity costs.

Besides a trade-off between costs and delays, there is also a trade-off between a carrier's strategy and delays. For instance, decreasing the length and frequency of delays is also possible by avoiding congested airports and choosing for secondary airports. The same reasoning applies to avoiding peak hours. Delays could easily be reduced if a carrier adapts its flight schedules to less congested schedule times.

2.2 Strategic alliances

Before the following paragraph explains how strategic alliances affect service quality from a theoretical and empirical perspective, first a short background about CSA is presented below.

2.1.1 Background CSAs

Strategic alliances have become widespread throughout the airline industry and are mostly identified in the literature in the form of CSA. These voluntary partnerships are reciprocal agreements between two or more carriers in which airline A, who operates the flight, permits its partner B to sell seats on airline A's flight segment[1]. The airline that actually transports the passengers is called the operating carrier (or operator). The partner airline, or the ticketing or marketing carrier, is the one who arranges flight reservations or sells a proportion of the tickets to passengers for flights that are not operated by itself. For illustration purposes, a codeshare agreement between Delta Air Lines (DL) and Northwest Airlines (NW), allows DL, as ticketing carrier, to sell tickets on flights operated by NW, and vice-versa. Although the flight is operated only once, tickets are listed twice (under both carrier names) in the computer reservation systems. A marketer receives a booking commission to cover handling costs for selling tickets on a codeshared flight, while the operators keep the remaining revenue of the tickets sold by the marketers. The specific arrangements differ between CSA and even between different routes within the same codeshare alliance. Marketers are authorised to sell a few seats, a whole block, or even an entire flight. One thing that is usually constant in a codeshare agreement is the balance between acting as a marketer or as an operator between airlines in an alliance. The reason for this is that revenue mostly accrues to the operating carrier, with the consequence that the benefits from the agreement are not equal when in CSA one party acts more often as an operator carrier compared to its partner.

In the literature, there is made a distinction between roughly three types of air travel products[2]. The first and largest type of air travel products are pure online flights; in this case, the same airline is the operator and marketer on all flights segments. The next group, traditional codeshares, consists of flights in which the ticketing carrier stays the same for all flight segments, but the operating carrier can differ between flights segments. For example, an itinerary operated by Delta Air Lines (DL) on

[1] A flight segment is a non-stop route between the origin and destination airports.

[2] An air travel product is a unique combination of an itinerary, marketer and operator airline. An itinerary can be described as a round trip ticket for passengers.

flight segment A and operated by Northwest Airlines (NW) on flight segment B, but marketed entirely by NW. The last group of air travel products are so-called virtual codeshares. These type of air travel products are offered by the same operating carrier during the entire flight, but, the marketer is on all flight segments different from the operator. For instance, an itinerary operated by DL on flight segment A and B, but marketed on both flight segments by NW.

2.1.2 Competitive and efficiency motives

The theory about CSA is further elaborated with the help of two different type of motives for starting a CSA, namely, competitive motives and efficiency motives.

On the one hand, carrier's motives for CSA are related to the benefits of reducing competitive pressure. Gayle (2007) argues that codeshare agreements are a consequence of collusive goals. Gayle claims that airlines attempt, especially on overlapping routes[3], to fix prices. Reducing competitive pressure can also take a less extreme form of dishonest behaviour. Bamburger et al. (2004) hypothesise that airlines use CSA as a tacit agreement between partners to prevent airlines from entering each other's markets. Airlines would have fewer incentives to enter each other's market in the case airline A offers codeshared flights with airline B at especially those markets where airline B is active as well, and vice-versa. A third competitive motive stems from the theory about frequent flyer programs. Since CSAs enable the ability to earn frequent flyer miles while travelling with the other carrier, the proportions of customers, which are characterised by higher switching costs, will increase. Making it harder for other airlines to win customers from the allied partners (Goetz & Shapiro, 2012).

On the other hand, motives, for especially traditional codeshares, are related to efficiency advantages. First of all, traditional-CSA enables airlines in the CSA to offer better-connected networks and a more 'seamless' travel with shorter and less frequent delays. A partner's network looks then like an extension of an airline's network, leading to the fact that carriers increasingly consider the impact of their delays on the time schedules of their partners. Allied airlines put in these alliances much effort to align their networks and it results, among other things, in close gates proximity, access to partner's lounges, eliminating the need to buy two separate tickets, aligned flight schedules to minimise layover times, more check-in posts and better luggage services. Another efficiency motive related to traditional CSA is expanding the network of an airline without the necessity for investing in additional aeroplanes. Even when a carrier has the authority to enter and land in another country's airspace, CSA are attractive since they allow airlines to offer new routes without investing in additional resources (Brueckner, 2001). The third efficiency motive for codesharing is lower fares on interline routes[4]. The theoretical model of Brueckner & Whalen (2000)

[3] Overlapping routes are routes at which allied partners faced each other before the CSA.

[4] Interline routes are routes with more than two operating carriers.

describes two reasons for this: Firstly, CSA prevent double marginalisation. Based on the work of Lerner (1934), Brueckner & Whalen explain that airfares are higher in markets where different airlines sell complementary goods, such as tickets for traditional codeshared flights, compared to markets in which only one monopolist sells tickets for both flight segments. Secondly, traffic will increase as a consequence of lower fares resulting on its turn in improved economics of density.

Besides the advantages, it is also important to consider the downsides of offering codeshared flights. Costs of codesharing often involve consolidation and coordination costs as a consequence of aligning flight schedules, rearranging airport facilities and sharing of equipment. These costs may seem negligible, but according to Goetz and Shapiro (2012), these costs make only 40% of all domestic flights worthwhile to be codeshared.

2.1.3 Empirical results

The literature is somewhat inconclusive about the relation between alliances and service quality (Yimga, 2017). More robust findings are related to the effect of alliances on fares (Brueckner & Whaalen, 2000; Brueckner, 2001). The literature focusing on fares mainly suggest that alliances negatively affect fares and increase traffic on interline routes (Brueckner and Whalen, 2000; Brueckner, 2003). On the other hand, these authors argue that alliances increase fares on overlapping routes. These findings are in line with the theoretical analysis of Park (1997). Park finds that the CSA on interline routes are more likely to be based on efficiency motive, while anti-competitive effects arise when airlines start CSA on overlapping routes.

Fewer papers explored the relationship between strategic alliances and service quality. However, since Tiernan et al. (2008), Gayle & Thomas (2015) and Yimga (2017), more research has been fulfilled in this area. Tiernan et al. (2008) hypothesise that strategic alliances value service quality to a more considerable extent, compared to individual airlines, since negative customers experiences caused by only one member, negatively affect the whole coalition. Their results, however, suggest that there is no evidence for better service quality for allied carriers. Gayle & Thomas (2015) and Yimga (2017) indicate that alliances positively affect service quality. They argue that CSA provide seamless service with shorter and less frequent delays since layover times can be better coordinated on interline routes when airlines cooperate with each other. Yimga (2017) additionally finds that the impact on service quality is more substantial on routes where the alliance partners competed each other before the CSA was established.

2.2 Competition and service quality

This paragraph describes the theory and empirical results related to the effect of market structures on service quality. Firstly, we describe why competition boards worry about CSA and the associated counterarguments of airlines. Secondly, we present previous results from the literature about the effect of market structure on service quality.

2.2.1 Competitions boards versus allied partners

Competition boards have shown their concern about CSA since they could be anti-competitive. The boards are especially concerned about CSA when they are practised on overlapping market because efficiency motives are then likely to be overwhelmed by competitive motives, causing a lack of incentives to maintain or improve OTP.

Carriers claim on the other hand that there are still enough incentives for allied partners to compete each other in a CSA. They argue that the ticketing carrier only receives a small compensation for booking costs and that airlines therefore still have enough incentives to gain market share from competitors and their allied partner(s).

2.2.2 Evidence from the literature

Numerous papers, both theoretical and empirical, analysed the effect of competition on service quality. Most of these findings are identified as robust results and provide significant proof for the positive impact of competition on service quality (Mazzeo, 2003; Mayer and Sinai, 2003; Rupp et al., 2006; Prince and Simon, 2009; Steven et al., 2016). These authors argue that reducing delays lead to increased market shares and that airlines therefore would have more incentives to offer higher quality goods on more competitive routes. Subsequently, in a concentrated market like a monopoly market, airlines would have more incentive to improve margins by saving costs on service quality (which increases delays), since there are no other airlines available for customers to switch to.

The effect of competition on service quality is often also indirect measurable. Market structures namely often affect the strength of the relationship between other independent variables and service quality. For example, Prince & Simon (2009) show that the mutual forbearance effect is stronger on more concentrated routes. The interaction effect of competition and strategic alliances has also been examined for mergers and pre-competition levels between merged airlines (Gayle and Chen, 2013). This paper suggests that the influence on service quality is like a U-shaped function of competition level prior to the merger. They find a quality increase on non-overlapping routes before the merger is settled. But a quality decrease on markets where airlines did compete each other prior to the merger. The results of Prince & Simon (2017) differ concerning the decrease of service quality on overlapping routes. They find supportive evidence for improvements regarding service quality on overlapping markets, especially for the impact on the long term.

Despite the overwhelming evidence for a positive effect of competition on service quality, it can be argued that more competitive routes experience relatively more delays compared to concentrated routes. The reason for this argument is based on the paper of Borenstein and Netz (1999). They examine the relationship between competition and differentiation. For this, they use the theory of spatial product differentiation, which states that firms can have two options regarding distinction in competitive markets: (1) firms try to steal customers from their competitors by offering the same type of product or (2) firms try to differentiate their product to reduce competition. The results of Borenstein and Netz suggest that airlines try to steal customers in competitive markets by choosing the same schedule times as their competitors as much as they can. This shift to popular arrival/departure times on competitive markets leads to more congested airports, and thus to more frequent delays.

2.3 Airline size and service quality

The first part of this paragraph shortly explains why larger firms are more likely to offer higher services quality concerning on-time performance than smaller firms. The second part provides the theory and empirical results that show that smaller airlines benefit more from cooperation than larger airlines.

2.3.1 Effect of Airline size

Larger airlines are probably more likely to reduce the magnitude and frequency of delays since they can achieve network benefits. These network benefits arise for sizeable airlines because these type of airlines can spread investments, such as additional aeroplanes and maintenance facilities, over more routes. Network benefits enable airlines to adapt flexibly to unexpected delays in several circumstances. The consequence of a suddenly damaged aircraft, for example, would be minimised when an additional unscheduled plane would be available, or if there is a maintenance crew available of considerable size, that could repair the aircraft rapidly.

2.3.2 Airline size as moderator variable

According to the theory of Economides (1999), efficiency motives are for cooperation (and thus also for airline alliances) especially likely to be the case for composite goods. Composite goods are products that are more valuable or efficient when they are produced cooperatively instead of individually. Examples of the types of products are interline-routes and virtual codeshared products on non-stop routes. Interline-routes fall into this category since two different markets are combined to create a composite service. A virtual code-shared product can be defined as composite goods as well since it enables airlines to provide a more frequent service to their customers.

Various papers note that especially smaller firms are more likely to favour compatibility compared to large firms (Katz and Shapiro, 1985; Barley et al., 1992). One way to support that this statement is also valid within the airline industry is by referring to the logic that smaller firms are more likely to benefit from improved network efficiency. Cooperation can cause higher growth opportunities for smaller carriers since larger carriers could have more resources to share. The relatively higher increase in route options in cooperation with a major firm makes a smaller carrier relatively better able to exploit economies of scope as a consequence of collaboration. Also, airlines probably realise a more significant increase in demand because cooperation leads to a rise in demand for both firms, but, again, to a relatively more considerable increase for minor airlines.

3. Hypotheses development

As the previous section covered the academic background related to the strategic alliances, market structure and firm sizes, it is now useful to mention our expectation about the impact of strategic alliances on service quality. Before we hypothesise the causal effect of strategic alliances on service quality and the casual effect of strategic alliances for different levels of market structure and firm sizes, we first hypothesise the individual impact of strategic alliances, market structure and firm sizes on service quality for the sake of robustness.

3.1 Effect of the key variables on service quality

Although the efficiency motives explained in section 2.1.2 clarify the positive relation between alliance and OTP, they are impossible to test in this research. They are primarily related to interline routes, while OTP-data only available is for non-stop routes. Fortunately, there is an underlying mechanism that supports a relation between alliances and service quality for non-stop routes. On non-stop routes, codeshared allied airlines namely have the advantage of removing flights on codeshared markets, which are more likely to be delayed. An airline in a CSA can easily transfer problematic flights on route A-B, without losing a destination, since it can still offer flights on route A-B by selling the tickets from its allied partner. Mainly code-shared routes with the following characteristics are more likely to be removed from an airline's network (Yimga, 2017):

- Flights operating on particular routes with on average poor OTP.
- Flights departing at peak hours. These types of trips increase congestion, especially at hub airports. An airline in a CSA could easily internalise this externality (Brueckner, 2005).
- Flights that compete each other since they have an equal schedule scheme.
- Flights that are operated by less efficient aeroplanes in terms of mechanical issues.
- Flights where the costs of delays are the highest.

> ***Hypothesis 1A*** *– Alliances, in the form of codeshare agreements, positively affect on-time performances, ceteris paribus.*

Based on the robust findings of the literature related to the impact of competition on service quality and the assumption that we control correctly for the findings of Bornstein & Netz (1999) by including control variables for congestion, we derive the following hypothesis:

> ***Hypothesis 1B*** *– Competition levels positively affect on-time performances, ceteris paribus.*

As mentioned in section 2.3.1, larger airlines face relatively fewer delays since they have on average more resources per route available to handle disruptive events. They can use their resources and additional benefits, such as extra landing slots, larger maintenance crews, and non-scheduled available aircraft, to increase their flexibility as a response to delays when for example a defect aeroplane needs to be repaired or replaced.

> ***Hypothesis 1C*** *– The size of an airline positively affects on-time performance, ceteris paribus.*

The current aviation literature is quite inconclusive concerning the causal effect of alliances on service quality. Besides the fact that service quality is difficult to measure, mixed results are perhaps caused by the mutual dependence between the proxies for strategic alliances, competition and firm sizes. When we consider for example all codeshare alliances of the past decade, it seems that especially larger airlines are more likely to be part of an alliance. Furthermore, it can be argued that airline alliances are more likely to form strategic alliances with firms with whom they compete on the same routes for competitive as well as efficiency motives. These type of routes where both firms operate on are likely associated with high demand and therefore also more likely to be competitive.

Because of the potential mutual dependence, it is necessary to control if the effect of strategic alliances on service quality stays the same when you control for the effect of strategic alliances, market structure and firm sizes on service quality together in one model. We still believe though that strategic alliances positively affect service quality in such a model. Even if a large part of the effect of strategic alliances on service quality is explained by the variation of market structure and firm sizes, allied partners would probably still be able to offer higher quality service compared to non-allied firms since they have the opportunity to remove flights on codeshared markets.

> ***Hypothesis 1D*** *– Alliances, in the form of codeshare agreements, positively affect on-time performances, ceteris paribus, even when we control for market structure and firm sizes.*

3.2 Market structure as interaction effect

An interaction term concerning CSA and competition levels is added to the main model to identify the effects of CSA on service quality for different levels of competition. Including this moderator extends the research of Yimga. He only controlled for route level competition and strategic alliances by estimating its direct effect on service quality while it could be possible that these two variables reinforce each other. As far as we are aware, is this the first research that investigates this intermediate effect concerning service quality, and therefore, including this hypothesis to our research, is a contribution to the literature in itself.

Although the interaction effect of competition on strategic alliances is unknown concerning service quality, it has been researched broadly affecting fares (Gayle, 2007; Bamberger et al., 2004). These authors find that the negative effect of alliances on fares is on average higher on more concentrated routes. Taking these findings into account, our thesis should hypothesise that alliances affect OTP more positively on more concentrated routes. Airlines would have in this type of markets fewer incentives for increasing market power which makes them more likely to enter CSA based on efficiency motives (Gayle, 2007). This argument may be suitable for studies concerning airfares. However, we do not expect that entering CSA is a choice based on the impact of efficiency motives related to service quality. On the contrary, we expect that the influence of CSA on service quality is something that comes into play only as a consequence of CSA, not as a reason for entering CSA. Following this argument, in combination with hypothesis 1A and the idea that codeshared allies would experience a relatively larger increase in market power as a result of CSA on more concentrated routes than on competitive routes, we argue that airlines experience relatively more disadvantages of strategic alliances on more concentrated routes. After all, a larger increase in market power leads to a higher preference of improving margins by saving cost related to service quality compared to a smaller increase in market power.

Hypothesis 2 – *Alliances positively affect on-time performance to a larger extent on more competitive markets, ceteris paribus.*

3.3 Firm size as intermediate effect

The relatively more substantial increase in route options in cooperation with a major firm makes a smaller carrier able to provide a relatively higher increase in service quality compared to a large firm that is going to collaborate with a smaller firm. After all, larger firms have relatively more resources to share in an alliance, which could potentially reduce delays, compared to smaller firms.

Hypothesis 3 – *Alliances positively affect on-time performance to a larger extent for small-sized firms compared to larger firms in codeshare agreements, ceteris paribus.*

4. Data and Methods

This section describes consecutively, from which sources we derive the datasets from, the way we aggregate the datasets, how we construct the datasets, which proxies we use to measure our key and control variables in a panel analysis, summary statistics, and finally, we describe our model.

4.1 Data sources

We make use of the following four different databases for analysis: (1) the Airline On-Time Performance Database, (2) the Airline Origin and Destination Survey (DB1B), (3) the T-100 Domestic Segment Database (U.S. Carriers) and (4) the Metropolitan and Micropolitan Statistical Area Dataset.

Most data for analysis stems from the Bureau of Transportation Statistics (BTS), an independent statistical agency within the U.S. Department of Transportation (DOT) [5]. One of the datasets that the BTS provides is the Airline On-Time Performance dataset (OTP-dataset). This dataset contains data which we use to calculate proxies for market structure, the total number of routes per carrier, congestion, airport dominance and off course service quality. The BTS publishes data for each month and only for non-stop flights. Airline companies are required to report their airline on-time performance data to the BTS when they are responsible for; at least 1% of total domestic revenue and/or at least 1% of all domestic passenger enplanements that have taken place.

The second dataset we use for creating our research sample is the Airline Origin and Destination Survey (DB1B) dataset from the BTS. This dataset covers a 10% random sample of all U.S. airline tickets from reporting carriers (BTS, 2017). Besides information about origin and destinations for non-stop routes, this survey also includes data to calculate proxies for allied markets, airline size regarding passengers, and finally, enplanements. The BTS published airline data for every quarter in three separated files, namely: DB1B_Coupon[6], DB1B_Market[7], and DB1B_Ticket[8]. We merge these files into one comprehensive dataset by using the unique itinerary_id and market_id for identifying similar observations in the three different datasets.

The third dataset we use for creating the research sample is the T-100 Domestic Segment (U.S. Carriers) [9]. We use the T-100 dataset only for determining available seat miles of a carrier for each month.

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[5] https://www.transtats.bts.gov/databases.asp?Mode_ID=1&Mode_Desc=Aviation&Subject_ID2=0

[6] This dataset contains specific information related to coupons. Each coupon in an itinerary resembles a different observation. A coupon is issued for each segment of an itinerary without a plane change.

[7] This dataset contains specific information related to markets. Each directional market in an itinerary resembles a different observation. Markets are in this thesis defined as directional air travel between an origin and destination airport pair.

[8] This dataset contains specific information related to itineraries. The ticket dataset includes one single observation for all data on an itinerary. Each itinerary is described as a round trip ticket for passengers. Thus, the ticket dataset consists data about two direction markets in the same observation.

[9] The T-100 domestic segment dataset is often preferred above the DB1B and OTP-dataset for calculating measurements throughout the literature. The OTP-dataset might underrepresent typical route-carrier characteristics. The literature argues that the OTP-sample is not an entirely random sample and that therefore the T-100 dataset should be used for robustness purposes. Still, this thesis makes only use of the DB1B-database and OTP-database for calculating proxies for the reason that it is not possible to separate CSA routes from non-CSA routes in the T-100-database. The T-100 database does not contain any data about ticketing and marketing carriers.

The last dataset used in this thesis is the Metropolitan and Micropolitan Statistical Area Dataset from the U.S. Census Bureau[10]. This dataset has been used to derive instrument variables (IV) to deal with endogeneity issues.

4.2 Data aggregation

This paragraph explains the chosen timespan of the research sample, how we correct for mergers in the dataset, how we aggregate the research sample and how we define routes.

The timespan is set from 2003q1 till 2016q4. We have chosen this timespan for the following three reasons. Firstly, it took the airline industry more than a year to recover from 9/11 and to achieve pre-attack levels. Secondly, a boost in domestic CSA from 2003 is observed onwards (Ito & Lee, 2007). The average increase of codeshared routes improves the sample to a more equally divided research sample, which is essential for comparing non-codeshared markets with codeshared routes. Thirdly, some of the datasets used in this research, such as the Metropolitan and Micropolitan Statistical Area Dataset, did not collect/published data yet for periods after 2016 at the moment of writing this thesis.

It is important to note that codes and names of airlines may change as a consequence of mergers during the timespan of the dataset[11]. Acquired airlines often continue to operate under its company name or code for several quarters following a merger, while the merged companies are already running as the same airline. Therefore, to determine the carrier's code and names accurately, the names and codes are altered to the targeting firm from the date they are merged. For instance, Delta and Northwest began reporting jointly in January 2010, following their 2008 merger announcement. To account for this adequately, we recode Northwest (NW) to Delta (DL) from 2008:q4 onwards.

All datasets are averaged and collapsed to route-carrier-quarter level before they are merged into one final dataset. A single observation is a row of data that contains all relevant information about a particular route operated by a particular carrier in a specific quarter. Since the OTP, T-100 and DB1B-datasets do not match perfectly, and the final sample only includes observations without missing data, the total number of observations finally decreases to 177.496. The three datasets do not ideally merge due to initial filtering of each dataset and as the consequence that the DB1B dataset and T-100 database define non-stop routes differently. The discrepancy is that the DB1B dataset does not correct

[10] In contradiction to the other datasets, this dataset is only available per year and is not provided by the DOT but by the United States Census Bureau: https://www.census.gov/programs-surveys/metro-micro.html.

[11] "America west and US airway started to report combined on-time data in January 2006 and combined traffic and financial data in October 2007 following their 2005 merger announcement. Delta and Northwest began reporting jointly in January 2010 following their 2008 merger announcement. Continental Micronesia was combined into Continental Airlines in December 2010, and joint reporting began in January 2011. United and Continental began reporting jointly in January 2012 following their 2010 merger announcement. Southwest (WN) and AirTran (FL) began reporting jointly in January 2015 following their 2011 merger announcement. American (AA) and US Airways (US) began reporting jointly as AA in July 2015 following their 2013 merger announcement" (BTS, 2017).

for connecting flights, flights that make a stop without changing from planes, while the T-100 dataset does control for connecting flights.

The choice for examining route-carrier level is in line with numerous recent papers (for instance: Mazzeo, 2003; Prince and Simon, 2009). These papers suggest that the level of service quality differs per carrier and route. Typical route and carriers characteristics that for example potentially influence service quality are respectively firm sizes and airport dominance. An additional benefit of using route-carrier-quarter level data is that it makes the research sample accessible for controlling for route-carrier fixed effects, such as distance and financial performances. The reason for choosing a quarterly time-interval is in line with the paper of Prince and Simon (2017). They focus on both daily and quarterly level and reason that using quarterly periods should be preferred since it prevents computer limitations. When you study such a large dataset as we do, and choose a daily time-interval, the computer power only allows you to use a limited proportion of the data. Using quarterly periods enables to use all data. However, the disadvantage of not using daily periods is that we cannot control for daily unobserved factors such as regular air traffic, long security lanes or extreme weather.

It is vital to define markets clearly when working with airline data. In this thesis, we describe markets as directional air travel between an origin and destination pair, in which all airports resemble a single origin or destination (Borenstein, 1990)[12]. Airports pairs are preferred above city pairs as a unit of observation since including airport pairs controls instantly for unobserved fixed airport effects, such as slot and airport capacity, in a fixed effect model. An additional reason for defining markets as airport pairs is related to control correctly for the impact of airport congestion on OTP.

4.3 Data construction

This paragraph describes step-by-step which adjustments need to be made to the combined datasets to enable a more manageable and valid research sample.

We make several adjustments to the DB1B database before the proxies for size, CSA etc. are calculated. Firstly, since this thesis focuses only on passenger flights, (1) all observation with *passengers* = 0 are dropped. Additionally, (2) all observations wherefore *distance* = 0 or *origin_airport* = *dest_airport* are dropped as well. These observations are likely to contain errors and missing data. The next step (3) is to limit the research sample to only U.S. major carriers. See *table 1* for an overview of the included airlines in the research sample. By restricting to major carriers, regional and small carriers that voluntarily submitted their data are automatically excluded from the dataset, creating a less heterogeneous sample. Additionally, it is necessary to exclude regional and small carries before we determine codeshared routes since these companies behave substantially

[12] With using the term 'directional flights', a differentiation is made between two different markets in the same itinerary. For example, a flight from New York (JFK) to Los Angels (LAX) is defined as a separate market compared to a flight from LAX to JFK.

different in CSA compared to major domestic airlines (Goetz & Shapiro, 2012). We identify major carriers with the help of the DOT's early Air Carrier Grouping list[13]. Next step to be taken (4) is to keep only non-stop routes[14]. This adjustment seems to be ambiguous. After all, congestion variables are less representative if they are calculated after a dataset is already filtered on non-stop routes. In this thesis, there is chosen to filter on non-stop routes before calculating the proxies since there would otherwise be a measurement error. An extreme example of a situation in which such a bias occurs is when interline routes are categorized as much more congested than non-stop flights. Furthermore, (5) all international routes and domestic routes operated by foreign carriers are excluded from the dataset. Reasons for focusing on the U.S. domestic airline industry are the large amount of available data for the U.S. airline industry and the fact that during the timespan of this research, almost all major U.S. carriers entered into broad domestic codeshare agreements. The total number of passengers on codeshared flights was almost 2 million in 2003 (Ito & Lee, 2007). At the end of the timespan of this research, codeshared flight became rather rare. These changes in the use of CSA enable us to examine the within variation which enables to isolate the effect of CSA on OTP for the same route-carrier observation over time. The third reason for focusing on the U.S. airline industry is associated with the focus on virtual-CSA in this paper[15]. Ito and Lee (2007 found that an overwhelming proportion of domestic codeshared flights involve virtual-CSA (85%), while international-CSA typically involve an itinerary for which two or more operating carriers wants to offer a traditionally connecting flight (=interline route). Thus, focusing on only domestic flights creates an effective control group concerning CSA. The sixth adaption (6) to the DB1B dataset is in line with this reasoning and excludes all observations with missing ticketing/operating carrier names. Step seven (7) is to drop all observations that contain data about markets that are served less than five times by a particular carrier in a specific quarter. Moreover, (8) the sample only keeps airline routes with more than 100 observations in total. Steps seven and eight guarantees that each route contains enough repeated observations.

[13] This list groups carriers every year according to their operating revenue in three groups. The third group consists of airlines that achieve an operating income of higher than 1 billion dollars. This research defines an airline as a major carrier when an airline has been listed at least once in Group III during the timespan of this research. Exceptions to this rule are regional and cargo carriers, these types of carries are always excluded from the dataset, independently from their operating revenue. Major hub-and-spoke carriers often cooperate with regional airlines. On these flights, the regional carrier often operates the flight under the name of the major carrier. When this is the case, the flight is defined as a CSA, since the operating and ticketing carrier differ. But, in practice, these regional partners are not acting as a codeshare ally but more as a subsidiary airline (Goetz and Shaprio, 2012). To control for this, we make sure that all observations, for which the operating or ticketing carrier is marked as a regional airline, are dropped. Failing to do so would overcount the number of codeshared routes.

[14] Non-stop routes are created by restricting the sample to include only observations to which applies $market\_coupons \leq 1$ and $coupons \leq 2$.

[15] The focus on virtual-CSA is related to the restriction of the OTP-dataset. This dataset contains only data for non-stop routes. Implying that all codeshared flights within the final dataset are defined as virtual codeshared flights since the marketer is different from the operator on all flight segments.

We also made some adjustments to the Airline On-Time Performance and the T-100 Domestic Segment database[16]. All cancelled and diverted flights are dropped (9). Including these variables requires too many ad hoc assumptions to make results comparable (Mazzeo, 2003). Furthermore, (10) all observations related to missing/incorrect OTP-proxies and missing tail number are useless and are excluded as well. (11) Delayed flights for more than 3 hours are counted as delays of 3 hours to reduce the impact of outliers. Next, (12) for preparing the T-100 Domestic Segment database, all observations for which the variables: Passengers, distance, and the number of seats are equal to zero, are dropped from the dataset. Additionally, the dataset is restricted to only keep domestic passenger flights. Finally, (13) the MSA population database is prepared by cutting all observations corresponding to missing values. This dataset is consequently merged with the final dataset by using airports as the unique variable.

*Table 1: Airlines included in the dataset * US Airways merged with American Airlines in 2013 ** Air Tran got acquired by Southwest Airlines in 2011 *** Continental merged with United Airlines **** Northwest Airlines merged with Delta in 2008 ***** America West merged with US Airways in 2005 ****** ATA Airlines was declared bankrupt in 2008 ******* Virgin America was acquired by Alaska Airlines in 2016.*

Airline Name	Airline Code	Mean arrival delay (in minutes)	Enplaned passengers in 2016 (in millions)
Alaska Airlines	AS	8.86	41.9
American Airlines	AA	12.68	198.7
Delta Air Lines	DL	10.04	183.7
Frontier Airlines	F9	14.06	12.6
Hawaiian Airlines	HA	8.29	11.1
Jet Blue	B6	14.84	38.2
Southwest Airlines	WN	10.11	151.7
Spirit Airlines	NK	17.99	21.6
United Airlines	UA	12.52	143.2
US Airways*	US	10.83	-
Air Tran**	FL	12.725	-
Continental***	CO	13.44	-
Northwest Airlines ****	NW	11.65	-
America West*****	HP	10.68	-
ATA Airlines ******	TZ	12.12	-
Virgin America *******	VX	11.83	-

4.4 Dependent variable

Below we discuss the proxies we use in this thesis to index on-time performance.

Departure delay in minutes

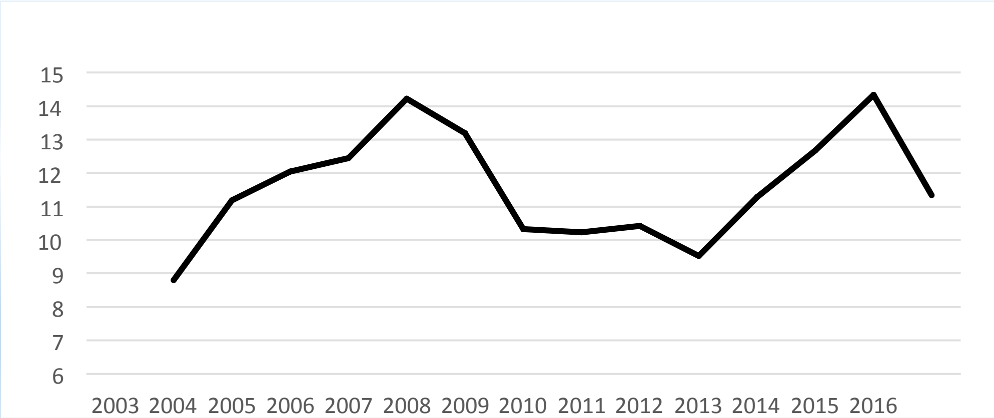
This proxy for OTP is measured by calculating the difference between actual departure time and scheduled departure time on a flight-by-flight basis. Just as for (most) other measurements for OTP mentioned below, the most critical disadvantage of using departure delays in minutes is that carriers have incentives to reduce delays on paper by adjusting schedule times, a phenomenon called 'schedule padding'. However, departure delays are generally speaking less subjected to schedule padding. Airlines namely often prefer manipulating arrival time over departure time (Rupp & Sayanak, 2008).

[16] For consistency purposes, steps; 1, 2, 3, 7 and 8 are repeated for preparing the OTP and T-100 database.

Arrival delay in minutes

The proxy arrival delay in minutes is the amount of time an aircraft arrives too late at the arrival gate. This proxy is often used in the literature for measuring OTP since it considers the type of delays were passenger truly suffer the most from.

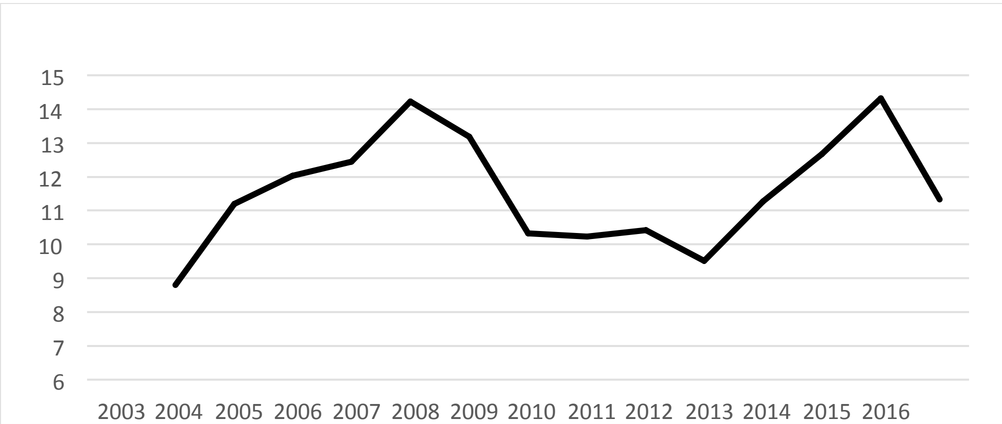
Figure 1: Average arrival delay in minutes



The proportion of nonstop flights that arrives at least 15 minutes too late

The percentage of flights that arrive more than 15 minutes later than scheduled is probably the most popular way for measuring delays in the literature. These proxies are already calculated in the on-time performance database as a binary variable which equals one when a flight arrives more than 15 minutes late[17].

Figure 2: Flights arriving more than 15 minutes delayed (in %)



[17] We also considered a 30 minutes difference between actual and scheduled arrival time since it means more from an economic perspective. However, we omitted this proxy in our analysis since this proxy represents rather extreme cases. A 30 minutes delay deviates too much from the average 11.43 minutes arrival delay.

Total travel time

Total travel time is the time elapsed from scheduled departure time till actual arrival time at the destination airport. This proxy is calculated by summing up the amount of departure delay in minutes to the total actual flight time. The advantage of using this proxy is that it is independent of the carrier's influence on scheduled arrival time and could therefore not be manipulated.

All in all, a dummy variable for arrival delays of longer than 15 minutes is used as a proxy for OTP in the main regression. This proxy is most commonly used throughout the literature and therefore interesting for this thesis for the sake of comparison. The other three above-mentioned proxies for OTP: *total travel time* and the proxies for *arrival and departure delay in minutes* are used for robustness purposes. Of these three proxies used for robustness, we mostly prefer *total travel time* since it is independent of schedule padding and therefore probably more accurate. Furthermore, we prefer 'arrival delay proxies' above 'departure delay proxies' since arrival delays measure the actual negative impact of delays on passengers.

4.5 Independent variables

This paragraph describes the proxies used to examine the (interaction) effect of the three key variables alliances, market structure and size on service quality.

4.5.1 Strategic alliances

Firstly, we explain why CSA, instead of international alliances and antitrust immunities, are used for identifying strategic alliances. Then, the problem of examining OTP-data in combination with CSA is discussed, followed by our unique approach to solve this issue.

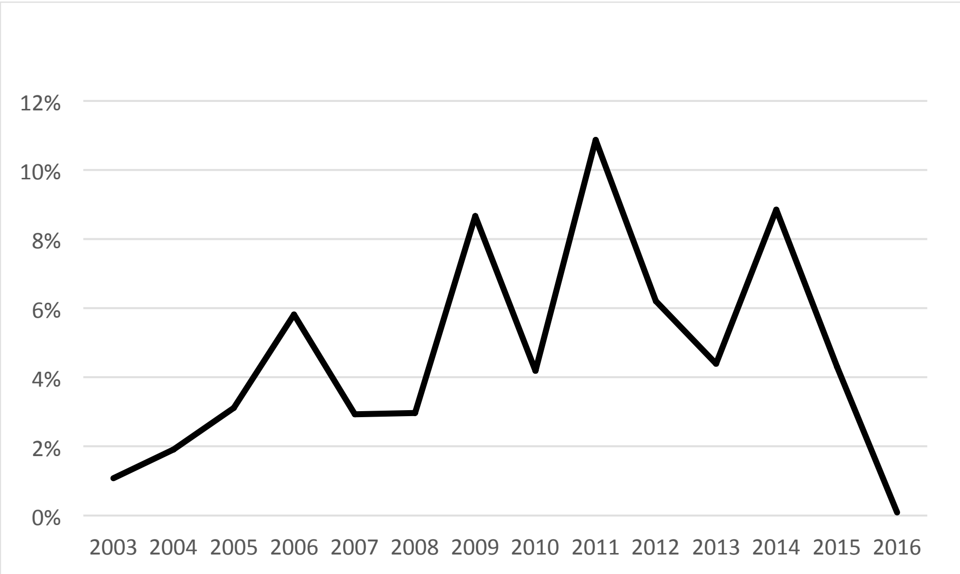
We based our choice for using CSA as an index for strategic alliances on an econometrical point of view. Airlines practice CSA in numerous markets at different times and between various carriers. This multiplicity of unique combinations improves the within variation as well as the variation between different observations. On the contrary, using international alliances as a proxy for alliances would contain much less variation across time and markets. Next, this thesis does not consider the impact of antitrust immunities (ATI) on service quality since there is much overlap between ATI and CSA. ATI are actually the same as CSA, but then with the additional privilege to set airfares cooperatively. Therefore, their effects on service quality are expected to be equal[18].

Although researching domestic CSA is beneficial from an econometrician perspective, examining virtual-CSA has one crucial limitation that needs to be taken in mind. As depicted in *figure 3*, the

[18] In contradiction to the similar effect of ATI and CSA on service quality, there exist differences between the effects of ATI and CSA concerning airfares. Brueckner (2003) examines this relationship on fares and shows that both type of alliances negatively affects fares, but that the presence of ATI impacts fares to a larger extent.

percentage of domestic flights operated by U.S. major carriers that were virtually codeshared on non-stop routed decreased to almost 0%. In 2016, U.S. carriers have apparently shifted their focus concerning non-stop routes practically completely to pure online flights. CSA on domestic non-stop routes are not considered useful anymore, as networks of airlines have increased, enabling them to offer more destinations within the U.S. by themselves. (Kieler, 2016). The shift from virtual CSA to pure online air travel products on non-stop routes weakens the practical relevance of my research somewhat, although, the results of this thesis are still interesting for airline companies. After all, the efficiency motives that could apply for non-stop routes are likely to be valid for traditional-CSA as well[19].

Figure 3: Proportion of domestic virtual codeshared flights operated by U.S. carriers on non-stop routes



The second problem of analysing CSA arises when the DB1B-dataset is matched with the OTP-database. This issue is a consequence of the fact that identifying ticketing carriers is not possible in the OTP-dataset. A codeshared route from Los Angels (LAX) to New York (JFK) can be distinguished from a non-codeshared route from LAX to JFK in the OTP-dataset. This limitation implicates that it is impossible to match a specific DB1B observation that resembles a particular codeshared market in a particular quarter with the associated observation in the OTP-dataset. The airline industry literature usually deals with this problem by using a difference-in-difference strategy[20]. This strategy compares relative changes in OTP between specific allied firms and non-alliance firms before and after those specific firms agreed to ally. Yimga (2017) for instance, analyses the airlines: Northwest, Delta and Continental with their domestic competitors before and after they

[19] See an efficiency motive that applies to virtual-CSA as well as traditional-CSA in section 3.1.

[20] See for example Yimga (2017) and Gayle (2015).

formed a codeshare alliance. The relative change between these two comparisons is in a difference-in-difference strategy identified as the effect of CSA.

Despite the difference-in-difference strategy is commonly used in the literature, we have developed a new way to identify CSA. The first reason for using another method for identifying CSA is related to the potential selection bias that could occur in a difference-in-difference strategy. Selection bias is the bias introduced by the selection of particular codeshare alliances for analysis that are not assigned randomly but deliberately chosen by researchers. If the selection bias is not taken into account, some conclusions of the study might not be accurate. The bias has then led to a research sample which would not be representative for the entire population. Fortunately, our method leads to less selection bias since we consider all large domestic airlines, see section 4.3. This brings us to our second argument in favour at our approach; we do not want to limit ourselves to only one or two codeshare alliances since we want to make use of the full sample to correctly measure the effect of firm sizes on service quality. The more codeshare alliances we include, the more accurate our estimations related to the impact of firm size on service quality will be.

Our new method is based on making a distinction between codeshared routes and non-codeshared routes. A codeshared route is determined as a route upon which at least 5% of all operating flights on a particular market in a particular quarter are defined as codeshared flights[21]. To identify codeshared routes at a particular time, a dummy variable is created which values one if more than 5% of all operated flights on a route during a particular quarter are considered as codeshared flights and zero otherwise. It is important to note that this dummy variable gives us the opportunity to explore the within variation since the dummy variable often varies over time within the same observation (see *figure 3*).

The higher the threshold is set for determining codeshared routes, the fewer markets are identified as codeshared routes. Furthermore, the average arrival delay in minutes constantly declines when higher thresholds are used. See *table 2* for more precise information and the total number of routes related to each threshold.

Table 2: OTP for codeshared and non-codeshared flights based on different thresholds.

Threshold level (%)	Number of observations (#)	Codeshared routes (in %)	Average arrival delay (in minutes)
1%	31,465	YES (17.2%)	11.37
1%	146,031	NO	11.44
5%	21,223	YES (11.9%)	11.15
5%	156,273	NO	11.44
10%	15,450	YES (8.7%)	10.89
10%	162,046	NO	11.48
15%	11,710	YES (6.6%)	10.73
15%	165,786	NO	11.48
20%	9,046	YES (5.1%)	10.56

[21] In line with the paper of Yimga (2017), we define flights as codeshared flights when the operating carrier differs from the ticketing carriers.

20%	168,450	NO	11.48
30%	7,197	YES (4.1%)	10.22
30%	170,299	NO	11.48
40%	6,657	YES (3.8%)	10.19
40%	170,839	NO	11.48
50%	6,289	YES (3.5%)	9.98
50%	171,207	NO	11.48

We keep it simple to put the threshold on 5% in all our analyses[22]. We expect that codeshared routes, based on a 5% boundary level, consist of a sufficient amount of observations and a sufficient difference in average delay between codeshared and non-codeshared routes to derive significant results. Additionally, a 5% level is chosen since it is close to the actual proportion of codeshared flights during the timespan of our research, which is 4.75 %.

4.5.2 Competition

The second key variable in our model is market structure. A commonly used proxy to control for route-level competition is the Herfindahl-Hirschman Index (HHI). This proxy is often used in the literature and is calculated by the sum of squares of an airline's proportion of the total number of flights between the origin and destination airports in a particular quarter. A value close to one indicates a monopoly market, while a value closer to zero is typical for extremely competitive markets.

$$HHI_{\text{it}} = \sum_{a=1}^{N} S_a^2$$

In the above equation, *a* reflects the airline, *i* the market and *t* the quarter period. Total number carriers operating on a specific route is denoted by N, while the market share of airline *a* is denoted by S_a.

The second proxy for market structure is created by dividing all routes in either monopoly, duopoly or competitive routes. Another frequently used method for forming categorical variables, based on market structure, is by separating all routes into three equally sized categories. In our

[22] We have taken several thresholds of codeshared flights in consideration for creating dummy variables that resemble codeshared routes. Our findings indicate that codeshared routes, based on a 1%, 5% or 10% boundary level, positively impact OTP. These results are robust for different OTP proxies and indicate that codeshared routes are associated with fewer delays. We find the opposite effect for codeshared routes based on a 40% and 50% boundary level. However, we argue that these routes probably resemble extreme circumstances. Routes with a high proportion of codeshared flights are likely correlated with concentrated markets. When the percentage of codeshared routes is high on a particular route, it is likely that those routes are dominated by the allied partners. Allied airlines could behave as monopolist on these type of markets, enabling them to enforce their market power and subsequently leading to worse OTP. In this thesis, we do not elaborate further on this topic since it is out of the scope of our research question. Finding more proof for the correct threshold would be interesting for further research though.

research, we prefer the first type of categorical variables. A change between zero and one competitors is after all experienced as more important, than a shift from for example seven to eight competitors.

The third proxy for market structure is the number of carriers that provide at least five non-stop flights at a particular route in a specific quarter. The latter restriction allows to only account for airlines that offer regular service on an origin-destination pair in a specific quarter.

This thesis makes use of the logged HHI in the main panel analysis. The other proxies are used for robustness purposes. Including the HHI instead of categorical variables for market structure enables to capture more of the heterogeneous impact of market structure. Furthermore, the choice for including HHI above the number of carriers operating a particular route is based on the benefit of HHI to give additional insights into the distribution of market share within a route.

4.5.3 Size

The third key variable of interest is firm size. Measuring firm size has been done in several ways throughout the literature. The most common proxies are mentioned below:

- The total number of routes of an airline in a particular quarter (Reeven and Pennings, 2016).
- The total number of domestic flights of a carrier in a particular quarter as a proportion of all domestic flight in the US.
- The total number of passengers of an airline in a particular quarter (Evans and Kessides, 1994); the disadvantage of this proxy is likely endogenous. The amount of passengers is similar to market demand, and market demand is on its turn related to congestion, which negatively impacts service quality.
- Available seat miles of an airline in a particular quarter; this proxy is less endogenous than the other proxies since capacity cannot change as fast as market demand. Additionally, it presents more information about the route than the first two proxies since it also tells something about the length and capacity of the planes serving the routes. For these reasons, we use available seat miles as a proxy for firm size. The first two measurements are used for robustness. We do not consider the total number of passenger in our robustness check since this proxy is probably too much related to the endogeneity concern.

4.6 Control variables

In this paragraph, we describe the variables used for confounding effects related to congestion and airport dominance.

OTP depends, among other things, on the congestion level at airports (Rupp and Sayanak, 2008). Congestion is positively related to competition since higher competition levels often mean higher traffic, and therefore, to estimate the isolated effect of competition accurately, it is necessary to control for congestion. One way to capture this effects is by controlling for hub airports[23]. Congestion often occurs at hub airports because airlines usually schedule flights at congested times at hubs. Probably the best way to control for hub airports is by making a distinction between OUT_OF_HUB and INTO_HUB. These proxies are included as a binary variable that values respectively one if a particular carrier operates from and to its hub airport. Flights to hub airports are expected to be less delayed compared to flights out of hub airports since airlines would have more incentives on this type of flights to reduce delays for connecting passengers. After all, the costs for rebooking passengers are high.

Table 3: Airlines and their hubs. Carriers and their hub airports are classified in line with the paper of Yimga (2017)[24].

Airline Code	Airline Name	Hub Airport code
AS	Alaska Airlines	SEA, PDX, LAX & PHX
G4	Allegiant air	NO HUBS
AA	American Airlines	ORD, DFW, LAX, MIA, JFK & LGA
DL	Delta Air Lines	ATL, CVG, JFK, LGA, BOS, LAX, MSP, SEA & DTW
F9	Frontier Airlines	AUS, ATL, RD, CVG, CLE, LAS, MIA, PHL, TTN & DCA
HA	Hawaiian Airlines	OGG & HNL
B6	Jet Blue	BOS, FLL, LGB, JFK & MCO
WN	Southwest Airlines	ATL, BWI, MDW, DAL, DEN, HOU, LAS, LAX OAK, MCA & PHX
NK	Spirit Airlines	ACY, ORD, DFW, DTW, FLL & LAS
UA	United Airlines	IAH, ORD, SFO, DEN, LAX, EWR & IAD
VX	Virgin America	LAX, SFO
US	US Airways	CLT, DVA, PHL & PHX
FL	Air Tran	BWI, MKE, ATL & MCO
WO	World Airways	NO HUBS
CO	Continental	EWR, CLE & IAH
NW	Northwest Airlines	DTW, MSP & MEM
HP	America West	PHX & LAS

This thesis also controls for congestion by including the flight frequency of a carrier at the destination and origin airport. A commonly used proxy for this effect is the number of departures the airline made on a particular market each quarter. The advantage of this method is that you control at the same time for economies of scope. However, since this variable is probably highly related to the proxies for firm size, another way is used to control further for congestion in this thesis: namely, the total number of *flights movements* at the origin and destination airport.

As argued above, hub airports are often more congested than other airports, leading to more delays. However, hub airports are also often concentrated airports where airlines achieve economies of scope. The variable “airport dominance” is included in our model to identify this positive impact on service quality. Airport dominance is determined by calculating the proportion of flights departing from an airport per quarter for each carrier. Subsequently, airports are classified as “dominant airports” for specific airlines during a specific quarter in the case of the airport dominance level of a particular airline is higher than 0.5.

[23] This thesis defines hubs as strategical airports where an airline’s major facilities and operations are located, and where most of its flights arrive at or depart from.

[24] We do not control for mergers during the timespan of this research for determining hub airports for specific carriers.

4.7 Summary statistics

This paragraph describes some characteristics of our dataset, such as the total number of observations, the unbalanced pattern in our panel analysis and motives for using a log-log model. Additionally, this paragraph provides tables concerning summary statistics and correlations between the variables used in the main regression.

The research sample contains data from 2003:q1 till 2016:q4 and consists of 177.496 observations. A noticeable disadvantage of this dataset is that it is unbalanced. This is not caused as a consequence of missing data but is caused by mergers. Since merged airlines proceed reporting airline data under the name of only one airline, observations of the airline that alters its unique airline code, end abruptly following a merger. Another cause for the unbalance in our dataset is the continual adaptions of airlines to its networks. An airline deciding to stop offering flights on a particular route ends after all in missing observations in the panel dataset.

Summary statistics can be found in *table 4*. All continuous variables in the model are logged. The first reason for using a log-log model is to generate variables with less skewed distributions. This is useful since the *sktest* rejects the "*H0 hypothesis: the variable is normally distributed*" for all variables[25]. The second reason for using a log-log model is for the convenience of interpreting the results in the model.

An essential condition in our model is that the within variation of the variable CSA_dummy (5%) should be large enough. Fortunately, the within variation is 0.218, almost equal to it's between variation. Indicating that the within variation is large enough to derive efficient results.

Table 4: Summary statistics for the variables used in the main regression.

Variable	Unit	Mean	S.D	Min	Max
Total travel time	Minutes	5.09	0.48	3.34	6.58
Arrival delay	Minutes	11.43	7.448	0	336
Departure delay	Minutes	10.71	7.197	0	332
Arrival delay (>15 min)	Binary	0.195	0.107	0	1
CSA (5%)	Binary	0.0870	0.282	0	1
HHI Route	Interval	0.757	0.259	0.185	1
Seat miles	Seat miles	2.193e+10	1.094e+10	1.170e+09	5.829e+10
Dominance origin airport	Interval	0.520	0.500	0	1
Dominance dest airport	Interval	0.520	0.500	0	1
Flights movements origin	Count	330,813	233,495	2,684	1.083e+06
Flights movements dest	Count	330,867	233,510	2,684	1.083e+06
Into hub	Binary	0.432	0.495	0	1
Out of hub	Binary	0.432	0.495	0	1

N = 177496, # rcid = 7,528

Although some considerable correlations exist between especially the control variables, such as between *into_hub* and *flights_movements_origin*, the validity of this study is not in danger. The variation influence factor (VIF) of all variables is always below 2, far below the rule of thumb of 10.

[25] A *sktest* is used to test if the continuous variables are normally distributed. The hypothesis that the variables are normally distributed is rejected for all variables.

Table 5: Correlation matrix for the variables used in the main regression.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	*Arrival delay (>15 min)*	1.00											
2	*CSA (5%)*	0.00	1.00										
3	*HHI Route*	-0.07	0.00	1.00									
4	*Seat miles*	-0.12	0.00	0.13	1.00								
5	CSA * HHI Route	0.00	0.94	0.10	0.00	1.00							
6	CSA * seat miles	-0.01	0.90	0.00	0.12	0.85	1.00						
7	*Flights movements origin*	0.17	0.01	-0.31	0.00	-0.02	0.02	1.00					
8	*Flights movements dest*	0.00	0.01	-0.31	0.00	-0.02	0.02	-0.21	1.00				
9	*Into hub*	0.19	-0.02	-0.03	-0.02	-0.02	-0.03	0.46	-0.25	1.00			
10	*Out of hub*	-0.09	-0.02	-0.02	-0.02	-0.02	-0.04	-0.25	0.46	-0.47	1.00		
11	*Dominance origin airport*	-0.01	-0.02	0.19	0.08	-0.01	0.00	-0.06	0.01	0.10	-0.06	1.00	
12	*Dominance dest airport*	-0.06	-0.02	0.19	0.08	-0.01	0.00	0.01	-0.06	-0.06	0.10	-0.03	1.00

4.8 Model

This paragraph describes the model used in the panel analysis and provides an overview of the advantages of using a route-carrier and carrier-year-quarter fixed effect model.

The base model used for analysis is a fixed effect model (FE). The empirical goal of this model is to determine the combined effects of the three key variables and the two moderators on OTP.

$$OTP_{tic} = \bar{\alpha} + \beta W_{tic} + \gamma X_{tic} + \delta Y_{tic} + \partial Z_{tic} + \lambda_{ic} + \upsilon_{tc} \; + \; \bar{\epsilon_{\iota}}$$

W_{tic} indexes market structure characteristics in quarter t, in market i, for carrier c, X_{tic} is a vector of dummy variables representing the presence of a CSA, Y_{tic} indexes the size of a firm, vector variable Z_{tic} includes the control variables for congestion and airport dominance.

Based on previous literature, we know that delays depend on many other factors which our model does not control for yet. Fortunately, a fixed effect model is able to deal with this appropriately. Our model controls namely for unobserved effects by including route-carrier fixed effects, indexed as λ_{ic}, and year-quarter-carrier fixed effects, indexed as υ_{tc}[26].

A route-carrier fixed effect model easily controls for unobserved constant factors over time. Controlling for route simultaneously enables to correct for the fact that carriers behave differently in various markets. Examples of unobserved route fixed effects are distance, speed and flight direction. Typical time-invariant airport-pair characteristics are landing and departing conditions, airport capacity and airport facilities

Carrier-year-quarter fixed effects are implemented by including dummy variables for each carrier at each quarter in the research sample. The first reason for using this type of fixed effect is to account

[26] A *Hausman test* is used to compare results of the fixed effects model and random effects model. The results of the *Hausman test* indicate that the estimations of the random and fixed model differ significantly from each other. This result suggests that the random effects models leads to inconsistent estimators, meaning that the fixed effect model is more appropriate to use.

for carrier-specific heterogeneity. Examples of differences between (or within) carriers over time are carriers' unique financial performances or when for instance a particular carrier suddenly starts a new strategy which impacts its OTP. The second reason why we add carrier-year-quarter fixed effects is to control for seasonal effects, such as weather and holidays. Examples of other unobserved time effects during the timespan of our research sample are the economic crisis, technological trends and fluctuations in kerosene prices. Controlling for these time fixed effects is beneficial since it mitigates the correlation between carrier-route effects that influence each observation universally.

5. Results

The following section is roughly divided into four parts. The first part presents the findings related to hypothesis 1A-1D. The second part of this paragraph describes *model 2*, in which the interaction terms are added for validating hypotheses 2 and 3. The third part describes the endogeneity issues related to the proxies used for identifying market structure. In the fourth paragraph, we show the results of our analysis for different proxies for market structure and firm size for the sake of robustness.

5.1 Model 1

Hypotheses 1A-1D are tested in five stages. First of all, three base regressions are estimated to facilitate comparison with earlier research. The first three columns of *table 6* show our findings related to respectively strategic alliances, market structure and firm size. Secondly, the key variables are added in one regression to assess whether the effect of strategic alliances on service quality stays the same when we control for market structure and firm size (*see column 4)*. The results in *column 4* should reveal whether there is empirical evidence for mutual dependence between the variables strategic alliances, market structure and firm size. Finally, in *column 5* we add our remaining control variables.

*Table 6: Impact of CSA on the probability of arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

MODEL 1	(1) Strategic Alliances	(2) Market Structure	(3) Firm Size	(4) All three key variables	(5) Including control variables
CSA_dummy5	-0.00479***			-0.00489***	-0.00524***
	(0.00137)			(0.00138)	(0.00138)
log_HHI_Route		0.00522***		0.00535***	0.00591***
		(0.00197)		(0.00197)	(0.00201)
log_seat_miles_per_carrier			1.588***	1.586***	1.519***
			(0.121)	(0.122)	(0.123)
log_flights_movements_dest					0.0247***
					(0.00827)
log_flights_movements_origin					0.0254***
					(0.00726)
dominance_origin_airport					-0.00483***
					(0.00152)
dominance_dest_airport					-0.00490***
					(0.00148)

Constant	0.158***	0.160***	-37.68***	-37.63***	-36.64***
	(0.00126)	(0.00149)	(2.895)	(2.896)	(2.909)
Observations	177,496	177,496	177,496	177,496	177,496
R-squared	0.225	0.225	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES	YES	YES
Control variables	NO	NO	NO	NO	YES

Column 1 shows the effect of codeshared routes on the probability of flights arriving more than 15 minutes late at the destination airport. The results are in line with the paper of Yimga (2017) and indicate that on codeshared routes, where at least 5% of the flights are considered as codeshared flights, fewer delays occur. More specifically, when a route is defined as a codeshared route the probability of an arrival delay of more than 15 minutes is on average lower at a 1% significance level compared to flights on non-codeshared routes, ceteris paribus. The economic mechanism that could cause the negative impact of codeshared routes on delays is probably the advantage that allied airlines have to remove problematic flights on codeshared markets (see section 3.1). Although this finding is statistically significant, we have our doubts about the economic significance of our finding. The magnitude of the effect of CSA is not very impactful. For example, when we consider its effect on arrival delays in minutes instead of a dummy variable that indicates arrival delays, an on average *exp (0.0223) =1.02* minute shorter arrival delay on codeshared routes is not really worth mentioning[27]. The problem of low, but significant magnitudes, is common in large panel datasets such as ours. Even the tiniest effects are fast recognized as statistically significant.

Column 2 presents the results of the impact of market structure on OTP. The panel regression presented in this column is similar to the one in *column 1*. The only difference is that market structure is examined instead of strategic alliances. The results in *Column 2* are in line with previous research (Mazzeo, 2003) and indicate that flights operating on more concentrated routes are significantly more likely to be delayed. These results support hypothesis 1B and are caused by the underlying economic mechanism that airlines operating in competitive markets have more incentives to offer higher quality goods.

Analysing *column 3*, we see that the size of a firm positively affects the dummy variable of arrival delays at a 1% significance level. This finding contradicts Hypothesis 1C. Airlines are apparently not able to benefit from economies of scope concerning service quality. In fact, larger airlines are associated with much higher probabilities of delays as well as longer delays. A possible clarification for this results is related to the fact that we only examine the within variation. Because we limit ourselves to the within variation, an increase in available seat miles means probably not per se an increase in resources. It means more likely an increase in utilisation rate of the resources. An increase in the utilisation rate leads subsequently probably to less available spare resources per flight. On

[27] Information for this calculation is derived from table 12.

average fewer resources per flight makes growing airlines less flexible in general and increases the probability of delays.

The fourth column in *table 6* shows almost identical results to *column 1, 2 and 3* in which the key variables are examined separately. Only the magnitudes change slightly in *column 4.* This finding is in line with hypothesis 1D and implicates that there is no mutual dependence between the three key variables. This is an important finding since it supports the causal positive effect of strategic alliances on service quality.

The fifth column is an extension of *column 4.* Our control variables are added to this model. The most important finding is that the results related to hypothesis 1A – 1D stay the same. Furthermore, *column 5* indicates a positive effect between flights movements at the origin and destination airport and the OTP dummy variable. The magnitudes are substantial and significant, implicating that airport congestion has a large influence on service quality. We also control for congestion by including dummy variables for hub airports. The first way we control for hub airports is by including dummy variables for flights arriving at hub airports and flights departing from hub airports. However, because these dummies are constant over time within the research sample, the fixed effects estimator takes out all the variance. There is nothing left for those dummies to explain. Fortunately, since these variables are only included as a control variable, it is not a problem for us that the effects do not become visible. Note that including these variables still (slightly) affect the impact of other variables used in the model. The second way we control for hub airports is by identifying *dominance airports.* Our results in *column 5* suggest that carriers on routes from or to *dominance airports* experience on average fewer delays. This result implicates that airlines gain advantages in handling flights operations on airports where they maintain a high market share. Hence, market power at airports enables carriers to reduce delays. A possible underlying mechanism for this result is that airlines have more resources available at airports where they are dominant, allowing an airline to react fast and effective when delays occur.

5.2 Model 2

The second model, reported in *table 7*, includes the interaction effect of CSA and market structure as well as the interaction effect of CSA and firm size. *Model 2* is used to identify respectively the impact of strategic alliances for different levels of competition and the impact of strategic alliances considering different firm sizes.

*Table 7: Impact of CSA on service quality for different levels of competition and different firm sizes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

MODEL 2	(1) CSA x Competition	(2) CSA x Firm Size
CSA_dummy5	-0.00210*	-0.0701
	(0.00172)	(0.0669)
log_HHI_Route	0.00491**	0.00591***

	(0.00203)	(0.00201)
log_seat_miles_per_carrier	1.520***	1.519***
	(0.123)	(0.123)
CSA5_x_log_HHI_Route	0.00843***	
	(0.00254)	
log_CSA5_x_seat_miles		0.00273
		(0.00281)
log_flights_movements_dest	0.0246***	0.0246***
	(0.00827)	(0.00827)
log_flights_movements_origin	0.0253***	0.0253***
	(0.00726)	(0.00726)
dominance_origin_airport	-0.00482***	-0.00480***
	(0.00153)	(0.00152)
dominance_dest_airport	-0.00488***	-0.00487***
	(0.00148)	(0.00148)
Constant	-36.65***	-36.64***
	(2.909)	(2.909)
Observations	177,496	177,496
R-squared	0.225	0.225
Number of rcid	7,528	7,528
Carrier-Route FE	YES	YES
Carrier-Year-Quarter FE	YES	YES

The results in *column 1* are in line with hypothesis 2 and indicate that the probability of offering higher service quality as a consequence of partnerships diminishes as *log_HHI_Route* increases. Otherwise stated, CSA are more likely to lead to fewer delays, especially on more competitive routes. When we consider for example the impact of CSA on arrival delays, our findings indicate that the overall effect of CSA on arrival delays is negative for all levels of market structure at a 1% significance level (see *table 13* in *Appendix B*). However, at levels of *HHI_Route* close to zero (an unlikely and extreme value), a 1% increase in *HHI_Route* on codeshared routes, leads to a larger decrease of arrival delays in minutes, compared to the impact of a 1% increase in *HHI_Route* at levels of *HHI_Route* close to one. A potential economic mechanism that could clarify our results related to hypothesis 2 is that CSA on more concentrated routes lead to a relatively larger increase in market power than on more competitive routes. Therefore, carriers operating on more concentrated routes have relatively fewer incentives to make use of the benefits in a CSA, such as the option to move flights which have a relatively high probability of being delayed.

The second model also includes the interaction effect of CSA and firm size. This model is used to identify the effect of codeshared routes on service quality for small firms compared to large firms. Unfortunately, the results in *column 2* are insignificant, implicating that we do not suggest that smaller airlines are more likely to benefit from a CSA compared to larger firms or vice versa.

5.3 Endogeneity issues

The simultaneous causality issue is a common problem while analysing the effect of competition on service quality. Market structure of course influences service quality, however, service quality could influence market structure as well on its turn. This paragraph shortly explains why this issue is relevant in our case and how we try to solve this problem.

The best way to explain why the endogeneity problem is relevant to consider in this thesis is probably by showing an example. Imagine an airline that acts as a monopolist in a particular market. This carrier has fewer incentives to offer high service quality and will probably even try to increase profit margins by saving on resources that could reduce delays. Hence, the monopolist is likely going to abuse its market power. Competitors will notice that the monopolist offers low service quality and will enter the monopolistic market. They know that the low service quality in the concentrated market enables them to steal more easily market share from the monopolist.

When there is not controlled for this simultaneity, the endogeneity problem results in a biased estimation of the effect of market structure on service quality (Greenfield, 2014). The causality between market structure and service quality is then overestimated. It is worth mentioning although that above-described endogeneity problem is somewhat mitigated in practice. It is namely often challenging for airlines to invest in new markets. The reason behind this is that changing an airline's network demands high investments and takes much time and effort.

We try to solve the potential endogeneity problem by estimating delays using a 2SLS estimation in which instrument variables (IV) are used to estimate the proxies for market structure. Good instrument variables should be correlated with the proxies for market structure but not with the error term. Also, the instrument variables are not allowed to be a direct cause of the dependent variable. The instrument variables we use are *pop_geo_mean, pop_geo_mean2, pop_arth_mean* and *enplanements* (see *appendix B*). These variables were first introduced by Borenstein and Rose (1994) and later on often practised in the literature (Gerardi and Shapiro, 2009; Dai et al. 2014).

*Table 8: Impact of strategic alliances, market structure and firm size on service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

MODEL 3	(1) Using IV for Market structure
CSA_dummy5	-0.00524***
	(0.00137)
log_HHI_Route	0.00591***
	(0.00203)
log_seat_miles_per_carrier	1.520***
	(0.122)
log_flights_movements_dest	0.0246***
	(0.00825)
log_flights_movements_origin	0.0253***
	(0.00724)
dominance_origin_airport	-0.00483***
	(0.00152)
dominance_dest_airport	-0.00488***
	(0.00148)
Constant	-36.65***
	(2.909)
Observations	177,496
R-squared	0.225
Number of rcid	7,528
Carrier-Route FE	YES
Carrier-Year-Quarter FE	YES

The results of our model using instrument variables, presented in *table 8,* are almost completely the same as the estimations of *model 1*. Only the magnitude changes somewhat.

Despite the little differences between the two models, and although *model 3* controls for the endogeneity issue, we strongly prefer the estimations of *model 2* for answering our hypotheses. The reason behind this is that the *Sargan Hansen Test* suggests that the instruments we use are inconsistent and invalid. Implicating that using the instrument variables lead to probably even more inconsistent results compared to the results of the fixed effect model, described in section 4.8. Note that because of this decision the endogeneity possible is not controlled for. The effect of market structure on service quality should therefore not be mistaken as a causal effect. However, we believe that our findings related to the effect of strategic alliances on service quality are not strongly biased though. We control namely step-by-step for many factors such as market structure, congestion, route-carrier fixed etc., while observing only very small changes in the coefficients. Meaning that the endogenous issue is likely to be nihil for the impact of CSA on OTP.

5.4 Robustness check

Although the variables in the main regressions are carefully chosen, we still perform some alternative analyses to check the robustness of hypothesis 1 – hypothesis 3 further. In our robustness check, we consider different measurements for OTP and different proxies for market structure and firm size.

Before we describe the results of our robustness check, note that this thesis does not include a robustness analysis by considering city pairs instead of airport pairs. The reason behind this is that our research sample contains several congestion proxies which would become useless when we define markets as routes between city pairs instead of airports pairs (Ito and Lee, 2007).

5.4.1 Hypothesis 1A

The negative effect of codeshared routes on service quality is robust at a 1% significance level for all measurements for OTP (see *table 12* in *Appendix B*).

5.4.2 Hypothesis 1B

The impact of *log_HHI_Route* on service quality looks somewhat inconclusive when we consider our results of model 1 in combination with our robustness check. Our robustness results indicate a negative relation between *log_HHI_Route* and total travel time and between *log_HHI_Route* and arrival delay in minutes, at respectively, a 1% and 10% significance level (see *table 13*). The economic mechanism that could explain the first described result, the negative relation between *log_total_travel_time* and *log_HHI_Route*, is that flights on more concentrated routes can achieve shorter total flight times since they operate on less congested routes. Although, this explanation does not seem very plausible since we control for airport dominance, flight movements at the airports and hubs in our model. A clarification of the negative relation between *log_HHI_Route* and arrival delay in minutes lacks as well. However, since this result is only significant at a 10% level, we do not elaborate this result further in this thesis.

The results presented in *table 14* also suggest that our results related to hypothesis 1B are less robust than mentioned in section 5.1.2. The robustness check indicates that *log_HHI_Route* is the only proxy that shows a significant effect between service quality and market structure.

However, since *HHI* and the dummy variable for *arrival delays of more than 15 minutes* are qualified as proper measurements for market structure and OTP in the literature, we still suggest that higher competition levels lead to higher service quality.

5.4.3 Hypothesis 1C

The robustness check concerning hypothesis 1C is in line with our findings mentioned in section 5.1. Hence, the size of a firm positively affects delays at a 1% significance level for all measurements for OTP and size in our analyses (see *tables 15* and *16*).

5.4.4 Hypothesis 1D

Compared to our earlier findings, our robustness check presented in *tables 17* and *18* show similar results when other proxies are used for finding evidence for hypothesis 1D. Thus, our robustness check strengthens our suggestions that there is no mutual dependence between the three key variables in model 1.

5.4.5 Hypothesis 2

We find some additional support for hypothesis 2 when we use other proxies for OTP and the key variables in model 2. Firstly, findings in *table 19* suggest that CSA also reduce delays to a more considerable extent for other proxies for OTP. Secondly, the robustness check presented in *table 20* shows that our first interaction effect is observable as well when the proxy *monopoly* is used instead of *log_HHI_Route* as a measurement for market structure.

5.4.6 Hypothesis 3

Tables 21 and *22* present some findings that suggest that the effect of the interaction effect between firm size and CSA is less ambiguous than mentioned in section 5.3.

The robustness results in *table 21* show that the interaction effect of CSA and firms size on actual travel time and proxies for departure delays is negative and significant at a 5% level. These findings implicate that flights operating on codeshared routes cause fewer departure delays for larger firms and contradicts thereby hypothesis 3. A possible reason why we observe that larger firms are more likely to benefit from CSA concerning service quality is associated with hypothesis 1. It can be argued that especially larger firms have the advantage of removing problematic and delayed flights from codeshared routes. The resources that become available when problematic flights are removed from an airline's network can probably become of better use for larger firms. They have more options available for switching the 'removed' aeroplane to. However, we do not want to put much weight on this underlying mechanism, and in fact on the results of table 12 in general, since the results of the interaction effects are only significant for total actual travel time and departure delays. While, as explained earlier, we prefer the proxies for arrival delays, since these proxies indicate the form of delays where passenger actually suffer from and are more commonly used throughout the literature.

We also find a significant and negative effect when we focus on other proxies for firm size (see *table 22*). However, we do put too much value on these findings as well since the endogeneity issue likely plays a role here.

6. Conclusion

As it has turned out, we find robust evidence for the positive effect of strategic alliances on service quality. Improvements in OTP are likely a consequence of the advantage that allied airlines have to remove problematic flights on codeshared markets. The impact of CSA on OTP stays the same when we take into account control variables and the potential mutual dependence between strategic alliance, market structure and firm size. This is an important finding since it supports the causal positive effect of strategic alliances on service quality. Furthermore, our findings suggest that the impact of CSA on service quality is more substantial on more competitive routes. CSA lead namely to a relatively smaller increase in market power on competitive routes compared to concentrated routes, and therefore, to a relatively less strong increase of preference for improving margins by saving costs related to service quality on more competitive routes.

From a welfare perspective, our results implicate that passengers experience fewer delays on codeshared routes, and benefit from shortened travel times when flying on a codeshared flight, especially if these routes are characterised by a high level of competitiveness. Of course, we should include other consequences of alliances in our model such as prices for a complete welfare analysis. However, based on the impact of CSA on proxies for OTP for different levels of market structure and firm size, there does not appear any reasons for competition boards to prevent U.S. airlines from engaging in domestic CSA. Therefore, we recommend competition boards not to interfere further into strategic alliances based on adverse competitive effects concerning service quality. Additionally, we recommend airline companies not to withhold assessing alliances based on the idea that it worsens OTP.

Despite our scientific contribution related to the findings for the mutual independence of the key variables and the interaction effect of market structure and strategic alliances, this thesis does not provide supportive (or contradicting) evidence for the hypothesis that smaller airlines are more likely to benefit in a CSA. A possible reason for this ambiguous result is that we, as a consequence of limitations related to the on-time performance dataset, only considered virtual-CSA. It would be interesting though to examine what the impact of traditional-CSA for different firm sizes is on service quality, especially since other underlying mechanisms would be at stake. Therefore, we hope that this thesis sufficient indicates the importance of the effect of CSA on OTP and that the U.S. DOT would add additional data, related to ticketing and operating carriers in the OTP dataset. Adding these data would enable to research the effect of traditional CSA for different firm sizes and competition levels on service quality without using a classic difference-in-difference strategy. Also, further research is needed to examine the impact of other forms of cooperation, such as international alliances, on service quality for the sake of robustness.

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8. Appendices

8.1 Appendix A: Variable description

Table 9: A-1 Main variables

Variables used in the main regressions	
Log_total_travel_time	Natural logarithm of the total time elapsed from scheduled departure time till actual arrival time at the destination airport.
Arr_del15	A dummy variable that equals one if a flight arrives more than 15 minutes later than scheduled.
Log_arr_delay_new	Natural logarithm of the amount of time (in minutes) an aircraft arrives later than scheduled.
Log_dep_delay_new	Natural logarithm of the amount of time (in minutes) an aircraft departs later than scheduled.
CSA_dummy5	A dummy variable that equals one if a route is defined as a codeshared route. Markets are marked as codeshared routes when more than 5% of all flights on a route in a particular quarter are identified as codeshared flights.
Log_HHI_Route	Natural logarithm of the sum of squares of an airline's proportion of the total number of flights between the origin and destination airports in a particular quarter. A value close to one indicates a monopoly market, while a value closer to zero is typical for competitive markets.
Log_seat_miles	Natural logarithm of the total amount of seat miles per carrier per quarter.
Log_flights_movements_dest	Natural logarithm of the total number of arrivals and departures at the destination airport per quarter.
Log_flights_movements_origin	Natural logarithm of the total number of arrivals and departures at the origin airport per quarter.
Dominance_dest_airport	A dummy variable that equals one if a particular destination airport is classified as a dominant airport for a particular airline. Airports are defined as a dominant airport for particular airlines when these particular airlines achieve a higher market share at the airport than 0.5. Market share at the airport is calculated by dividing airline's total flight movement at a particular airport in a particular quarter by total flights movement at an airport in a particular quarter.
Dominance_origin_airport	A dummy variable that equals one if a particular origin airport is classified as a dominant airport for a particular airline. Airports are defined as a dominant airport for particular airlines when these particular airlines achieve a higher market share at the airport than 0.5. Market share at the airport is calculated by dividing airline's total flight movement at a particular airport in a particular quarter by total flights movement at an airport in a particular quarter.
Into_hub	A dummy variable that equals one if a particular carrier operates to its hub airport. Hub airports are identified based on the paper of Yimga (2017).
Out_of_hub	A dummy variable that equals one if a particular carrier operates from its hub airport. Hub airports are identified based on the paper of Yimga (2017).

Table 10: A-2 Instrument variables

Variables used in the 2SLS regressions	
Log_enplanements	Natural logarithm of the enplanement instrument. This instrument is calculated by the following formula: $$\log(enplanements) = \log\frac{\sqrt{(enpl_{a1} * enpl_{a2})}}{\sum k \sqrt{enpl_{k1} * enpl_{k2}}}$$ In the above equation, *a* reflects the airline, *k* indexes all airlines and $enpl_1$ and $enpl_2$ are the quarterly enplanements at respectively the origin and destination airports.
Log_pop_geo_mean	Natural logarithm of the geometric mean of the metropolitan area population at the origin and destination airports.
Log_pop_geo_mean2	The squared natural logarithm of the geometric mean of the metropolitan area population at the origin and destination airports.
Log_pop_arth_mean	Natural logarithm of the arithmetic means of the metropolitan area population at the origin and

destination airports.

Table 11: Other proxies for the three key factors

Variables used for robustness purposes	
Nr_carriers	The number of carriers that provide at least five non-stop flights at a particular route in a specific quarter.
Monopoly	A dummy variable that equals one if only one carrier offers flights on a particular route in a specific quarter.
Duopoly	A dummy variable that equals one if only two carriers offer flights on a particular route in a specific quarter.
Competitive_route	A dummy variable that equals one if more than two carriers offer flights on a particular route in a specific quarter.
log_tot_nr_routes	The natural logarithm of the total number of routes that a particular airline offers in a particular quarter.
log_nr_flights_absolute	The natural logarithm of the total number of flights that a particular airline offers in a particular quarter.

8.2 Appendix B: Robustness results

*Table 12: Impact of CSA on several proxies of service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Hypothesis 1A	(1) log_total_actual_time	(2) log_dep_delay_new	(3) log_arr_delay_new
CSA_dummy5	-0.00321***	-0.0460***	-0.0180**
	(0.000845)	(0.00857)	(0.00752)
Constant	4.363***	-7.487***	-5.497***
	(0.113)	(0.880)	(0.853)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 13: Impact of HHI on several proxies for service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Hypothesis 1B (1)	(1) log_total_actual_time	(2) log_dep_delay_new	(3) log_arr_delay_new
log_HHI_Route	-0.00412***	-0.00997	-0.0216*
	(0.00133)	(0.0127)	(0.0118)
Constant	4.388***	-7.403***	-5.366***
	(0.113)	(0.883)	(0.858)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 14: Impact of different measurements for market structure on the probability of arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hypothesis 1B (2)	log_HHI_route	nr_carriers	monopoly duopoly log_HHI_route	monopoly duopoly nr_carriers	monopoly log_HHI_route	monopoly nr_carriers	monopoly duopoly	monopoly
monopoly			-0.00587*	0.00140	-0.00233	0.00111	0.00191	0.00149
			(0.00306)	(0.00406)	(0.00186)	(0.00170)	(0.00183)	(0.00129)
duopoly			-0.00262	0.000190			0.000462	
			(0.00165)	(0.00233)			(0.00138)	
log_HHI_Route	0.00579***		0.0103***		0.00795***			
	(0.00200)		(0.00339)		(0.00285)			
nr_carriers		-0.000779		-0.000251		-0.000358		
		(0.000814)		(0.00180)		(0.00107)		
Constant	-0.438***	-0.415***	-0.424***	-0.418***	-0.434***	-0.417***	-0.419***	- 0.416***
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)

Observations	177,496	177,496	177,496	177,496	177,496	177,496	177,496	177,496
R-squared	0.225	0.225	0.225	0.225	0.225	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528	7,528	7,528	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES	YES	YES	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES	YES

*Table 15: Impact of firm sizes on several proxies for service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Hypothesis 1C (1)	(1) log_total_actual_time	(2) log_dep_delay_new	(3) log_arr_delay_new
log_seat_miles_per_carrier	0.535***	12.10***	14.73***
	(0.0841)	(0.792)	(0.835)
Constant	-8.383***	-295.8***	-356.6***
	(1.986)	(18.79)	(19.83)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 16: Impact of different measurements for firm sizes on arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Hypothesis 1C (2)	(1) Log total number of seat miles	(2) Log total number of routes	(3) Log total number of flights
log_seat_miles	1.526***		
	(0.123)		
log_tot_nr_routes		2.438***	
		(0.196)	
log_nr_flights_absolute			4.741***
			(0.381)
Constant	-36.78***	-15.91***	-56.65***
	(2.907)	(1.236)	(4.503)
Observations	177,496	177,496	177,496
R-squared	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES
Control variables	YES	YES	YES

*Table 17: Impact of CSA, market structure and firm sizes on several proxies for service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Hypothesis 1D (1)	(1) log_total_actual_time	(2) log_dep_delay_new	(3) log_arr_delay_new
CSA_dummy5	-0.00314***	-0.0459***	-0.0176**
	(0.000845)	(0.00858)	(0.00753)
log_HHI_Route	-0.00405***	-0.00887	-0.0211*
	(0.00133)	(0.0127)	(0.0118)
log_seat_miles_per_carrier	0.540***	12.11***	14.76***
	(0.0841)	(0.792)	(0.835)
Constant	-8.474***	-296.0***	-357.0***
	(1.987)	(18.79)	(19.83)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 9: Impact of different measurements for firm sizes and CSA on the probability of arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Hypothesis 1D (2)	(1) mono	(2) mono duo	(3) mono HHI	(4) mono duo HHI	(5) log_tot_nr_routes_per_carrier	(6) log_nr_flights_absolute
CSA_dummy5	-0.00518***	-0.00520***	-0.00523***	-0.00515***	-0.00524***	-0.00524***
	(0.00137)	(0.00137)	(0.00138)	(0.00137)	(0.00138)	(0.00138)
monopoly	0.00157	0.00216	-0.00230	-0.00556*		
	(0.00129)	(0.00183)	(0.00186)	(0.00305)		

duopoly		0.000640		-0.00242		
		(0.00138)		(0.00165)		
log_seat_miles_per_carrier	1.525***	1.524***	1.519***	1.520***		
	(0.123)	(0.123)	(0.123)	(0.123)		
log_HHI_Route			0.00804***	0.0102***	0.00591***	0.00591***
			(0.00285)	(0.00338)	(0.00201)	(0.00201)
log_tot_nr_routes_per_carrier					2.426***	
					(0.196)	
log_nr_flights_absolute						4.719***
						(0.381)
Constant	-36.75***	-36.74***	-36.64***	-36.64***	-15.88***	-56.42***
	(2.908)	(2.908)	(2.909)	(2.909)	(1.237)	(4.505)
Observations	177,496	177,496	177,496	177,496	177,496	177,496
R-squared	0.225	0.225	0.225	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES	YES	YES	YES

*Table 10: Impact of CSA for different competition levels on several proxies of service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

	(1)	(2)	(3)
Hypothesis 2 (1)	log_total_actual_time	log_dep_delay_new	log_arr_delay_new
CSA_dummy5	-0.00196*	-0.0345***	-0.00224
	(0.00107)	(0.0106)	(0.00935)
log_HHI_Route	-0.00443***	-0.0125	-0.0261**
	(0.00133)	(0.0128)	(0.0120)
log_seat_miles_per_carrier	0.540***	12.11***	14.76***
	(0.0841)	(0.792)	(0.835)
CSA5_x_log_HHI_Route	0.00316**	0.0304**	0.0411***
	(0.00157)	(0.0155)	(0.0139)
Constant	-8.477***	-296.0***	-357.1***
	(1.987)	(18.79)	(19.83)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 20: Impact of different measurements of CSA for different competition levels on the probability of arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

	(1)	(2)	(3)	(4)	(5)	(6)
Hypothesis 2 (2)	mono	mono duo	mono HHI	mono duo HHI	log_tot_nr_routes_per_carrier	log_nr_flights_absolute
CSA_dummy5	-0.00924***	-0.00840***	-0.0112***	-0.0111	-0.00210	-0.00210
	(0.00163)	(0.00241)	(0.00372)	(0.00713)	(0.00172)	(0.00172)
monopoly	0.000282	0.00119	-0.00391**	-0.00678**		
	(0.00133)	(0.00186)	(0.00194)	(0.00320)		
duopoly		0.00103		-0.00215		
		(0.00141)		(0.00172)		
CSA5_x_monopoly	0.00915***	0.00829***	0.0111***	0.0110		
	(0.00203)	(0.00271)	(0.00383)	(0.00714)		
CSA5_x_duopoly		-0.00129		7.52e-05		
		(0.00259)		(0.00379)		
log_seat_miles_per_carrier	1.525***	1.524***	1.519***	1.520***		
	(0.123)	(0.123)	(0.123)	(0.123)		
log_HHI_Route			0.00855***	0.0105***	0.00491**	0.00491**
			(0.00293)	(0.00351)	(0.00203)	(0.00203)
CSA5_x_log_HHI_Route			-0.00277	-0.00274	0.00843***	0.00843***
			(0.00477)	(0.00688)	(0.00254)	(0.00254)
log_tot_nr_routes_per_carrier					2.427***	
					(0.196)	
log_nr_flights_absolute						4.720***
						(0.381)
Constant	-36.76***	-36.75***	-36.64***	-36.64***	-15.88***	-56.44***
	(2.908)	(2.908)	(2.910)	(2.909)	(1.237)	(4.505)
Observations	177,496	177,496	177,496	177,496	177,496	177,496
R-squared	0.225	0.225	0.225	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES	YES	YES	YES

*Table 21: Impact of CSA for different firm sizes on several proxies of service quality. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Hypothesis 3 (1)	(1) log_total_actual_time	(2) log_dep_delay_new	(3) log_arr_delay_new
CSA_dummy5	0.124***	1.508***	-0.0264
	(0.0377)	(0.428)	(0.379)
log_HHI_Route	-0.00405***	-0.00886	-0.0211*
	(0.00133)	(0.0127)	(0.0118)
log_seat_miles_per_carrier	0.540***	12.11***	14.76***
	(0.0841)	(0.792)	(0.835)
log_CSA5_x_seat_miles	-0.00534***	-0.0655***	0.000369
	(0.00159)	(0.0180)	(0.0159)
Constant	-8.475***	-296.0***	-357.0***
	(1.987)	(18.79)	(19.83)
Observations	177,496	177,496	177,496
R-squared	0.209	0.225	0.227
Number of rcid	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES
Control variables	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES

*Table 22: Impact of different measurements of CSA for different firm sizes on the probability of arrival delays of more than 15 minutes. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.*

Hypothesis 3 (2)	(1) mono	(2) mono duo	(3) mono HHI	(4) mono duo HHI	(5) log_tot_nr_routes_per_carrier	(6) log_nr_flights_absolute
CSA_dummy5	-0.0692	-0.0692	-0.0713	-0.0718	0.0248	0.00562*
	(0.0668)	(0.0668)	(0.0669)	(0.0668)	(0.0157)	(0.00292)
monopoly	0.00156	0.00214	-0.00232	-0.00559*		
	(0.00129)	(0.00183)	(0.00186)	(0.00305)		
duopoly		0.000639		-0.00243		
		(0.00138)		(0.00165)		
log_seat_miles_per_carrier	1.525***	1.524***	1.519***	1.520***		
	(0.123)	(0.123)	(0.123)	(0.123)		
log_CSA5_x_seat_miles	0.00270	0.00270	0.00278	0.00281		
	(0.00280)	(0.00280)	(0.00281)	(0.00281)		
	(0.00148)	(0.00148)	(0.00148)	(0.00147)	(0.00148)	(0.00148)
	(0.00297)	(0.00298)	(0.00298)	(0.00298)	(0.00298)	(0.00298)
log_HHI_Route			0.00806***	0.0102***	0.00596***	0.00610***
			(0.00285)	(0.00339)	(0.00201)	(0.00201)
log_tot_nr_routes_per_carrier					2.427***	
					(0.196)	
log_CSA5_x_tot_routes					-0.00487*	
					(0.00249)	
log_nr_flights_absolute						4.720***
						(0.381)
CSA5_x_nr_flights_absolute						-6.76e-08***
						(1.46e-08)
Constant	-36.75***	-36.74***	-36.64***	-36.64***	-15.88***	-56.44***
	(2.908)	(2.908)	(2.909)	(2.909)	(1.237)	(4.506)
Observations	177,496	177,496	177,496	177,496	177,496	177,496
R-squared	0.225	0.225	0.225	0.225	0.225	0.225
Number of rcid	7,528	7,528	7,528	7,528	7,528	7,528
Carrier-Route FE	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES
Carrier-Year-Quarter FE	YES	YES	YES	YES	YES	YES

8.3 Appendix C: Remaining tables and figures

Table 23: Metropolitan Area, Airport Code and Population for 2003 and 2016

City, state	Airport Code	Population 2003	Population 2016
New York	EWR, JFK, LGA	18671320	20153634
Los Angeles, CA	LAX, BUR, LGB, SNA	12717433	13310447
Chicago, IL	MDW, ORD	9286162	9512999
Philadelphia, PA	PHL	5787788	6070500
Dallas, TX	DAL, DFW	5582033	7233323
Miami, FL	FLL, MIA	5280671	6066387
Washington, DC	DCA, IAD	5086376	6131977
Houston, TX	HOU, IAH	5084017	6772470
Atlanta, GA	ATL	4673146	5789700
Detroit, MI	DTW	4492756	4297617
Boston, MA	BOS, PVD	4458187	4794447
Oakland, CA	OAK	4153143	4679166
San Francisco, CA	SFO, NT	4153143	4679166
Phoenix, AZ	PHX	3600163	4661537

Seattle, WA	SEA	3138938	3798902
Minneapolis, MN	MSP	3078253	3551036
San Diego, CA	SAN	2926814	3317749
St. Louis, MO	STL	2743862	2807002
Baltimore, MD	BWI	2621815	2798886
Tampa, FL	TPA	2522780	3032171
Pittsburgh, PA	PIT	2400193	2342299
Denver, CO	DEN	2297441	2853077
Cleveland, OH	CLE	2136026	2055612
Cincinnati, OH	CVG	2066256	2165139
Portland, OR	PDX	2034000	2424955
Sacramento, CA	SFM	1967052	2296418
Kansas City, KS	MCI	1912368	2104509
San Antonio, TX	SAT	1808267	2429609
Orlando, FL	MCO	1803474	2441257
San Jose, CA	SJC	1723138	1978816
Columbus, OH	CMH	1678827	2041520
Virginia Beach, VA	ORF	1631596	1726907
Indianapolis, IN	IND	1600165	2004230
Las Vegas, NV	LAS	1572924	2155664
Milwaukee, WI	MKE	1528417	1572482
Charlotte, NC	CLT	1436890	2474314
Nashville, TN	BNA	1386743	1865298
Austin, TX	AUS	1382693	2056405
New Orleans, LA	MSY	1312039	1268883
Memphis, MS	MEM	1238075	1342842
Jacksonville, FL	JAX	1194706	1478212
Louisville, KY	SDF	1190011	1283430
Hartford, CT	BDL	1173575	1206836
Buffalo, NY	BUF	1154212	1132804
Richmond, VA	RIC	1139312	1281708
Oklahoma City, OK	OKC	1131487	1373211
Birmingham, AL	BHM	1073439	1147417
Rochester, NY	ROC	1039674	1078879
Salt Lake City, UT	SLC	1016377	1186187
Tucson, AZ	TUS	903320	1016206
Raleigh-Cary, NC	RDU	889313	1302946
Hawaii, HA	KOA, LIH, OGG, HNL	888026	992605
Tulsa, OK	TUL	876919	987201
ALBANY, NY	ALB	839741	881839
Omaha, NE	OMA	790535	924129
Albuquerque, NM	ABQ	766154	909906
El Paso, TX	ELP	694672	841971
Wichita, KS	ICT	579800	644672
Colorado Springs, CO	COS	572399	712327
Boise, ID	BOI	510,787	691423
Fort Myers, FL	RSW	490,139	722336
Dayton, OH	DAY	465,989	637674
Spokane, DC	GEG	430,867	556634
Lexington, KY	LEX	426187	506751
Reno, NE	RNO	374743	457667
Anchorage, AL	ANC	339131	402557